UNIVERSITY OF LJUBLJANA

SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

BEHAVIORAL BIASES OF ESG INVESTING AND THEIR IMPACT ON STOCK MARKET: THE CASE OF EUROPEAN UNION

Ljubljana, December 2025 LIDIJA RADUSINOVIĆ

AUTHORSHIP STATEMENT

The undersigned Lidija Radusinović, a student at the University of Ljubljana, School of Economics and Business, (hereafter: UL SEB), author of this written final work of studies with the title Behavioral Biases of ESG investing and their impact on stock market: The Case of European Union, prepared in collaboration with mentor Assistant Professor, PhD Riste Ichev,

DECLARE

1. this written final work of studies to be based on the results of my own research;

2. the printed form of this written final work of studies to be identical to its electronic form;

3. the text of this written final work of studies to be language-edited and technically in adherence with the UL SEB Technical Guidelines for Written Works, which means that I cited and / or quoted works and opinions of other authors in this written final work of studies in accordance with the UL SEB Technical Guidelines for Written Works;

4. to be aware of the fact that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code of the Republic of Slovenia;

5. to be aware of the consequences a proven plagiarism charge based on the this written final work could have for my status at the UL SEB in accordance with the relevant UL SEB Rules;

6. to have obtained all the necessary permits to use the data and works of other authors which are (in written or graphical form) referred to in this written final work of studies and to have clearly marked them;

7. to have acted in accordance with ethical principles during the preparation of this written final work of studies and to have, where necessary, obtained permission of the Ethics Committee;

8. my consent to use the electronic form of this written final work of studies for the detection of content similarity with other written works, using similarity detection software that is connected with the UL SEB Study Information System;

9. to transfer to the University of Ljubljana free of charge, non-exclusively, geographically and time-wise unlimited the right of saving this written final work of studies in the electronic form, the right of its reproduction, as well as the right of making this written final work of studies available to the public on the World Wide Web via the Repository of the University of Ljubljana;

10. my consent to publication of my personal data that are included in this written final work of studies and in this declaration, when this written final work of studies is published;

11. that I have verified the authenticity of the information derived from the records using artificial intelligence tools.

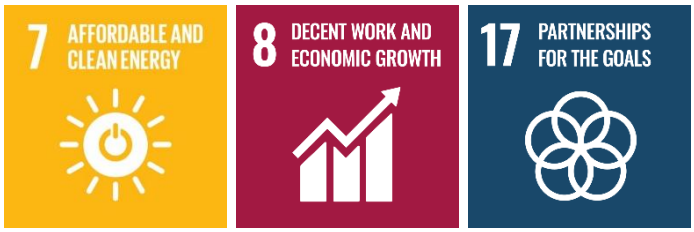
Ljubljana, December 26th, 2025 **Author's signature**: 

Abstract

This master's thesis explores ESG investing in relation to potential behavioral biases and focuses this issue on the European Union (EU) market. ESG investing is prone to various biases, such as investors' illogical behavior during decision-making and misleading information presented to them, due to inconsistent rating methodologies and greenwashing as misconduct behavior. To explore this further, research is conducted through regression analysis on 664 EU companies for the period 2018–2023. This research investigates whether the ESG score can affect total returns and market volatility. For the total returns analysis, the issue is examined through several analyses. The effect on total returns is presented through long-term predictions and the separation of the original sample into the top and bottom 10% based on the average ESG score, with the aim of investigating whether the significance of the relationship changes under these filters. In addition, the study examines whether the establishment of the EU Taxonomy in 2020 influenced investors' behavior and the stock market. The goal of the research is to provide insights into investing behavior that shapes the ESG investment field, alongside the usefulness of the ESG score as a key variable in investment decisions.

Key words: Behavioral Biases, Behavioral Finance, ESG Investing, ESG Score, EU Taxonomy, European Union, Greenwashing, Regression Analysis, Stock Returns, Volatility

SUSTAINABLE DEVELOPMENT GOALS



Povzetek

To magistrsko delo raziskuje povezavo med ESG naložbami ter morebitnimi vedenjskimi pristranskostmi in to vprašanje nanaša na trg Evropske unije (EU). ESG naložbe so nagnjene k različnim pristranskostim, kot so nelogično vedenje vlagateljev med odločanjem in zavajajoče informacije, ki so jim predstavljene, zaradi nedoslednih metodologij ocenjevanja in lažnega zelenega oglaševanja kot oblike neprimernega vedenja. Da bi to podrobneje raziskali, je bila izvedena regresijska analiza na 664 podjetjih v EU za obdobje 2018–2023. Magistrsko delo skozi več analiz raziskuje, ali lahko ESG ocena vpliva na skupne donose in nestanovitnost trga. Učinek na skupne donose je predstavljen z dolgoročnimi napovedmi in ločevanjem prvotnega vzorca na zgornjih in spodnjih 10 % na osnovi povprečne ESG ocene, da bi preverili, ali se pomembnost odnosa pod temi filtri spreminja. Poleg tega delo proučuje, ali je

vzpostavitev taksonomije EU leta 2020 vplivala na vedenje vlagateljev in delniški trg. Cilj raziskave je zagotoviti vpogled v naložbeno vedenje, ki oblikuje področje ESG naložb, ter v uporabnost ESG ocene kot ključne spremenljivke pri naložbenih odločitvah.

Ključne besede: vedenjske pristranskosti, vedenjske finance, ESG vlaganje, ESG ocena, taksonomija EU, Evropska unija, greenwashing, regresijska analiza, donosi delnic, nestanovitnost trga

CILJI TRAJNOSTNEGA RAZVOJA

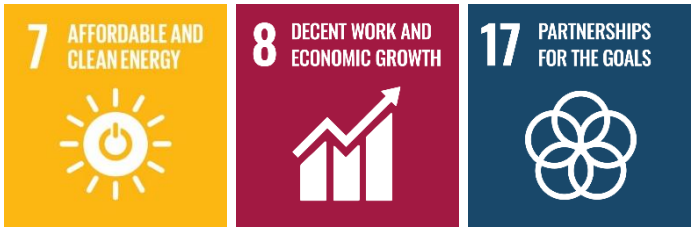


TABLE OF CONTENTS

1 INTRODUCTION 1
2 RELATED WORK 3
2.1 ESG background 3
2.2 ESG through Behavioral Finance 4
2.3 ESG ratings determination 7
2.3.1 ESG ratings and EU 8
2.3.2 ESG rating providers as bias indicators 9
2.4 Insights on greenwashing as misconduct behavior 13
2.5 Investing and trading outcomes on ESG field 15
2.5.1 ESG investing and stock returns 15
2.5.2 Investors' trust and financial literacy 16
2.6 European Union's regulations 17
2.6.1 Preceded the EU Taxonomy 17
2.6.2 EU Taxonomy Regulation 19
3 METHODOLOGY 20
3.1 General approach 20
3.2 Case description 21
3.3 Data selection and sampling 22
3.4 Getting the data 23
3.5 Methodology limitations 24
4 REGRESSION RESULTS 25
4.1 Effect of EU Taxonomy through whole model 25
4.2 ESG score effect on market volatility (VSTOXX) 31
4.3 Long-run prediction based on ESG score 33
4.4 Effect of high and low ESG companies on returns 35
4.5 Reasoning of regression results in the context of behavioral biases 41
5 CONCLUSION 43
LIST OF KEY LITERATURE 46

REFERENCE LIST **47**

LIST OF TABLES

Table 1: Overview of main ESG rating agencies 9
Table 2: Correlations of ESG ratings from CFA research 10

LIST OF FIGURES

Figure 1: Correlation plot for S&P vs. Sustainalytics 11
Figure 2: Count of companies under NAICS codes 24
Figure 3: Normal Q–Q plot for demonstrating the normality assumption 26
Figure 4: Cook's distance plot before removing significant outliers 27
Figure 5: Cook's distance plot after removing significant outliers 28
Figure 6: Spearman heatmap for correlations among model variables 29
Figure 7: Residuals vs. fitted plot for model representation 30
Figure 8: Actual vs. predicted plot for model representation 31
Figure 9: Visualization of ESG regression coefficients with 95% CI for market volatility 33
Figure 10: Residuals vs. fitted plot for representation of the long-run prediction model 34
Figure 11: Actual vs. predicted plot for representation of the long-run prediction model 35
Figure 12: Company count by NAICS code (top 10% sample) 36
Figure 13: Company count by NAICS code (bottom 10% sample) 37
Figure 14: Visualization of ESG regression coefficients with 95% CI for the top 10% sample 39
Figure 15: Visualization of ESG regression coefficients with 95% CI the bottom 10% sample 40

APPENDICES

Appendix 1: Povzetek (Summary in Slovenian) 1
Appendix 2: Attachments to Results 3

LIST OF ABBREVIATIONS

Short	Full Form
CFA	Chartered Financial Analyst designation
CSRD	Corporate Sustainability Reporting Directive
E	Environmental pillar
EEA	European Economic Area
EIKON	Refinitiv Workspace (Eikon)
ESG	Environmental, Social and Governance
ESMA	European Securities and Markets Authority
EU	European Union
G	Governance pillar
G20	Group of Twenty
GRI	Global Reporting Initiative
IFRS	International Financial Reporting Standards
ISSB	International Sustainability Standards Board
NFRD	Non-Financial Reporting Directive
OECD	Organization for Economic Co-operation and Development
ROA	Return on Assets
ROE	Return on Equity

S	Social pillar
SFDR	Sustainable Finance Disclosure Regulation
TCFD	Task Force on Climate-related Financial Disclosures
TR	Total Return

1 INTRODUCTION

Behavioral finance is a growing field which, together with psychology, tries to understand the behavior of stock market participants and the way they make decisions on the market. This discipline shows that there are numerous heuristics that people often rely on, which can lead to behavioral biases (Ackert & Deaves, 2009). This part of finance can be very useful in the investing field and presents the origin of many issues on the market. According to the analysis, biases are mirrored in the way investors think, feel, and process information, so they can be seen as a negative influence on stock performance and can lead to idiosyncratic risk (Deka et al., 2023).

In the investing field, this discipline can be particularly relevant for Environmental, Social and Governance (ESG) investing. This term arises from global concern for non-financial issues, including climate change, pollution, social welfare, and various moral and business practices (Deka et al., 2023). ESG investing has been present in the EU for more than 20 years, but in recent years it can be said that it has reached its peak (Edmans, 2023; Sipiczki, 2022).). More precisely, since the Paris Agreement was signed in December 2015, ESG has gained a more prominent role worldwide, including in investing (Talman, 2023). However, the background is not as positive as it may seem. According to an analysis by Giglio et al. (2023), investors exhibit illogical behavior regarding returns, financial performance, and ESG scores. ESG scores are numerical ratings for companies based on their environmental, social, and governance commitment. They are determined by rating agencies, but even though their goals are similar, their criteria or calculation methods differ significantly. Consequently, ESG scores often do not match, which can be considered one of the reasons for investors' inconsistent and illogical behavior (Sipiczki, 2022).

Even though ESG investing has been developing for over two decades, Giglio et al. (2023) point out that there is still not enough historical data to analyze important components for investors' evaluation. In addition, some events related to corporate behavior have appeared questionable (Lev et al., 2010). Furthermore, it is a fact that this type of sustainable activity is mainly driven by human factors, which is another reason why it can be susceptible to behavioral biases. Some of these, such as investing while expecting underperformance or investing without clear financial reasons, sometimes purely ethical, are highlighted in the analysis by Giglio et al. (2023) , and these types of biases directly inspired this research.

In recent years, one of the most discussed issues has been the green premium, or "greenium". According to the definition by Balitzky and Reiche (2023),), it refers to "pricing benefits based on the logic that investors are willing to pay extra or accept lower yields in exchange for sustainable impact". This can result in various problems, but one that attracts particular attention is greenwashing, or the deception of the public regarding

a company's sustainable objectives (Balitzky & Reiche, 2023). It can be identified through misleading information and misrepresentation of goals and investments, and in some cases it is considered a criminal offense (Vargas & Kuhn, 2023).

It is evident why this issue attracts considerable attention and why it requires regulation. Therefore, the European Commission introduced several regulations and directives to protect investors and the market. Among the most important are the Non-Financial Reporting Directive (NFRD), the Corporate Sustainability Reporting Directive (CSRD), and the Sustainable Finance Disclosure Regulation (SFDR), each addressing different aspects of sustainability reporting. The most recent regulation, in force since 2020, is Regulation (EU) 2020/852 of the European Parliament and of the Council of 18 June 2020 on the establishment of a framework to facilitate sustainable investment and amending Regulation (EU) 2019/2088, commonly known as the EU Taxonomy. It has been upgraded over the years by setting objectives aimed at providing investor protection, preventing greenwashing, and encouraging businesses to move in a more sustainable direction (European Commission, 2023; European Union, 2020).

The problem of behavioral biases is evident, and even though regulations can partly reduce information asymmetry, understanding this issue remains crucial in the investing world. Its significance is reflected in the fact that if investors are more aware of these biases, their decisions and strategies may take different directions.

It is clear that there is a connection between behavioral finance and ESG investing. Although there are significant findings in both fields, there is still room for further development. Therefore, well-structured research can contribute to this area of the economy. This master's thesis analyzes investors' behavior and its effects on the stock market and the environment through EU regulations and ESG scores, which represent the primary objectives of the master's thesis. The main hypothesis (H0) is that the introduction of EU Taxonomy regulations did not affect investors and/or the stock market. In addition, the key research questions include: 1) Does a higher or lower ESG score lead to higher or lower returns? 2) Do EU Taxonomy regulations affect the stock market and investors' behavior? 3) Can focusing solely on ESG in long-term investing lead to better results? 4) Does the ESG score affect market volatility?

The European Union case is particularly relevant for this research due to the EU Taxonomy, which regulates sustainable reporting and indirectly influences investor behavior. With the aim of exploring its impact on investors and the stock market, this research includes regression analysis. It analyzes approximately 1,000 companies over the period from 2018 to 2023, with 2020 as the key year when the EU Taxonomy was introduced.

This master's thesis contributes by providing a deeper understanding of behavior in the ESG market within the EU and offers improved insight into both fields. For a clearer

presentation of the research, besides the introduction, the master's thesis is divided into four sections. The following section presents related work, outlining the ESG background, its growing popularity, and its connection with behavioral finance. The next section addresses the stock market and behavioral biases, including greenwashing and rating inconsistency as key issues. A further subsection discusses EU regulations, including the EU Taxonomy, its significance, and objectives. The third and fourth chapters present the methodology and regression analysis results, and finally, the master's thesis concludes with a summary of the main findings.

2 RELATED WORK

2.1 ESG background

Socially responsible investing, or sustainable investing, dates back to the last century. Later, it took a more official form, named ESG, which is short for environmental, social, and governmental, implying greater responsibility in taking care of the planet. ESG, as environmental, social, and governmental standards, has been developing through the decades as one of the most important strategies for investors around the world. Even though ESG as a principle was officially introduced in 2004, the idea had been present for a longer period, dating back to the last century (Krantz, 2024).

In the 1970s, socially responsible investing (SRI) appeared as a way for investors to add value to their portfolios. This movement evolved over time and became much closer to the form of corporate social responsibility (CSR) as it is known today, and in the 1990s it started to be part of investment strategies. It is also recognized as a way to improve financial performance by focusing on ESG-related greenhouse gas emissions. Although it started as a social initiative primarily focused on human rights, with the establishment of the Global Reporting Initiative (GRI) in 1997, the movement soon broadened to include social, environmental, and governmental issues. At the beginning of the 2000s, the Carbon Disclosure Project was founded, helping to introduce ESG reporting as a practice (Krantz, 2024). It is discussed that its emergence came from the demand to capture how companies use different forms of capital and how this affects the environment (Kotsantonis & Serafeim, 2019). In 2004, "ESG" officially appeared as a term, for the first time in the report Who Cares Wins. The report presented how to include ESG factors in business operations while separating the concept into three main aspects: environmental, social, and governmental (Krantz, 2024).

By now, ESG has gained significant popularity. Edmans (2023) states that today represents a peak of ESG. Furthermore, Drei et al. (2019) note that, according to recent market changes, it is the most driving sector in the investment management industry, and in most parts of the Eurozone it has become a beta strategy. The Paris Agreement played

a key role, as the sustainability framework gained substantial attention (Martini, 2021). The Paris Agreement was signed in 2015 at the Climate Change Conference (COP21) held in Paris, resulting in a historic agreement (Stallard & Poynting, 2025). What brought the Paris Agreement into force was concern about climate change, as for the first time global warming exceeded a 1.5°C increase for an entire year. The aim of the agreement is to prevent further temperature rises and achieve net-zero emissions by 2050. According to scientific evidence, temperatures closer to 2°C compared to 1.5°C pose greater risks and significantly stronger effects on the planet (Stallard & Poynting, 2025). With shared goals, on 12 December 2015, 196 nations committed to addressing climate change and aiming for net-zero emissions. In the business world, this marked the beginning of the ESG 'movement', as companies began to focus their decisions and strategies on environmental, social, and governance issues (Talman, 2023).

By 2015, the sustainable movement had also introduced the Sustainable Development Goals (SDGs). These goals defined 17 sustainable objectives and set the global agenda for sustainable development by 2030. With the aim of improving the quality of a sustainable future, the SDGs established 169 specific targets with unique indicators to track progress. Through this initiative, ESG was no longer merely a way of thinking, but something that could and should be measured (Krantz, 2024).

However, even though it emerged with good intentions, ESG has also created confusion. It is discussed that the fragility of the ESG movement lies in its name. According to Professor Alex Edmans, the words within the term do not naturally belong together, as the environment and society are meant to serve broader societal goals, while governance focuses on generating returns. It is argued that these elements are functionally incompatible, and that the main issue arises from combining all three into a single concept (Talman, 2023). This can make practical application difficult, as a company may meet one component while violating another, or prioritize one over the others, which is often the case with environmental and governance aspects being favored over the social dimension (Glück et al., 2021; Talman, 2023). Due to the lack of a clear definition and action plan, ESG has become a term that represents different meanings to different stakeholders. In the business world, corporations use ESG descriptors for a wide range of decisions, providing opportunities to enhance their stock prices. At the same time, this has led to overuse, or the 'weaponization' of the term, which has reduced its usefulness and overall meaning (Talman, 2023).

2.2 ESG through Behavioral Finance

ESG investing is a relatively new research field that has emerged in response to global concerns. Environmental aspects relate to ensuring minimal environmental damage and addressing climate change, while social aspects focus on corporate actions related to

social well-being, and governance addresses corporate structure and business regulation (Deka et al., 2023).

Although ESG encompasses many concerns, climate change appears to be among the most important. However, despite climate change being a critical issue, there is a strong need to promote ESG awareness, which the United Nations (UN) address through the Sustainable Development Goals, including key aspects and regulations aimed at ESG responsiveness (Beerbaum & Puaschunder, 2019; Deka et al., 2023).

Due to its benefits, ESG has quickly become an important part of the present and aims to remain relevant in the future. With this in mind, investors and their behavior represent an important topic of study. Consequently, behavioral finance has become a significant direction within finance, as it represents the application of psychology to financial behavior. In the financial world, practitioners are prone to committing significant errors (Deka et al., 2023; Shefrin, 2002). Behavioral finance helps them recognize the mistakes of others, as well as their own. Incorporating behavioral finance into decision-making can provide a better understanding of the entire process, offering more realistic and valuable insights (Beerbaum & Puaschunder, 2019). It is important to be aware of investing issues, as one investor's mistakes can be profitable for another. Conversely, an investor's mistake can also represent a risk for someone else. For this reason, awareness among practitioners such as managers, investors, analysts, and others is crucial for more effective market trading (Shefrin, 2002).

