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Analysing the ESG stocks: Are they less volatile?

Master's thesis

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Abstract

In this thesis, we investigate the relationship between ESG (Environmental, Social, and Governance) scores and stock volatility using panel data analysis. Focusing on data from 2 095 companies from three major stock exchanges - NASDAQ, NASDAQ Nordic, and Johannesburg stock exchange in the time window of 2016-2023, we employ fixed effects and random effects models with robust standard errors. We examine the overall impact of ESG scores on volatility, the influence of individual pillar scores, industry and stock exchange-specific effects, and time-specific effects. The thesis enhances existing literature by exploring three previously unexamined trends: non-linear dynamics between low-ESG score and volatility, the evolution of the trend over time by using an expanding time-window approach, and geographically and market-specific effects by utilizing data from different stock exchanges. The results from our analysis indicate that while the influence of ESG scores on overall stock volatility across the dataset is insignificant, significant correlations were observed in certain industry-specific models. The Technology, Industrials, and Healthcare sectors displayed a significant negative correlation between Governance scores and volatility. Moreover, for stocks listed on NASDAQ Nordic, there was a significant negative effect of Environmental scores and a positive effect of Social scores on volatility, suggesting cross-market heterogeneity.

JEL Classification	C33, C58, G11, G14
Keywords	ESG, Stock volatility, Panel data analysis, Financial markets
Title	Analysing the ESG stocks: Are they less volatile?

Abstrakt

V této práci zkoumáme vztah mezi ESG skóre a volatilitou akcií pomocí analýzy panelových dat. Zaměřujeme se na údaje od 2 095 společností z tří hlavních burz - NASDAQ, NASDAQ Nordic a Johannesburg Stock Exchange v období 2016-2023 a používáme modely s pevnými a náhodnými efekty s robustními standardními chybami. Zkoumáme celkový dopad skóre ESG na volatilitu, vliv skóre jednotlivých ESG pilířů, dále vliv ESG skóre v jednotlivých odvětvích, burzách a časových horizontech. Práce rozšiřuje stávající literaturu zkoumáním tří dříve nezkoumaných trendů: nelineární dynamiku mezi nízkým ESG skóre a volatilitou, vývoj trendu v čase s využitím roztahujícího se časového okna a geograficky či tržně specifické faktory využitím akcií z různých burz. Výsledky naší analýzy ukazují, že zatímco vliv ESG skóre na celkovou volatilu není významný, významné korelace byly zaznamenány u několika odvětví a jedné burzy. Odvětví technologií, průmyslu a zdravotnictví vykazovaly významnou negativní korelaci mezi Governance skóre a volatilitou. U akcií zalistovaných na burze NASDAQ Nordic byl pozorován negativní vliv environmentálního skóre a pozitivní vliv sociálního skóre na volatilitu, což naznačuje heterogenitu napříč trhy.

Klasifikace JEL	C33, C58, G11, G14
Klíčová slova	ESG, Volatilita akcií, Panelová data, Finanční trhy
Název práce	Analýza ESG akcií: Jsou méně volatilní?

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Acronyms

API Application Programming Interface

ARCH Autoregressive Contitional Heteroskedasticity

CFP Corporate financial performance

CSR Corporate Social Responsibility

DJSI Dow Jones Sustainability Index

ETF Exchange-Traded fund

EGARCH Exponential Generalized AutoRegressive Conditional Heteroskedasticity

ESG Environmental, Social, Governance

ESGC Environmental, Social, Governance Controversy

FE Fixed effects

FTSE Financial Times stock exchange

GARCH Generalized AutoRegressive Conditional Heteroskedasticity

GES Global Engagement Services

HAR Heterogenous Autoregressive

KLD Kinder, Lydenberg, Domini and Co.

LOCF Last observation Carried Forward

LT DtE Long-term Debt-to-Equity

MAR Missing at Random

MCAR Missing Completely at Random

MNAR Missing not at Random

MSCI Morgan Stanley Capital International

NA Not available

NARDL Non-linear autoregressive distributed lagged

NASDAQ National Association of Securities Dealers Automated Quotations

NGO Non-Governmental organization

NOCB Next observation carried backwards

NYSE New York Stock Exchange

OLS Ordinary Least Squares

RE Random effects

ROE Return on Equity

SV Stochastic Volatility

TRBC The Refinitiv Business Classification

Chapter 1

Introduction

Ethical investing has gained quite a lot of popularity in recent years. According to a study by PwC (2022) 8 out of 10 investors are considering investing in ESG-related financial instruments. But before discussing the significance of ESG, it is essential to understand, what ESG means. It is an acronym for three words - Environmental, Social, and Governance. The Environmental part encompasses the company's carbon footprint, usage of reusable materials and renewable energy sources, limited use of chemicals, or waste reduction. The social pillar accounts for an ethical supply chain operation, child labor avoidance, not outsourcing workplaces with questionable safety and work protocols, policies against sexual misconduct, supporting the rights of minorities, and diversity, and paying a fair wage. The Governance pillar includes the diversity of the board of directors, transparent corporate policy, or separation of CEO and board chair roles (Refinitiv 2022).

There are several reasons, why investors may consider putting money into ESG stocks. Companies, that follow ESG principles usually align with investors' values and principles better, which is one of the reasons why people implement or at least consider implementing these stocks into their portfolios. Another reason is closely tied to the Environmental part. 84% of Americans between 16 and 25 years of age reported fears related to global climate change and supporting companies, that are trying to be "better" in this field might be one of the ways to help it (Forbes 2023). And the third, for many people, the ultimate goal of investing is return on investment. Some studies, such as Ashwin Kumar *et al.* (2016) claim, that ESG portfolios might have better returns while maintaining lower volatility. However, these results differ across the studies, with some saying the opposite and others having inconclusive results.

The objective of this thesis is to create a thorough analysis and to find out, whether ESG stocks are less volatile across different industries, stock exchanges, and time windows using panel regression. We want to test the hypothesis, that a good ESG score decreases the volatility of the stock, and see if a bad ESG score has the opposite effect and increases volatility. We also want to find out if the influence of ESG score on volatility changes over time, as some claim, that ESG is more important than ever (Forbes 2022), while others argue, that it is now becoming just a buzzword and companies overvalue their statements about their ESG performance to catch the attention of these potential "ethical investors" interested in high-ranking ESG stocks (investor 2022).

To answer the questions laid in the paragraph above, we conducted a panel data analysis utilizing data from Refinitiv, spanning the years 2016 and 2023, and encompassing three major stock exchanges: NASDAQ, NASDAQ Nordic, and the Johannesburg Stock Exchange. We explored the impact of ESG scores as a whole and the impact of individual ESG pillar scores across various dimensions, such as industry subsets, individual exchanges, and distinct time windows. Additionally, robustness checks were conducted to ensure the reliability of our findings. The results suggest, that ESG scores do not significantly influence stock volatility when talking about the whole dataset, however, there are some outliers. While the majority of scenarios showed no significant difference attributable to ESG scores, some industries, such as the Healthcare, Technology, and Industry sectors exhibited notable correlations for Governance scores. Interestingly, the NASDAQ Nordic exchange, unlike its US counterpart, NASDAQ, demonstrated significant correlations with two pillars. Negative with Environmental scores and positive with Social scores.

In the second chapter, we will look into existing literature in the literature review, the third part describes the data used in the thesis, where we gathered the data, how we handled them, and the structure and reasoning behind each ESG rating. The fourth chapter describes the methods used and defines the models. The fifth part is about commenting on our results and implementing them into our hypotheses and the sixth part is the conclusion, where we sum the thesis up.

Chapter 2

Literature review

2.1 ESG stock research

The research on ESG scoring and its influence on investing has been around for quite some time. Authors such as Halbritter & Dorfleitner (2015), and Matos (2020) create critical reviews of ESG-based investment strategies. To do so, Halbritter & Dorfleitner (2015) use Fama Macbeth regression and the four-factor model to evaluate the influence of ESG ratings of three different providers. Asset4, now known as Refinitiv, KLD (now MSCI - Morgan Stanley Capital International) and Bloomberg. They claim, that even though they find several factors influencing the returns, it is hard to be taken advantage of by investors, as the direction and magnitude of the effects heavily rely on the ESG scoring provider, the sample of the companies picked, and the time period. Matos (2020) arrives at similar results, stating that "there is no consistent evidence that SRI (Socially responsible investing) strategies have produced enhanced returns."

Another aspect of ESG investing, that has been studied, is the motivation behind the use of ESG scoring in investments. Such papers were done by Amel-Zadeh & Serafeim (2018) or Giglio *et al.* (2023). Amel-Zadeh & Serafeim (2018) inspect why and how investors use information regarding ESG performance. They used a global survey with 652 responses from senior investors in asset-managing and asset-owning institutions to get their data. Their results show that investment performance is the most frequent motivation of the survey participants to work with ESG data, followed by client demand, product strategy, and then, ethical considerations. The reason for not using the ESG information was mainly that there was no demand by clients to use them or a lack of reliable nonfinancial data. Some of the main barriers, that they have to overcome when wanting to use ESG information are the lack of reporting standards, not big enough difference in ESG scoring between relevant companies, ESG information being too general, or that the data are not audited and reliant enough. Another study, published by Giglio *et al.* (2023) uses the results of an online survey for retail investors conducted by Vanguard. Their findings suggest, that most investors expect lower returns from ESG portfolios and the motivation of ethical consideration is three times more common than higher expected returns among the respondees. Another commonly reported reason to invest in ESG stocks was hedging. They also investigate the link between reported and actual investing behavior, finding, that both people expecting higher returns and those with ethical reasons tend to have a higher percentage of ESG-related investments than investors with other or no motives.

With an increasing number of ESG papers, a number of meta-analyses have been conducted, first by Friede *et al.* (2015), and in recent years by Huang (2021), Khan (2022) or Atz *et al.* (2023). All of them created a meta-analysis of studies concerned with the relationship between ESG performance and corporate financial performance (CFP). All but Atz *et al.* (2023) report, that on average, the ESG strategies seem to have a positive correlation with CFP, with for example Friede *et al.* (2015) using over 2000 studies and academic papers to aggregate their results and report, with over 90 percent of the studies indicating a non-negative relationship between ESG score and CFP and the majority of them reporting positive results. Huang (2021) advises being cautious about these results, claiming, that the significance and effect of these findings are either very modest or none at all. Atz *et al.* (2023) arrive to the conclusion, that the results of ESG investing are indistinguishable from conventional investing, with only one-third of papers out of 1 500 studies and 27 meta-reviews reporting enhanced returns.

2.2 Volatility of ESG stocks

Several research papers have already examined the issue of the correlation between stock volatility and ESG ratings. Hübner (2005), Ashwin Kumar *et al.* (2016), Meher *et al.* (2020) or Shakil (2022) try to examine a relationship between ESG score and stock volatility. Zhou & Zhou (2021) and Mousa *et al.*

(2021) try to do so specifically for COVID-19 times in an event-specific study. Capelli *et al.* (2021) look into using ESG score to enhance the predictive power of volatility forecasts and Sabbaghi (2022) examines the effect of the news on highly rated ESG companies.

To quantify ESG performance, two different methods are generally used. Some papers, such as Zhou & Zhou (2021), Shakil (2022) or Sabbaghi (2022) use the ESG score directly and others, such as Meher *et al.* (2020) and Mousa *et al.* (2021) use ESG indexes, containing firms with high ESG scores as a dummy variable for good ESG results. As for volatility, the usual approach, used in most of the studies is annualized volatility. This approach is commented on in Section 3.3 and is chosen by the researchers mostly due to ESG scores being published on a yearly basis.

Both Meher *et al.* (2020) and Shakil (2022) perform panel data regression analysis. Meher *et al.* (2020) focus solely on the Indian stock market. Their goal is to prove that a higher ESG rating is correlated with both returns and volatility of the company. Their dataset consists of 43 companies included in NIFTY 100 Enhanced ESG. Being listed in this index also serves as a dummy variable for high ESG ratings. They arrive at inconclusive results, saying that neither returns nor volatility can be predicted by ESG rating. The only finding that is at least weakly significant is, that Governance and Environmental score is negatively correlated with volatility. The Shakil (2022) tries to figure out the role of ESG performance on the stock price volatility of companies in the textile industry. He examines 44 companies between the years 2010 and 2018. As a proxy for ESG performance, he uses data from Refinitiv. He argues that the ESG results have a significant negative effect on market volatility (the higher the ESG results, the lower the volatility). In contrast, the firm size has no significant effect. They get partially similar results with the study of Meher *et al.* (2020), as they found a significant negative correlation between the Environmental and Governance part of ESG and volatility.

