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"Navigating ESG Impact: A Comparative Study of Investment Strategies within the DAX Index companies"

by

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Abstract

This thesis examines the relationship between Environmental Social and Governance (ESG) factors and investment strategies. Specifically, it focuses on how ESG scores can influence investment decisions within companies listed on the DAX Index, the benchmark German stock market index. Using Granger causality on individual companies from the DAX and on portfolios built on the ESG score of companies with average stock market price performance created for the paper, we will focus on the discovery of temporal dependency. Going further in the portfolios created based on prior ESG performance, we will specifically investigate the differences between their ROI, inequality using the Gini coefficient, and predictive power using ensemble methods of different groups. The results mainly show an advantage for the groups with better ESG scores in terms of ROI and the use of ensemble methods however, we note that they are also more unequal based on Gini coefficients. This study contributes to the understanding of how ESG factors influence investment strategies inside stock markets, providing a foundation for more sustainable investment practices.

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Introduction

In recent years, there has been a noticeable increase in societal interest and commitment towards sustainability and sustainable development. The growing consciousness mirrors a deepening awareness that balancing growth with environmental protection and fairness to the people is not only important - it is essential!

Moreover, the European Union itself called attention to the importance of Environmental, Social, and Governance (ESG) investment by increasing reporting requirements to promote transparency and comparability across financial markets (O'Leary and Hauman, 2020). The European Commission initiative was also highlighted in Bruno and Lagasio (2021) both emphasize the strategic role of the banking sector in promoting sustainable finance by ESG principles, illustrating the legislative role in the direction of sustainability within financial systems. Similarly, the European Central Bank's Review shows the increasing importance of management with ESG criteria by showing a stand-up of assets under management of ESG funds (European Central Bank, 2020). The significance of corporate social responsibility is also not a new topic as it was discussed by Friedman (2007) and Freeman and Mcvea (2001) in the XX century and later evolved into ESG, marking a shift from only profit-centric to stakeholder-inclusive approaches in business.

The ESG itself is integral for the sustainable development of the global economy and society, showing the importance of equally environmental, social, and governance factors in promoting coordinated development (Li et al., 2021). In the case of the mentioned financial market, ESG certification can significantly lower a firm's cost of capital and enhance its value demonstrating the financial benefits of corporate social responsibility, especially in countries that are developing (Wong et al., 2021). Additionally integrating ESG into a financial portfolio can be achieved based on the classification of firms, for example, based on material or industry-specific ESG factors which allows efficient use of ESG data in large portfolio investments that promote an equilibrium between good and bad ESG scores at the portfolio level, rather than focusing on individual firms (Henriksson et al., 2019).

Our study will focus on the relationship between ESG factors and investment strategies, focusing on the consequences of over-investing in companies with high ESG performance and under-investing in those with low ESG performance and vice versa based on the German Deutscher Aktienindex (DAX).

DAX is a main indicator for the German stock market, reflecting the performance of 40 major companies listed on the Frankfurt Stock Exchange.
It is the principal measure of economic health in Germany and also the European

Union, showing the interaction between stock market dynamics and economic trends (https://www.investopedia.com/terms/d/dax.asp).

The performance of DAX can be significantly influenced by many factors, for example - macroeconomic conditions like GDP growth or inflation. These indicators act as stimulants for stock market performance showing the effect on companies listed on the DAX (Karakostas, 2023). Moreover, the sentiment of the investors shaped by market, survey, and media data can explain some fluctuations in stock market data (Zhou, 2017).

The ESG practices emerged as important factors influencing companies' financial performance and credit rating, which consequently can influence the DAX index. A high eco-efficiency score may indicate companies that have higher investment returns, potentially leading to stable stock prices and a positive impact on the index (Kim and Li, 2021). By adopting ESG disclosures, firms can not only meet regulatory demands but also attract environmentally aware stakeholders, improving their market and financial outcomes (Carnini Pulino et al., 2022).

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Literature review

As stated, incorporating ESG criteria into investment decision-making significantly shifts the financial world. A study by Amel-Zadeh and Serafeim (2017) provides valuable insights into how big investment companies are starting to pay more attention to ESG information, as it tends to enhance investment performance. The multiple literature documented how ESG integration can influence financial performance, investors' behavior, or even market reactions, which is our goal present.