There is still no standardized ESG model for investment activities, but investors' actions clearly indicate growing ESG awareness, as they increasingly include environmental and social aspects in their decision-making processes. Increased awareness has brought investor behavioral biases to the forefront, which have quickly become an important characteristic of investment decisions. These biases can also be viewed as a threat to investing, as behavioral science indicates that various biases shape investors' decisions and their risk assessments (Deka et al., 2023). Some findings suggest that hope and fear are among the strongest drivers of risk-taking behavior (Shefrin, 2002). In addition, numerous studies show that investors frequently deviate from rational decision-making. This occurs because behavioral biases reflect how investors absorb information, feel, and think, allowing decisions to easily depart from rationality. Biases can be identified through preset agendas, also referred to as "choice structures". This represents the act of making judgments by organizing available but limited information relevant to decisions, usually accompanied by a restricted ability to consider alternative choices. Essentially, this can be understood as a distortion of judgment that departs from expected utility and probability, often by ignoring important aspects or considering irrelevant data as contributory (Deka et al., 2023).

Such cognitive features influence risk perception, and when assessing various risks, investors tend to incorrectly weigh or incorporate information into the trading and

decision-making process. This tendency to prejudge forms a significant part of the 'choice structure' and is identified as a behavioral bias. A common term for such features is heuristics, meaning that the process of developing and selectively including information can lead to further mistakes and affect market efficiency, which relies on accurate valuation of information (Taleb et al., 2020). According to behavioral finance, some of the core biases identified by Ackert and Deaves (2009) and Siegel (2022) that dominate investors' decisions are described below.

Availability bias occurs when occasional events are overestimated, and investors retain them in memory while making decisions. This means investors rely on perceived availability, which leads to misjudging and focusing on incorrect risks.

Herding bias represents investors' tendency to blindly follow their social groups, family members, or brokers. In other words, they uncritically follow others in their environment and make group-based decisions regarding potential future investments and profits. These investors are often those who lack investment knowledge and rely heavily on others' advice.

With regret aversion, investors aim to avoid the regret resulting from poor decisions. Since investors generally care about profits and gains, negative investment outcomes may lead them to save money or withdraw instead of continuing to invest for potential future benefits. This behavior can also arise among risk-seeking investors who take higher risks while expecting positive outcomes. Conversely, loss-averse and risk-averse investors avoid such situations and turn toward seemingly safer decisions.

Gambler's fallacy bias is conceptually associated with gambling, reflecting the belief that a future event is more likely to occur based on past outcomes. For example, in gambling, a player may believe that rolling a six is more likely if previous rolls produced low numbers. Similarly, investors assess investment probabilities by relying on similar past events.

Overconfidence is one of the most prevalent biases in investors' decision-making. It often arises from an exaggerated sense of confidence based on skills, experience, or abilities. This bias commonly leads to the overestimation or neglect of information, particularly when it originates from unfamiliar sources.

Anchoring reflects investors' tendency to rely heavily on initial information or advice and use it as an 'anchor'. This bias is particularly strong, as it is difficult to overcome even when individuals are aware of its presence. A related bias is representativeness, through which a selected characteristic guides subsequent judgment or decision-making.

As ESG has gained popularity, sustainable information has become more accessible to investors. In decision-making, investors consider a company's ESG characteristics as important information, which helps them assess risks related to their investment

decisions. However, as noted earlier, risk perception is influenced by investors' emotions, and each investor may frame risks according to personal perception. This shapes how different events are experienced and is further influenced by individual beliefs and judgments. Consequently, no two investors share identical risk perceptions, which significantly influences their decisions and risk assessments (Deka et al., 2023).

2.3 ESG ratings determination

When discussing data and ESG, it is important to address issues related to ESG ratings. According to research by Sipiczki (2022), ESG rating agencies use a wide variety of definitions for ESG aspects. As a result, there are numerous sets of different and inconsistent indicators across the ESG market, which makes ESG scores difficult to compare and can potentially lead to misleading results (Zehir & Aybars, 2020). The data included in the scoring process need to be of high quality and reliable; however, in practice this is often not the case, as these characteristics are questionable. One possible reason for this is that the data originates from different sources, such as companies' voluntary disclosures and other unstandardized, self-reported information. Furthermore, Sipiczki (2022) that highlights that significant discrepancies appear between ratings from different agencies for the same company, mainly because ESG researchers use different methods to address missing data in the rating process. Consequently, this worsens the overall rating process, reduces its usefulness, and negatively affects investors' decision-making. Therefore, ESG rating agencies require stronger regulation and legislative initiatives.

According to the European Commission, ESG rating agencies operate with insufficient regulation and represent a "black hole" in the system (European Commission, 2023). The EU report points out that market participants seek improvements in the ESG rating market, as reliance on current ratings can increase the risk of greenwashing for users. Greenwashing, or greenium, as defined by ESMA in the paper by Balitzky and Reiche (2023), refers to a "pricing benefit in which investors are willing to pay extra for green bonds compared to conventional debt, consequently leading to financial stability concerns". Their paper identifies the drivers of the greenium and shows its dependence on credibility. This is reflected in both the bond and the issuer, meaning that the credibility of a bond depends on whether it is externally reviewed or issued by a company operating in the green sector. The findings also show that the greenium is statistically significant, indicating that increasing climate concerns drive investors' demand for sustainable assets. Additionally, similar findings demonstrate a strong dependence of the greenium on issuers' characteristics and the reliability of the instrument. This means that externally verified instruments exhibit a higher level of greenium compared to non-verified ones (Balitzky & Reiche, 2023).

2.3.1 ESG ratings and EU

As demand for sustainable bonds has expanded in recent years, the greenium has also increased. In response, the European Union has established global standards with the aim of achieving its defined goals. The European Commission has pointed out that, to meet the EU's 2030 climate and energy targets, an additional EUR 480 billion in annual investment is required. The European Commission's action plans for financing sustainable strategies and growth emphasize that the private sector can play a significant role in this green transition. This approach also aims to ensure financial stability by incorporating ESG components into financial risk management practices (Sipiczki, 2022).

In this context, investors can be a significant factor by exerting pressure on companies to improve their corporate sustainability behavior, primarily by selecting assets with high ESG scores for their portfolios and excluding those with critical profiles. To do so, investors need high-quality data on the sustainability performance of portfolio companies, and they therefore rely on ratings and reports provided by ESG rating agencies. As these ratings guide investors' decisions, their importance has increased significantly in recent years (Sipiczki, 2022). On the other hand, the lack of high-quality ESG data and the sensitivity of rating processes, also highlighted by IOSCO (2021) respondents, emphasize the need for ESG regulations, disclosures, and common reporting standards aimed at improving and enabling effective sustainable investing. The sensitivity of rating processes refers to the subjectivity and unreliability of ESG data, which can result in incomplete and potentially inaccurate ratings. One point raised by Sipiczki (2022) is that the ESG investment market can be viewed as a "dangerous placebo", as ESG bonds tend to have higher fees, giving financial institutions incentives to promote them due to higher profitability.

As greenwashing spreads through misleading information and various scandals, the International Monetary Fund (IMF) and the Organization for Economic Co-operation and Development (OECD) have urged the introduction of regulations to protect investors from such practices. The EU has taken measures to regulate the sustainable sector, although the results are yet to be fully observed, as it has been argued that these measures do not offer substantial immediate benefits (Sipiczki, 2022).

The EU plays an important role in investor protection through its legislative initiatives. The Non-Financial Reporting Directive (NFRD) applied reporting requirements only to large companies with more than 500 employees. With the aim of expanding these reporting rules, the new Corporate Sustainability Reporting Directive (CSRD) removed the threshold of more than 500 employees, regardless of whether companies are listed, and also includes small and medium-sized enterprises. As a result, the number of companies required to comply with reporting requirements increased from approximately 11,000 under the NFRD to nearly 50,000 under the CSRD. Despite being a strong

directive, concerns remain regarding the quality of sustainable data and ratings provided by third-party providers. A major challenge is the low correlation among ratings issued by different agencies, which can contribute to biases such as greenwashing and weaken investor protection (Sipiczki, 2022).

2.3.2 ESG rating providers as bias indicators

Over the past decade, the number of ESG standards, data providers, and indices has expanded, currently exceeding 600 ESG ratings worldwide. Although rating agencies pursue similar goals, their methodologies are inconsistent and often present different narratives regarding companies' sustainability performance. Table 1 presents some of the largest ESG rating agencies and illustrates these differences (Sipiczki, 2022).

Table 1: Overview of main ESG rating agencies

ESG rating agency	Description	Rating
MSCI ESG Research Rating	Assigns firms ESG scores calculated by aggregating the weighted average of key issue scores.	Rating system ranges from best (AAA) to worst (CCC).
S&P Global ESG Rank	Yields a total sustainability percentile rating derived from the total sustainability score and based on the S&P Global ESG Rank.	Offers a percentile score with 1 being the worst and 100 being the best.
Sustainalytics Industry Rank	Provides a percentile rating to companies based on their ESG total score relative to their industry peers. Aggregate ESG performance encompasses a firm's level of preparedness, disclosure, and controversy involvement across all three ESG themes.	Offers a percentile rating with 1 being the worst and 100 the best.
Carbon Disclosure Project (CDP) Score	Reflects a company's degree of commitment to climate change mitigation, adaptation, and transparency. Only firms that respond on time to an investor-requested questionnaire are rated.	CDP climate scores range from 0 (failure) to 8 (A).
Institutional Shareholder Services (ISS) Governance Score	Assesses a company's governance practices.	ISS scores range from 1 (best) to 10 (worst).

Bloomberg ESG Disclosure Score	A proprietary rating derived from the extent of a company's ESG disclosure.	ESG disclosure scores range from 0 (no information provided) to 100 (all possible information provided).

Source: Sipiczki (2022).

There is still no regulatory definition of ESG, nor standardization and transparency regarding ESG rating criteria, which explains the existence of numerous definitions of these aspects. In addition, there is significant disagreement among ratings that individual companies receive from different agencies. Berg et al. (2022) identified three main sources of rating disagreement. The first relates to scope, as rating agencies consider different sets of attributes. When one agency includes factors that another excludes, the resulting ratings diverge. The second source is measurement divergence, as agencies may assess the same attribute using different indicators. The third source is weight divergence, which arises from differing views on the relative importance of attributes. These disagreements are problematic, as they can introduce uncertainty into investors' decisions, potentially lead to underinvestment, and distort research findings (Berg et al., 2022).

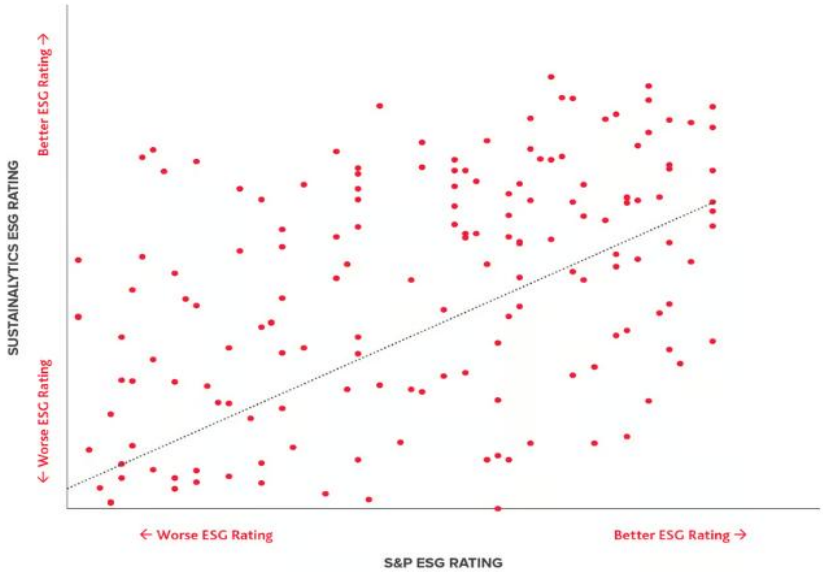
Further literature argues that inconsistency among ESG ratings limits the effectiveness of the information used to evaluate companies' resilience and performance, which is the primary purpose of ESG ratings (Berg et al., 2022; Sipiczki, 2022). In research conducted by the Chartered Financial Analyst (CFA) Institute, this issue is illustrated through correlation percentages and correlation plots, where divergence is clearly visible. Table 2presents an analysis of correlations among numerous rating agencies, showing that correlations can be as low as 7% (Prall, 2021).

Table 2: Correlations of ESG ratings from CFA research

	MSCI	**S&P**	**Sustainalytics**	**CDP**	**ISS**	**Bloomberg**
MSCI	—	0,357	0,351	0,163	0,330	0,374
S&P	0,357	—	0,645	0,350	0,139	0,744
Sustainalytics	0,351	0,645	—	0,293	0,217	0,584
CDP	0,163	0,350	0,293	—	0,070	0,441
ISS	0,330	0,139	0,217	0,070	—	0,213
Bloomberg	0,374	0,744	0,584	0,441	0,213	—

Source: Prall (2021).

Figure 1: Correlation plot for S&P vs. Sustainalytics



Source: Prall (2021).

The situation in Figure 1 is far from ideal. For the results to appear more satisfactory, the dots would need to be very close to the diagonal line. Instead, they are widely dispersed and represent significant disagreement between the two agencies. In fact, the plot clearly shows that while one agency assigns a high score, the other assigns a low score, revealing the point at which differences in their methodologies become evident.

When it comes to data agencies used for rating determination, they also face challenges related to companies' ESG data reporting. According to several findings, ESG data can be inconsistent, which can significantly affect ratings. In the study by Kotsantonis and Serafeim (2019), which examined 50 large companies from the Fortune 500 across various sectors, the authors identified 20 different ways of reporting Employee Health and Safety data, using different terminology and units of measurement. At this level, it becomes difficult to compare companies or determine a leading company within that category. Consequently, this creates confusion in describing company performance and makes the decision-making process more difficult (Kotsantonis & Serafeim, 2019).

One of the main criticisms of ESG ratings relates to the questionable sources, quality, and reliability of the data used. Most of the information used for ESG scores comes from companies' voluntary disclosures, which are largely unaudited. Research indicates that audited sustainability reports include more environmental information than unaudited reports, which often contain data omissions and inaccurate figures. In response, EU regulations such as the CSRD are emerging to harmonize companies' sustainability disclosures (Sipiczki, 2022).

Numerous greenwashing scandals in the corporate ESG environment have raised questions about the accountability mechanisms investors use to integrate ESG factors into the investment process. These issues are often described as moral hazard, which arises when companies, investors, or other entities use the "green" label without being properly held accountable for their ESG claims. According to Berg et al. (2022), misleading practices also occur when company management optimizes one part of the rating while underperforming in other important ESG areas. In this way, management may achieve targets without significantly improving overall ESG performance. Since the costs of verifying ESG compliance are high, this creates fertile ground for greenwashing. Additionally, as ESG agencies are paid for their services, potential conflicts of interest are considered substantial (Sipiczki, 2022).

The most common biases observed in the ESG rating process are company size bias, geographical bias, and industry bias. Company size bias refers to larger companies receiving higher scores than small and medium-sized enterprises, despite similar levels of compliance with sustainability factors. One reason for this is that larger companies have better access to resources and know-how related to sustainable practices. Geographical bias, which relates to companies' locations, shows a tendency to favor firms operating within the EU. This is mainly due to the higher quality and availability of data resulting from mandatory reporting standards. As a result, companies operating in the EU are often awarded higher ESG scores compared to peers without such requirements. Industry bias does not involve awarding higher scores but rather assumes that companies within the same industry share similar business models and are exposed to comparable ESG risks. This highlights the importance of individualized weighting, as failure to do so can lead to biased and misleading scores for investors (Sipiczki, 2022).

As noted, the importance of ESG ratings is increasing, yet supervision over them remains insufficient. One study identified several imperfections in the ESG ratings market, including issues related to transparency, timelines, and low correlation among ratings used by market participants. It also highlighted the high number of indicators employed by different rating providers and the lack of clear terminology, which complicates the comparability of ratings across the industry (Sipiczki, 2022). To address these issues, the European Securities and Markets Authority (ESMA) has advised the European Commission to introduce a regulatory framework that aligns the growing demand for ESG rating products with quality requirements. ESMA suggests three main steps: developing a common legal definition of ESG ratings that encompasses a broad range of assessment tools; requiring all legal entities providing ESG rating services to be registered and supervised by a public authority; and establishing product-specific requirements based on high-quality, transparent, timely, and reliable data sources. Implementing these measures would increase the likelihood that investors operate under the same minimum level of safeguards.

Additionally, to enhance investor protection in sustainable investing, the EU should propose initiatives aimed at strengthening sustainable financial knowledge among the European population, enabling individuals to better evaluate and make investment decisions. Furthermore, sustainable finance regulations should be understandable and accessible to non-professional investors (Balitzky & Reiche, 2023; Sipiczki, 2022).

2.4 Insights on greenwashing as misconduct behavior

In recent years, the market size of sustainable debt issued in the European Economic Area (EEA) has increased. This growth has been reflected in the expanding supply of sustainable debt instruments offered to investors, but it has also raised concerning questions about the credibility of sustainability claims (Balitzky & Reiche, 2023).

In this context, the term greenium has emerged, which, according to the definition of the United Nations Development Program cited in Balitzky and Reiche (2023) is "Pricing, refers to "pricing benefits based on the logic that investors are willing to pay extra or accept lower yields in exchange for sustainable impact". This means that investors are willing to accept lower yields on sustainable debt instruments, at equal or higher prices, compared to conventional debt counterparts. Even if investors' sustainability preferences can justify pricing differences, a systematic greenium may signal price distortions in the market. This concern is important because it can increase financial stability risks, which may manifest as high price volatility or reduced liquidity in sustainable bond markets, ultimately affecting investor protection (Balitzky & Reiche, 2023).

Greenium has been the subject of numerous studies because it raises questions about why sustainable instruments are priced higher than conventional equivalents, despite carrying similar risks for investors. Some studies provide different explanations for this pricing premium. One explanation highlights "impact-focused investors", who tend to hold debt instruments until maturity, thereby reducing trading activity and contributing to greater price stability. Another explanation suggests that the pricing premium arises from investors' confidence in sustainable instruments, which may stem from lower perceived risk associated with sustainability-related products (Balitzky & Reiche, 2023).

Additionally, price divergence between sustainable and conventional debt instruments raises several concerns. First, the market may already price in existing climate risks, making sustainable instruments more expensive as they are viewed as protection against those risks. Second, higher prices for green bonds may result from strong demand driven by the preferences of non-traditional investors. Third, price divergence may arise from greenwashing practices, particularly in cases where issuers mislead the public about the objectives and characteristics of sustainable bonds. All of these issues warrant careful consideration, as pricing divergence can affect the stability of the bond market (Balitzky & Reiche, 2023).

Vargas and Kuhn (2023) describe greenwashing as a divergence between words and actions. To illustrate this concept, they present one of the major greenwashing scandals involving Deutsche Bank's remuneration system. Specifically, ESG targets were linked to bonuses, after which false sustainability achievements were reported, leading to increased bonuses. Such misconduct represents misleading behavior, and greenwashing can therefore be understood as a form of bias within the sustainable finance field.