A similar approach, just using only descriptive statistics to capture the effect of ESG scoring, is used by Ashwin Kumar *et al.* (2016). They calculate the average volatility and returns of ESG stocks and compare them with the control group consisting of random stocks. Their sample consists of 157 companies, that should be top of the class in terms of ESG, which is ensured by their enlisting in the Dow Jones Sustainability Index (DJSI) and 809 not enlisted control companies between 2014 and 2015. They then break the companies into clusters according to their industry. Materials, energy, automotive, durables, food & beverages, banks, insurance, healthcare, capital goods, transportation, technology and utilities. They find lower volatility for the ESG companies for all of the industries. According to their results, the ESG companies in all of the industries had on average lower volatility than the control group, with the biggest difference for the energy and materials industries (over 40% higher volatility) and the lowest for food & beverages (by 6%). For the returns, the results were not that unambiguous as in 8 out of 12 industries ESG stocks outperformed the control group while in 4 industries it was the opposite. Other than that, they also test their results using the Trenyor ratio, which is a measure comparing the return earned on a stock against the market risk of a stock (Hübner 2005) with similar results of ESG stocks outperforming the control group in 9 out of 12 industries.

In the context of COVID-19-related studies, Zhou & Zhou (2021) use the difference in differences model on 1 021 companies and their volatility from 1.12.2019 to 31.3.2020. They use daily volatility and high and low price data. ESG performance is derived from MSCI scoring index and to make results more robust they use control variables in Tobin Q values and cash holding ratio. Their results show a negative correlation between volatility and good ESG scores during times of crisis, which can be important as overall volatility got higher during the pandemic, and implementing ESG stocks into the portfolio might help manage risks and make more robust portfolios. Mousa *et al.* (2021) use GARCH models to quantify shock and non-linear autoregressive distributed lagged (NARDL) regression model to display the relationship between COVID-19 and ESG score. Similarly to Zhou & Zhou (2021), they find lower volatility for ESG stocks compared to a control group in times of crisis, while being similar before COVID-19.

Papers using ESG to predict the volatility rather than report it and find correlation in the past are Capelli *et al.* (2021) and Guo *et al.* (2020). Capelli *et al.* (2021) tried to forecast volatility by integrating financial risk and ESG score. They used the ECPI Global Ethical Equity index as a proxy for ESG score on almost 18 000 observations of 3 332 firms between 2007 and 2015. For data regarding volatility they used historical volatility from Bloomberg, calculated as weighted daily volatility over 1 year period. Other than that several control variables were introduced. Firm size, financial solvency ratio, dummy for organizational structure (either holding or operating firms), industry classification, geographical location, and temporal effect encoded in year dummy variables. They found out that incorporating ESG variables in volatility forecasting can increase the prediction power of the model, especially on 3-year forecasts. Guo *et al.* (2020) do not use ESG score directly. They use language models to capture ESG-related news and then incorporate them into volatility predictions and obtain similar results to Capelli *et al.* (2021), claiming that ESG news helps predict the stocks, that will have the highest volatility. Sabbaghi (2022) also looks into the relationship between ESG-related news and volatility. They use MSCI indices as a proxy for ESG performance and focus on the stocks, that are the best-in-class and incorporate the EGARCH (Exponential GARCH) framework. Their study claims, that the bad news affect volatility more strongly than the good news and this effect is larger for mid and big-sized firms compared to the small ones. This would align with findings of Guo *et al.* (2020), as their model correctly predicts mainly stocks with higher volatility.

2.3 ESG scoring agencies comparison

There are a lot of different ESG rating agencies and most of the papers take information from one of those as a proxy to determine if the company has a good ESG rating or not. But as seen in studies, that focus on more than one rating agency, such as Dorfleitner *et al.* (2015), Semenova & Hassel (2015), Gibson Brandon *et al.* (2021), Berg *et al.* (2022) or Serafeim & Yoon (2022) the correlation between scores among different rating providers is not high enough to make them interchangeable.

Studies of Dorfleitner *et al.* (2015), Semenova & Hassel (2015), and Berg *et al.* (2022) compare different rating agencies, their methodology, and scores. Dorfleitner *et al.* (2015) compare the ESG scores of three rating providers. Asset4, which is now known as Refinitiv, Bloomberg and KLD, now known as MSCI. Their sample selection includes all rated companies from Refinitiv and MSCI between 2002 and 2012 and Respective companies from Bloomberg. They find a high correlation between the total score of each rating agency and its respective subscores for the Environmental, Social, and Governance sectors with the Governance pillar being the least correlated. But the correlation between providers seems to be quite low with for example Environmental scores of now Refinitiv and MSCI having a correlation of 0.05. They also find very different distribution and descriptive statistics of scores among the different providers as a histogram of Refinitivs scores is quite uniformly distributed or u-shaped, the MSCI is much more normally distributed and Bloomberg is heavily left-tailed. Semenova & Hassel (2015) compares not only the scores but also the methodology of MSCI, Refinitiv, and Global Engagement Services (GES). They find that the methodology of those agencies is somewhat similar, with each having strengths in different areas.

Berg *et al.* (2022) make the most comprehensive study out of these three with six different rating agencies. MSCI KLD, Sustainalytics, Moody's, RobecoSam from S&P Global, Refinitiv Asset4, and MSCI. They find an average correlation of 0.54 between the overall scores, 0.53 for Environmental, 0.42 for Social, and 0.3 for Governance part of the scoring. They explain the differences by three factors - scope, measurement, and weight. The first factor, scope, is about different areas being considered in each scoring, as every agency has a different methodology and is focused on different things in their evaluation when the methodology is broken down. This seems to account on average for over a third of the difference. Measurement, which describes how the agencies quantify their findings, seems to be most important in explaining more than half of the divergence, and the third factor, weight, describes how big of a role each part of the score has accounted for around 6% of the differences. These numbers differ among individual pairs as some of the scorings have similar scope while others have more similar measurements, such as KLD and MSCI, that are issued by the same agency. This supports the findings of Dorfleitner *et al.* (2015) and Semenova & Hassel (2015), that the choice of ESG rating agency is important and the results for each scoring agency may differ.

Gibson Brandon *et al.* (2021) tried to capitalize on these differences in ratings between the agencies and tried to find the relationship between the disagreement between the ratings and financial returns. They use 7 different rating agencies. Reuters Asset4, Sustainalytics, Inrate, Bloomberg, FTSE (Financial Times stock exchange), and 2 ratings from MSCI. MSCI KLD and MSC IVA (Intangible value assessment). They found a significant positive effect between disagreements in the Environmental sector and returns and argued that this may be caused as a result of the theory of heterogeneous beliefs in the financial market.

Serafeim & Yoon (2022) investigate the relationship between ESG ratings and future ESG news and potential market reactions. For the score, they use MSCI, Sustainalytics, Thomson Reuters Asset 4, the average of those, and the difference from the average as a proxy for disagreement. They have a total of almost 32 000 samples between 2010 and 2018 across multiple industries. They find little correlation between the ratings with the highest being 0.47. In their results, they claim, that if the rating agencies agree on the rating, there is substantial predictive power of future ESG news and it diminishes with increasing disagreement of the ratings. This could be interesting to incorporate into studies of Guo *et al.* (2020) and Capelli *et al.* (2021) to further enhance the predictive power of ESG news.

2.4 Hypothesis and motivation

We have decided to include three main hypotheses.

Hypothesis #1: Stocks with high ESG scores have lower return volatility than non-ESG stocks across all the fields.

There has already been some literature on this, but the results of the analyses vary and we would like to confirm this hypothesis with up-to-date data, using methodology and data controlling for time-specific influences and omitted variable bias applying control variables known to influence stock volatility.

Hypothesis #2 Stocks with poor ESG scoring (worst in class) have on average higher volatility than randomly selected stocks.

The previous studies focus either on the overall score or compare "best performing" stocks in terms of ESG score with randomly selected populations with various results. However, none of the studies investigate the question, of whether the opposite is true as well, meaning, that the "worst performing" stocks in terms of ESG score have, in fact, higher volatility than randomly selected stocks. One might argue, that this is implicitly said in some studies, that indicate that ESG score has a negative correlation with volatility, but does not implicitly say, that the worst-in-class correlate is positive. We also want to disprove the hypothesis, that "bad behavior pays" as following ESG principles might be costly.

Hypothesis #3: The effect of ESG scoring on stock volatility performance gets stronger over time

The third hypothesis stems from the opinions, such as Jaros *et al.* (2022) or Díaz *et al.* (2021), that the influence of ESG ratings is getting stronger over time. On the other hand, Edmans (2023) warns about putting too much emphasis on ESG performance nowadays and implies, that the other intangible assets such as customer loyalty or innovative capability are just as important to a company's value as those, that are under the ESG label. However, this still may support our hypothesis as it indicates, that importance is put on ESG.

Using rolling and expanding windows for panel data analysis we strive to isolate the effect and confirm or deny the hypothesis, that the effect on volatility is also getting stronger as the interest in ESG stocks, bonds, portfolios ETFs, and sustainability issues in general rises amongst the general population.

Chapter 3

Data

To test the hypotheses established in this thesis, we had to obtain a concise dataset of stocks and information about them. We have decided to work with companies that are listed on the NASDAQ (National Association of Securities Dealers Automated Quotations) stock exchange with available information between the years 2016 and 2023, as NASDAQ has a robust market representation and diversity across various industries, providing ample opportunities for comprehensive market insights. It is the second biggest stock exchange by market capitalization (23.4 trillion $ as of December 2023) and monthly trade volume (over 1.2 billion$ as of 2023), right behind NYSE (New York Stock Exchange) (Statista 2023a), but we have chosen NASDAQ over NYSE, as it contains more stocks listed. (Statista 2023b) Most of the stocks on the primary NASDAQ stock exchange originated from the USA, so we added some more from NASDAQ Nordics exchanges (NASDAQ Stockholm, NASDAQ Helsinki, and NASDAQ Copenhagen). To have another control group, we have decided to include stocks listed on the Johannesburg Stock Exchange as well. We will also use these stocks to test our hypothesis, that the effect of ESG is not the same around the globe.

The dependent variable we will be looking at is summarized yearly volatility. This is calculated from either daily, weekly, or monthly volatility and is described below. We will, in some cases, also look into the revenue of the companies. Independent variables used are ESG information, consisting of overall ESG score, Environmental score, Governance score, and Social score. Those will be implemented either as absolute scores or as dummy variables, depending on the models. The other independent variables, that will be used as control ones are company size, calculated as a logarithm of market capitalization, return on equity, and long-term debt-to-equity ratio.

3.1 Data collection

As there is not a reliable method in Eikon to obtain a list of tickers, we have used NASDAQ (2023) to obtain all NASDAQ-listed companies as of July 2023, which consisted of 3 469 unique tickers. To obtain tickers of companies listed on NASDAQ Nordic exchanges we have used NASDAQ Nordics (2024) and for the Johannesburg stock exchange, we used data published on ListCorp (2024). After cleaning up the data, we created a list of all tickers and their relevant stock exchange indication to use for further scraping.

To obtain the additional information we want to know about the tickers (volatility, returns, ESG data, control variables) we used Eikon's built-in codebook environment, which works as a native Jupyter Notebook with Python3 kernel (LSEG 2024). After connecting via API we could download all the relevant information about the stock performances.

3.2 ESG variables

For the data about the ESG performance of the stocks, we used the index by Refinitiv. The initial idea was to use more ESG scoring providers due to differences in ratings, which were commented on in Section 2.3 to make the results more robust, but as the data from the agencies are not publicly available, only the data from the Refinitiv were used. Refinitiv index started tracking ESG performance in 2002 and currently includes data about over 12 500 companies in their portfolio across all industries in seventy-six countries around the world. They measure more than 700 metrics and update their score every week. In our analysis, we will use the overall ESG score, which is calculated through the methodology described below, but we will also look into the effects of partial ESG scores (Environmental, Social, and Governance pillars) and their parts.