The study of Gunnar Friede and Bassen (2015) conducted one of the most comprehensive meta-analyses in the field, analyzing more than 2,000 empirical studies focusing on the relationship between ESG and financial performance. Most studies show a positive correlation, suggesting that companies that engage strongly in ESG practices tend to show superior financial performance. This groundbreaking work highlighted the potential of the ESG factor to enhance shareholder value and suggest that responsible investment strategies can boost the financial gains of the companies.

Khan et al. (2016) further clarifies this understanding by highlighting the importance of materiality in their study. Authors argue that companies that stand out at ESG issues that are particularly relevant to their business operations perform better financially than those that do not, showing that the materiality of specific ESG factors plays a major role in determining financial impact.

The growing interest in ESG investing has not only resulted in new insights into investment strategies but has led to a significant accumulation of research exploring its impact across various market segments. The research on the integration of ESG criteria extends into areas like renewable energy and large, more established market indices, showing the potential of ESG to give a new meaning to investment strategies and outcomes in these areas. Studies - for instance, the one made by Liu and Hamori (2020) showed the potential of ESG investment in the renewable energy sector, demonstrating the market's preference for sustainable investments. Chang et al. (2021) introduces an ESG index with considerable predictive power for stock market risk premiums, evidencing the financial implications of ESG in a broader market context.

Looking at long-term value creation, Eccles et al. (2014) examined how a strategic approach to sustainability is connected with strong financial performance over time. They found that companies focusing on sustainability have higher profitability, lower volatility, and fewer management concerns, suggesting that ESG practices can contribute to long-term value creation and increase overall corporate resilience.

Regarding market behavior and investor perception, some contrasting views are presented by Riedl and Smeets (2017), which sheds light on the behavioral aspects influencing the ESG-financial relationship. They emphasize that individual investors may project ethical standards on investment decisions, which can lead to biased assessments of the financial importance of ESG. This observation shows the complexity of interpreting the financial implications of ESG, as investor sentiment can significantly influence market dynamics.

Moreover, there are visible differences in ESG effectiveness in different industries, a topic explored by Derwall et al. (2005). They showed that ESG factors have different levels in different sectors. For example, industries such as energy and utilities, more directly affected by environmental regulations, show a bigger correlation between ESG practices and financial performance than less regulated sectors. This study supports the notion that the effectiveness of ESG integration in boosting financial performance may be highly dependent on sector dynamics.

However, despite the wealth of information on the role of ESG in transforming investment strategies, there is a lack of research on its relationship with single European markets, especially in Germany. We are against such an oversight! As we see the strong correlations observed in the stock market and their reflection on the prices of European companies, we want to fill this research gap. In a study by Gavrilakis and Floros (2023), it is mentioned that the results of the DAX index showed a lack of correlation between the German market and ESG between 2010 and 2020, which is in contrast to the article by Dziadkowiec and Daszynska-Zygadlo (2021). This article shows a slightly better and more visible correlation in the German market after 2009, which is still not fully explored, as the data was collected from a different source, which we believe may have been driven by the companies involved in the data collection. Additionally, the correlations shown were mainly on governmental ESG aspects without checking long, mid, terms and without much model analysis on a broader horizon.

The sustainable investment landscape, particularly within DAX index companies, highlights the increasing integration of ESG criteria within financial performance analysis (Nerlinger, 2020). This fascinating paradigm is further explored by Plagge et al. (2022), who analyze the risk-return characteristics of ESG equity strategies, highlighting the key role of traditional sources of risk in driving the performance of ESG.

Still, we do not see any relevant and significant research about those topics containing time series and machine learning model analyses. his is important for the stock markets, as it has already been proven that the use of machine learning techniques, such as those used by Patel et al. (2015) that adaptation of advanced techniques allows for better prediction of market changes. Furthermore, most of the available studies have analyzed the co-integration of the DAX index taking into account other European markets but rarely the DAX index as the independent variable. We consider this a major oversight given that we are talking about the 4th largest market globally, which is also a major player in Europe. Research on further approaches and how the German market reacts and deals with ESG has not been presented from the official resource aspects. While Caporale et al. (2022) touched on the persistence of ESG and conventional stock indices in both developed and emerging markets, giving us a brief glimpse of the homogeneity of ESG impact in markets of different sizes, the mechanism and results of ESG integration in other indices presented as standalone companies remain largely unexplored.