According to stakeholder theory, companies need to balance the sustainable interests of stakeholders to generate long-term benefits, and empirical evidence suggests that the adoption of ESG practices can also improve firm performance (Sahut & Pasquini-Descomps, 2015; Treepongkaruna et al., 2024). Heath et al. (2023) found that even when companies implement sustainable practices, they may still overstate ESG data, thereby undermining potential long-term benefits. Treepongkaruna et al. (2024) present research based on a survey of greenhouse gas emissions from 431 EU firms, confirming the importance of stakeholder involvement. Their findings show that external stakeholder pressure significantly affects greenhouse gas emissions, which in turn influences corporate decision-making and carbon disclosure practices. A related theoretical framework is legitimacy theory, which suggests that activities perceived as acceptable and desirable are those aligned with socially accepted norms and values. In this context, carbon emission reduction can be viewed as beneficial for a company's sustainable development. The study further documents a significant decline in firm value for every additional thousand metric tons of carbon emissions, amounting to approximately a USD 212,000 decrease. Moreover, the same research finds that firms publicly reporting carbon emissions data have an average market value around 2.3 billion dollars higher than firms that do not. These findings indicate that carbon emissions and transparency are economically relevant, as markets penalize both high emissions and non-disclosure of environmentally significant data (Treepongkaruna et al., 2024).

As noted in the literature, higher ESG ratings are expected to lead to changes in carbon emissions, suggesting a disciplinary effect of such ratings. However, other studies report a negative correlation between ESG ratings and carbon emissions, which is suspected to result from greenwashing. Furthermore, symbolic or selective ESG reporting may reduce transparency by presenting data in a more favorable manner to justify corporate decisions. In such cases, ESG reporting may not result in meaningful carbon mitigation (Treepongkaruna et al., 2024).

In addition to reviewing existing research, the authors present their own empirical study. They examine global carbon-emitting companies over the period from 2005 to 2018 and report notable findings. According to their analysis, companies with high scores in the environmental pillar of ESG increase carbon emissions by approximately 0.005%. In other words, firms with higher environmental scores appear to emit more carbon dioxide, whereas firms with lower environmental scores reduce emissions. Furthermore, the

results indicate that overall ESG scores have little effect on carbon mitigation (Treepongkaruna et al., 2024).

2.5 Investing and trading outcomes on ESG field

2.5.1 ESG investing and stock returns

The ESG phenomenon has been investigated and discussed in numerous studies. Although it is a growing field Giglio et al. (2023), the reasons behind investors' engagement are still not fully understood. In addition, ESG investing has not been present in the market for a long time and remains relatively new to investors. Due to its shorter history, there are limited events from which investors can learn and evaluate performance. Further research by Giglio et al. (2023) confirms that investors often exhibit illogical behavior in ESG investing, particularly regarding financial performance, returns, and ESG scores. Their study presents various motives for investing, showing that approximately 45% of surveyed investors report having no specific reason for investing. The remaining investors are divided among those who believe in excess ESG returns, climate risk hedging, financial performance, and ethical motivations (Giglio et al., 2023). Based on these motives, investors can be classified into three groups: financially oriented investors, investors with mixed objectives, and investors with altruistic motivations (Deka et al., 2023). Giglio et al. (2023) indicate that investors motivated by excess returns expect, on average, to outperform the market by approximately 1.4% per year. In contrast, those investing for ethical reasons, hedging purposes, or without a clear motive expect, on average, to underperform the market by approximately 0.4% to more than 2% per year. Regarding ethical motivations, Drei et al. (2019) highlight that ethical perceptions differ among investors, although they share a common vision of improving the world, which may explain why they do not expect financial benefits. Nevertheless, despite differing beliefs, the strongest motivation across all groups remains financial returns, which ultimately determine participation in sustainable investments (Deka et al., 2023; Giglio et al., 2023).

Numerous studies examine the relationship between ESG scores and stock returns, yet no consensus has been reached. However, an interesting observation based on evidence from the United States suggests that improvements in ESG scores are not strongly associated with higher stock returns, whereas declines in ESG scores have a negative impact on stock returns (Yin et al., 2023). Furthermore, Yin et al. (2023), in their study of Chinese listed companies, report notable regional differences in the relationship between ESG performance and stock returns. They find that this relationship is statistically significant in the eastern region of China, while no significant relationship is observed in non-eastern regions. The authors attribute this disparity to differences in economic development and financial environments, as the eastern region hosts a larger number of listed companies, many of which are oriented toward technology and innovation (Yin et al., 2023).

The above-mentioned findings may help explain the inconsistent results reported in the literature examining the relationship between ESG performance and stock returns. As this topic encompasses multiple dimensions, it is also addressed in the present analysis.

2.5.2 Investors' trust and financial literacy

According to Gurun and Booth (2024), trust plays a significant role in market participation and pricing. They emphasize that trust impacts the economy by extending interactions, or more precisely, by stimulating investment. One of their findings shows that individuals with low levels of trust are less likely to participate in the stock market. This directly demonstrates the importance of trust in financial markets. Moreover, their study shows that trust among financial professionals declined between 1976 and 2016. They further examine firms involved in corporate misconduct and find that such firms lose approximately 92.7 billion dollars in market value per year. Additionally, they observe significant capital outflows from these companies, highlighting the importance of management initiatives in restoring trust (Gurun & Booth, 2024).

Studies suggest that a lack of investment knowledge leads to investment biases. Empirical evidence shows that individuals with less knowledge and experience are more prone to overconfidence. In addition, they tend to sell assets that are increasing in value while holding onto those with declining value. This behavior is known as the disposition effect bias. Considering the potential risks associated with such biases, it is crucial to educate investors, alongside regulatory measures, to help mitigate the impact of investment mistakes. Evidence also indicates that the financial advisory industry grew by 57 dollars in 2019 due to increased investment demand. This finding is accompanied by observations that financial advice can help investors achieve better portfolio diversification. However, further analysis of 1.2 million financial advisers shows that between 2005 and 2015 there was a significantly high number of advisers engaged in misconduct (Gurun & Booth, 2024).

Following this finding, it is assumed that misconduct behavior can be contagious, meaning that investors are more likely to engage in financial misconduct if they are professionally surrounded by individuals with a history of such behavior. It is noted that much misconduct stems from conflicts of interest between advisers and investors, where advisers tend to prioritize their own benefits. Studies suggest that financial advice is not always beneficial to investors, as it can be of low quality or misleading. One related observation indicates that a major reason for misguided advice is the lack of customization to investors' characteristics, such as age and risk aversion. Such practices cost investors, on average, approximately 2.5% of asset value per year. This can further expose firms to the risk of losses and regulatory sanctions. Additionally, studies find that incidents of misconduct increase during stock market downturns, as advisers face losses

and may resort to unethical practices to compensate for underperformance (Gurun & Booth, 2024).

As noted earlier, regulation is necessary to ensure compliance with advisory standards. Furthermore, it is important to recognize that once investors lose trust, they may withdraw their investments. Financial knowledge is essential for understanding investment advice, enabling investors to ask relevant questions, evaluate responses, and identify trustworthy advisers (Gurun & Booth, 2024). According to Weixiang et al. (2022), investors with low levels of financial literacy are more prone to irrational behavior and biases, which can lead to market distortions. According to Gurun and Booth (2024), the most financially literate countries in the EU are Norway, Sweden, and Denmark. However, research by the European Union (2023) indicates that only 18% of the EU adult population has a high level of financial literacy, further emphasizing the importance of this topic.

2.6 European Union's regulations

2.6.1 Preceded the EU Taxonomy

The European Union is one of the leaders in global sustainable finance regulation. A more comprehensive approach began in 2018 with the EU Action Plan. Initially, the Non-Financial Reporting Directive (NFRD) required large companies with more than 500 employees to disclose non-financial statements as part of their annual reporting obligations. Due to its limited impact, the European Parliament and the Council proposed the Corporate Sustainability Reporting Directive (CSRD), which expanded the scope to include a larger number of organizations, while excluding small and medium-sized enterprises. The CSRD aims to provide a comprehensive reporting framework and ensure consistency with the Sustainable Finance Disclosure Regulation (SFDR). The SFDR is considered a mandatory ESG disclosure obligation for market participants, introduced to improve transparency in the sustainable finance market and prevent greenwashing. One of its key features is the requirement for investors to disclose how environmental, social, and governance factors are integrated at both organizational and business levels. Through the SFDR classification of funds based on their level of contribution to sustainability, the regulation is expected to enhance transparency in sustainable investment decision-making (Degimbe & Desmet, 2022).

An important observation regarding transparency is that it cannot be linked solely to sustainability-related standards. According to Armstrong et al. (2010), the introduction of International Financial Reporting Standards (IFRS) also contributed to increased transparency, particularly among firms with previously low-quality data. However, in the context of sustainability, although numerous mandatory reporting standards exist, there is still no unified standard guiding how investors should identify and apply sustainability-related information in their decision-making. Consequently, several organizations have

expressed willingness to develop a universal reporting system for environmental data. The goal is to simplify the process for the investment community in assessing and reporting sustainable information (Degimbe & Desmet, 2022).

According to Degimbe and Desmet (2022), several standards contributed to the development of this unified reporting framework. The Task Force on Climate-related Financial Disclosures (TCFD) represents a standardized framework that promotes cooperation among existing regulations and G20 jurisdictions. Through its focus on climate-related risks, it is considered one of the frameworks closest to regulatory requirements and an important step toward integrating climate risk into traditional financial reporting. Another standard is the Sustainability Accounting Standards Board (SASB), which operates on a sector-specific basis. Under this framework, organizations disclose information on long-term sustainability impacts, enabling investors to compare ESG performance within the same industries. A key concept within this framework is double materiality, which captures both the impact of a company on the environment and how sustainability issues affect the company itself. Another major framework is the Global Reporting Initiative (GRI), the most widely used sustainability reporting framework worldwide. Organizations reporting in accordance with GRI standards must comply with nine requirements across the Universal, Sector, and Topic Standards. GRI requires organizations to explain how they identify material sustainability issues, enabling investors to access relevant information more easily. However, a limitation of these standards is the lack of an objective definition of what constitutes sustainable activities, leaving stakeholders to determine sustainability criteria independently. Another relevant framework is the Climate Disclosure Standards Board (CDSB), which provides companies with guidance for environmental and social reporting at a level of rigor comparable to financial reporting. Its primary objective is to enable clear and consistent disclosures that support informed investment decision-making.

In September 2020, TCFD, CDSB, GRI, and SASB, along with other organizations, began collaborating on the development of a single global corporate reporting system. One year later, with the support of the IFRS Foundation, the establishment of the International Sustainability Standards Board (ISSB) was announced. This standard aims to provide a consistent and universal set of guidelines that companies must follow to ensure reliable sustainability reporting and support informed investment decisions (Degimbe & Desmet, 2022).

At the end of 2019, the European Commission introduced a major initiative to advance the EU's sustainability agenda: the European Green Deal (European Commission, 2019). The European Green Deal represents a renewed commitment to addressing environmental challenges. In response to climate change, biodiversity loss, pollution, and environmental degradation, the initiative seeks to protect both the environment and the health and well-being of citizens. Through the European Green Deal, the EU aims to accelerate the transition across all sectors. Although achieving these goals requires substantial public

investment and efforts to redirect private capital toward environmentally sustainable activities, the EU is considered capable of leading the economy and society toward a more sustainable path. The Organization for Economic Co-operation and Development (OECD) estimates that achieving the Paris Agreement goals by 2030 will require annual investments of EUR 6.35 trillion. To achieve climate neutrality by 2050, the European financial sector will need between EUR 175 billion and EUR 290 billion in additional annual investment (European Commission, 2019, n.d.–c). According to Degimbe and Desmet (2022), the EU financial sector manages approximately EUR 100 trillion in assets, indicating that investment decisions within the EU will play a crucial role in financing global climate mitigation efforts.

The European Green Deal will be updated as necessary, and all EU policies and actions are expected to contribute to its objectives. One of the most important initiatives supporting these goals is the EU Taxonomy (European Commission, 2019).

2.6.2 EU Taxonomy Regulation

The EU Taxonomy Regulation, which entered into force on 12 July 2020, is a tool that supports companies and investors in sustainable decision-making processes (European Commission, n.d.–a, n.d.–b).). The EU Guide emphasizes that the taxonomy is neither a list of investments nor a set of mandatory sustainability performance requirements for companies. It is also stated on the EU Taxonomy website that the regulation does not represent a mandatory investment list or a rating of a company's "greenness" (European Commission, n.d.–a). Rather, the regulation establishes a common understanding of economic activities that contribute to achieving the EU's environmental objectives. To this end, it defines six key objectives that support the implementation of the European Green Deal: climate change mitigation, climate change adaptation, sustainable use and protection of water and marine resources, transition to a circular economy, pollution prevention and control, and the protection and restoration of biodiversity and ecosystems. In addition, the regulation aims to protect investors from greenwashing and to help companies structure and plan their sustainable transitions. As part of EU Taxonomy reporting, companies are required to disclose how and to what extent they use the taxonomy in shaping sustainable investments, including the share of investments aligned with the taxonomy at the level of funds or portfolios. Furthermore, companies must report on which environmental objectives of the EU investments contribute to. The regulation also seeks to reduce information asymmetry and to direct investments toward activities that best support the EU's environmental goals (European Commission, n.d.–a, n.d.–b).

In line with these objectives, four conditions must be met for an economic activity to be considered environmentally sustainable. First, the activity must make a substantial contribution to at least one of the environmental objectives. Second, it must not cause significant harm to any of the other five objectives. Third, it must comply with minimum

safeguards. Finally, it must meet the relevant technical screening criteria. The regulation also recognizes “transitional” activities under the climate change objectives. These activities play an important role in supporting the transition toward a climate-neutral economy by contributing to limiting the global temperature increase to 1.5°C above pre-industrial levels (European Commission, n.d.–b).

In December 2021, two legally binding acts were published in the Official Journal of the European Union and later incorporated into the Taxonomy Regulation. These are referred to as Delegated Acts. The first is the Climate Delegated Act, which defines the technical screening criteria for economic activities that contribute to climate change mitigation and adaptation while ensuring that they do not significantly harm other environmental objectives. According to Eurostat data from 2021, the Climate Delegated Act covers economic activities in sectors responsible for nearly 64% of direct greenhouse gas emissions in Europe (European Commission, n.d.–b). This does not imply that activities not included in the act are automatically harmful or unsustainable; rather, it indicates that their impacts have not yet been sufficiently assessed for inclusion (European Commission, n.d.–a, n.d.–b). The second is the Disclosures Delegated Act, which specifies the content, methodology, and structure of information to be disclosed by non-financial and financial undertakings. A third delegated act, the Environmental Delegated Act, is still under development and is intended to cover activities that potentially contribute to one or more EU Taxonomy objectives (European Commission, n.d.–a).

Like any regulatory framework, the EU Taxonomy has limitations. From the perspective of users, it can appear binary, categorizing activities as either environmentally sustainable or not, with limited room for intermediate assessments. Such classification may therefore be misleading for investors. Nevertheless, according to the findings of Sothmann (2022)), the EU Taxonomy has already helped reduce reporting asymmetry. However, the author also notes that the taxonomy alone is insufficient for fully communicating companies’ sustainable transitions or guiding investors’ sustainable decisions, particularly in the short term. Despite these limitations, the EU Taxonomy remains a significant regulatory tool with which reporting entities are required to comply.

3 METHODOLOGY

3.1 General approach

The main analysis of this thesis includes behavioral biases and ESG investing in the European Union. The thesis uses a simple methodological approach combined with secondary data, with the aim of examining previously discussed issues while focusing on ESG scores, investing, and EU regulation.

As discussed earlier in this paper, ESG scores are an important part of sustainable investing. To support a suitable environment, the EU, as one of the most significant actors in this area, established the EU Taxonomy Regulation as an important investment tool. To explore the impact of this regulation, the research focuses on how its introduction affects sustainable investors' behavior, which is examined through changes in total returns (TR) and ESG scores using regression analysis (with R in RStudio).

3.2 Case description

The research is composed of both qualitative and quantitative data. Some qualitative data have already been discussed and presented in this paper. These data are collected from publicly available and relevant sources such as books, reports, research papers, and various articles.

Quantitative data for this research is collected mainly for regression analysis, which, as already stated, will be used as the main method for answering the research questions of this thesis. The primary source of these data is Refinitiv Workspace (Eikon), which provides relevant stock market information together with sustainability- and ESG-related analyses and reports. In addition to Eikon, numerical data used in the descriptive part of this thesis are collected from official EU websites and relevant research articles.

It is planned that variables for the regression analysis will be collected for approximately 1,000 companies over the period from 2018 to 2023. The dependent variable, which is being examined, is total returns (TR) as a stock market indicator. Total returns represent the accumulation of all earnings, including interest, capital gains, and dividends, that are reinvested over time (Siegel, 2022). Through this variable, as a reflection of investment behavior, the research aims to evaluate the importance of the effects of EU regulations. Data for TR is obtained from the aforementioned source on a quarterly basis.

On the other hand, the independent variables that may potentially affect TR include ESG score as the main variable, representing the sustainability path of regulated companies. In addition to the main independent variable, the following control variables are included to obtain more robust results and a clearer assessment of EU effects. These variables, also collected on a quarterly basis, include leverage, total assets (size), revenue growth, liquidity, operating margin, cash flows from investing activities, return on assets, and return on equity. As noted above, financial data are used on a quarterly basis, while the ESG score is available only on an annual basis from Refinitiv Workspace. This is the reason for selecting a larger sample of approximately 1,000 companies over a six-year period, which is expected to yield more reliable results.

The regression model (1) is specified as follows:

$$Total\ returns\ i,t\ =\ \alpha 0\ +\ \beta 1\ x\ ESG\ score\ i,t\ +\ Leverage\ i,t\ +\ Size\ in\ total\ assets\ i,t\ +\ Revenue\ growth\ i,t\ +\ Liquidity\ i,t\ +\ Operating\ margin\ i,t\ +\ CF\ from\ investing\ activities\ i,t\ +\ ROA\ i,t\ +\ ROE\ i,t\ +\ \varepsilon \quad (1)$$

In addition to the main analysis, ESG scores will also be used to examine the top 10% and bottom 10% of companies based on ESG performance, with the aim of obtaining clearer insights into returns, ratings, and potential illogical investor behavior.

3.3 Data selection and sampling

The selected timeframe is chosen with the aim of capturing changes, specifically the impact of the EU Taxonomy, which was officially enforced on 12 July 2020. In this way, the research can provide a more relevant picture, as the analysis enables a comparison of years before and after the regulations were established. With the additional aim of covering more cases and obtaining robust results, a larger sample size is selected. Total returns (TR) are chosen as an indicator of the stock market, as this variable can be influenced by multiple factors.

As stated earlier, the ESG score is the main independent variable, selected to reflect changes in companies' sustainability activities. It is also important because investors rely on it in various ways for their investment decisions. Control variables are selected to contribute to the results, as each of them can affect stock market performance, specifically total returns, which may reflect changes in investors' behavior. Leverage is included because it indicates a company's dependence on debt and how debt is used to finance operations (Wilson, 2025). Company size, measured by total assets, reflects stability as well as available resources and growth capacity. Revenue growth measures a company's ability to generate profit over time, which can potentially lead to higher returns (Kaushik, 2025). Closely related to revenue, operating margin assesses how effectively a company converts revenue into operating profit. Liquidity refers to a company's ability to meet short-term obligations, where higher liquidity is generally viewed as positive for both returns and ESG performance (Luo, 2022; Remesh, 2024). Cash flows from investing activities are included because they reflect the cash generated or used in investment activities. Return on assets (ROA) and return on equity (ROE) are also commonly used indicators in investment decision-making. ROA measures how efficiently a company uses its assets to generate profit, while ROE reflects the return generated on shareholders' equity. Since ROA and ROE data were not directly available from the data provider, they were calculated manually. ROA was calculated as net income before tax divided by total assets, while ROE was calculated as net income divided by the difference between total assets and equity (Kaushik, 2025). By using all the above-mentioned variables, it is possible to obtain a comprehensive picture of a company's financial efficiency, stability, and growth, which can further support sound investment decision-making.