3.2.1 Refinitiv methodology

The ESG scoring starts with data processing. The data are taken from websites of the companies, annual reports, websites of non-governmental organizations

(NGOs), stock exchange filings, credible news sources or CSR (Corporate social responsibility) reports so all of the information is publicly available. The ESG score itself is calculated from a subset of 186 metrics in three pillars depending on the specific industry.

The Environmental pillar, containing 68 metrics can be further divided into resource use, emissions, and innovations. Resource use concerns water use, energy use, utilization of sustainable packaging, or supply chain environmental-friendliness. It reflects how the company can reduce the usage of those assets and find solutions, that are more Eco-friendly by improving their supply chain. Emissions account for carbon dioxide emissions, the total amount of waste produced, impact on biodiversity or environmental management systems. Innovation is about product innovation, accounting for for example so-called environmental products, research and development, and capital expenditures into environmental issues.

The Social pillar consists of four parts: community, human rights, product responsibility, and workforce. The community category measures the social responsibility of the company, its actions to protect and not harm public health, and its commitment to following business ethics. In the human rights theme, the policy regarding the implementation of human rights in the code of conduct and human rights violations are taken into account as well. Product responsibility tries to reflect if the company is trying to produce quality goods and services and it further breaks down into responsible marketing, product quality, and data privacy. The workforce consists of four themes. Diversity and inclusion measure how diverse is the workforce in terms of gender, career development options, or hours spent on training and education. Working conditions, which take data points from trade union representatives and health and safety, which are calculated from lost days due to sickness and injuries. In total, there are 62 metrics, that might be used to calculate the overall score with almost half being in the workforce part.

The Governance pillar consists of three parts. CSR strategy, management, and shareholders. The CSR strategy category shows, how effectively the company integrates economic, environmental, and social dimensions into the decision-making processes and it further breaks down into the implementation of CSR strategy itself by the company and ESG reporting and transparency. The management part evaluates the structure of the management, from independence, and diversity to the existence and unbiasedness of committees and compensations. The third part, shareholders, looks at shareholder rights and takeover defenses. Out of 56 metrics used in this pillar, 35 are in the management part, 12 are about shareholders and 9 are about CSR strategy.

The individual category ESG score is then calculated as a percentile rank scoring in the respective industry for the Environmental and Social pillar while for the Governmental pillar, the country of origin is used, as governance practices are similar within one country rather than industry. This means that the score is calculated as follows.

$$\text{Score} = \frac{\text{No of firms with a worse value} + \left(\frac{\text{No of firms with the same value}^{*}}{2}\right)}{\text{No of firms}} \tag{3.1}$$

*Including current one

So if there are 40 companies in your industry and you are better than 38 and have the same value as one other company, your overall score would be ((38+2/2)/40), having a category score of 0.975. This number is then multiplied by the weight for each category, summed up and the overall ESG score is calculated. The weight of Environmental and Social categories varies across industries with governance issues remain always the same.

They also account for ESG-related controversies in their ESGC score. This measure controls for 23 ESG controversy topics. All companies get a base controversy score of 100 and points are deducted for each controversy the company had in the past fiscal year. To calculate the ESGC score, the lower one of the ESG score and controversy score is counted. This means that if the company has an ESG score of 75 and a controversy score of 77, both its ESG and ESGC score would be 75, but if the ESG score is 77 and the controversy score is 75, its ESG score remains 77, but the ESGC score would be 75. (Eikon 2022)

Table 3.1 shows the amount of data points in each cluster of ESG scores and annualized daily volatility quantiles per cluster. Most of the companies are in the ESG score range of 11-60 with almost none having less than 10 or more than 90 in overall ESG score. This might be caused by the strict ESG methodology of Refinitiv with only the best in class getting that over 90 ESG score. The volatility follows the trend we would expect from assumptions laid by Ashwin Kumar *et al.* (2016) or Shakil (2022), with higher ESG-scored companies having lower volatility in almost every quantile. From this distribution, we can see that the approach we planned with creating dummy variables for static intervals of ESG scores higher than 10, 20 up to 90 might not be the best approach for modeling as the edge values in our dataset would divide the data very unevenly and we will rather use quartiles, that can achieve similar results while distributing the data more evenly.

Table 3.1: Descriptive Statistics of ESG Scores by Volatility quantile

ESG Score	**Count**	**10%**	**25%**	**50%**	**Mean**	**75%**	**90%**
1-10	241	0.24	0.35	0.53	0.64	0.81	1.11
11-20	1428	0.28	0.38	0.58	0.68	0.81	1.12
21-30	2264	0.29	0.38	0.56	0.64	0.79	1.04
31-40	2186	0.27	0.36	0.50	0.59	0.71	0.95
41-50	1633	0.24	0.30	0.43	0.50	0.61	0.84
51-60	1235	0.23	0.29	0.39	0.45	0.54	0.72
61-70	875	0.22	0.27	0.35	0.40	0.47	0.61
71-80	597	0.21	0.27	0.35	0.40	0.47	0.59
81-90	250	0.19	0.24	0.30	0.33	0.39	0.50
91-100	43	0.20	0.22	0.25	0.28	0.33	0.38

When looking at the ESG pillars individually, we can see, that only 2/3 of stocks have data regarding the Environmental Score for the requested year in Refinitiv. We will discuss how we would handle these missing data further in our thesis, but for this analysis, we will keep them as NA. Even with missing values not counted, the Environmental pillar has the lowest ratings across the metrics with the mean being lower by 8 points than the Social and 13 points lower than the Governance pillar. This difference gets even higher for the first quartile, indicating that most companies are doing at least something right in Social and Governance parts, but have a substantial deficiency in Environmental issues. On the other hand, the third quartile difference is smaller, indicating smaller differences in best-in-class companies.

Table 3.2: Summary Statistics of Environmental, Social, and Governance Scores

Variable	Environmental	Social	Governance
Count	7199.00	10 752.00	10 752.00
Mean	34.36	42.78	47.28
SD	25.40	21.61	22.03
Min	0.03	0.51	0.17
Q_1	11.69	25.50	29.46
Median	30.22	40.06	47.33
Q_3	53.63	58.23	64.70
Max	98.31	97.97	98.56

3.3 Volatility data

Based on the fact, that ESG scores do not usually change during the year and are recalculated mostly once a year and previous literature implementing the same approach as well (Ashwin Kumar *et al.* 2016), we have decided to employ annualized daily volatility as a metric to investigate the relationship between ESG scores and stock volatility. By focusing on yearly ESG scores and annualized daily volatility, this study aims to capture the long-term effects of ESG performance on stock market stability and fluctuations as our hypothesis states, that long-term volatility is influenced by ESG scores.

Annualized daily volatility offers a robust framework to examine the relationship between ESG scores and stock volatility over time. By aggregating volatility measures at the yearly level, this approach enables a comprehensive assessment of the cumulative impact of ESG factors on stock price dynamics. It allows for the identification of potential patterns or trends in stock market behavior associated with changes in ESG scores. Additionally, utilizing yearly data allows for a more holistic evaluation of the effects of ESG practices on stock volatility, considering the time required for companies to implement and adapt their sustainability initiatives.

To test the robustness of the results and to control for the possibility, that even the effect on volatility is not only on the high granularity of daily data, which can account for more of the sudden spikes, that correct themselves within the next day but also in the longer term, we will also perform the analysis with annualized weekly and annualized monthly volatility data as well.

The volatility itself is calculated as the standard deviation of returns multiplied by the square root of the number of measurements. The returns are calculated as percentage change of Close prices of individual stocks. This means that for daily volatility the percentage change of the Close price between each day is measured to calculate returns for each day, and then the standard deviation of these returns is calculated and multiplied by the number of measurements, which is the number of days, where the stock price was published in the specified year. It usually does not include weekends. For weekly and monthly volatility, the formula remains the same, with the only difference being the frequency of the Close prices being measured. This results in less noise from short-term stock price deviations.

$$\sigma_T = \sigma \times \sqrt{n} \tag{3.2}$$

Where:

σ_T : Represents the volatility of the stock

σ : Denotes the standard deviation of returns

$\sqrt{n}$: Represents the square root of the number of measurements

The standard deviation (σ) of a set of n data points $(x_1, x_2, \ldots, x_n)$ is calculated using the following formula, calculating the square root of the average of the squared differences between each data point and the mean. :

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{3.3}$$

Where:

σ is the standard deviation,

x_i represents each individual data point,

$\bar{x}$ is the mean (average) of the data points,

n is the total number of data points.

In Table 3.3 we can see the descriptive statistics of the different volatility periods we have defined. All three have very similar distributions, with the average around 0.5 and most values ranging between 0.3 and 1. However, there are some big outliers. The reason for them can be for example huge jump in price, such as ticker UONE.O, belonging to the company Urban One Inc Class A rising in the stock price in one week in 2020 from $1.8 per stock to $36 per stock and then sharply declining again. This one jump created a whole outlier of this stock. We believe that the reason for other outliers is similar, which was confirmed by checking the biggest outliers' percentage returns over the time periods in question and seeing similarly big changes.

The last two columns depict statistics for the difference and absolute difference between daily and monthly volatility for each stock. As the difference and absolute difference portray different numbers, we can say, that monthly volatility can be both higher and lower than daily volatility and it is not unusual for them to be quite different. The company may be in the third quartile of monthly volatility with a value of 0.6 while being under the median in daily volatility if it belongs to the fourth quartile in the change difference or even in the first quartile if it belongs to the highest 5% of daily-monthly changes.

This phenomenon is further portrayed in graphs in Figure 3.1 for the distribution of daily and weekly volatility and Figure 3.2 for the distribution of daily and monthly volatility. One interesting outlier in the bottom right corner has a daily volatility of 15 and weekly and monthly volatility of less than one. This stock is ticker MCZJ.J, which is MC Mining Ltd from Australia, according to Refinitiv, lost 95% of value on November 27$^{\text{th}}$ and gained it back 3 days later, thus this sudden drop is not being seen in weekly and monthly volatility.

Table 3.3: Statistics for Volatility Variables

Variable	Daily Volatility	Weekly Volatility	Monthly Volatility	Diff D-M	Abs Diff D-M
Count	10 751.00	10 751.00	10 751.00	10 751.00	10 751.00
Mean	0.55	0.54	0.50	0.05	0.14
SD	0.43	0.48	0.46	0.35	0.33
Min	0.02	0.02	0.01	−10.76	0.00
Q_1	0.32	0.31	0.28	−0.03	0.03
Median	0.46	0.44	0.40	0.04	0.07
Q_3	0.67	0.65	0.60	0.11	0.15
90^{th} perc	0.92	0.91	0.87	0.23	0.27
95^{th} perc	1.12	1.12	1.10	0.32	0.39
Max	15.00	26.02	15.25	14.65	14.65