Moreover, further literature analysis reveals a quite complex interaction between ESG corporate reporting and market valuations of DAX index companies. Dziadkowiec and Daszynska-Zygadlo (2021), the article mentioned earlier gave evidence of negative market reaction to government relations in ESG, showing the growing importance that investors attach to ethical management. Their analysis is also reflected in discoveries of Banke et al. (2022), which illustrate the positive impact of ESG rating on both professional and non-professional stakeholders, improving corporate reputation and share prices that can further improve the portfolio performance. Additionally Zaccone and Pedrini (2020) examined how private equity incorporates ESG factors, providing insights into why companies choose to do so, the methods they use, and the challenges they face in matching investment strategies with ESG standards.

These studies pave the way for understanding the complexities of how ESG increasingly influences investment strategies within the DAX index, marking a shift towards more sustainable and responsible investment practices. They additionally underscored the critical role of transparent and accountable practices in shaping market perceptions.

Given the research across market segments on the impact of ESG, it is clear that there is a rich data set highlighting its impact on larger indices and specific large sectors such as renewable energy. However, the relative lack of insight into the dynamics and performance of ESG investing within the construction of portfolios of the best and worst performing companies and the focus on carving out known techniques and databases of ESG in terms of over and under-investing is also an apparent hole that we intend to fill, which we will focus more on in later sections of the paper.

Despite many positive associations in the abovementioned studies, inconsistencies and methodological challenges require careful interpretation. The discrepancies in the results across studies suggest that external factors such as market conditions and sector-specific dynamics can often play a significant role in shaping ESG integration outcomes. These elements highlight the complex and context-dependent nature of ESG-financial linkage.

By focusing on the DAX index as a single dependent variable, we want to contribute to filling all the research gaps mentioned above, providing valuable insights into how ESG factors can affect the European market and valuable insights into sustainable investment strategies. We additionally want to present and focus on categorizing and building our research questions as grouped portfolios. We hope that using portfolios developed in later sections of the paper and simultaneously found in Appendix B will add value to existing research. Furthermore, we wish to draw attention to the preprocessing itself and to structure once and for all the methodologies that we believe should be examined before starting any such research.

The literature has often underestimated the importance of the DAX and ESG by focusing on the US or European markets as one. Therefore, further analysis is important and will serve the existing literature and investors well.

3

Data

In our thesis, we employed two primary sources for data collection: the Sanctify ESG scoring system and Yahoo Finance API.

The Sanctify ESG system provides comprehensive ESG scores derived from over 55,000 news sources, covering a wide range of publications, from niche trade magazines to the leading international business press. The system rates new articles related to companies, categorizing them and analyzing their sentiment from an ESG perspective. Coverage includes 13,738 companies listed on 22 stock exchanges, providing a broad representation of the market.

The Yahoo Finance API complements this data by offering financial data and performance indicators for DAX companies. It also offers tools for tracking investments and real-time trading information across a wide range of asset classes to help us understand the DAX market.

The reliability and representativeness of our data are ensured by Sanctify's advanced ESG methodologies, which use sophisticated NLP techniques for scoring, and Yahoo Finance, known for its accurate and broad coverage. This comprehensive approach provides a broad view of ESG issues and financial metrics critical to assessing a company's performance on sustainable business practices. The combination of detailed ESG scores and reliable financial data allows for robust analysis of companies, confirming the validity of our data for assessing sustainable success. Together, these sources provide a broad view of the companies surveyed, integrating both financial performance and ESG impact.

3.1 Sample used in our thesis

The first dataset, provided by Sanctify, offers a wide range of ESG-oriented scores, including long-term, mid-term and short-term ESG performance scores, among many other scores that are building blocks for the scores mentioned above. This data provides a detailed analysis of these companies' ESG performance, allowing us to explore the correlation between their ESG performance and their investment attractiveness.

The second dataset includes stock market performance data from the Yahoo Finance API, covering the one-year period from 20 March 2023 to 20 March 2024, giving us the entire 365 days counted from midnight. At the same time, excluding major holidays and weekends, as stock markets do not operate then, this gives us a whole 257 unique days. This dataset provided us a comprehensive overview of stock price movements for companies listed in DAX index making a detailed examination of market reactions to ESG scores easily approachable.