3.4 Getting the data

The source of numerical data was Refinitiv Workspace, which is available at the Faculty of Economics through the FinLab network. For clearer data presentation and extraction, the main Refinitiv tool used was the Screener. The Screener provides filtering options that facilitate data selection. The main filter settings included the Euro currency, company type, and country of headquarters. Based on these criteria, publicly listed companies from the 27 European Union member states were selected. Subsequently, the above-mentioned variables were added individually for the selected period. The companies represent various industries, and no additional industry-based filtering was applied.

The output for annual data was clearly structured, with each observation explicitly linked to a specific year and company. However, this was not the case for quarterly data, as the reporting quarters were not clearly indicated and the associated dates were inconsistent, which posed a risk of assigning observations to incorrect periods. To address this issue, Excel formulas embedded in the Screener were used. After downloading data for specific variables using this option, a formula-based code in the output could be adjusted to match the required time period. This approach ensured that only quarters belonging to the selected period were included, thereby eliminating the aforementioned risk. The procedure was straightforward and consistent across variables, with only minor adjustments required for different headquarters, involving reassignment of country-specific identifiers.

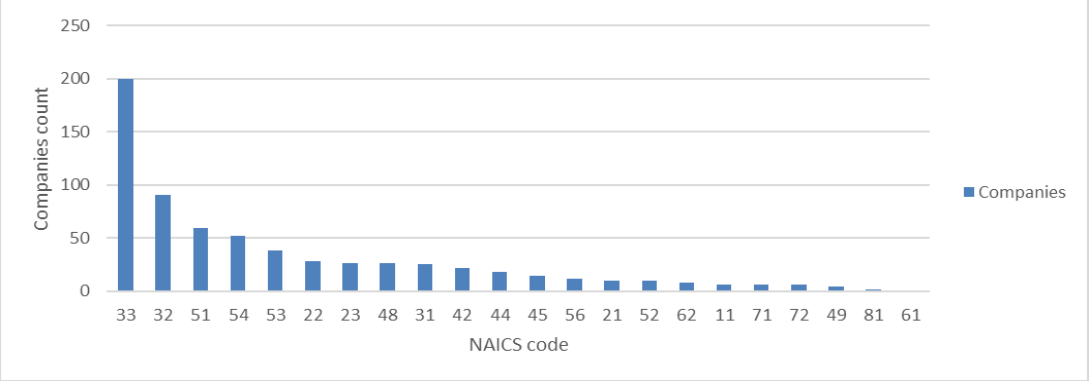
After data collection, the initial dataset included approximately 7,900 companies. Due to the presence of older companies and firms that did not report data consistently, a large number of missing observations were identified, necessitating data cleaning. This process was conducted using the R programming environment, applying code to identify and remove "null" values. The criterion for retaining companies in the sample was a maximum of two missing observations in both quarterly and annual data, ensuring higher data quality and reliability of results. As the number of observations varied across variables, the most effective approach was to retain only companies common to all datasets, resulting in an intersection of observations. After data cleaning, the final sample comprised 664 companies. One remaining issue was that the presence of up to two missing values per variable caused instability in regression results; therefore, these missing values were replaced with the mean of the corresponding variable across the company's observations. This ensured a complete dataset with no missing values for regression analysis.

To improve data robustness, the variables were winsorized at the 1% level. Following this procedure, the dataset retained the same number of observations, with extreme values adjusted accordingly. The resulting sample was then used for assumption testing and regression analysis. Additionally, to enhance model accuracy, North American Industry Classification System (NAICS) industry codes were extracted from Refinitiv Workspace

and included as dummy variables. NAICS classifies industries based on establishments using a six-digit code. Given the high level of detail of the full six-digit classification, the analysis used sector-level codes, represented by the first two digits of the NAICS code. Regression results were tested both with and without the inclusion of these industry dummies, and coefficient estimates were more reliable when the industry codes were included. Therefore, the final analysis proceeded with the inclusion of sector-level NAICS codes.

Figure 2 below illustrates the dominant industries within the sample, which may potentially influence the results. NAICS codes 32 and 33 represent manufacturing industries, including chemicals, leather, and textiles, followed by information and technical services. Together, these sectors account for approximately 50% of the total sample. A full list of industry code descriptions is provided in **Appendix *2***.

Figure 2: Count of companies under NAICS codes



Source: Own work based on Refinitiv Workspace (2025).

3.5 Methodology limitations

Although the chosen methodology represents a structured approach to achieving the intended results, several methodological limitations should be acknowledged. The first issue relates to the sample size: from the initially collected sample of 7,900 companies, only 664 met the requirements for the regression analysis, specifically the condition of having no more than two missing values per variable. The originally intended sample size was approximately 1,000 companies to ensure more reliable results. Consequently, missing values had to be addressed using the selected approach, as retaining the original sample with "null" values resulted in approximately 400 missing observations, preventing the regression from producing meaningful results and meeting the necessary assumptions.

As illustrated in the previous figure, the sample includes companies from various industries, which may pose a potential issue if certain industries disproportionately influence the results. In addition, the research period itself may represent a limitation. The timeframe includes the key year 2020, when the EU Taxonomy was introduced. However,

this year was also significantly affected by the COVID-19 pandemic, which may obscure the isolated effects of the EU Taxonomy. While the impact of EU regulations may begin to appear from 2020 onward, it is possible that their full effects extend beyond the observed period and may become more visible after 2023, as the scope and enforcement of the EU Taxonomy expands. Nevertheless, the analysis is conducted within the defined timeframe of 2018–2023.

Although ESG scores are applied across quarterly observations, they are available only on an annual basis, as this is the only option provided by Refinitiv Workspace. This results in an emphasis on annual ESG information, while potential quarterly ESG effects cannot be clearly identified. Furthermore, as discussed earlier, ESG scores are inherently biased due to differences in rating methodologies across agencies, leading to inconsistencies in ESG assessments. Consequently, if the same sample were evaluated using data from alternative rating providers, the results related to ESG scores might differ.

Finally, although the focus of this paper is on biases, the applied methodology is not capable of identifying specific biases or measuring their magnitude. Such insights would require more in-depth analysis and expert evaluation. Instead, this methodology examines the potential existence of biases and presents them as a possible risk to financial markets.

4 REGRESSION RESULTS

4.1 Effect of EU Taxonomy through whole model

After the first regression run, the results show that the residual standard error, which represents the average distance from the regression line, is 68 with 420 degrees of freedom. This means that after estimation there are 420 observations, and that, on average, the model's predictions deviate by 68 units from the actual values. The multiple R-squared, which indicates how much of the model is explained by the independent variables, is 0.60, meaning that 60% of the variability in the model is explained by the included variables. The significance of the model is demonstrated by the F-statistics of 2.683 with a very low p-value of 2.2e-16. Such a low p-value indicates a statistically significant model, meaning that, despite the above-mentioned results, some predictors contribute to explaining the model. Therefore, this model requires deeper examination.

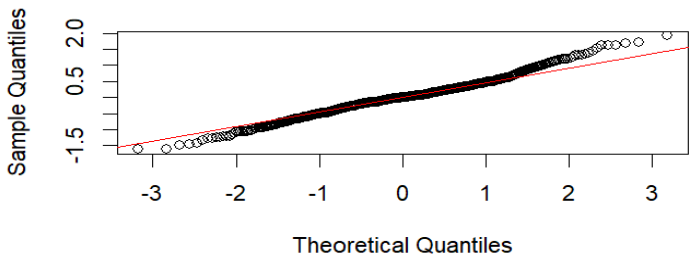
To provide more detail, it is important to analyze the coefficients of the independent variables. The model is statistically significant, and technically it can be stated that the ESG score can be used to explain total returns. However, the coefficients show that ESG as an explanatory variable is statistically significant only in the first two years, namely 2018 and 2019, and exhibits both positive and negative directions. The directions of ESG relationships are discussed in further analysis. After 2019, the ESG coefficients become highly insignificant. This may indicate that certain events occurred from 2020 onward

that caused investors to focus more closely on stock fundamentals and performance rather than ESG scores alone. It is well known that COVID-19 affected the entire world, including financial markets, and significantly altered global perceptions of risk and sustainability. In addition, an important event for the European Union in 2020 was the introduction of the EU Taxonomy, which redefined ESG investing by introducing new requirements and standards. These two events are considered highly influential and marked a shift in market behavior from 2020 onward. Regarding the control variables, all variables except revenue from business had at least one statistically significant coefficient during the research period. This indicates that they explain part of the variability in the dependent variable; however, since the main explanatory variable loses significance after 2020, the role of control variables is less relevant for drawing conclusions about the ESG–return relationship.

The results clearly show statistical significance in 2018 and 2019, indicating that during those years ESG scores influenced total returns, suggesting that investors considered ESG an important factor in investment decisions. The remaining results are insignificant, which may indicate a change in behavior or perception, as the division between significant and insignificant periods is clearly visible. This division is particularly relevant for the purpose of this research, as 2020 marks the introduction of the EU Taxonomy, and the results appear to change from that year onward. Although COVID-19 had a substantial impact, it is unlikely to have caused a long-lasting or consistent effect throughout the entire period. From the perspective of this study, the findings provide a basis to suggest that investors began to interpret ESG scores differently in the investment process, which may reflect a broader shift in investor perception in financial markets.

The main assumptions tested include normality, multicollinearity, autocorrelation, and heteroscedasticity. Normality refers to whether the residuals of the model are normally distributed. This was tested using the Shapiro–Wilk normality test, which yielded W = 0.98713 and a p-value of 1.386e-05. While the test statistic itself suggests near-normality, the low p-value leads to rejection of the null hypothesis, indicating that the residuals are not normally distributed. These results are further illustrated using a normal Q–Q plot shown in Figure 3.

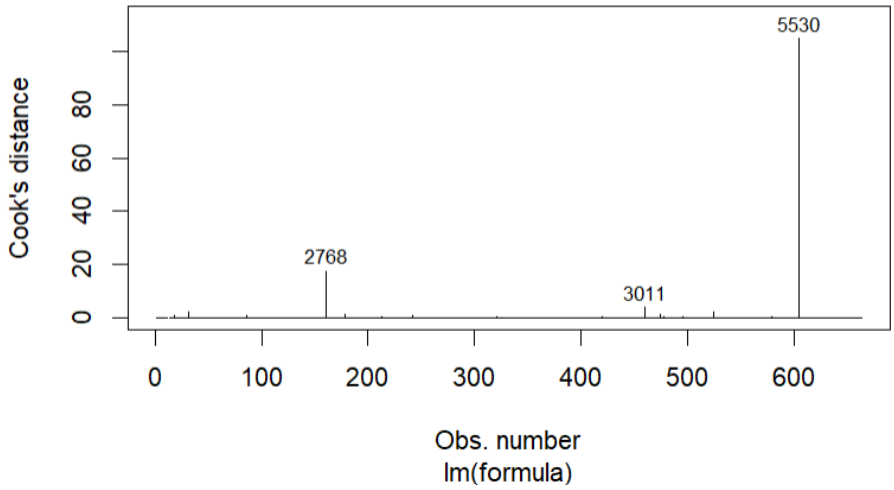
Figure 3: Normal Q–Q plot for demonstrating the normality assumption



Source: Own work based on Refinitiv Workspace (2025).

From Figure 3, it is evident that a large portion of the residuals lies around the central quantile, which indicates that residuals are approximately normally distributed. The issue appears in the tails, where, in the upper part, larger residuals deviate above the line, while on the lower side negative residuals deviate below the line. Thus, although the central part of the data follows a normal distribution, the tails indicate the presence of outliers. Even though the test indicates near-normality with a high test statistic, the statistically significant p-value suggests that the model should be further checked for robustness. Cook's distance is therefore used to visualize outliers, which are clearly shown in Figure 4 below.

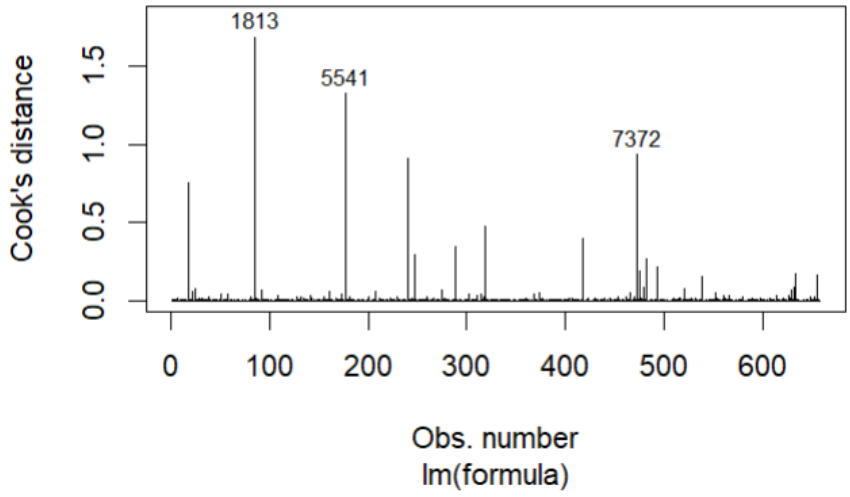
Figure 4: Cook's distance plot before removing significant outliers



Source: Own work based on Refinitiv Workspace (2025).

Outliers in the plot are marked with their indices in the data frame. The most visible and most influential outlier is the company with index 5530, for which Cook's distance reaches approximately 100, indicating a potentially disturbing observation. Two other indices, 2768 and 3011, are also visible, but their Cook's distance values are close to zero and therefore less concerning. For robustness checking, the company with the identified index was removed, after which additional outliers appeared. During the robustness process, a total of six outliers were removed, all of which exhibited lower Cook's distance values. After their removal, the remaining observations had Cook's distance values around 1 and were considered not sufficiently influential to warrant further exclusion, as shown in Figure 5.

Figure 5: Cook's distance plot after removing significant outliers

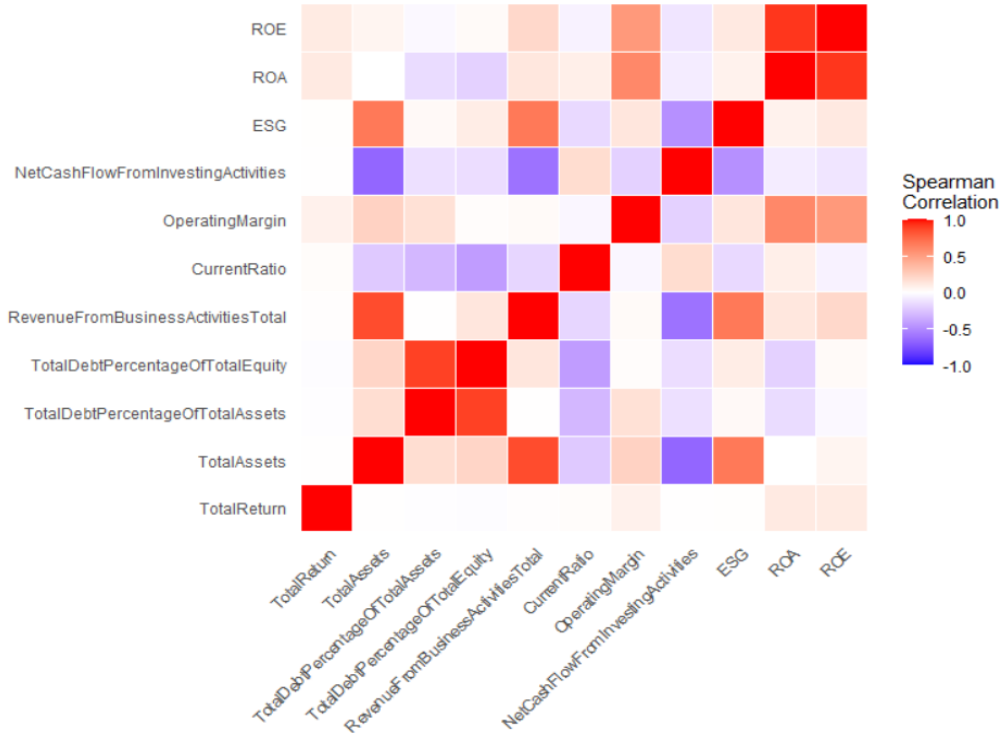


Source: Own work based on Refinitiv Workspace (2025).

Once the sample was defined without significant outliers, the regression analysis was repeated. The results were largely unchanged, with the R-squared increasing by approximately 1.5 percentage points, while the p-value remained practically the same. The model assumptions also remained valid, with only slight changes in p-values that were still statistically significant. Regarding normality, as the leading assumption in this process, the results remained similar, except that the starting sample quantile shifted from 1.5 to 1. Based on these findings, it can be concluded that the main outlier (index 5530) is not substantially influential, as its removal does not materially alter the model results. Consequently, the presence of such outliers does not represent a major issue, since the model largely satisfies the normality assumption.

Multicollinearity assesses the correlation among independent variables and is most commonly tested using the variance inflation factor (VIF). As the dataset contains 24 quarterly observations, VIF values were calculated for each quarter and for each variable. After winsorization, the results show that the VIF values for all variables range between 1 and 4 on average, indicating low multicollinearity. Without winsorization, the results were notably worse, with some extreme values observed across quarters. Therefore, based on these findings, no variables were identified as candidates for removal. To further examine correlations, Spearman correlation was used as a visualization tool. Figure 6 below presents the Spearman correlation heatmap of the variables, allowing the strength of relationships to be easily observed.

Figure 6: Spearman heatmap for correlations among model variables



Source: Own work based on Refinitiv Workspace (2025).

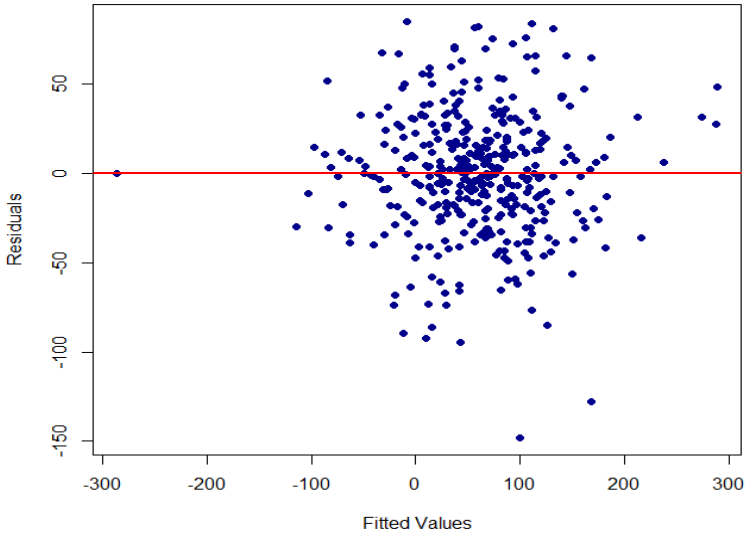
From this perspective, the strongest positive correlation appears between revenues and total assets, while these variables also show the strongest negative correlation with net cash flows from investing. However, since this heatmap cannot and is not intended to determine which variables should be retained or removed, all variables were included in the regression analysis, as presented earlier. According to the regression results, only revenues from business activities did not show statistical significance, even though the heatmap suggests that several variables might be strongly correlated. Therefore, the results indicate that the heatmap alone is not a reliable tool for variable selection.