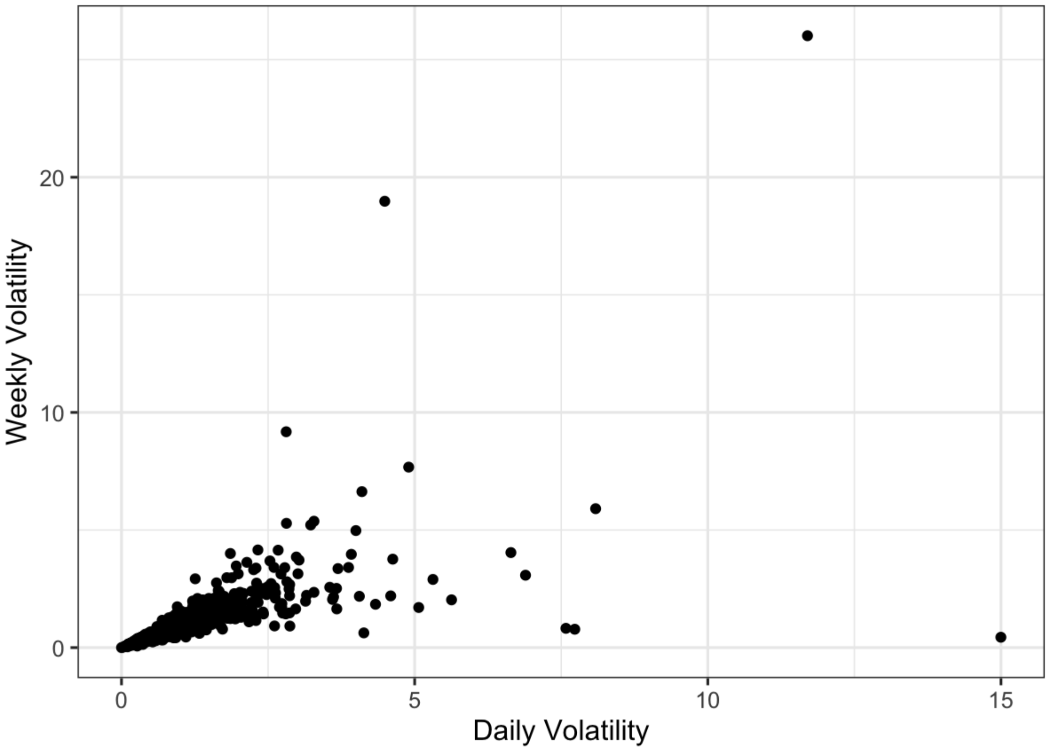

Figure 3.1: Daily x Weekly Annualized Volatility

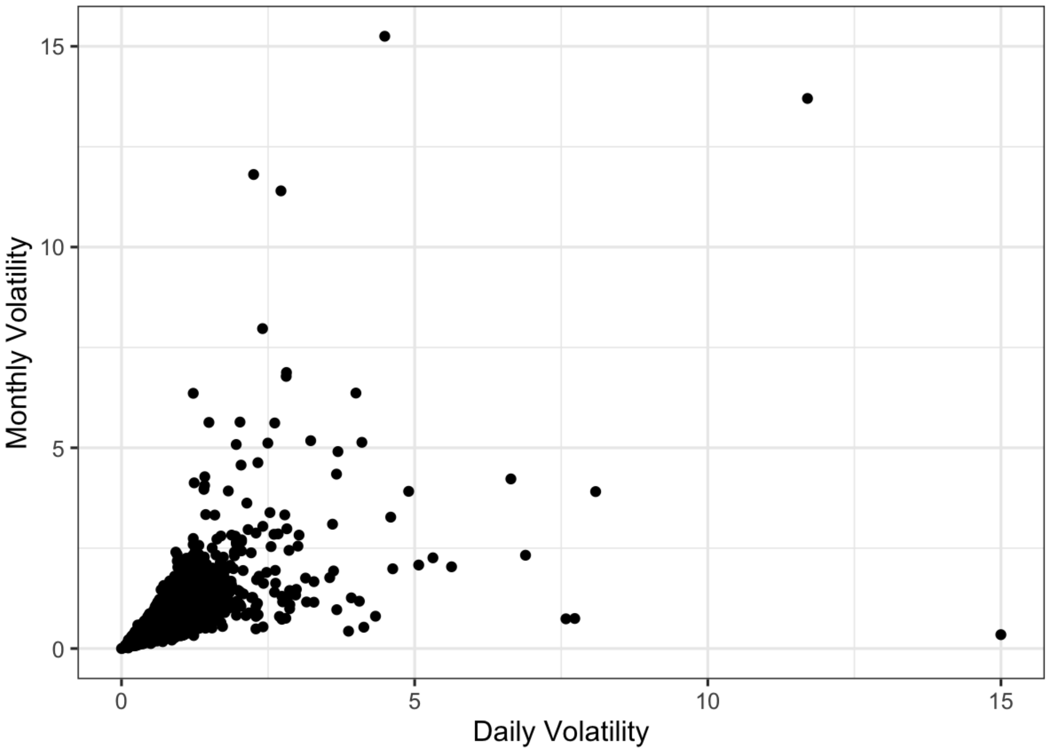

Figure 3.2: Daily x Monthly Annualized Volatility

3.4 Control variables

As other papers have already proven some other variables are known to influence the volatility of the stocks we will include them as control variables, so that we can isolate only the effect of ESG scoring and avoid omitted variable bias. The control variables, we will include, are company size, financial leverage, represented by long-term debt-to-equity ratio, profitability in the form of return on equity (ROE), industry of the company, and year dummy to control for time.

3.4.1 Company size

For the company size, which was previously used as a control variable by for example Shakil (2022), Capelli *et al.* (2021) and Sabbaghi (2022) the logarithm value of market capitalization is used, as it was found to be highly correlated to firms size and is commonly used as a proxy for the size in different papers (Dang *et al.* 2018). In the case of the Refinitiv database, the company market capitalization represents the sum of market value for all relevant issue-level share types. The value is calculated from the default latest close price, in our case at the end of the year (Refinitiv 2024). In Table 3.4 you can see the descriptive statistics and also a reason why the logarithm of market capitalization rather than market capitalization itself is used. The market capitalization scales logarithmically with the highest value being eighty times bigger than 95th percentile and standard deviation being higher than most of the values. On the other hand, the logarithm of the market cap is nicely distributed with values ranging from 0.4 up to 14.7 with the difference between the first and third quartile being only 2.5.

Table 3.4: Statistics for Market Cap and Log(Market Cap)

Variable	**Market Cap**	**Log(Market Cap)**
Sample size	10 752.00	10 752.00
NA values	106.00	106.00
Mean	11 305.15	7.13
Standard deviation	76 875.43	1.91
Min	1.49	0.40
Q_1	332.19	5.81
Median	1127.15	7.03
Q_3	4081.09	8.31
90th percentile	15 518.90	9.65
95th percentile	32 931.36	10.40
Max	2 552 461.00	14.75

3.4.2 Financial control variables

The long-term debt-to-equity ratio is defined as a percentage of total debt for the respective fiscal period divided by total shareholder equity for the said period, in our case, the fiscal year. (Refinitiv 2024). We have decided to take a logarithm of this value, as it helps us make the ratio more comparable between companies, as the debt can rise very quickly and is thus heavily skewed to the right with very high extreme values. The return on equity is profitability calculated as a company's net income divided by total equity of common shares (Refinitiv 2024).

Table 3.5: Statistics for LT DtE Ratio and ROE Mean

Variable	LT DtE Ratio	Log(LT DtE Ratio)	ROE Mean
Count	10 752.00	10 752.00	10 752.00
NA values	2899.00	3367.00	5475.00
Mean	114.35	3.53	4.80
SD	959.26	1.95	101.85
Min	0.00	−7.67	−5173.29
Q_1	0.40	2.88	0.48
Median	30.63	3.90	11.00
Q_3	82.85	4.64	21.50
90^{th} Percentile	176.99	5.38	36.28
95^{th} Percentile	313.83	5.93	52.41
Max	67 916.62	11.13	1683.90

3.4.3 Company industry

For the company industry dummy, The Refinitiv Business Classification (TRBC) Economic sector was used. TRBC is a classification system, which categorizes companies based on their primary line of business or industry. It provides a standardized framework for organizing and analyzing companies across different sectors of the economy. It has 5 levels of granularity, top-down being the Economic sector, business sector, industry group, industry, and activity. The others are the Business sector, Industry group, industry, and Activity. For companies operating in multiple economic segments or industries, the dominant segment of the company is determined. When determining the segments of the company its revenue, assets, profitability in each industry, market perception, or growth perspective are taken into account (Refinitiv 2020).

The stocks used are divided into 11 economic sectors. Industrials, Technology, Healthcare, Basic Materials, Energy, Consumer Cyclicals, Utilities, Real Estate, Academic & Educational Services, Consumer Non-Cyclicals, and Financials. Industrials consist of companies engaged in industries of aerospace and defense, industrial machinery and equipment, heavy machinery and vehicles, electrical components and equipment, heavy electrical equipment, shipbuilding construction, and engineering, environmental services and equipment, diversified industrial goods and wholesale, commercial printing services, employment services, business support services and supplies, professional information services, freight and logistic services, airlines, passenger transportation or transport infrastructure. Technology encompasses those involved in technology development and distribution with business sectors of Technology equipment (Electronic equipment and parts, Semiconductors, Semiconductor equipment and Testing, Communications and networking, computer hardware, phones, and handheld devices, household electronics, and Integrated Hardware and software), software and IT technology (IT services and Consulting, Software and Online Services), Financial technology and infrastructure (Fintech, Crowd collaboration, Blockchain, and Cryptocurrency) and Telecommunications Services (Integrated telecommunications services and Wireless Telecommunications services).

Healthcare includes healthcare services such as advanced medical equipment and technology or medical equipment, supplies and distribution, healthcare facilities and services, managed healthcare, pharmaceuticals, biotechnology, and medical research. Basic Materials involve extraction and distribution of raw materials, with industry groups involved being chemicals (commodity, agricultural, specialty), metals and mining (minerals, iron, and steel, aluminum, gold, etc.), construction materials, forest & wood products, paper products and containers & packaging. Energy encompasses the exploration, production, and distribution of energy resources. It is also divided by primary substance manufactured, with industries such as coal, oil and gas, renewable energy, and uranium. Consumer Cyclicals produce non-essential goods. This sector contains retail stores, the automotive industry, companies in residential construction, lodging facilities, restaurants, footwear, textile & apparel, furniture, or entertainment companies. On the other hand, Consumer Non-Cyclicals produce essential items and are in theory less reliant on the economic cycle and thus less volatile. Example industries are beverages, food & tobacco personal & household products, personal services, food & drug retailing, and consumer goods conglomerates. Utilities provide essential services like electricity, natural gas, or water, and Real Estate deals with property development and management. Academic & Educational Services focus on education provision either in school and college or in professional & business education. Lastly, financials include banks, consumer lending, corporate financial services, investment banking & brokerage services, investment management and fund operators, life & health insurance, property insurance, funds, trusts, or investment holding companies. The two sectors, from which no firms were used in our analysis, are the government sector and Institutions, Associations & Organizations (London Stock Exchange Group 2024).

A dummy variable for each industry was created with a value of 1 if the stock is part of the industry and 0 otherwise. The same approach was followed for the year dummy variable, which can help us isolate year-specific influences even when using the panel data approach.

The biggest industry in our dataset is Healthcare with 2 639 data points, followed by Technology, Consumer Cyclical, and Industrials. Academic and Educational Services and Utilities have less than 200 data points, which might not be sufficient for later industry-specific models. Average daily volatility is the highest for the Energy sector followed by the Healthcare one. The lowest average volatility is in utilities and Consumer Non-Cyclical industries.

Table 3.6: Descriptive Statistics by Industry

Industry	**Count**	**Avg(Volatility)**	**Var(Volatility)**
Academic & Educ. Services	64	0.54	0.22
Basic Materials	503	0.53	0.33
Consumer Cyclicals	1672	0.52	0.14
Consumer Non-Cyclicals	587	0.41	0.07
Energy	319	0.75	0.81
Financials	492	0.43	0.07
Healthcare	2639	0.70	0.18
Industrials	1310	0.46	0.09
Real Estate	467	0.42	0.26
Technology	2543	0.53	0.15
Utilities	156	0.38	0.09

3.4.4 Stock Exchange

The last control dummy variables we will use in our models are stock exchanges. We are using data from three stock exchanges. First, the biggest exchange is NASDAQ, containing companies mostly from the USA, NASDAQ Nordic, which is an umbrella term for Exchanges from the NASDAQ family in Copenhagen, Stockholm, and Helsinki, and lastly Johannesburg Stock Exchange. In Table 3.7 you can see the number of companies from each country listed on each stock exchange. For all stock exchanges, most of the companies come from within the country, where the stock exchanges lie. This is especially true for NASDAQ Nordic exchanges with less than 5% companies from abroad.

Table 3.7: Ticker Counts by Stock Exchange and Country

Exchange group	Country	No of companies
NASDAQ	USA	1502
NASDAQ	China	53
NASDAQ	Canada	38
NASDAQ	Bermuda	10
NASDAQ	Israel	21
NASDAQ	United Kingdom	18
NASDAQ	Ireland	10
NASDAQ	Others	88
NASDAQ Nordic	Sweden	118
NASDAQ Nordic	Finland	73
NASDAQ Nordic	Denmark	32
NASDAQ Nordic	Others	8
Johannesburg	South Africa	102
Johannesburg	United Kingdom	12
Johannesburg	Others	14

3.5 Data transformation

As the data were downloaded in two datasets with volatility data being calculated separately due to higher computational difficulty, and other variables only being static for each year in Refinitiv, the data frames were merged by year ticker combination. For further analysis and models dummies for industry, Exchange, and Year were created with values of 0 or 1 indicating if the stock belongs to the particular group. ESG dummies were created as well to group ESG scores and explore non-linear influences. The zero values in the long-term debt-to-equity ratio were replaced by NAs, as we could not determine which companies did not report their results and which were debt-free.