Selecting the one-year data range for our study had two main reasons. First, it ensures the relevance and applicability of our analysis to current investment practices. Second, this year has been identified as a period of stability in the DAX index, meaning no changes in its composition, which is essential as it reduces disturbance in data variables during our analysis.

During our pre-processing work, we came across the absence of one automotive company, Daimler Truck, in the Sanctify databases. Moreover, company Airbus SE was also excluded from the analysis as it is categorized under "Netherlands" in the Sanctify database, despite its substantial operations in Germany. This classification discrepancy necessitates its omission to maintain geographic consistency of our study which focuses exclusively on German companies listed in the DAX index. That is why our research will be based on 38 companies rather than the full 40 on the DAX list (List of all companies: Appendix A). We believe that this will not affect our analysis, particularly as Daimler Truck is part of the Mercedes-Benz group, which we contain in our analysis.

In addition, our data were converted into portfolios specifically designed for this work and subsequent hypothesis testing. The portfolios and their breakdowns can be found in Appendix B. In order to test the collected data, we decided to divide the best- and worst-performing companies according to the ESG index and then calculate their average share price. These companies were calculated based on their average annual environmental, governmental and social performance. As we wanted to present several portfolios of approaches, the results were divided into the 5,10,15 best and worst performing companies for the individual long, mid, and short terms. With this method, we were able to present 18 different portfolios.

3.1.1 Dependent variable

In our study, the main dependent variable we have chosen is the adjusted closing price of a stock derived from the Yahoo Finance API for companies listed in the DAX index. The adjusted closing price was chosen as an important indicator because it reflects the value of a stock after taking into account any corporate actions such as dividends, stock splits etc. providing a true measure of stock performance over time. In addition, the choice compared to any other economic parameter, such as revenue growth, profit margins, or dividend yield, share prices are a more straightforward indicator that can be easily benchmarked between companies and industries without the need for extensive normalization or adjustments. This indicator is crucial to our analysis, allowing us to see exactly how the market reacts to changes in ESG performance. During data collection, we found only 4 missing values in our dependent variable; given the size of our set, we decided to fill in the above missing values with the average.

In order to understand the period in which we face the challenge of analyzing ESG indicators, it is useful to understand the nature of the volatility problem in the DAX equity market, as can be seen in Figure 3.1. The beginning of 2023 was a period of stabilization after the strong declines of 2022 associated with the post-covid recovery of the country's economy. This was also the time when the war in Ukraine began, and companies such as Rheinmetall were up +54.3% in 2022 (The tops and flops in the Dax 2023 - MarketScreener). This also enabled the German economy to emerge from the crisis.

However, October 2023 saw a sharp decline due to rising inflation in the US and high energy prices reduced profit margins for German companies, worsening the market outlook (Germany's economy brightens up: Could the DAX Index reflect that? - Euronews).

In addition, the recession in Germany, caused by falling production and strikes, exacerbated economic concerns, contributing to market declines. However, the end of the year with forecasts of interest rate cuts improved credit conditions, stimulating investment and growth in the stock market (DAX reaches historic highs: What's behind the surge in German stocks? - Euronews). Improved economic expectations and export prospects, especially against the backdrop of China and a weakening dollar, contributed to the stock market's rises in the (Why German stock index DAX breaks record as recession looms – DW – 03/13/2024).