As the dataset consists of time series data, it is standard practice to test for autocorrelation, which examines the correlation of residuals over time. One of the most commonly used tests for this purpose is the Durbin–Watson test, which was applied in this analysis. The test results are DW = 2.0219 with a p-value of 0.7619. Durbin–Watson values close to 2 indicate the absence of autocorrelation. Given the non-significant p-value (> 0.05), it can be concluded that there is no or only a very low level of autocorrelation among the residuals in the model (Johnston & Dinardo, 1997; Pfajfar et al., 2012).

Heteroscedasticity refers to non-constant variance of residuals across levels of independent variables. If present, it indicates that the variance of residuals changes, whereas homoscedasticity implies constant variance and is therefore more desirable for regression models. Heteroscedasticity is commonly tested using the Breusch–Pagan test

or examined through residuals versus fitted values plots. In this case, the Breusch–Pagan test produced the following results: BP = 216.83, df = 243, p-value = 0.8863. According to Yobero (2016), when a critical value is not provided, conclusions are based on the p-value. Since the p-value is high, the null hypothesis cannot be rejected, indicating that heteroscedasticity is not present in this model.

Figure 7: Residuals vs. fitted plot for model representation

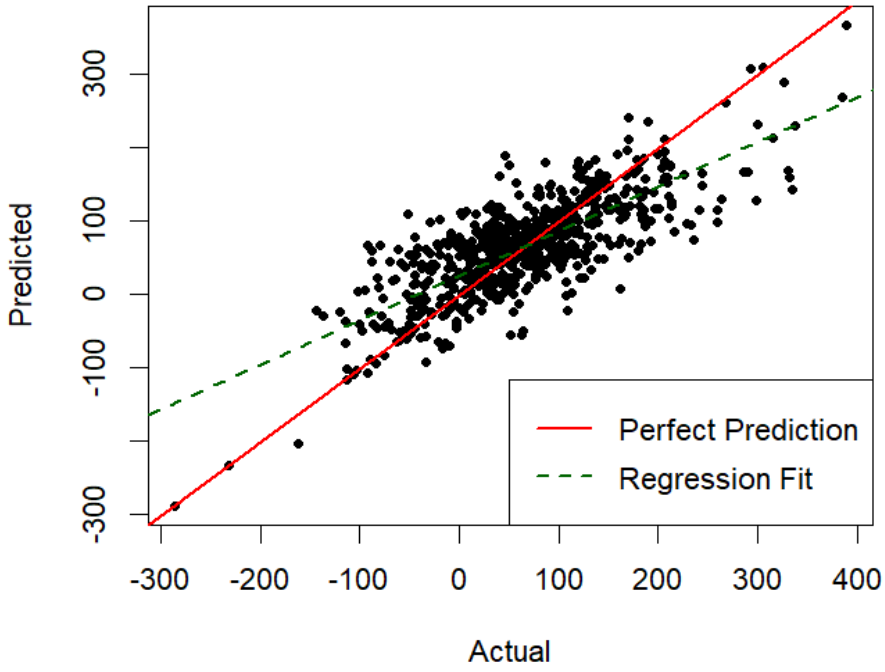


Source: Own work based on Refinitiv Workspace (2025).

Figure 7, which presents the residuals versus fitted values, confirms the results obtained from the statistical test. It is evident that there is no clear pattern or shape indicating heteroscedasticity; instead, the residuals appear relatively constant across the fitted values (Frost, n.d.–a). However, even though heteroscedasticity is not present, the residuals are large, or more precisely widely dispersed.

To complement Figure 7, the model is also presented using an actual versus predicted values plot. Figure 8 below displays the actual and predicted values, scattered around two reference lines. The red line represents the perfect prediction line, while the green line represents the regression fit. In theory, these two lines should have the same or very similar slopes; however, as shown in the figure, this is not the case, and substantial differences are clearly visible. This issue may indicate the presence of systematic bias. In the case of systematic bias, the model underpredicts large true values and overpredicts small true values, which can be observed on the right and left sides of the lines (Lee & Chen, 2024). These findings further suggest that the model does not provide a good fit and requires deeper investigation.

Figure 8: Actual vs. predicted plot for model representation



Source: Own work based on Refinitiv Workspace (2025).

To examine yearly effects, separate regressions were conducted for each year. All yearly regressions are statistically significant, with p-values well below 0.05, while R-squared values vary across years. The highest explanatory power is observed in 2022, with an R-squared of 0.286. However, issues arise when examining the coefficients. Although most control variables are statistically significant at some point during the year, the main variable, ESG score, is not statistically significant. This indicates that ESG did not have a measurable effect on total returns in 2022. Similar results are observed for all years except 2020 and 2021. In those years, not only were control variables statistically significant at certain points, but ESG scores also showed statistical significance, with p-values below 0.05. Although the effect was negative and very small, the results indicate that ESG scores played a minor role in investment decisions during this period. The year 2020 marks both the introduction of the EU Taxonomy and the onset of the COVID-19 pandemic. These overlapping events may reflect heightened investor concerns, which, according to the sample, persisted only in the short term.

4.2 ESG score effect on market volatility (VSTOXX)

In addition to effects on returns, a common topic of interest is whether ESG scores affect market volatility. For the purpose of deeper analysis, market volatility is also included in this research. More specifically, since ESG score is one of the main factors of analysis, the research question examines whether it influences market price fluctuations.

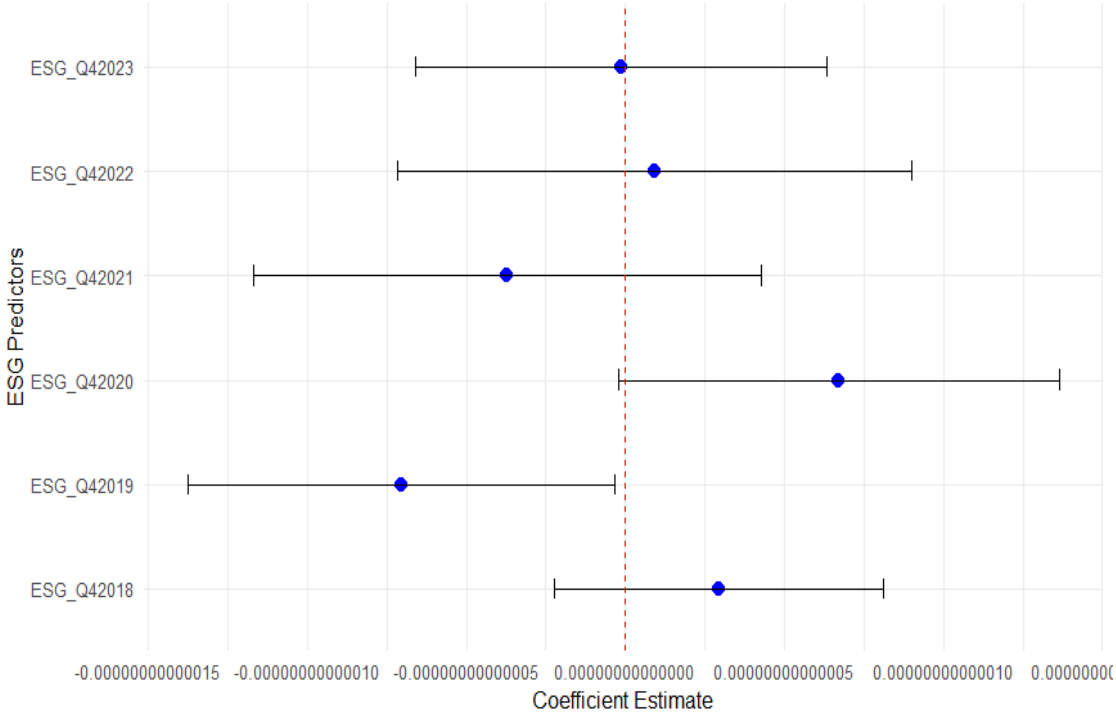
As the research focuses on the European Union, the VSTOXX index is used as an appropriate measure of market volatility for the EU market, with closing values applied. The analysis is conducted using regression analysis. The index is collected for the research period from 2018 to 2023 from the Refinitiv Workspace database and is used as the dependent variable. On the other side, ESG score is included as the main independent variable, while return on assets (ROA) is used as a control variable.

The results of this analysis are statistically significant, with a p-value well below 0.05. The R-squared value is 0.50, indicating that the included variables explain a substantial portion of market volatility. To better understand the results, the regression coefficients are examined. The ESG coefficients are not consistent across the entire period, as they are statistically significant only in 2019 and 2020. Although statistically significant, both the coefficients and their standard deviations are very small, indicating that the effect of ESG on market volatility is minimal. The results for ROA show that only one coefficient is statistically significant. Considering the results as a whole, the research question can be partially confirmed. More precisely, while ESG score appears to affect market volatility, an examination of the coefficients suggests that the effect is present only at certain points in time and that its magnitude is very small. Therefore, although ESG score shows some influence on the dependent variable, the practical significance of this effect remains questionable. Assumptions related to normality and heteroscedasticity were also tested, and the results are presented visually in **Appendix *2*** using appropriate plots.

The results described above are visually presented in the coefficient plot shown in Figure 9. As coefficients differ in magnitude and the full plot does not provide a clear overview, Figure 11 focuses on the ESG score as the most relevant variable (the complete plot is provided in **Appendix *2***). From the scale, it is evident that the coefficients are close to zero. In Figure 9 only coefficients whose confidence intervals do not cross zero are considered statistically significant, and the direction of the effect depends on which side of zero the coefficient lies. Although the effect remains small, the ESG coefficient for 2019 is clearly significant, while the coefficient for 2020 lies at the threshold of significance[1]. Figure 9 thus supports the described findings and confirms that, even when statistical significance is observed, the effect is weak and inconsistent. This leads to the conclusion that there is no strong or reliable evidence that ESG scores have a meaningful impact on market volatility. Additional residual and Q–Q plots are presented in **Appendix *2***).

[1] Since the ESG score is the same for all quarters, as it is derived from annual data, only the last quarters (Q4) of each year are presented in the plot.

Figure 9: Visualization of ESG regression coefficients with 95% CI for market volatility



Source: Own work based on Refinitiv Workspace (2025).

4.3 Long-run prediction based on ESG score

When investing, investors often focus on long-term investments. Since ESG has emerged as an important factor in decision-making, a relevant question is whether focusing on ESG, as an indicator of a company's business practices, can lead to better investment results in the long run.

According to Edmans (2023), when investors consider ESG investing, especially in the long term, ESG should not be treated as a separate category. Rather, it should simply be viewed as investing, as other business factors are equally important and must also be considered in decision-making. Furthermore, as emphasized by Edmans (2023, 2024), markets need good companies that aim for long-term value creation, not just companies that score well on ESG metrics. This perspective motivates the question of whether a focus on ESG has a measurable long-term effect. The long-term impact of ESG focus is therefore analyzed by predicting total returns based on ESG scores during the sampled period.

To address this research question, an additional regression analysis is conducted. The underlying assumption is that next year's total returns can be predicted based on the current period's ESG score and one control variable. In RStudio, the model is estimated for each year, and the regression specification is given in formula (2):

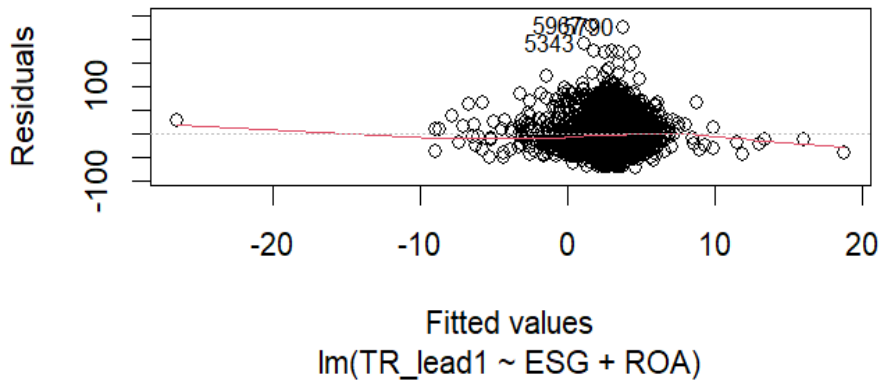
$$TR_t + 1 \sim ESGscore_t + ROA_t \quad (2)$$

Formula (2) implies, for example, that total returns in 2019 are predicted using ESG data from 2018, continuing in this manner up to 2023. As the sample covers a six-year period, the model is assumed to reflect long-term prediction. The control variable ROA is selected from the set of variables used in the main regression model, as it demonstrated the strongest performance in terms of R-squared and p-values. The same regression approach is applied and later adapted for subsamples derived from the original model, which are presented and analyzed in subsequent sections.

The results show that the model is statistically significant, with a p-value well below 0.05. At a basic level, this suggests that focusing on ESG scores in the long term may be associated with investment outcomes. However, despite statistical significance, the very low R-squared value of approximately 0.002 and small coefficient estimates indicate that the effect is highly questionable. Focusing specifically on ESG, the estimated coefficient is −0.02 with a standard deviation of 0.009. Although statistically significant, the magnitude of this effect is extremely small, implying that its economic relevance is almost negligible.

The model is illustrated through a residual versus fitted values plot in Figure 10. The plot shows that most values are clustered around zero rather than being evenly spread across residuals, which further supports the regression findings and indicates a lack of strong explanatory power. Therefore, the conclusion for this sample is that, while ESG focus may appear statistically significant when considering p-values alone, the actual long-term effect on total returns is minimal and nearly imperceptible.

Figure 10: Residuals vs. fitted plot for representation of the long-run prediction model

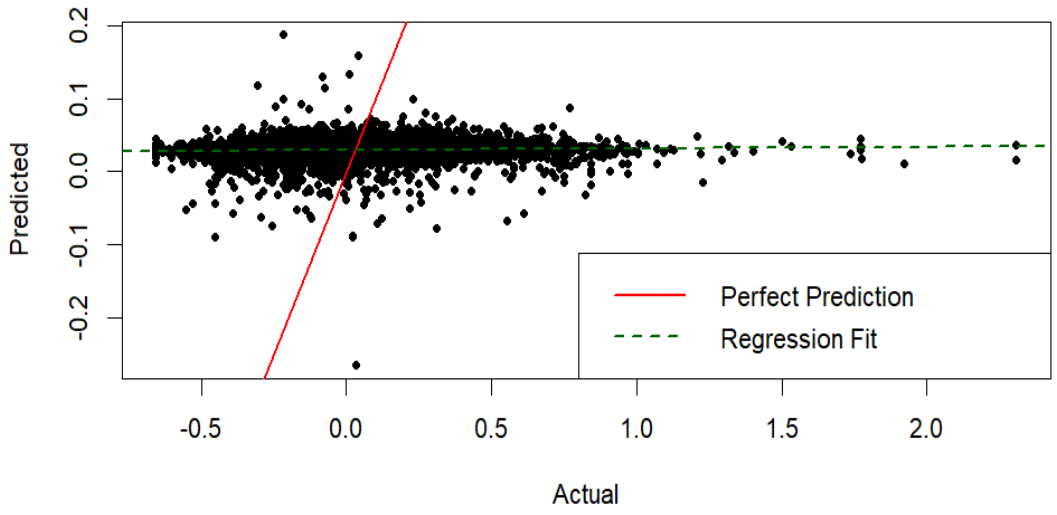


Source: Own work based on Refinitiv Workspace (2025).

To visually represent the results, the model is also presented through a plot of actual versus predicted values (Figure 11). The first noticeable aspect is the large distance between the perfect prediction line and the regression fit. This gap indicates that the values are clustered mainly around the regression line, making the perfect prediction line

largely irrelevant. Although both predicted and actual values lie on a low-value scale and their differences may appear small, the distance between the two lines represents very weak predictive power. Thus, even though the overall results show statistical significance, the predictive outcomes, reflected in the low R-squared values and small coefficients, are confirmed by Figure 11.

Figure 11: Actual vs. predicted plot for representation of the long-run prediction model



Source: Own work based on Refinitiv Workspace (2025).

During further analysis, long-run prediction of total returns based on ESG scores for all companies was also examined. Technically, the results suggest that predicting total returns is possible based on p-values; however, the coefficient values are very small, and conclusions regarding reliable long-term prediction of total returns cannot be drawn. The analysis indicates that the effect exists but is minimal. To further illustrate this, the prediction model is again presented through the actual versus predicted plot (Figure 11). It is clearly visible that the perfect prediction line deviates substantially from the regression fit. Even though the range of predicted values is narrow, the issue persists due to the mismatch between the two lines. Therefore, while statistical significance based solely on p-values might suggest that prediction is possible, in practical terms such predictions are not reliable given the magnitude of the results.

4.4 Effect of high and low ESG companies on returns

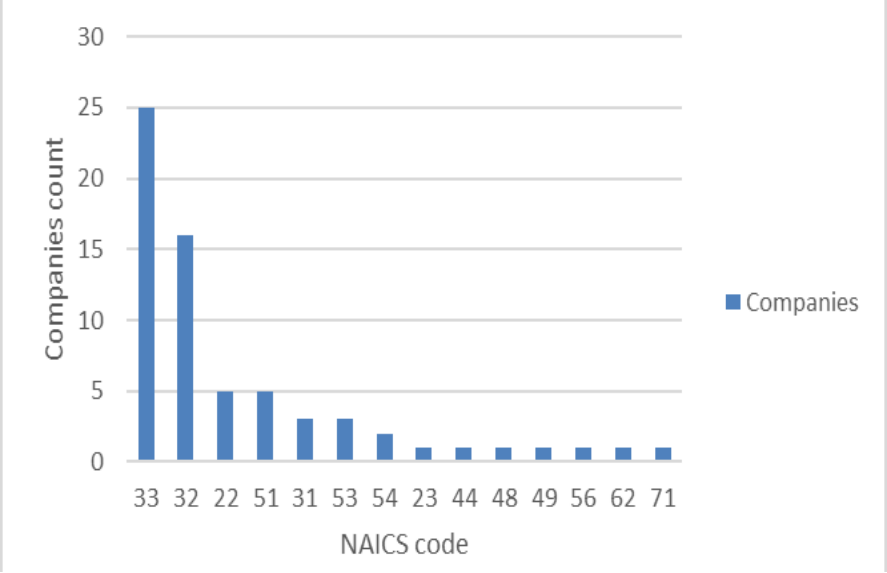
In the previous long-term model, all 664 companies were included. To further examine the potential effects of ESG, two additional subsamples were created from the original dataset. These were defined as the top 10% and bottom 10% of companies based on average ESG scores. This approach aims to provide clearer insights into the relationship between ESG and total returns, or more precisely, investor behavior. According to market

efficiency theory, high-quality companies should be priced appropriately and lower-quality companies at lower prices. However, markets are not always efficient, as investors are susceptible to behavioral biases, which may result in lower-ESG companies achieving higher returns than higher-ESG companies in certain cases (Ackert & Deaves, 2009; Luo, 2022). Based on the outcomes, the analysis may reveal potential market inefficiencies within the observed timeframe.

To better understand these subsamples before conducting regression analysis, they are first presented by industry classification. Specifically, the companies are grouped by NAICS industry codes to identify dominant sectors within each subsample. For the top ESG subsample, where ESG scores range from 78 to 90, Figure 12 shows that manufacturing industries under codes 32 and 33 are the most prevalent, covering chemical, machinery, and electronic product manufacturing. For the bottom ESG subsample, with ESG scores ranging from 7 to 28, Figure 13 indicates that manufacturing, particularly under code 33, is also the dominant sector, similarly accounting for approximately 50% of the sample.