3.5.1 Handling missing data

As some of the data points we used are incomplete, especially those in earlier years, we need to handle missing data. There are few options on how to handle them. First, we need to determine the nature of missing data. Three options available are, that the data are missing at random (MAR), which means, that the data points are missing only on some sub-sample of the test, for example only for some years or groups of stocks, missing completely at random (MACR), where there is no connection between missing data and the variables and is the easiest case to handle, as it is okay to delete the variables if the sample is big enough as it should not cause any bias in the results. The last case is missing not at random (MNAR), where the data missing are due to the nature of one of the variables used, and simply deleting those observations might create biased results.

When handling MAR or MANR, the options commonly used to handle the data are imputation methods, which means that the missing data are replaced by some value. The first methods, that come to mind are mean, median, or mode imputation methods. All three might be valid approaches, but their main limitation is, that they change the distribution of the treated variable. Other methods, that are used specifically for time series are Last Observation Carried Forward (LOCF), Next Observation Carried Backward (NOCB), and linear interpolation methods. In LOCF and NOCB every missing value is replaced with either the last observed value or the next one and linear interpolation is used if both value in the previous and next data points is known and the average of those is imputed. The strength of these methods is, that they do not change the distribution of the variable and in our case might predict the missing variable better than the mean or median as they work only within the observations within the one ticker. The weakness of this method is, that it does not account for seasonality. This is resolved with seasonal adjustment LOCF and NOCB methods. In this case, the averages for each period are calculated and the next or previous year adjusted by the average value is imputed. (Little & Rubin 2019)

The variables we need complete and thus have to either delete or impute with a value are *Volatility*, *ESG Score*, *Environmental score*, *Social Score* and *Governance score*. The year-ticker data points, for which volatility was not available were removed from our analysis, as the absence of volatility (returns, from which volatility is calculated) in the Refinitiv database means, that for that year the company either did not exist yet or was not listed on the stock exchange and there is no reason to simulate such data. We have decided to delete data points with incomplete ESG Score data as well, as it would be hard to impute correct values, without skewing the distribution too much. Another reason is, that for variables with ESG scores missing all Environmental, Social, and Governance scores are missing as well, and would be impossible to calculate them. We also believe that the number of observations we will remain with is sufficient, as we still have over 10 000 observations. The last missing observation we will be dealing with is missing Environmental scores. The Governance and Social scores are always present in the dataset remaining after deleting missing volatility and ESG records. We won't be treating missing control variables such as liquidity ratio.

After inspecting the other ESG parts of scores for missing and non-missing environmental data in Table 3.8 we can say, that the data are most likely missing not at random and we should use some imputation method to replace the data rather than delete them completely. As this is a time series with seasonality, as the average Environmental score changes for each year and the data availability gets better with time we decided to use a seasonality-adjusted Next Observation Carried Backward approach for tickers with at least one observation for Environmental score and mean imputing for tickers with no observation of Environmental score.

Table 3.8: Missing Environmental score statistics

Subset	**Count**	**Avg Soc Score**	**Avg Gov Score**
Env score missing	3533	30.79	37.20
Env score present	7199	48.68	52.24

The return on equity has a lot of missing values as well. We will be using the Next Observation Carried Backward approach without seasonal adjustments, as it is hard to determine the correct trend from our analysis with the first quartile having a negative 36% change year-over-year and the third quartile having a 22% increase. This means, that one value for seasonal adjustment might worsen the prediction of true value rather than make it more precise, as seen in Table 3.9. The same goes for *Log(LT_DtE_Ratio)* with the first quartile lowering by 6% year-over-year and the third quartile raising the ratio over 5%. Mean values are skewed in this case as outlier values go into thousands of percentages in both cases, which is caused by very small values in one year and significantly higher in another year. This is caused by the fact, that ROE can have both negative and positive values, so it is not uncommon to jump from a really small number, which results in a high percentage increase, especially with so many observations. For example, the maximum value increase by 101 248 percent was an increase from ROE of 0.00450 to 4.56067 and was followed by ROE of 4.53067 next year, not another 100 000 percent increase. It can be seen in the difference between 95$^{\text{th}}$ percentile and maximum value. We input only values for tickers with at least one value, the others will be omitted, as we have no way to reasonably assume these values.

Table 3.9: Year-over-year percentage difference by ticker

Variable	**log(LT DtE Ratio)**	**ROE Mean**
SD	21.73	22.17
Min	−11 694.41	−26 962.04
Q_1	−6.39	−36.66
Median	−1.00	−3.91
Q_3	5.24	22.69
95$^{\text{th}}$ percentile	34.98	189.08
Max	45 169.29	101 248.20

3.6 Descriptive statistics

One of the ways to describe the basic relationships between the data with descriptive statistics is a correlation matrix. In Figure 3.3 we can see, that daily, weekly, and monthly volatility are highly correlated, which we expected, as they are all calculated from returns with the only difference being the frequency of measurements. However, the correlation is lower than 0.8, which means, that there could be some differences, and can be worthwhile to try to use them all in our models for robustness checks. Another high correlation is between the ESG score and all three ESG pillar scores, which can be also explained by the ESG score being calculated from the results of the pillars. The highest correlation seems to be between the ESG and Social pillar and the lowest for the Governance pillar. The Environmental and Social pillar seems to be highly correlated as well with a correlation over 0.7, while the correlation between Governance and other pillars is less than 0.4. All ESG-related scores are also highly positively correlated with *log(Markety_cap)*. Drempetic *et al.* (2020)

point out, that bigger companies tend to have better ESG ratings for several reasons. They have more resources, that can be utilized more efficiently, resulting in better ESG results, they tend to be more precise in reporting the ESG data to the rating agencies or rating agencies can be biased towards smaller companies.

The last interesting correlation to point out is the negative relationship between volatility and almost all independent variables. The highest negative correlation is for *log(Market_cap)*. This would make sense as small companies tend to be viewed as riskier investments due to their volatility while most blue chip companies with the lowest volatility are big established companies. However, all ESG-related variables are negatively correlated with volatility as well. This indicates, that there might be an interesting relationship worth investigating further by more advanced models.

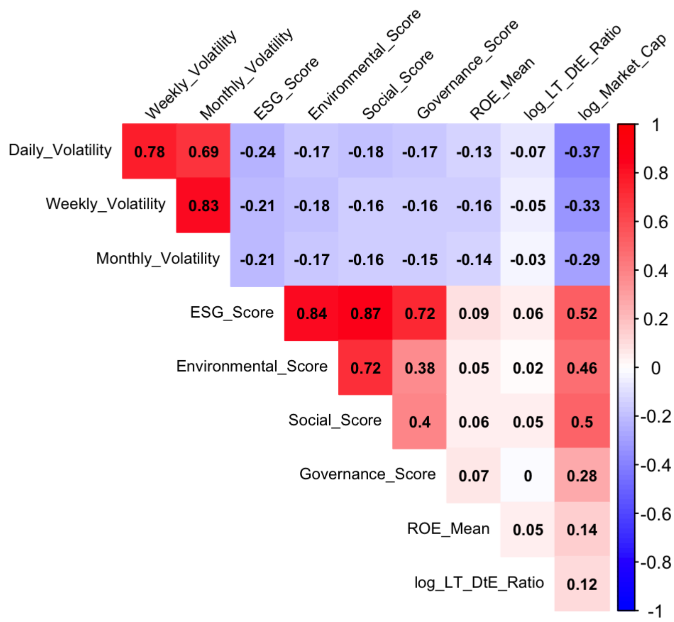

Figure 3.3: Correlation plot

Chapter 4

Methodology

In our analysis, we adopt a linear regression framework to examine the relationship between Environmental, Social, and Governance (ESG) scores and stock market volatility. We propose the following basis for our regression model:

$$\sigma_{i,t} = \alpha + \beta_1 \text{ESG\_Score}_{i,t} + \sum_{j=2}^{n} \beta_j \text{Control\_Variable}_{j,i,t} + u_{i,t} \tag{4.1}$$

Where $\sigma_{i,t}$ represents the volatility at time t for entity i, while α denotes the intercept term capturing the baseline volatility. β_1 signifies the coefficient of the ESG score variable, indicating the impact of ESG scores on volatility. Additionally, β_j (for $j = 2$ to n) corresponds to the coefficients of control variables, where n denotes the total number of control variables included in the model. These control variables, denoted as $\text{Control\_Variable}_{j,i,t}$, capture additional factors influencing volatility at time t for entity i. Finally, $u_{i,t}$ represents the error term, encompassing unobserved factors affecting volatility not accounted for by the model.

In the basic models, $\sigma_{i,t}$ will denote volatility calculated from daily returns, but in robustness checks, it will be replaced by weekly or monthly volatility. ESG_Score is there as a proxy for the variable we are researching with this paper. In some models it's ESG_Score and ESG_Score^2 , in others, it can be Environmental, Social, and Governance score individually or ESG_Dummy variable with values of 0 and 1. The control variables used also vary. In fixed effects models it is only *log(Market_Cap)*, *log(LT_DtE_Ratio)*, *ROE_Mean* and year-specific dummy variables as they account for variables constant through each ticker inherently, while for other models other variables, that are same throughout one ticker such as industry dummy variables or stock exchange dummies are present in the models.

4.1 Volatility modeling

When modeling stock volatility on a time series data usually models from the GARCH family (Bollerslev 1986), such as ARCH (Autoregressive Conditional Heteroskedasticity), GARCH, or E-GARCH are used. These models perform particularly well when modeling daily volatility data with serial autocorrelation of variance of the error term. Another modeling approach would be to use SV (Stochastic Volatility) models (Barndorff-Nielsen & Shephard 2002) or HAR (Heterogenous Autoregressive) models introduced by Corsi (2009).

However, due to the specific structure of the dataset, panel data models were chosen instead of traditional econometric models for modeling volatility. All the models described above are suitable for high-frequency data, especially for low numbers of stocks. We opted for a high number of stocks with one data point for each year, as the ESG rating changes once a year.

4.2 Panel data models

As indicated above, to examine the relationship between ESG scores and stock volatility, panel data regression is chosen as the appropriate analytical framework. The dataset consists of multiple observations over time, with yearly data points capturing the dynamics of both ESG scores and stock market volatility. As this is time series data and also as there are indications in articles and papers, that ESG is becoming more and more important (Jaros *et al.* 2022), there is a potential presence of time-specific effects that can influence the relationship between these variables. By employing panel data regression techniques, it becomes possible to take these time-specific effects into account and derive more robust estimations.

The three options for panel data regression, that we will be looking at are Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE) models. Each of these models has its strengths and assumptions, which need to be considered in selecting the most appropriate approach for the analysis.

4.2.1 Pooled OLS

Pooled OLS regression is a commonly used approach in panel data analysis. It treats the data as a single large sample, disregarding individual effects and assuming no correlation between the independent variables and the individual-specific effects. This model assumes that there is no time-invariant unobserved heterogeneity present in the data and that the regressors are not correlated with the individual-specific effects. Pooled OLS regression provides efficient estimators of the coefficients when the assumptions hold, and it is suitable for situations where the focus is on estimating the average relationship between the independent variables and the dependent variable across all individuals and time periods.

4.2.2 Fixed Effects

Fixed Effects (FE) panel regression is an alternative approach that controls for time-invariant unobserved heterogeneities. It includes individual-specific dummy variables in the regression model, capturing the individual-specific effects that remain constant over time. By accounting for these fixed effects, the FE model allows for the examination of within-individual variations and identifies the relationship between the independent variables and the dependent variable specific to each individual. This model is particularly useful when there are time-invariant unobserved factors that might be correlated with the independent variables. It provides unbiased estimators of the coefficients by differencing out the individual-specific effects.