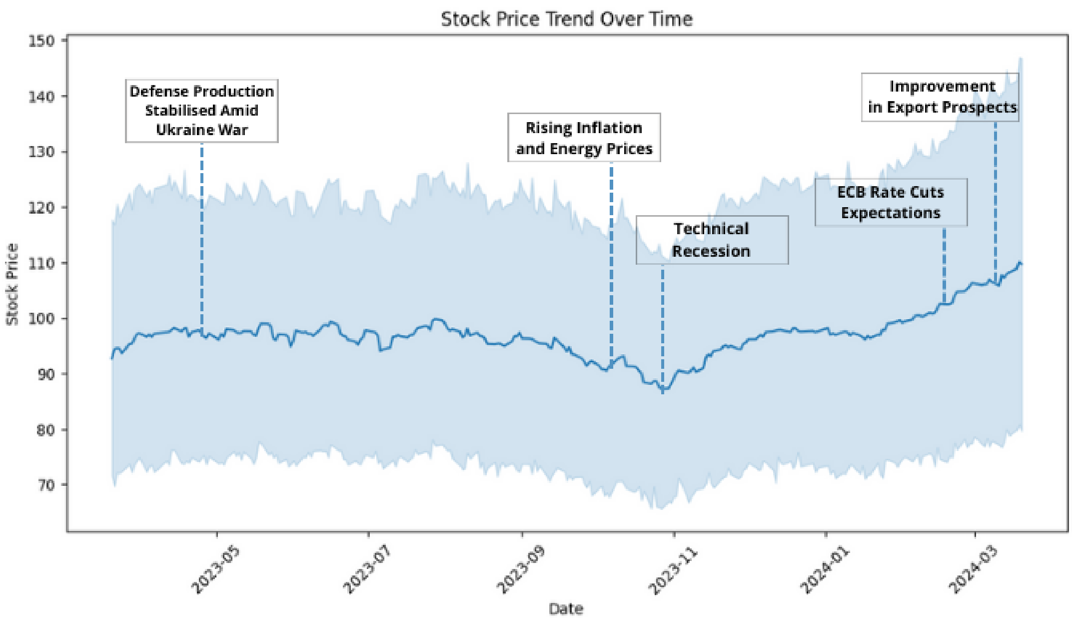

Figure 3.1: Events shaping stock markets price in DAX index

In preparing our EDA, we looked at the volatility of share values over a given period. On it, we see that the 5 best-performing companies with the highest market price value at the end of the year are Rheinmetall AG, Münich Re, Allianz SE, Hannover Rück SE, and Sartorius AG while covering the lead and the top half of 250 to 500 stock values. Rheinmetall AG is the first and the best-performing company over the years. Their operations contain armaments and military technology creation. The next companies listed above are in the Financial & Service sector. The last one mentioned above is in the Healthcare sector.

What can be said about the categorical distribution of share prices on the DAX by looking at Figure 3.2 is that, in most cases, one company is in the leading position in all the categories given. In addition, looking at the scales, there is a strong drop in Utilities & Energy, which is the weakest performing category on the German market. This obviously makes sense, as Germany's biggest import is connected with the energy market. The leading categories with stable growth rates all over the year are Chemicals & Minerals, Healthcare & Pharmaceutical, and Financial & Services. The rest show no characteristic differences from the norm.