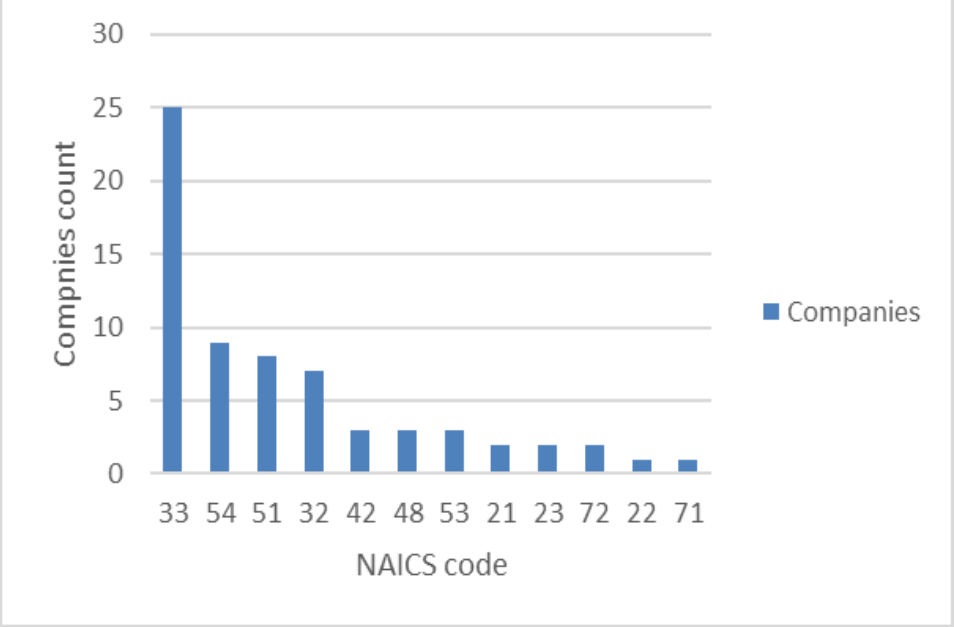
Given that manufacturing is the dominant sector in both subsamples, this may point to a structural characteristic of the industry, suggesting greater exposure to market fluctuations. This aspect is further examined in the results section.

Figure 12: Company count by NAICS code (top 10% sample)



Source: Own work based on Refinitiv Workspace (2025).

Figure 13: Company count by NAICS code (bottom 10% sample)



Source: Own work based on Refinitiv Workspace (2025).

Starting with the top 10% ESG companies, the results show that the model is not statistically significant, with a p-value of 0.43. In addition, the R-squared value is very low at 0.001, which, together with the p-value, indicates that the model does not adequately explain total returns or support return prediction. Regarding the coefficients, ESG score shows a small positive relationship with total returns; however, the p-value of 0.42 indicates that this relationship is not statistically significant. The final conclusion is that there is no statistically significant evidence that higher ESG scores lead to higher total returns.

Companies in the bottom 10% ESG subsample show slightly stronger results. The model is statistically significant, with a p-value well below 0.05. The R-squared value is higher than in the top 10% model but remains low at 0.01, meaning that only 1% of the variation in total returns is explained. The ESG coefficient exhibits a small but negative relationship with total returns and is statistically significant. Technically, based on p-values alone, this suggests that lower ESG scores are associated with lower total returns. According to Frost (n.d.–b, n.d.–c), even when R-squared values are low, statistically significant coefficients may still indicate an effect on the dependent variable. Therefore, the conclusion for this model is that some level of predictability of total returns based on low ESG scores exists, although the effect is limited.

Even though the predictions of total returns are not fully significant, there is still an important comparison between the two samples. As shown above, the contrast is reflected in the large difference between p-values, which indicates differences in the significance of relationships within the models. This difference drives the main asymmetry between

the samples. The top 10% sample shows a positive but insignificant relationship, while the bottom 10% sample shows the expected negative and statistically significant relationship. This means that high ESG scores do not guarantee the prediction of higher total returns, whereas for low ESG scores, total returns may be predictable. From this perspective, long-term investing and predictions based on low ESG scores may be technically possible; however, given the negative effect on total returns and the low R-squared value, such investments would not lead to desirable outcomes. Since the research question concerns whether focusing solely on ESG in the long run can lead to better results, the conclusion is clear: the explanatory power is very low, and from an investor's perspective, predicting negative relationships is not attractive. Even though ESG is not the only factor that should be considered in investment decisions, investing in low ESG score companies can be regarded as risk-seeking behavior (Edmans, 2023). This represents a bias, as environmentally and socially irresponsible companies may carry higher risk, particularly in long-term investments. On the other hand, for high ESG score companies, there is no evidence that total returns can be predicted. Therefore, based on the analyzed results, ESG (together with the control variable) does not exhibit sufficient predictive power. Even companies perceived as "good" are susceptible to scandals that may negatively affect their performance. Consequently, investment decisions should incorporate additional variables and factors to guide analysis toward more reliable and beneficial conclusions.

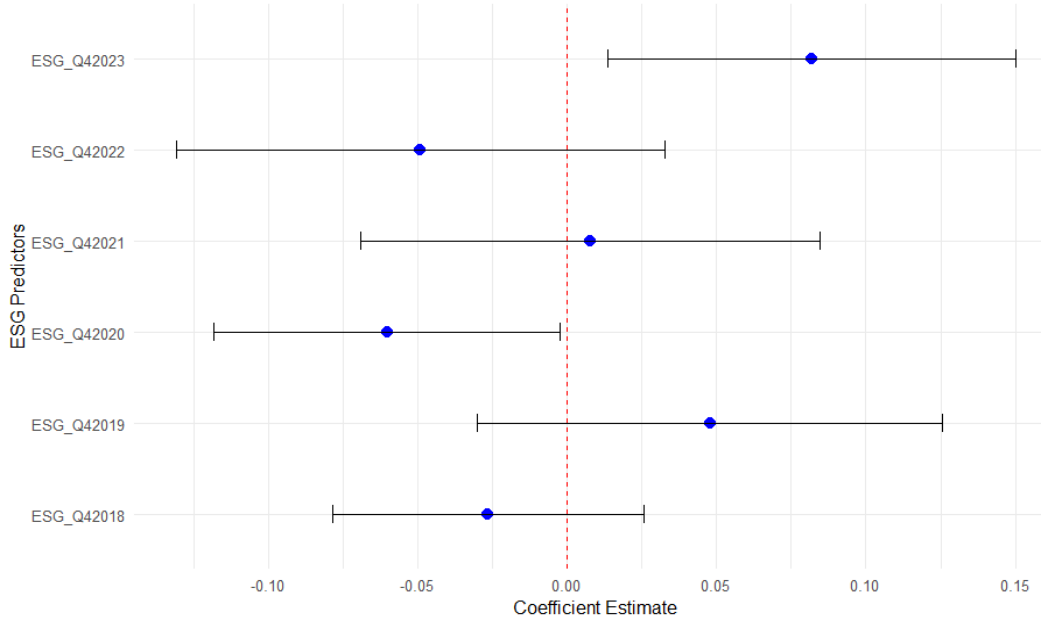
Since the previous analysis focused on long-run prediction, the current situation is also examined to compare predictive and explainable models. To assess whether ESG can explain total returns in the current period, top 10% and bottom 10% samples are again extracted from the original model. Due to the relatively small sample size of 66 companies, the model allows only one control variable; therefore, ROA is retained, as in the prediction model, to ensure comparability. Additionally, as previously noted, NAICS codes are included as dummy variables.

The results for the top 10% sample indicate statistical significance, with a p-value of 0.01 and an R-squared value of 0.83. These results suggest that, technically, total returns can be explained by ESG score and the selected control variable in this case. However, when examining the coefficients more closely, ESG score is statistically significant in only two years, despite the overall model significance. The remaining coefficients do not show reliable significance in explaining total returns, meaning that the above conclusion is only partially supported. An interesting observation in this sample is that, when focusing only on significant coefficients, the coefficients are negative in 2020 and positive in 2023, indicating differing directions of total returns and potential behavioral biases, which are discussed later in the paper. These findings support the results of the prediction model, which concludes that future total returns cannot be reliably predicted for high ESG score companies. This is due to market variability, reflected in fluctuating coefficient signs and magnitudes, which complicate prediction. Since the results lack consistent significance,

it suggests that additional explanatory factors are needed to better explain the dependent variable.

These results are illustrated in the coefficient plot shown in Figure 14, where both significance and direction of effects are clearly visible[2] (the full coefficient plot is provided in **Appendix *2***). As shown in Figure 14, the most notable results occur in 2020 and 2023, confirming the findings discussed above. Furthermore, the scale indicates that the magnitude of the effect is very small, suggesting that even when ESG has an effect, it remains limited. Although the results are inconsistent across years and do not provide significant explanatory power throughout the entire period, the year 2020 deserves particular attention due to the occurrence of major events. Therefore, even though statistical significance is observed only in certain years, the significance in 2020 suggests that ESG score may have played a role in explaining changes in total returns during that period.

Figure 14: Visualization of ESG regression coefficients with 95% CI for the top 10% sample



Source: Own work based on Refinitiv Workspace (2025).

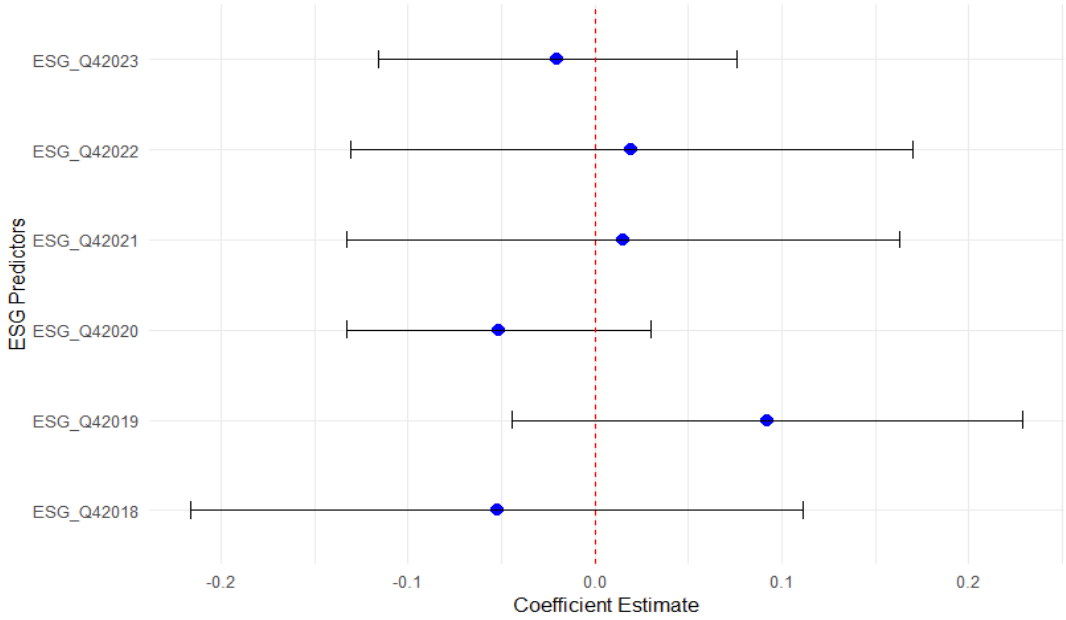
Results for the bottom 10% sample, on the other hand, are not statistically significant, with a p-value of 0.40. The R-squared value is 0.65, and none of the coefficients show statistical significance, which means that total returns cannot be explained by ESG score in the low-score segment. ESG coefficients exhibit both positive and negative directions, but due to their insignificance, this suggests that additional factors are required to explain the dependent variable. The key difference for the bottom 10% models is that the

[2] Since the ESG score is the same for all quarters, as it is derived from annual data, only the last quarters (Q4) of each year are presented in the plot.

prediction model is statistically significant. However, due to the low explanatory power indicated by R-squared, prediction remains unreliable, which is further confirmed by insignificant and directionally inconsistent coefficients throughout the research period. The conclusion for the low ESG score segment is that total returns cannot be reliably explained or predicted, as less sustainably responsible companies are subject to higher uncertainty, as noted by Edmans (2023).

Evidence for the above results in the explanatory model is presented below through the coefficient plot for the ESG variable[3] (Figure 15), while the full coefficient plot is provided in **Appendix *2***. As noted earlier, all coefficient lines crossing zero are statistically insignificant. In addition, the low values on the scale indicate that even if statistical significance were present, the explanatory power would remain weak. Thus, analysis of Figure 15 confirms that ESG coefficients are effectively negligible for the low ESG score segment.

Figure 15: Visualization of ESG regression coefficients with 95% CI the bottom 10% sample



Source: Own work based on Refinitiv Workspace (2025).

A possible market explanation for these outcomes regarding high and low ESG companies is the presence of an ESG premium, which may explain why returns of top ESG companies cannot be reliably predicted or expected to be high. This premium, or more precisely the gap between prices of high-ESG and low-ESG companies, may be driven by behavioral biases on both sides. For high ESG companies, a prominent bias is representativeness, where investors invest in a company primarily due to its high ESG

[3] Since the ESG score is the same for all quarters, as it is derived from annual data, only the last quarter (Q4) of each year is presented in the plot.

score, assuming it is a good company overall (Ackert & Deaves, 2009). As mentioned earlier, the dominance of the same industry in both the top and bottom samples may further contribute to the ESG premium. When companies belong to the same industry, investors can more easily compare them and favor certain firms, thereby amplifying price movements through biased judgments (Carannante et al., 2024; Ciciretti et al., 2023). However, such a premium cannot persist indefinitely, and at some point, prices adjust downward, leading to lower returns. At lower price levels, overconfident investors and risk seekers may enter the market (Ackert & Deaves, 2009; Ciciretti et al., 2023). This further supports the conclusion that total returns in the ESG context cannot be reliably predicted.

So, based on the results from both filtered samples, examined in both long-term and current contexts, which do not show consistent contributions to increasing or decreasing returns, the question of whether high/low ESG score investments lead to higher/lower returns cannot be conclusively answered.

Since the results indicate non-rational behavior in both the top and bottom ESG segments, the presence of biases is expected in both groups. When analyzing human behavior and decision-making, it is not possible to definitively attribute outcomes to a single bias without deeper investigation. From this perspective, multiple biases may be simultaneously influencing the observed results. Accordingly, in the following subsection, behavioral biases are linked to the analyzed samples based on their conceptual definitions.

4.5 Reasoning of regression results in the context of behavioral biases

Cognitive behavior is more complex than it may appear, as emotions—both positive and negative—affect risk attitudes, investment decisions, and market pricing as a whole (Ackert & Deaves, 2009). Since investors' decisions are influenced by emotions, as discussed earlier, biases cannot be directly assigned to specific market situations, and exact biases cannot be identified without more in-depth and professional analysis. Therefore, in exploratory research such as this, biases can only be assumed based on their characteristics and associated emotions, which was also one of the reasons for separating the top and bottom ESG samples.

According to Upadhyaya et al. (2023), highly sustainable companies are more resilient to risks and may therefore be considered safer investment options. However, as explained by Ackert and Deaves (2009),), a good company does not necessarily represent a good investment, as investors may be influenced by representativeness bias. Such companies are often more exposed to overvaluation and ESG premiums rather than reduced risk (Edmans, 2024; Kräussl et al., 2024). As noted by Ferriani (2023) and Li et al. (2022), an ESG premium was evident in recent years, particularly during the COVID-19 period, when investors used high-ESG companies as a hedge against downside risk. Since these

motives are driven by representativeness heuristics, it is important to emphasize the need for awareness of this bias, especially within the top ESG segment. As discussed earlier in the paper, Talman (2023) argues that ESG components (E, S, and G) are not always aligned, as companies may perform well in environmental aspects while underperforming in social dimensions. Basing investment decisions on only one ESG component or a single aggregated score can therefore be misleading. As shown in the results above, relying solely on ESG scores to assess stock performance does not yield satisfactory outcomes. Consequently, representative characteristics should not guide ESG investment decisions. In addition to representativeness bias, other biases associated with valuing companies based on ESG scores include availability and recency biases, as investors tend to focus on recently encountered information—whether positive or negative—and apply it immediately in their decision-making processes (Amgain, 2024; Shefrin, 2002).

Among other biases that may be present and applicable to the top ESG segment is loss aversion. Upadhyaya et al. (2023) document that due to this bias, investors tend to avoid ESG companies with poor ratings and performance and instead focus on strong performers, with the aim of avoiding losses, sometimes at the expense of potential profits. Depending on the level of loss aversion, investors exhibit different attitudes toward risk-taking (Rizani et al., 2023). Rizani et al. (2023) highlight that investors with lower levels of loss aversion are more inclined toward risk-taking than those with higher levels. Referring to the previously described results for the top ESG segment, it is possible that investors with lower loss aversion are more prevalent in the sample, as the results are not consistently positive enough to support the perceptions of fully risk-averse or loss-averse investors.

Low ESG score firms, represented here by the bottom 10% sample, are even more susceptible to behavioral biases, as they are inherently riskier, and investment decisions in such firms are more easily influenced by biases (Edmans, 2023; Rizani et al., 2023). 2023). In line with this observation, the long-term prediction results based on ESG scores, which are statistically significant and indicate negative total returns, appear reasonable, since, as explained by Edmans (2023)), such firms are not safe long-term investments. Biases that stimulate irrational investment behavior may arise because investors in this segment are more likely to be risk-seekers, which is associated with additional behavioral biases (Ackert & Deaves, 2009). One of the most common biases in this context is overconfidence, which can lead to unrealistic expectations and forecasts that guide investment strategies and decision-making processes (Antony & Joseph, 2017; Rizani et al., 2023). According to Ackert and Deaves (2009), overconfidence is particularly problematic because it leads to excessive trading, which in turn affects market prices and investor behavior. It is among the most prevalent biases and can become contagious, especially when investors experience periods of favorable outcomes that reinforce their confidence. Furthermore, investors often process information selectively, placing greater weight on information that confirms their beliefs, thereby exhibiting confirmation bias,

which, like overconfidence, has been shown to significantly affect ESG investing decisions (Amgain, 2024; Upadhyaya et al., 2023).

Common biases that may affect both high and low ESG companies include herding behavior and framing effects. Herding behavior can easily spread, as it involves investors following dominant market trends. More specifically, investors influenced by this bias may contribute to market inefficiencies that are disconnected from underlying economic fundamentals (Rizani et al., 2023; Upadhyaya et al., 2023). As documented by Rizani et al. (2023), this behavior may lead investors to overlook long-term risks and other critical aspects of investment analysis. Instead of conducting thorough evaluations, they proceed with investments simply because they are popular or widely adopted by other market participants (Rizani et al., 2023).

Framing also has a significant impact on investors' perceptions, regardless of whether information is presented positively or negatively, or whether it is communicated by market participants or the media. As emphasized by Rizani et al. (2023), framing plays an important role in shaping decisions, as the way information is presented can influence the direction of the decision-making process. Positive framing may encourage investors to pursue perceived opportunities and take on greater risk, while negative framing can prompt investors to focus on uncertainty and avoid risk. Both effects can distort rational investment decision-making (Rizani et al., 2023).

Based on Amgain (2024) research, which identifies 35 distinct behavioral biases, several of the most common biases in ESG investing can be linked to the analyzed company segments based on the regression results presented. Although ESG scores did not demonstrate strong predictive power for returns, they are nonetheless confirmed as potential indicators of investment-related behavioral biases (Deka et al., 2023).