4.2.3 Random Effects

Random Effects (RE) panel regression takes into account both time-invariant and time-varying unobserved heterogeneities by treating them as random effects. This model assumes that there is no correlation between the individual-specific effects and the regressors. It allows for the estimation of both the individual-specific effects and the relationship between the independent variables and the dependent variable. The RE model is suitable when there is no correlation between the unobserved heterogeneities and the independent variables. It provides more efficiency in estimation compared to the FE model when the random effects assumption is valid.

4.2.4 ESG threshold model

This approach uses fixed and random effects models in the same way as the other models, with the difference, that instead of using ESG score as a variable, we will be creating ESG dummies for each model with different thresholds. We will employ this approach for testing our second hypothesis, which suggests, that volatility not only decreases as the ESG score rises or when comparing the best-in-class companies with others, but also increases when comparing the worst-in-class ESG-rated companies with the general population. We will create dummy variables for different thresholds of ESG score to see, how the dynamics change as the split between what we consider the good/bad ESG score changes. This will help us create a similar split as Ashwin Kumar *et al.* (2016) or Meher *et al.* (2020) in case of the high ESG score threshold, but will give us insight, into whether the results change when if we account not only for the best in class as "good ESG stocks".

4.2.5 Time-varying window length

To test the third hypothesis regarding the strength of the ESG effect increasing over time, we propose employing expanding window models. The time-varying window length approach is used in econometrics to adaptively adjust the size of the estimation window over time, allowing for more flexibility in capturing changing relationships between variables and improving the accuracy of parameter estimates. This is particularly important for controlling long-term effects or trends that may vary over time, which in our third hypothesis, we believe, might be a case for ESG scores. These models allow us to systematically assess the relationship between ESG factors and volatility across different time intervals.

Consider a dataset spanning from year t_1 (start year) to year t_n (end year). The expanding window approach involves constructing regression models for consecutive time windows, incrementally expanding the sample period. Specifically:

Expanding Window Analysis

- **Initial Estimation:** Begin with data from year t_1 to t_2 and estimate the relationship.
- **Yearly Re-estimation:** Update the model for each year, incorporating new data.
- **Full Period Analysis:** Proceed until the full sample period from t_1 to t_n is included.
- **Trend Observation:** Monitor the ESG effect's evolution over time to detect trends.

Contracting Window Analysis:

- **Reversal Process:** After the full period analysis, reverse the estimation process.
- **Model Construction:** Start from year t_2, constructing models with data from t_2 to t_n, then t_3 to t_n, and so on.
- **Effect Assessment:** Catch any trends of the ESG effects as the sample size decreases.

In summary, by comparing the results from expanding and contracting window models, we can gain insights into the temporal dynamics of the ESG effect and make informed conclusions about its strength over time.

4.2.6 Heteroskedasticity and autocorrelation

In our model, we employ the Heteroskedasticity and Autocorrelation Consistent robust covariance matrix estimator (White 2014). We believe, that the panel data might exhibit heteroskedasticity and serial correlation, which is solved by utilizing a robust covariance matrix estimator, which produces robust standard errors that are clustered by group, in our case, ticker. This accommodates potential within-group correlation and heteroskedasticity. This approach ensures that our estimates are reliable and accurate, providing more robust inference in the presence of potential data dependencies and heterogeneity.

4.2.7 Model Selection and Hypothesis Testing

When deciding between pooled OLS, FE, and RE models„ several tests and considerations can be applied. The choice between the pooled OLS model and the FE model is done using the F-test. The null hypothesis of the F-test is, that the individual effects are not relevant, in our case meaning that all the time-specific effects are equal to 0, which would mean that the pooled OLS test is sufficient. In the case of the alternative hypothesis, we can say, that the FE model performs better and we will be deciding between the FE model and the RE model. To choose between these two models we commonly use the Hausman specification test. It tests the null hypothesis that the preferred model is the one without a correlation between the regressors and the unobserved individual-specific effects. The null hypothesis assumes, that both of the models, FE and RE, are consistent, but RE is asymptotically more effective. In the case of the alternative hypothesis, the FE model remains consistent while the RE model does not. So in the case of the null hypothesis, we will be choosing the RE model and in the case of the alternative hypothesis, the FE model will be selected. In case both the null hypothesis of the F-test and the Hausman specification test are rejected, we will choose the FE model from those three. As the FE model performs better than the pooled OLS and the FE model performs better than the RE model. If both of the hypotheses are confirmed, we will use the Breusch-Pagan Lagrange Multiplicator test to decide between pooled OLS and RE models. The null hypothesis of the test states, that the variances across entities are zero. If the hypothesis is rejected, we can say that the RE regression model is better than the pooled OLS.

Chapter 5

Results

In this chapter, we present and discuss the results of our fixed effect and random effect estimations on different models. First, we will discuss results on the whole dataset with ESG scores and individual pillar scores. Then, we will take a closer look at specific industry models, stock exchange models, models with different ESG dummy thresholds, and expanding window models. To verify our results, we conduct robustness checks using models, where annualized volatility is calculated from weekly and monthly volatilities.

5.1 Panel data analysis

In the first approach to test our first hypothesis about ESG scores having a negative correlation with stock volatility, we used ESG score and (ESG Score)^2 to control for non-linear impact. From the results of Table 5.1, it is clear, that the pooled OLS model will not be a good fit for our data, as the p-value is far below the threshold of 0.05 and heteroscedasticity is present in the data. We will not be discussing the pooled OLS models further in the results, as the results of F-tests and Breusch-Pagan tests throughout the models were always the same, suggesting we don't use pooled OLS models.

The other two models for panel data analysis, fixed and random effects, are represented in Table 5.2. The results of the RE model show, that the R^2 and adjusted R^2 are higher and the ESG score is negatively correlated and significant, which supports our hypothesis. On the other hand, our fixed effects model does not assign the ESG scores any significance and has negative adjusted R^2. Due to the Hausman test results in Table 5.1 for these two models, it is clear, that we will choose FE, as it suggests that individual-specific effects are correlated with the independent variables and the RE model is inconsistent, making it worse fit than the FE model.

As for the results of our control variables in Table 5.2 - we can see that the logarithm of market capitalization is significantly negatively correlated with volatility, as bigger companies tend to be less volatile, while the logarithm of long-term debt to equity is significantly positively correlated. This might be due to higher debt meaning higher risk for the company, which might turn into volatility. Return on equity is not significant in this model. The year-specific dummies are significant for certain years. For example, the year 2020 is significant and increases the volatility, the same as 2021 and 2022. We assume, that this might be the result of the COVID-19 pandemic, as discussed by Chowdhury *et al.* (2022) or the start of the conflict between Russia and Ukraine, which led to higher volatility in the market. (Izzeldin *et al.* 2023).

As the fixed effect model drops the variables, that are the same across one ticker, the industry-specific dummies and stock exchange-specific dummies are not reported in the results of the FE model. However, if we were to account for the results of the RE model, we can see, that the Energy and Healthcare sectors have a significant positive correlation with volatility, while being listed on NASDAQ Nordic has a negative significant correlation.

Table 5.1: Comparison of F-test Breusch-Pagan and Hausman Test Results

Test	**ESG Score model**	**ESG pillars model**
F-test p-value	2.2e-16	2.2e-16
Breusch-Pagan p-value	2.3e-08	3.4e-08
Hausman p-value	2.2e-12	2.1e-14

Table 5.2: ESG score tests

	Random effects (1)	Fixed effects (2)
ESG_Score	−0.003***	0.001
ESG_Score^2	0.000**	0.000
ROE_Mean	0.000*	0.000
log(LT_DtE_Ratio)	0.002	0.008***
log(Market_Cap)	−0.059***	−0.058***
Year_2017	−0.040**	−0.046***
Year_2018	−0.003	−0.012
Year_2019	0.018	0.005
Year_2020	0.301***	0.280***
Year_2021	0.067***	0.040**
Year_2022	0.151***	0.120***
Year_2023	0.053***	0.030*
Industry_Acad&Edu	−0.069	
Industry_Basic.Materials	0.077	
Industry_Cons.Cycl	0.020	
Industry_Cons.Non.Cycl	−0.057	
Industry_Energy	0.235***	
Industry_Financials	−0.052	
Industry_Healthcare	0.141***	
Industry_Industrials	−0.013	
Industry_Real.Estate	−0.063	
Industry_Technology	0.053	
NASDAQ.Nordic	−0.159***	
Johanesburg_Group	−0.002	
Constant	0.902***	
Observations	7454.000	7454.000
R^2	0.237	0.140
Adjusted R^2	0.234	−0.045
Note:	*p<0.1; **p<0.05; ***p<0.01	

When replacing the ESG score with Environmental, Social, and Governance scores separately, the R^2 of the models rises a little bit. However, the FE model still assigns no significance to any of the ESG scorings. These results are similar to what Meher *et al.* (2020) found in their study, not supporting the hypothesis, that the ESG scores are significant predictors of volatility, and the opposite of what Shakil (2022) found in his study. However, he uses a small sample of 44 companies from one industry. We also found different results than him regarding the role of firm size on volatility as discussed above. Random effects model would support the hypothesis, with a significant positive correlation of Environmental scores and a negative significant correlation of Social and Governance scores, but this model is inconsistent as we can see from the results of the Hausman test in Table 5.1.

Table 5.3: ESG pillars score tests

	Random effects	**Fixed effects**
	(1)	**(2)**
Environmental_Score	0.001**	0.000
Social_Score	−0.001*	0.000
Governance_Score	−0.001**	0.000
ROE_Mean	0.000*	0.000
log(LT_DtE_Ratio)	0.001	0.008***
log(Market_Cap)	−0.061***	−0.058***
Year_2017	−0.042**	−0.045***
Year_2018	−0.004	−0.010
Year_2019	0.016	0.006
Year_2020	0.298***	0.282***
Year_2021	0.064***	0.043**
Year_2022	0.146***	0.122***
Year_2023	0.047***	0.034**
Industry_Acad&Edu	−0.062	
Industry_Basic.Materials	0.086	
Industry_Cons.Cycl	0.029	
Industry_Cons.Non.Cycl	−0.049	
Industry_Energy	0.237***	
Industry_Financials	−0.041	
Industry_Healthcare	0.151***	
Industry_Industrials	−0.002	
Industry_Real.Estate	−0.055	
Industry_Technology	0.061	
NASDAQ.Nordic	−0.169***	
Johanesburg_Group	−0.013	
Constant	0.880***	
Observations	7454.000	7454.000
R^2	0.236	0.140
Adjusted R^2	0.234	−0.046
Note:		*p<0.1; **p<0.05; ***p<0.01

5.1.1 Industry-specific models

As the ESG ratings indicate how the company performs in ESG terms compared to other companies in their industry, we have decided to create models for each industry. After filtering out the industry of Academic and Educational services and Utilities, due to a low amount of data points, we performed the same analysis as above, using fixed effects and random effects models on a subset per industry. We believe, that this might make sense as the ESG score is reported as a performance within the industry. This effect was previously partially studied by Ashwin Kumar *et al.* (2016), but they performed only descriptive statistics per industry.

When calculating the models per industry subset, the Hausman test shows, that for most industries, we would prefer a random effects model, as the p-values go far over the threshold, as seen in Table A.5. Out of the nine industries, for which we have created the models, six showed some level of significance for at least one ESG variable. However, only the Technology sector, as seen in Table 5.4 showed a high significance of p-value < 0.001, specifically a significant negative correlation for the Governance score. One possible answer for this might be, that the technology industry nowadays is undergoing quite a lot of changes in regulations and policies, particularly surrounding issues such as data privacy, antitrust measures, and intellectual property rights. As governments strive to adapt to the rapid pace of technological innovation, they often introduce new laws and regulations to govern the behavior of tech companies. In this context, a significant negative correlation between Governance score and volatility could suggest that investors perceive companies with stronger governance practices as being better equipped to navigate regulatory challenges and mitigate potential risks arising from regulatory changes. This interpretation implies that as governance standards improve, companies may become more adept at anticipating and complying with regulatory requirements, thereby reducing uncertainty and volatility in the market.

At the same time, the model reports R^2 over 0.5, which is so far the highest from our models. It also shows significance for most of our control variables. All of the years but 2019 had a significant impact on volatility, both NASDAQ Nordic and Johannesburg exchange dummies have significant negative effects, market capitalization reports a negative effect, and long-term debt-to-equity ratio has a positive effect. Our subset of Technology companies is one of the more robust ones with 1 778 data points for 308 companies.