5 CONCLUSION

This thesis presents some significant findings regarding ESG investing and investors' behavior. As mentioned earlier, ESG is a relatively new term in investing, and there are not many historical events from which it could be learned. In 2000, it was slowly introduced into practice, but from 2004 it appeared as an official term. Nevertheless, after the Paris Agreement, it gained value and popularity, so it can be said that ESG is currently at its peak. Since ESG is mainly driven by human factors, it goes hand in hand with behavioral finance. It helps investors better understand possible biases and common mistakes in the market that affect other traders and investors. Behavioral biases reflect how investors absorb information, which consequently affects their decisions. Many findings point to illogical behavior in ESG investing, such as investing while expecting underperformance or investing without clear reasons. It is clear that biases are present,

but due to their nature and the role of behavior, not just one bias can be attributed to such decisions.

Besides biases related to investor behavior, misleading information used in investment decisions can also be considered a bias or an issue in this process. One of the main issues concerns ESG rating agencies, which do not use consistent methodologies for rating companies. They apply different indicators, perceptions, and even rating scales, which makes ESG scores difficult to compare. In addition, they often lack quality data because companies do not report it properly. One such issue, also considered misleading, is greenwashing, where companies selectively report data that favor their image rather than investors, and numerous scandals confirm this practice. Some findings show that companies committing misconduct reporting can lose up to 92.7 billion euros in market value annually. One study found that companies with high environmental (E) scores actually emit more carbon dioxide, while companies with low E scores emit less. This issue highlights the importance of publicly available, transparent reporting and accurate company ratings. This scenario indirectly confirms the statement by Alex Edmans that ESG components are not necessarily compatible, as each serves a different purpose, and strong performance in one area does not imply progress in others. In this way, companies may use such issues to boost their image and instrumentalize the ESG concept. Since most investors are primarily attracted by returns, the relationship between ESG scores and returns is an important topic. Although there is still no consensus, several interesting findings exist. Many studies, particularly in the US context, show that ESG scores do not affect returns unless a company has a low ESG score, in which case returns tend to be negative. In addition, research from China shows that the relationship between ESG scores and returns is significant in more economically developed and progressive countries. Therefore, there is clearly no single answer to this question, as it depends on multiple factors.

Regarding investing as a central subject of this thesis, where fair and sustainable reporting is crucial, the EU has taken important measures to guide markets in the desired direction. One of the more recent regulations is the EU Taxonomy, which serves as a tool for identifying activities that contribute to achieving EU sustainability goals. Its limitation lies in the fact that it classifies activities in a binary manner, which reduces its standalone usefulness for investment decisions. Nevertheless, it remains a significant regulation that promotes fair and high-quality sustainable reporting.

The EU Taxonomy is one of the main subjects of this research, and its introduction in 2020 is crucial for several findings. In the original model of 664 companies, the main objective, besides examining the effect of ESG on total returns, was to analyze the impact of the EU Taxonomy on investor behavior and the market. The results are statistically significant. The main variable was the ESG score as a proxy for the EU Taxonomy effect, and its coefficient was significant only for 2018 and 2019, confirming a relationship with total returns. From 2020 onwards, the results become insignificant, indicating that the

introduction of the EU Taxonomy affected investing behavior. This finding answers the research questions and leads to the rejection of the H0 hypothesis. Furthermore, the relationship between returns and ESG scores was examined through long-term predictions over a six-year period. On a lag basis, predicting total returns based on current ESG scores and control variables yields statistically significant results. However, the coefficients and explanatory power are very low, which makes the actual economic effect unreliable.

The same procedure is applied to the top and bottom 10% of the original sample, which is determined based on the average ESG score. The goal is to explore whether returns can be predicted based on high and low ESG scores, that is, to examine whether higher scores can provide higher returns, and vice versa. Results for the top 10% show insignificance, meaning that returns cannot be predicted in the long run based on the ESG score. In addition, the analysis shows a very low percentage of variability in the model, so even if significance were present, the real effect would still be questionable. The bottom 10%, on the other hand, shows statistical significance and a negative relationship with total returns, meaning that predicted long-term returns would move in a negative direction. However, the variability of the model, more precisely the R-squared value, is very low, at around 1%. Thus, technically, according to statistical significance, prediction is possible, and results regarding lower returns are explainable to some extent, as low ESG score companies are riskier and long-term investment in higher risk may not be beneficial.

In addition, to complement the previous findings, the top and bottom 10% samples are also examined based on current data to assess the explanatory power of the ESG score for total returns. The results show that for the top 10% of companies, the model is statistically significant, and ESG score coefficients are significant only for 2020 and 2023. The coefficients show different directions, which means that even for high ESG score companies, there is no certainty that higher returns can be achieved without decline. This confirms previous findings that returns for high ESG score companies cannot be reliably predicted. For the bottom 10%, the outcome is insignificant, indicating that returns cannot be explained solely based on a low ESG score. Together with the previous outcome for the bottom 10%, the conclusion is that short-term investment decisions require additional factors, while in the long term, prediction is statistically possible, acknowledging that prolonged exposure to higher risk may not lead to positive outcomes. To summarize, investment in a high ESG score does not represent an immediate path to higher returns. Although results for the bottom segment are statistically significant and technically indicate lower returns, these findings cannot be relied upon due to very low explanatory power, suggesting that stronger predictions would require the inclusion of additional factors.

One of the research subjects is also market volatility and its relationship with the ESG score. The results show statistical significance, with ESG score coefficients being significant in only two years. Technically, this indicates that an effect of ESG score on

volatility exists. However, as in previous analyses, the remaining results are very weak, which prevents strong conclusions about the actual effect. As with earlier findings, this analysis would require additional research factors for more reliable conclusions.

Based on the results described above, the final conclusion regarding the ESG score is that, although significance appears in some outcomes, its explanatory and predictive power is very low. On its own, it does not contribute to efficient investment decisions without the inclusion of additional variables, especially in the long term. Nevertheless, even if the results do not show strong significance across all analyses, this master's thesis contributes by confirming and complementing previous research and may serve as inspiration for future researchers focusing on ESG investing and its key issues.

LIST OF KEY LITERATURE

1. Ackert, L., & Deaves, R. (2009). *Behavioral finance: Psychology, decision-making, and markets* (1 ed.). South-Western, Cengage Learning.
2. Balitzky, S., & Reiche, P. (2023). The European sustainable debt market–do issuers benefit from an ESG pricing effect. *European Securities and Markets Authority (ESMA)*.
3. Degimbe, F., & Desmet, C. (2022). *Will the European Taxonomy be a game changer for the financial market?* Louvain School of Management, Université catholique de Louvain].
4. Deka, J., Sharma, M., Agarwal, N., & Tiwari, K. (2023). Linking ESG-Investing Consciousness Behavioral Biases and Risk-Perception: Scale Validation with Specifics of Indian Retail Investors. *European Journal of Business Science and Technology*, *9*(1), 70–91.
5. Edmans, A. (2023). The end of ESG. *Financial Management*, *52*(1).
6. European Commission. (2023). *Commission Staff Working Document, Impact Assessment Report, Accompanying the document: Proposal for a Regulation of the European Parliament and of the Council on the transparency and integrity of Environmental, Social and Governance (ESG) rating activities.*
7. European Commission. (n.d.–b). *EU Taxonomy User Guide*. https://ec.europa.eu/sustainable-finance-taxonomy/assets/documents/Taxonomy%20User%20Guide.pdf
8. Giglio, S., Maggiori, M., Stroebel, J., Tan, Z., Utkus, S., & Xu, X. (2023). Four facts about ESG beliefs and investor portfolios. *Journal of financial economics*, *164*, 103984.
9. Krantz, T. (2024). *The history of ESG: A journey towards sustainable investing*. IBM. Retrieved 25 September 2025 from https://www.ibm.com/think/topics/environmental-social-and-governance-history
10. *Refinitiv Workspace*. (2025).

11. Shefrin, H. (2002). *Beyond greed and fear: Understanding behavioral finance and the psychology of investing*. Oxford University Press.
12. Sipiczki, A. (2022). *A critical look at the ESG market*. CEPS Brussels, Belgium.
13. Talman, K. (2023). *How 'ESG' came to mean everything and nothing*. BBC. Retrieved 24 September 2025 from https://www.bbc.com/worklife/article/20231114-how-esg-came-to-mean-everything-and-nothing
14. Treepongkaruna, S., Au Yong, H. H., Thomsen, S., & Kyaw, K. (2024). Greenwashing, carbon emission, and ESG. *Business Strategy and the Environment*, *33*(8), 8526–8539.

REFERENCE LIST

15. Amgain, P. N. (2024). Examining the Behavioral Biases Influencing on ESG Investing: A Systematic Review using PRISMA. *GMMC Journal of Interdisciplinary Studies*, *13*(1), 182–211.
16. Antony, A., & Joseph, A. I. (2017). Influence of behavioural factors affecting investment decision—An AHP analysis. *Metamorphosis*, *16*(2), 107–114.
17. Armstrong, C. S., Barth, M. E., Jagolinzer, A. D., & Riedl, E. J. (2010). Market reaction to the adoption of IFRS in Europe. *The accounting review*, *85*(1), 31–61.
18. Beerbaum, D., & Puaschunder, J. M. (2019). A behavioral economics approach to sustainability reporting. *Julia M., A Behavioral Economics Approach to Sustainability Reporting (May 2, 2019)*.
19. Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, *26*(6), 1315–1344.
20. Carannante, M., D'amato, V., & Staffa, M. S. (2024). How ESG corporate reputation affects sustainability premiums in the insurance industry. *Frontiers in Applied Mathematics and Statistics*, *10*, 1474565.
21. Ciciretti, R., Dalò, A., & Dam, L. (2023). The contributions of betas versus characteristics to the ESG premium. *Journal of Empirical Finance*, *71*, 104–124.
22. Drei, A., Le Guenedal, T., Lepetit, F., Mortier, V., Roncalli, T., & Sekine, T. (2019). ESG investing in recent years: New insights from old challenges. *Available at SSRN 3683469*.
23. Edmans, A. (2024). Rational sustainability. *Journal of Applied Corporate Finance*.
24. European Commission. (2019). *Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions: The European Green Deal*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52019DC0640
25. European Commission. (n.d.–a). *EU Taxonomy Navigator*. https://ec.europa.eu/sustainable-finance-taxonomy/

26. European Commission. (n.d.–c). *Factsheet: Financing sustainable growth*. https://finance.ec.europa.eu/system/files/2020-01/200108-financing-sustainable-growth-factsheet_en.pdf
27. European Union. (2020). *Regulation (EU) 2020/852 of the European Parliament and of the Council of 18 June 2020 on the establishment of a framework to facilitate sustainable investment, and amending Regulation (EU) 2019/2088,* L 198, 13–43. *Official Journal of the European Union.* https://eur-lex.europa.eu/eli/reg/2020/852/oj/eng
28. European Union. (2023). *Monitoring the level of financial literacy in the EU*. https://europa.eu/eurobarometer/surveys/detail/2953
29. Ferriani, F. (2023). Issuing bonds during the Covid-19 pandemic: Was there an ESG premium? *International Review of Financial Analysis*, *88*, 102653.
30. Frost, J. (n.d.–a). *Heteroscedasticity in Regression Analysis*. Statistics By Jim. Retrieved 25 September 2025 from https://statisticsbyjim.com/regression/heteroscedasticity-regression
31. Frost, J. (n.d.–b). *How To Interpret R-squared in Regression Analysis*. Statistics By Jim. Retrieved 24 september 2025 from https://statisticsbyjim.com/regression/interpret-r-squared-regression/
32. Frost, J. (n.d.–c). *How to Interpret Regression Models that have Significant Variables but a Low R-squared*. Statistics By Jim. Retrieved 24 september 2025 from https://statisticsbyjim.com/regression/low-r-squared-regression/
33. Glück, M., Hübel, B., & Scholz, H. (2021). ESG rating events and stock market reactions. *SSRN*.
34. Gurun, A., & Booth, G. G. (2024). The importance of trust to financial markets and institutions: Exploring the current literature. *Theoretical Economics Letters*, *14*(1), 27–40.
35. Heath, D., Macciocchi, D., Michaely, R., & C. Ringgenberg, M. (2023). Does socially responsible investing change firm behavior? *Review of Finance*, *27*(6), 2057–2083.
36. IOSCO, B.-l. S. F. T. F. b. (2021). *Environmental, Social and Governance (ESG) Ratings and Data Products Providers - Final Report*.
37. Johnston, J., & Dinardo, J. (1997). *Econometric methods* (4 ed.). MCGraw-Hill.
38. Kaushik, R. (2025). *Financial Analysis: Importance, Types, and Examples*. Knowcraft Analytics. Retrieved 25 September 2025 from https://www.knowcraftanalytics.com/financial-analysis/
39. Kotsantonis, S., & Serafeim, G. (2019). Four Things No One Will Tell You About ESG Data. *Journal of Applied Corporate Finance*, *31*(2), 50–58. https://doi.org/https://doi.org/10.1111/jacf.12346
40. Kräussl, R., Oladiran, T., & Stefanova, D. (2024). A review on ESG investing: Investors' expectations, beliefs and perceptions. *Journal of Economic Surveys*, *38*(2), 476–502.

41. Lee, H., & Chen, S. (2024). A Systematic Bias of Machine Learning Regression Models and Its Correction: an Application to Imaging-based Brain Age Prediction. *arXiv preprint arXiv:2405.15950*. https://arxiv.org/abs/2405.15950v2
42. Lev, B., Petrovits, C., & Radhakrishnan, S. (2010). Is doing good good for you? How corporate charitable contributions enhance revenue growth. *Strategic management journal*, *31*(2), 182–200.
43. Li, Z., Feng, L., Pan, Z., & Sohail, H. M. (2022). ESG performance and stock prices: evidence from the COVID-19 outbreak in China. *Humanities and Social Sciences Communications*, *9*(1), 1–10.
44. Luo, D. (2022). ESG, liquidity, and stock returns. *Journal of International Financial Markets, Institutions and Money*, *78*.
45. Martini, A. (2021). Socially responsible investing: from the ethical origins to the sustainable development framework of the European Union. *Environment, development and sustainability*, *23*(11), 16874–16890.
46. Pfajfar, L., Verbič, M., & Rogelj, R. (2012). *Handbook of Basic Econometrics*. Ekonomska fakulteta.
47. Prall, K. (2021). *ESG Ratings: Navigating Through the Haze*. CFA Institute – Enterprising Investor. Retrieved 24 September 2025 from https://blogs.cfainstitute.org/investor/2021/08/10/esg-ratings-navigating-through-the-haze/
48. Remesh, A. (2024). *Financial Ratio Analysis: Definition, Types with Examples, Frameworks, Uses*. Strike. Retrieved 25 September 2025 from https://www.strike.money/fundamental-analysis/financial-ratio-analysis
49. Rizani, A., Rasyad, R. Z., Budiarti, L., & Sulistyawati, U. S. (2023). Analysis of financial decision-making with a behavioral economics approach: Perspectives on capital market investors. *International Journal of Management Science and Information Technology*, *3*(2), 205–216.
50. Sahut, J.-M., & Pasquini-Descomps, H. (2015). ESG impact on market performance of firms: International evidence. *Management international*, *19*(2), 40–63.
51. Siegel, J. J. (2022). *Stocks for the Long Run by Jeremy Siegel* (4 ed.). McGraw-Hill.
52. Sothmann, A. (2022). *The effects of the EU Taxonomy regulation on institutional investor behavior* Aalto University School of Business].
53. Stallard, E., & Poynting, M. (2025). *What is the Paris climate agreement and why has Trump withdrawn?* BBC. Retrieved 24 September 2025 from https://www.bbc.com/news/science-environment-35073297#:~:text=To%20%22pursue%20efforts%22%20to%20limit,zero%20%2D%20between%202050%20and%202100
54. Taleb, W., Le Guenedal, T., Lepetit, F., Mortier, V., Sekine, T., & Stagnol, L. (2020). Corporate ESG news and the stock market. *SSRN*.

55. Upadhyaya, C., Khan, S., Sandhanshive, V., & Awasthi, G. (2023). A study of impact of behavioural factors on ESG investment. *Journal of Contemporary Issues in Business and Government*, *29*(1).
56. Vargas, M., & Kuhn, M. (2023). *DWS — Big Bonuses for Greenwashing: Remuneration System Report*. Greenpeace.
57. Weixiang, S., Qamruzzaman, M., Rui, W., & Kler, R. (2022). Retraced: An empirical assessment of financial literacy and behavioral biases on investment decision: Fresh evidence from small investor perception. *Frontiers in psychology*, *13*, 977444.
58. Wilson, H. (2025). *Financial Leverage: Definition, Calculation and Importance*. Investing.com. Retrieved 25 September 2025 from https://www.investing.com/academy/analysis/financial-leverage-definition/
59. Yin, X.-N., Li, J.-P., & Su, C.-W. (2023). How does ESG performance affect stock returns? Empirical evidence from listed companies in China. *Heliyon*, *9*(5).
60. Yobero, C. (2016). *Methods for Detecting and Resolving Heteroskedasticity*. RPubs by RStudio. Retrieved 25 September 2025 from https://rpubs.com/cyobero/187387
61. Zehir, E., & Aybars, A. (2020). Is there any effect of ESG scores on portfolio performance? Evidence from Europe and Turkey. *Journal of Capital Markets Studies*, *4*(2), 129–143.

APPENDICES

Appendix 1: Povzetek (Summary in Slovenian)

Magistrsko delo raziskuje odnos med vedenjskimi pristranskostmi in ESG vlaganjem. ESG vlaganje je na splošno razmeroma nov pojem na finančnih trgih, znan približno 20 let, vendar je od Pariškega sporazuma leta 2015 postal bolj priljubljen in bolj vključen v trg. Kljub temu ni veliko zgodovinskih dogodkov, iz katerih bi se bilo mogoče učiti. Zaradi tega je ESG bolj dovzeten za težave, kot so nelogično vedenje vlagateljev, neusklajenost ESG ocen in neprimerno vedenje, kot je »zeleno zavajanje« (greenwashing). Posledično je ESG bolj nagnjen k vedenjskim pristranskostim, ki lahko vplivajo na odločitve vlagateljev in jih oblikujejo ter s tem vplivajo tudi na delovanje finančnih trgov.

Nekonsistentnost ESG ocen in zeleno zavajanje sta predstavljena kot ena izmed najbolj znanih zavajajočih dejavnikov, ki vplivajo na odločitve vlagateljev in zato zahtevajo več regulacije. Regulativni okvir Evropske unije ima pomembno vlogo pri zaščiti vlagateljev pred takšnimi praksami. Evropska unija to uresničuje s številnimi predpisi, ki jih morajo poročevalski subjekti upoštevati. Najnovejši med njimi je Taksonomija EU (EU Taxonomy), katere namen je povečati preglednost, spodbuditi kakovostno poročanje o trajnostnih podatkih in izboljšati trajnostne prakse. Učinek Taksonomije EU je v magistrskem delu raziskan z namenom ugotoviti, ali je njena uvedba leta 2020 vplivala na vedenje vlagateljev in dogajanje na borzi. Poleg tega sta proučena tudi vpliv ESG ocene na tržno nestanovitnost (VSTOXX) ter dolgoročno napovedovanje donosov na osnovi ESG ocene kot neodvisne spremenljivke.

Analiza je bila izvedena z regresijsko metodo na vzorcu 664 podjetij iz Evropske unije v obdobju od leta 2018 do 2023. Da bi se učinek ESG ocene jasneje pokazal, je iz osnovnega vzorca izločenih zgornjih 10 % in spodnjih 10 % podjetij glede na povprečno ESG oceno. Raziskovalno vprašanje se osredotoča na to, ali lahko visoka oziroma nizka ESG ocena vodi do višjih oziroma nižjih donosov.

Rezultati so pokazali statistično pomembnost ESG ocene v letih 2018 in 2019, v kasnejših letih pa njeno nepomembnost. To je dalo osnovo za domnevo, da je uvedba Taksonomije EU lahko vplivala na investicijsko vedenje po letu 2020. Dolgoročna napoved donosov je sicer pokazala statistično pomembnost, vendar zaradi zelo nizkih koeficientov njena dejanska uporabnost ostaja vprašljiva. Podobno velja za analizo tržne nestanovitnosti, kjer je sicer zaznan tehnično pomemben učinek, vendar je zaradi nizkih koeficientov njegov dejanski pomen omejen. Analiza zgornjih 10 % in spodnjih 10 % ESG ocen je pokazala, da visoka ali nizka ESG ocena sama po sebi ne zagotavlja višjih oziroma nižjih donosov. Izjema je dolgoročna napoved v spodnjem delu vzorca, kjer je model pokazal statistično pomembnost, vendar nizko pojasnjevalno moč, rezultati pa kažejo na možnost napovedi nižjih donosov zaradi večjega tveganja teh podjetij.

Kljub temu rezultati raziskave kažejo, da je za zanesljivejše ugotovitve potrebna vključitev več spremenljivk in kazalnikov, saj ESG ocena sama po sebi ni zadosten pokazatelj in nima močne razlagalne niti napovedne moči.

Appendix 2: Attachments to Results

2.1 Named NAICS sector codes

NAICS Sector Name	NAICS Sector Code
Accommodation and Food Services	72
Administrative and Support and Waste Management and Remediation Services	56
Agriculture, Forestry, Fishing and Hunting	11
Arts, Entertainment, and Recreation	71
Construction	23
Educational Services	61
Finance and Insurance	52
Health Care and Social Assistance	62
Information	51
Manufacturing	31
	32
	33
Mining, Quarrying, and Oil and Gas Extraction	21
Other Services (except Public Administration)	81
Professional, Scientific, and Technical Services	54
Real Estate and Rental and Leasing	53
Retail Trade	44
	45
Transportation and Warehousing	48
	49
Utilities	22
Wholesale Trade	42

Source: Own work based on Refinitiv Workspace (2025).

2.2 Named NAICS sector codes for leading industries

NAICS Subsector Name	NAICS Subsector Code
Chemical Manufacturing	325
Computer and Electronic Product Manufacturing	334
Electrical Equipment, Appliance, and Component Manufacturing	335
Fabricated Metal Product Manufacturing	332
Furniture and Related Product Manufacturing	337
Machinery Manufacturing	333
Miscellaneous Manufacturing	339
Nonmetallic Mineral Product Manufacturing	327
Paper Manufacturing	322
Petroleum and Coal Products Manufacturing	324
Plastics and Rubber Products Manufacturing	326
Primary Metal Manufacturing	331
Transportation Equipment Manufacturing	336
Wood Product Manufacturing	321

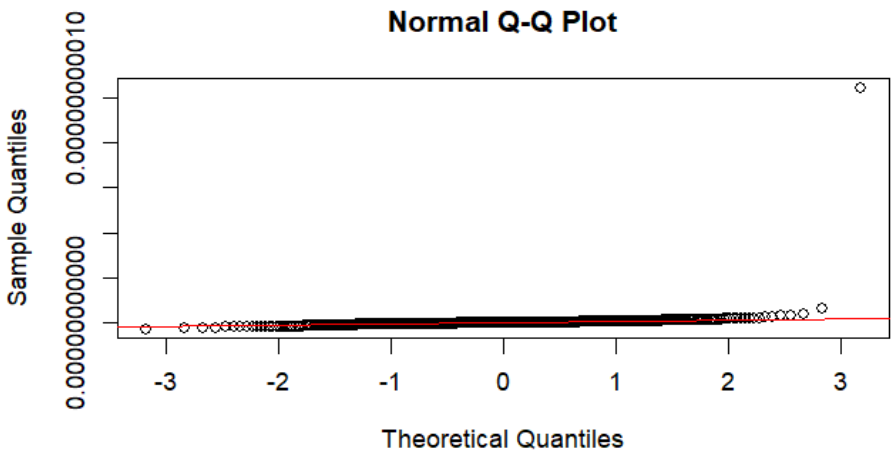
Source: Own work based on Refinitiv Workspace (2025).

2.3 Table of VIF values per quarter for multicollinearity

	Quarter	ESG	TA	DTA	DTE	Revenue	Liquidity	OM	CF	ROA	ROE
1	Q4_2023	1.308941	2.462755	2.634255	2.698536	3.569573	1.297294	1.388875	2.644647	1.313514	1.174882
2	Q3_2023	1.296816	2.730312	2.891231	2.943795	2.945125	1.398392	1.611137	2.324732	2.496494	2.155956
3	Q2_2023	1.263605	2.487003	2.887506	3.082913	3.246326	1.519014	1.775116	2.043241	2.219251	2.016178
4	Q1_2023	1.280095	2.656675	2.649056	2.680036	3.291314	1.235733	1.803498	1.535884	3.034590	2.326467
5	Q4_2022	1.351069	2.798204	2.616998	2.627095	3.730835	1.454879	1.590683	2.713508	4.692087	4.323518
6	Q3_2022	1.363813	2.491844	2.091242	2.044170	3.387425	1.340781	1.591442	2.083826	2.340195	1.883479
7	Q2_2022	1.367988	2.509725	2.216856	2.204634	2.649455	1.367363	1.657174	1.940319	3.480698	2.841713
8	Q1_2022	1.379487	2.406889	2.209831	2.228308	2.813193	1.461769	1.778307	1.380948	3.406714	2.852123
9	Q4_2021	1.367365	2.856548	2.418945	2.387609	3.022799	1.331320	1.573239	2.563992	2.883264	2.350377
10	Q3_2021	1.364084	2.658673	2.602882	2.714660	3.041355	1.480550	1.753685	2.515652	4.483593	3.783957
11	Q2_2021	1.361226	2.832247	2.669198	2.618157	2.849040	1.636355	1.789819	1.772754	2.863148	2.305500
12	Q1_2021	1.332929	2.729832	2.353961	2.243008	3.052539	1.422491	1.732100	1.751031	3.315761	2.571150
13	Q4_2020	1.431854	2.601516	1.986116	2.029829	3.101405	1.344923	1.303497	1.987788	1.562288	1.458554
14	Q3_2020	1.420979	2.826188	2.291513	2.340546	3.061253	1.500889	1.575817	1.984071	1.608999	1.436148
15	Q2_2020	1.416514	2.877852	2.156396	2.269842	3.378621	1.285832	1.354894	2.360845	4.009443	3.813516
16	Q1_2020	1.357412	2.855504	2.413524	2.411125	3.326478	1.670735	1.663641	2.033832	1.945082	1.823524
17	Q4_2019	1.397660	3.038342	2.671113	2.644075	3.492979	1.579871	1.683575	2.188516	1.614018	1.516223
18	Q3_2019	1.404768	2.785255	2.777488	2.836725	3.364592	1.769276	2.057649	2.265096	4.898247	4.094762
19	Q2_2019	1.420676	2.866684	3.074772	3.276454	3.289538	2.107970	2.384918	2.085198	6.656089	5.606246
20	Q1_2019	1.381900	2.943786	3.048485	2.947179	3.324594	1.997505	2.214800	1.801086	2.670909	2.249943
21	Q4_2018	1.419881	2.937263	3.279112	3.151086	3.425826	1.821897	1.833132	2.248175	4.522787	4.037909
22	Q3_2018	1.444873	2.597742	2.985521	2.944833	3.744766	1.339938	1.824799	2.479909	6.480068	5.074157
23	Q2_2018	1.448246	2.788159	2.876440	3.331219	3.110299	1.519667	1.662924	1.870684	8.336721	7.657130
24	Q1_2018	1.418306	2.644473	3.308674	3.348764	3.616721	1.936097	2.470509	2.350084	5.967369	4.835947

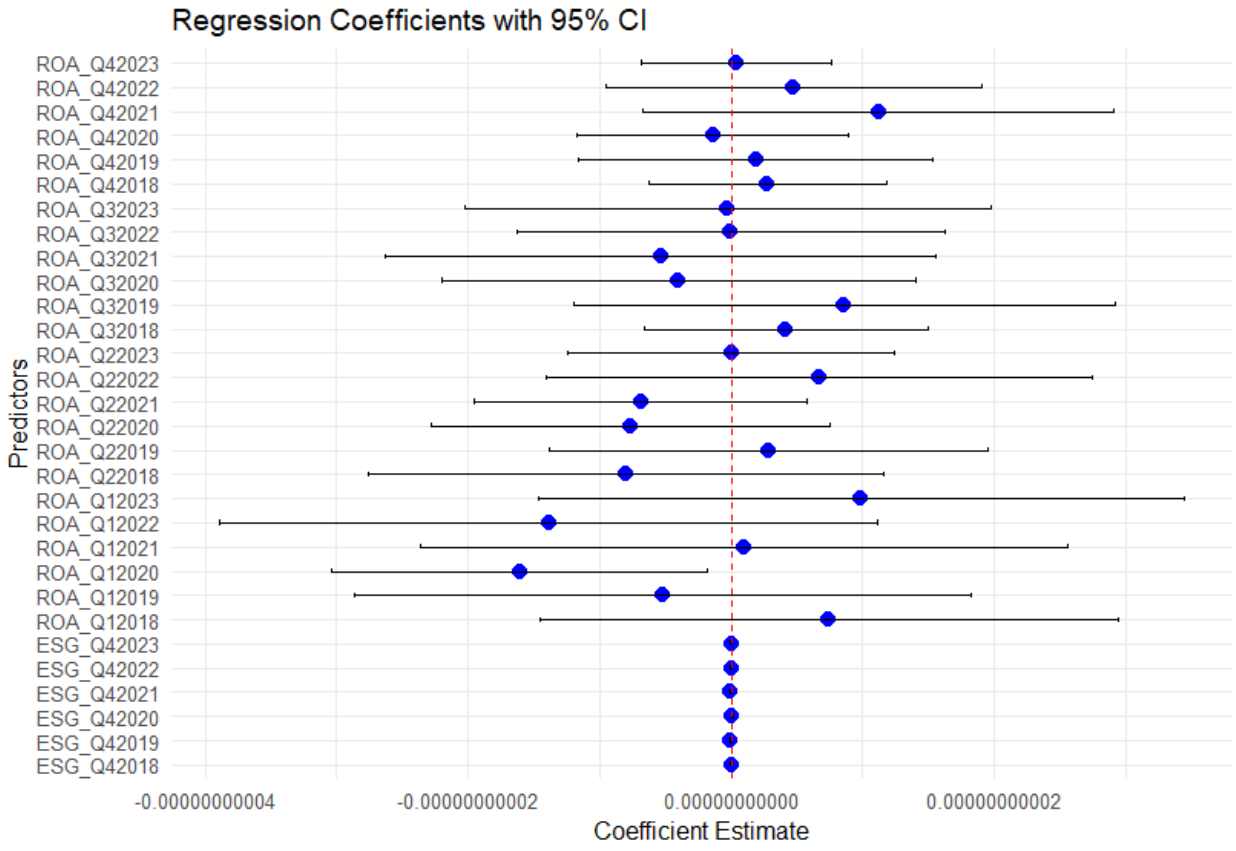
Source: Own work based on Refinitiv Workspace (2025).

2.4 Normal Q–Q plot for volatility



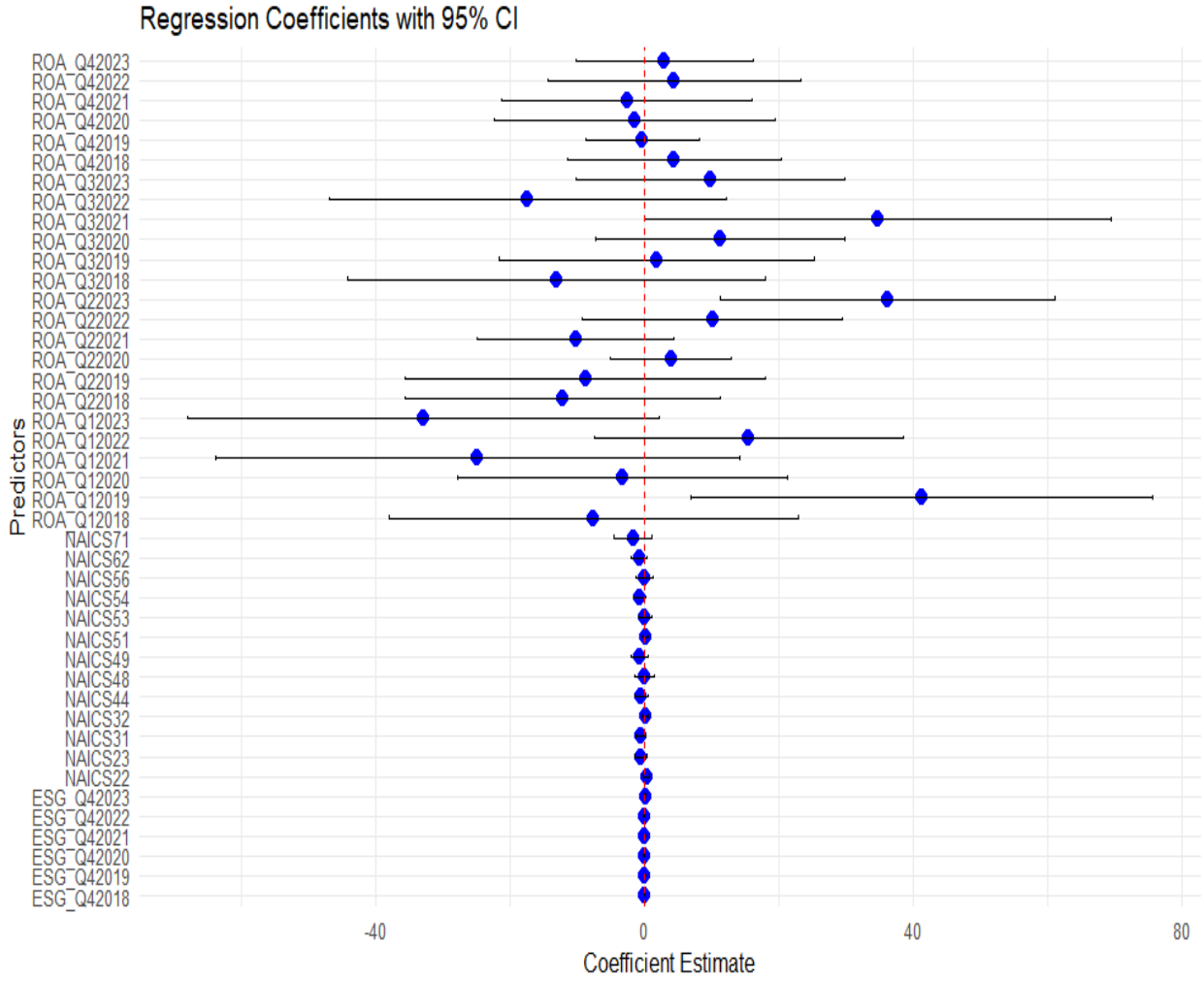
Source: Own work based on Refinitiv Workspace (2025).

2.5 Full coefficients plot – all variables (VSTOXX)



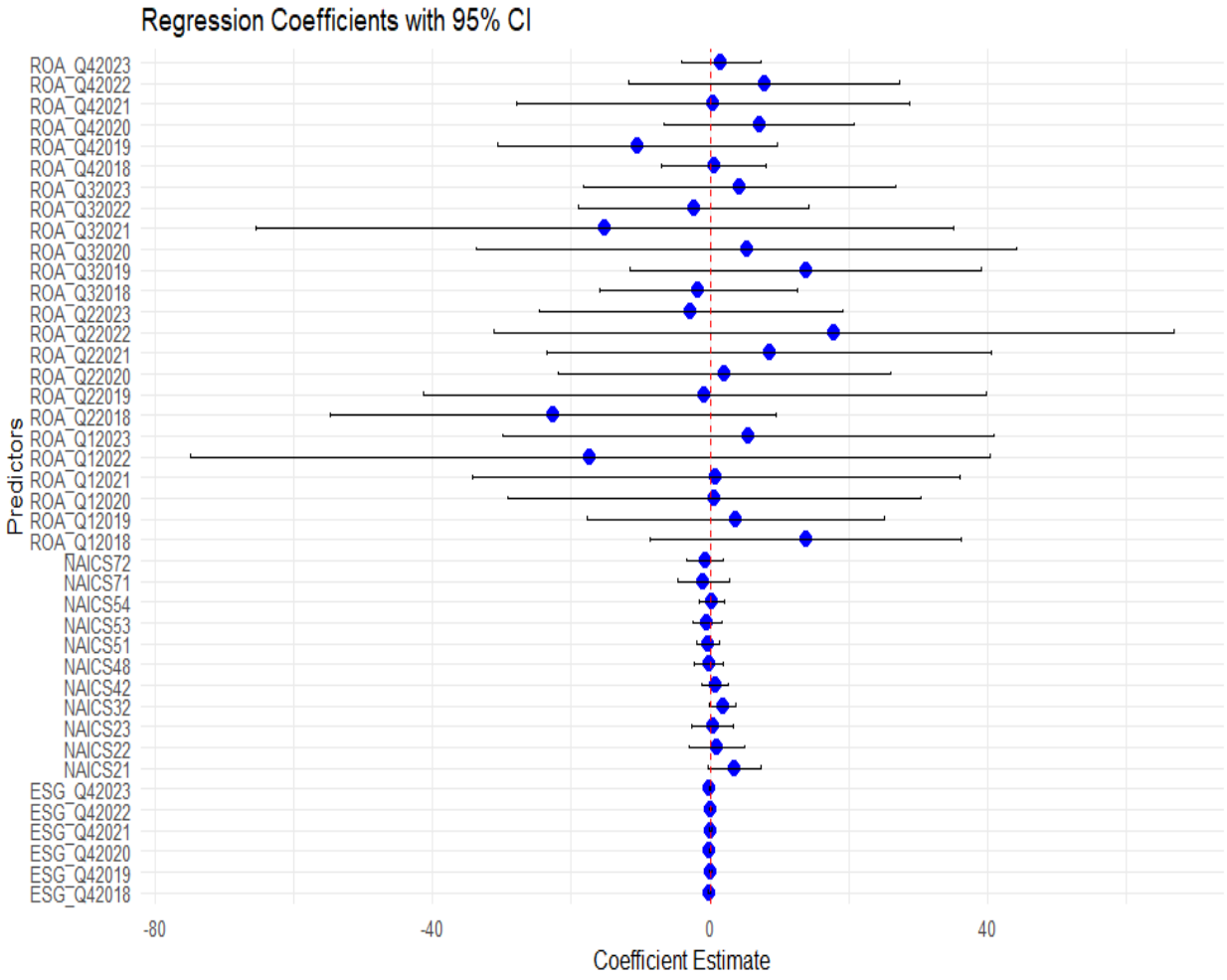
Source: Own work based on Refinitiv Workspace (2025).

2.6 Full coefficients plot for the top 10% sample (current model)



Source: Own work based on Refinitiv Workspace (2025).

2.7 Full coefficients plot for the bottom 10% sample (current model)



Source: Own work based on Refinitiv Workspace (2025).