Similar effects of Governance score, only with lower significance can be seen for the Industrial and Healthcare sectors. The healthcare sector is also heavily regulated, so this might support our hypothesis when explaining the correlation for the Technology sector. On the other hand, the energy sector reports a positive correlation for Governance score with a p-value < 0.05.

As for the other industries - the Consumers Cyclical, as seen in Table 5.4 reports a significant positive value for the Social score with a p-value < 0.05 while having R^2 of 0.53. This significance gets just over the 0.1 significance threshold after clustering the standard errors. They are also one of the two industries, for which the Hausman test shows, that the random model is inconsistent. The second industry is Industrials. The detailed results, together with Hausman tests of all models can be seen in the appendix.

Table 5.4: ESG score per industry

	Technology (RE)	Consumers Cyclical (FE)
Environmental_Score	0.000	0.000
Social_Score	0.000	0.001
Governance_Score	−0.001***	0.000
ROE_Mean	0.000	0.000
log(LT_DtE_Ratio)	0.006*	0.009**
log(Market_Cap)	−0.042***	−0.061***
Year_2017	−0.037***	−0.047***
Year_2018	0.043***	0.018
Year_2019	0.019	0.013
Year_2020	0.245***	0.369***
Year_2021	0.082***	0.079***
Year_2022	0.201***	0.129***
Year_2023	0.072***	0.040*
NASDAQ.Nordic	−0.184***	
Johannesburg_Group	−0.075**	
Constant	0.782***	
Observations	1778.000	1233.000
R^2	0.502	0.539
Adjusted R^2	0.498	0.438
Note:		*p<0.1; **p<0.05; ***p<0.01

5.1.2 Threshold models

To create the threshold models, meaning creating dummy variables 0 and 1 depending on whether the company is over a certain ESG score threshold we used a percentile approach, rather than fix split of scores, such as 10, 20, or 80, as the data are unevenly split among the ESG scores as seen in Table 3.1. In Table 5.5 we can see, what are the cutoff values for the ESG dummy in our models. This means that we will create 5 models, where the ESG dummy will be 0 if the ESG score is below the value in the second column and 1 else.

Table 5.5: Percentile values of ESG score

Percentile	10^{th}	30^{th}	50^{th}	70^{th}	90^{th}
Value	16.77	26.83	36.36	48.49	67.30

The results of the Hausman test for all 5 models suggest, that we should use the fixed effects model's results. For fixed effects, the ESG dummy is not significant for any of the models with lower R^2 and adjusted R^2 than random effects models. If we were to use the results of random effects, it would confirm our hypothesis, that the ESG dummy has a significant negative correlation with volatility for 30^{th}, 50^{th}, which is shown in Table 5.6, and 70^{th} percentile. On 10^{th} and 90^{th} percentile, the correlation is insignificant and positive. All the other dummy model tables are shown in the appendix.

Table 5.6: ESG dummy variable test (50^{th} percentile)

	(50^{th} percentile) (FE)	**(50^{th} percentile) (RE)**
ESG_Dummy	0.008	-0.026^{***}
ROE_Mean	0.000	0.000
log(LT_DtE_Ratio)	0.008^{***}	0.002^{*}
log(Market_Cap)	-0.058^{***}	-0.061^{***}
Year_2017	-0.046^{***}	-0.042^{***}
Year_2018	-0.012^{*}	-0.004
Year_2019	0.005^{*}	0.015
Year_2020	0.280^{***}	0.298^{***}
Year_2021	0.040^{***}	0.063^{***}
Year_2022	0.119^{***}	0.145^{***}
Year_2023	0.030^{**}	0.048^{***}
Industry_Basic.Materials		0.100^{**}
Industry_Cons.Cycl		0.044
Industry_Cons.Non.Cycl		-0.032
Industry_Energy		0.259^{***}
Industry_Financials		-0.025
Industry_Healthcare		0.165^{***}
Industry_Industrials		0.012
Industry_Real.Estate		-0.038
Industry_Technology		0.076^{*}
NASDAQ.Nordic		-0.163^{***}
Johanesburg_Group		-0.007
Constant		0.838^{***}
Observations	7454.000	7454.000
R^2	0.140	0.236
Adjusted R^2	-0.045	0.234
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

5.1.3 ESG influence over time

To test our third hypothesis we used the expanding window approach. To be able to compare the models among each other, we will use FE models, as the Hausman test suggests it for most of them anyway, and for those, where the RE model is suggested, FE models are still consistent. Environmental, Social, and Governance scores were used separately to catch individual time-specific effects of each variable. All control variables were used with year-specific variables for years t_1 to $t_n - 1$, where t_1 and t_n vary depending on the model and lie within the range of 2016 to 2023. Higher significance of all ESG variables was expected the closer to present the time window is.

Our hypothesis is not supported by the results of the models, as none of the time windows show a significant correlation between any of the ESG pillars and volatility. The results are reported in Table 5.7

Table 5.7: ESG Scores by time window

Years	Environmental Score	Social Score	Governance Score
2016-2017	0.0006	−0.0010	−0.0003
2016-2018	0.0003	−0.0002	−0.0003
2016-2019	−0.0001	−0.0004	−0.0003
2016-2020	−0.0004	−0.0008	−0.0001
2016-2021	−0.0001	−0.0006	0.0000
2016-2022	−0.0003	−0.0001	−0.0002
2016-2023	−0.0003	0.0001	−0.0002
2017-2023	−0.0004	0.0003	−0.0002
2018-2023	−0.0003	0.0004	−0.0002
2019-2023	−0.0001	0.0006	−0.0003
2020-2023	0.0007	0.0005	−0.0003
2021-2023	0.0001	−0.0002	0.0000
2022-2023	−0.0004	−0.0010	0.0002

In a detail of 2 chosen time periods in Table 5.8, we can see, that the scores remain insignificant, with R^2 being negative, suggesting a very low predictive value of our model. Even though both time windows are four years long, the second model has more observations. This is caused by several factors. Not all of the companies in the analysis have been operating since 2016 and even those who sometimes do not have an ESG rating on Refinitiv for all years.

Table 5.8: Time window models

	2016-2019 (FE)	**2020-2023 (FE)**
Environmental_Score	0.000	0.001
Social_Score	−0.001	0.001
Governance_Score	0.000	−0.001
ROE_Mean	0.000*	0.000
log(LT_DtE_Ratio)	0.007	0.013**
log(Market_Cap)	−0.045***	−0.059***
Year_2016	0.018*	
Year_2017	−0.060***	
Year_2018	0.003	
Year_2020		0.244***
Year_2021		0.004
Year_2022		0.068***
Observations	2965.000	4489.000
R^2	0.070	0.188
Adjusted R^2	−0.383	−0.149
Note:	*p<0.1; **p<0.05; ***p<0.01	

5.1.4 Stock exchange specific models

In this section, we focus on models specific to each stock exchange, to explore potential geographical influences on stock volatility as stock-listing is a good proxy for the country of origin of the company as seen in Table 3.7. From our previous results, we can already see, that the volatility of our observations of stocks listed on NASDAQ Nordic tend to exhibit lower volatility compared to others. To investigate this further and explore potential exchange-specific effects, we constructed separate models for each exchange in our dataset.

From the results in Table 5.9 we see, that for the companies listed in NASDAQ Nordic, the correlation between Environmental score and volatility is negative and significant, which has been the case for neither NASDAQ nor Johannesburg stock exchange. This result corresponds with the sayings of the European Investment Bank (2024) about Europeans being more concerned about climate change and the environment. On the other hand, the Social score is correlated positively and is significant as well. One possible explanation might be, that as the workforce in Europe already has better work conditions in many ways than the rest of the world (Tuncturk 2023) and the Social pillar is about community, human rights, product responsibility, and workforce, it might eventually be disadvantageous for the company to excel in this part even further.

Table 5.9: Stock exchanges models

	NASDAQ Nordic (FE)	**NASDAQ (FE)**	**Johannesburg (FE)**
Env_Score	−0.001*	0.000	−0.001
Social_Score	0.001**	0.000	−0.003
Gov_Score	0.000	0.000	0.001
ROE_Mean	0.001*	0.000	0.004
log_LT_DtE	−0.001	0.007**	0.019
log(Market_Cap)	−0.060***	−0.059***	−0.079
Year_2017	−0.054	−0.063***	0.172
Year_2018	−0.008	−0.012	0.085
Year_2019	−0.012	−0.013	0.270
Year_2020	0.137***	0.286***	0.523***
Year_2021	0.033	0.047***	0.137
Year_2022	0.112**	0.141***	0.114
Year_2023	0.035	0.039***	0.116
Observations	925.000	5846.000	683.000
R^2	0.400	0.332	0.057
Adjusted R^2	0.218	0.191	−0.139
Note:			*p<0.1; **p<0.05; ***p<0.01

5.1.5 Robustness checks

To make the results more robust we will change the dependent variable from annualized volatility calculated from daily returns to the volatility calculated from weekly and then monthly returns. We believe, that the results might be different, as in the descriptive analysis of volatilities in Table 3.3 it is shown, that the daily, weekly, and monthly volatility sometimes differ.

For the industry-specific models, the results for all three industries, that reported significant negative Governance scores the results still hold with weekly volatility used as a dependent variable, as seen in Table 5.10. The RE models were chosen as the p-values of the Hausman test for all three models were over the threshold (Industrials - 0.24, Technology - 0.92, Healthcare - 0.7)

Table 5.10: Weekly volatility - Industry-specific models

	Industrials (RE)	**Technology (RE)**	**Healthcare (RE)**
Environmental_Score	0.001	0.000	0.001**
Social_Score	0.000	−0.001	−0.001
Governance_Score	−0.001*	−0.001***	−0.001**
ROE_Mean	0.001	0.000	0.000
log(LT_DtE_Ratio)	0.013**	0.007*	−0.006
log(Market_Cap)	−0.055***	−0.039***	−0.083***
Year_2017	−0.076***	−0.041**	−0.087***
Year_2018	−0.017	0.047***	−0.055**
Year_2019	−0.020	0.010	−0.028
Year_2020	0.269***	0.238***	0.201***
Year_2021	0.034	0.080**	0.012
Year_2022	0.087***	0.170***	0.139***
Year_2023	0.045**	0.078***	0.024
NASDAQ.Nordic	−0.122***	−0.169***	−0.212***
Johanesburg_Group	−0.015	−0.078	−0.298***
Constant	0.771***	0.764***	1.263***
Observations	957.000	1778.000	1609.000
R^2	0.445	0.427	0.214
Adjusted R^2	0.436	0.422	0.207
Note:			*p<0.1; **p<0.05; ***p<0.01

When using weekly and monthly volatility as a dependent variable for stock-exchange-specific models, the results of the NASDAQ Nordic exchange differ. The effect of the Social score remains significant, but the Environmental score gets just slightly below the significance threshold, which is shown in Table 5.11. As for the NASDAQ model, the Hausman test suggests using a random effects model, with a p-value of 0.16. This would result in a negative significant effect on Social and Governance scores.

Table 5.11: Weekly volatility - Stock exchanges models

	NASDAQ Nordic (FE)	NASDAQ (RE)	Johannesburg (RE)
Environmental_Score	−0.001	0.001	0.001
Social_Score	0.001*	−0.001*	0.000
Governance_Score	0.000	−0.001***	−0.001
ROE_Mean	0.001***	0.000***	0.000
log(LT_DtE_Ratio)	0.002	0.004*	0.003
log(Market_Cap)	−0.066***	−0.059***	−0.067***
Year_2017	−0.065	−0.070***	−0.051
Year_2018	−0.006	−0.009	0.006
Year_2019	−0.017	−0.016	0.063
Year_2020	0.160***	0.297***	0.382***
Year_2021	0.028	0.060***	0.051
Year_2022	0.092*	0.144***	0.006
Year_2023	0.029	0.054***	−0.004
Industry_Basic.Mat		0.055	0.251***
Industry_Cons.Cycl		0.116***	0.023
Industry_Cons.Non.Cycl		0.050	0.024
Industry_Energy		0.233***	0.248***
Industry_Financials		0.039	−0.071
Industry_Healthcare		0.228***	−0.001
Industry_Industrials		0.035	0.097
Industry_Technology		0.125***	0.110
Constant		0.824***	0.765***
Observations	925.000	5846.000	683.000
R^2	0.351	0.327	0.293
Adjusted R^2	0.154	0.324	0.270
Note:			*p<0.1; **p<0.05; ***p<0.01

Chapter 6

Conclusion

In this thesis, we aimed to examine the relationship between ESG scores and stock volatility. Our analysis consisted of various perspectives, examining the overall impact of ESG scores on volatility, the influence of individual pillar scores, industry-specific effects, and temporal variations across different years. Our dataset comprised over 10 000 observations spanning the years 2016-2023 from major stock exchanges - NASDAQ, NASDAQ Nordic, and Johannesburg Stock Exchange.

Creating fixed effects and random effects panel data models we concluded, that the effect of ESG scores and ESG pillar scores on the whole dataset does not affect stock volatility in a significant manner. These findings are in line with studies of Meher *et al.* (2020) and meta-analyses of Atz *et al.* (2023) and Huang (2021) but contrast with the conclusions drawn by Shakil (2022) and Ashwin Kumar *et al.* (2016). We have not found any changes to these results during any time window nor by implementing the ESG score as a dummy variable for different thresholds. However, when analyzing subsets of the data, we have found a significant correlation for certain industry-specific models. The Technology, Industrials, and Healthcare sectors reported a significant negative correlation between Governance scores and volatility. Additionally, for stocks listed on NASDAQ Nordic, we found a significant negative effect of Environmental scores and a significant positive effect of Social scores on volatility. To ensure the robustness of our findings, we conducted further analyses using weekly and monthly volatility as dependent variables, which strengthened the credibility of our initial results. Notably, all findings remained consistent across these robustness checks, except for the significance of Environmental scores for

NASDAQ Nordic.

We see three main contributions of this study compared to previous literature. Firstly, by introducing stocks from different exchanges, thus different countries we examine geographical-specific nuances and heterogeneity between markets. Thanks to extending the analysis over a longer time frame and using an expanding window approach we tackle previously unexamined questions regarding the evolution of the effects over time. We also explore the nonlinear impact of low ESG scores on volatility, which differs from previous studies that mainly focused on either the linear effect or the impact of high ESG scores. On top of these reasons, we also believe, that another contribution lies in using heteroskedasticity and autocorrelation consistent robust covariance matrix estimators in our panel data analysis, which makes the results more reliable.

The main limitation of the thesis is data availability constraints, such as the lack of ESG reporting, especially in earlier years or companies not being listed throughout the whole study period may have introduced biases into our analysis. We also couldn't compare the ESG scores of Refinitiv with other ESG scoring providers due to their ratings being behind the paywall.

The last reason, ESG reporting data from different companies being behind a paywall brings us to our potential future research. We think, that it might be interesting to explore the dynamics between volatility and scoring from different providers. We would also like to explore the influence of disagreement between the ratings. Similar to what Gibson Brandon *et al.* (2021) did with returns and different ESG scorings. We would also suggest further researching different dynamics in the European stock market compared to the rest of the world, as the results from the NASDAQ Nordic Exchange were significant.

In closing, while our study did not find significant correlations between ESG scores and stock volatility in general, it suggests that certain sectors, such as the highly regulated Healthcare sector and Technology, or specific markets like the northern European market, may exhibit significant effects worth exploring further and being mindful of.

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Appendix A

Threshold models

Table A.1: ESG dummy variable test (10^{th} percentile)

	(10^{th} percentile) (FE)	(10^{th} percentile) (RE)
ESG_Dummy	−0.008	−0.025*
ROE_Mean	0.000	0.000***
log_LT_DtE_Ratio	0.010***	0.004**
log(Market_Cap)	−0.053***	−0.058***
Year_2017	−0.073***	−0.070***
Year_2018	−0.015	−0.010
Year_2019	−0.019	−0.011
Year_2020	0.270***	0.283***
Year_2021	0.030**	0.044***
Year_2022	0.098***	0.114***
Year_2023	0.028**	0.037***
Industry_Basic.Mat		0.109***
Industry_Cons.Cycl		0.060
Industry_Cons.Non.Cycl		−0.011
Industry_Energy		0.193***
Industry_Financials		−0.001
Industry_Healthcare		0.181***
Industry_Industrials		0.015
Industry_Real.Estate		−0.038
Industry_Technology		0.075**
NASDAQ.Nordic_Group		−0.171***
Johanesburg_Group		−0.085***
Constant		0.827***
Observations	7454.000	7454.000
R^2	0.213	0.306
Adjusted R^2	0.043	0.304
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.2: ESG dummy variable test (30^{th} percentile)

	(30^{th} percentile) (FE)	**(30^{th} percentile) (RE)**
ESG_Dummy	0.006	-0.027^{***}
ROE_Mean	0.000	0.000^{***}
log_LT_DtE_Ratio	0.009^{***}	0.004^{**}
log(Market_Cap)	-0.053^{***}	-0.056^{***}
Year_2017	-0.074^{***}	-0.069^{***}
Year_2018	-0.016	-0.008
Year_2019	-0.021	-0.009
Year_2020	0.268^{***}	0.286^{***}
Year_2021	0.027^{**}	0.049^{***}
Year_2022	0.095^{***}	0.119^{***}
Year_2023	0.025^{*}	0.042^{***}
Industry_Basic.Mat		0.108^{***}
Industry_Cons.Cycl		0.057
Industry_Cons.Non.Cycl		-0.015
Industry_Energy		0.193^{***}
Industry_Financials		-0.005
Industry_Healthcare		0.179^{***}
Industry_Industrials		0.012
Industry_Real.Estate		-0.040
Industry_Technology		0.073^{**}
NASDAQ.Nordic_Group		-0.167^{***}
Johanesburg_Group		-0.081^{***}
Constant		0.814^{***}
Observations	7454.000	7454.000
R^2	0.213	0.307
Adjusted R^2	0.043	0.305
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.3: ESG dummy variable test (70th percentile)

	(70th percentile) (FE)	**(70th percentile) (RE)**
ESG_Dummy	−0.012	−0.030***
ROE_Mean	0.000	0.000***
log_LT_DtE_Ratio	0.010***	0.004**
log(Market_Cap)	−0.052***	−0.055***
Year_2017	−0.072***	−0.069***
Year_2018	−0.014	−0.008
Year_2019	−0.018	−0.009
Year_2020	0.272***	0.286***
Year_2021	0.032**	0.048***
Year_2022	0.101***	0.120***
Year_2023	0.031**	0.043***
Industry_Basic.Mat		0.113***
Industry_Cons.Cycl		0.058
Industry_Cons.Non.Cycl		−0.014
Industry_Energy		0.195***
Industry_Financials		−0.008
Industry_Healthcare		0.177***
Industry_Industrials		0.011
Industry_Real.Estate		−0.043
Industry_Technology		0.072**
NASDAQ.Nordic_Group		−0.163***
Johanesburg_Group		−0.076***
Constant		0.792***
Observations	7454.000	7454.000
R^2	0.213	0.307
Adjusted R^2	0.044	0.305
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.4: ESG dummy variable test (90^{th} percentile)

	(90^{th} percentile) (FE)	**(90^{th} percentile) (RE)**
ESG_Dummy	−0.001	0.005
ROE_Mean	0.000	0.000^{***}
log_LT_DtE_Ratio	0.010^{***}	0.004^{**}
log(Market_Cap)	-0.053^{***}	-0.058^{***}
Year_2017	-0.073^{***}	-0.071^{***}
Year_2018	−0.015	−0.011
Year_2019	−0.020	−0.013
Year_2020	0.270^{***}	0.281^{***}
Year_2021	0.029^{**}	0.042^{***}
Year_2022	0.097^{***}	0.110^{***}
Year_2023	0.027^{**}	0.034^{**}
Industry_Basic.Mat		0.109^{***}
Industry_Cons.Cycl		0.061
Industry_Cons.Non.Cycl		−0.010
Industry_Energy		0.194^{***}
Industry_Financials		0.001
Industry_Healthcare		0.181^{***}
Industry_Industrials		0.016
Industry_Real.Estate		−0.037
Industry_Technology		0.075^{**}
NASDAQ.Nordic_Group		-0.174^{***}
Johanesburg_Group		-0.088^{***}
Constant		0.812^{***}
Observations	7454.000	7454.000
R^2	0.213	0.306
Adjusted R^2	0.043	0.304
Note:		*p<0.1; **p<0.05; ***p<0.01

Industry-specific models

Table A.5: Results of Hausman Test for Industry-specific models

Model	Test Statistic	P-Value
Industrials	16.03	0.25
Cons non-cyclical	0.43	1.00
Technology	6.44	0.93
Healthcare	9.89	0.70
Basic materials	17.31	0.19
Energy	6.31	0.93
Cons cyclical	75.23	0.00
Real estate	33.72	0.01
Financials	24.04	0.03

Table A.6: Industry-specific models - part 1

	Industrials (RE)	Cons non-cycl (RE)	Technology (RE)
Environmental_Score	0.001	−0.001	0.000
Social_Score	0.000	0.001	−0.001
Governance_Score	−0.001**	0.001	−0.001***
ROE_Mean	0.001***	0.000	0.000
log_LT_DtE_Ratio	0.013***	0.002	0.007***
log(Market_Cap)	−0.055***	−0.060***	−0.039***
Year_2017	−0.076***	−0.055	−0.041**
Year_2018	−0.017	−0.014	0.047***
Year_2019	−0.020	−0.011	0.010
Year_2020	0.269***	0.212***	0.238***
Year_2021	0.034	−0.010	0.080***
Year_2022	0.087***	0.051	0.170***
Year_2023	0.045*	−0.003	0.078***
NASDAQ.Nordic_Group	−0.122***	−0.235***	−0.169***
Johanesburg_Group	−0.015	−0.138***	−0.078
Constant	0.771***	0.858***	0.764***
Observations	957.000	409.000	1778.000
R^2	0.445	0.351	0.427
Adjusted R^2	0.436	0.327	0.422
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A.7: Industry-specific models - part 2

	Healthcare (RE)	Basic materials (RE)	Energy (RE)
Environmental_Score	0.001*	0.001	−0.001
Social_Score	−0.001	−0.001	−0.001
Governance_Score	−0.001*	−0.001	0.001
ROE_Mean	0.000*	0.001	0.000
log_LT_DtE_Ratio	−0.006	−0.004	0.007
log(Market_Cap)	−0.083***	−0.064***	−0.031*
Year_2017	−0.087*	−0.086	−0.118
Year_2018	−0.055	−0.053	−0.018
Year_2019	−0.028	0.073	−0.017
Year_2020	0.201***	0.300***	0.409***
Year_2021	0.012	0.055	0.175*
Year_2022	0.139***	0.034	0.150
Year_2023	0.024	0.025	−0.001
NASDAQ.Nordic_Group	−0.212***	−0.062	−0.184
Johanesburg_Group	−0.298***	0.131*	0.035
Constant	1.263***	0.963***	0.817***
Observations	1609.000	416.000	218.000
R^2	0.214	0.198	0.359
Adjusted R^2	0.207	0.168	0.312
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.8: Industry-specific models - part 3

	Cons Cyclicals (FE)	**Real Estate (FE)**	**Financials (FE)**
Environmental_Score	−0.001	0.001	−0.001
Social_Score	0.001	0.001	0.0003
Governance_Score	−0.001	0.001	−0.001
ROE_Mean	0.000	0.001*	0.000
log_LT_DtE_Ratio	0.015***	−0.020	0.040***
log(Market_Cap)	−0.048***	−0.053***	−0.035**
Year_2017	−0.058**	−0.063	−0.107***
Year_2018	0.020	−0.016	−0.060
Year_2019	0.000	−0.034	−0.078**
Year_2020	0.419***	0.507***	0.192***
Year_2021	0.078***	0.036	−0.024
Year_2022	0.113***	0.067	0.033
Year_2023	0.047*	0.077	−0.020
Observations	1233.000	397.000	312.000
R^2	0.513	0.534	0.421
Adjusted R^2	0.406	0.414	0.250

Note: *p<0.1; **p<0.05; ***p<0.01