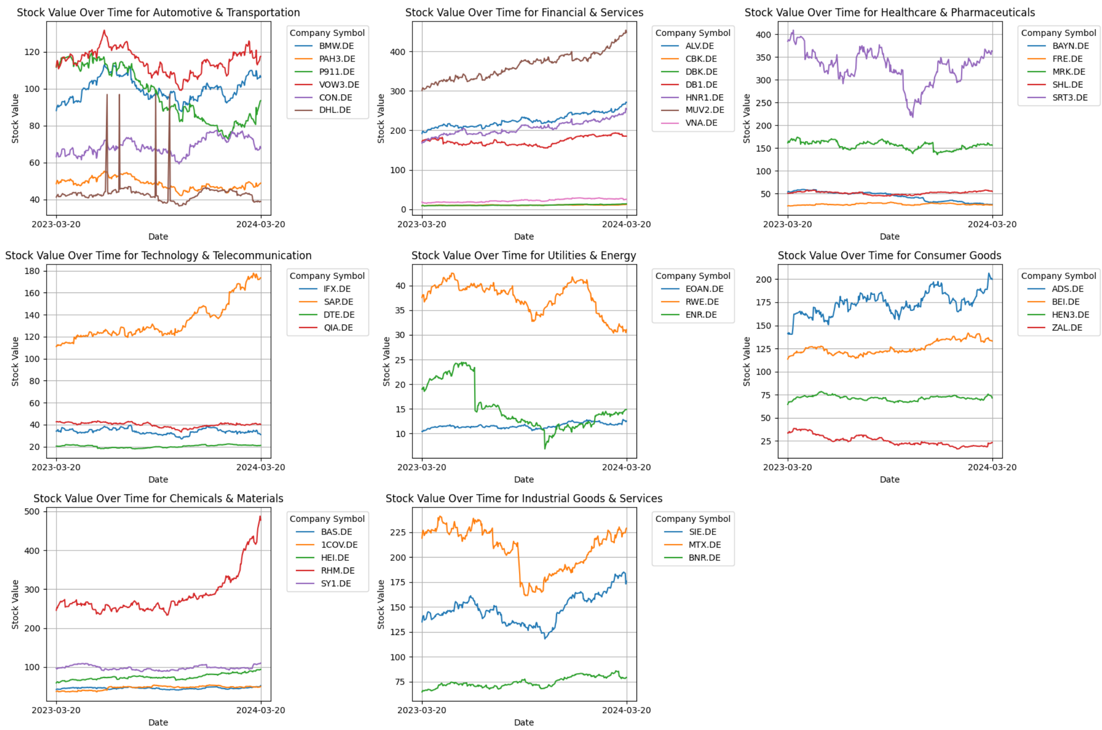

Figure 3.2: Stock prices by category of company characteristics on the DAX index

3.1.2 Explanatory variables

Our analysis includes a set of explanatory variables - ESG indicators provided by Sanctify. The primary ESG indicators included in our analysis are short-term, medium-term, and long-term ESG performance. These scores reflect companies' performance on ESG criteria over different time horizons, allowing us to assess the temporal impact of ESG factors on stock valuations. Short-, medium- and long-term results correspond to the impact of the previous result, which has decreased to 5% of the initial impact after ninety days, one year, or five years, respectively, as can be seen in Figure 3.3, which comes from Sanctify's page explaining the characteristics of the breakdown. The distribution of ESG scores on our specific data can be seen in Figure 3.4. Short-term ESG scores typically focus on immediate challenges and practices that may affect a company's operational performance during its rapid growth. Medium-term results assess a company's readiness and strategic alignment to deal with ESG issues that are expected to be significant over the next one to five years. This may include assessing progress on an ambitious annual strategy. In this case, the response is felt over a long period of time. Long-term ESG scores assess the overall outlook and post-shock effects of companies' already implemented plans. In this case, it is more about a company's overall compliance with sustainability goals.

The short-term ESG indicator is volatile, reflecting rapid market reactions. It dropped in Q3 2023, followed by a significant increase at the beginning of Q4 and then fluctuations in early 2024. In contrast, medium—and long-term ESG indicators have remained stable throughout the year, in line with the overall performance of the DAX. These observations are in line with the ESG trends at the end of 2023, as detailed in Section 3.1.1 on stock market events.

The choice of a single independent variable divided into long, medium and short periods was deliberate to test its relationship with stock market prices, the dependent variable. This targeted approach aims to identify key variables for future investment analysis. Different time frames may reveal different risk exposures: short-term performance may depend on recent events or policy changes, while long-term performance may indicate strategic positioning and readiness for future challenges.

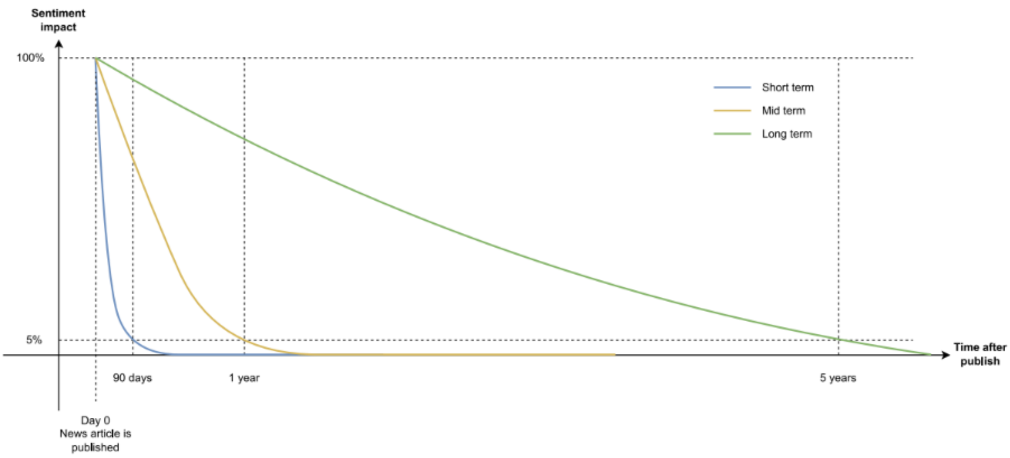

Figure 3.3: Sentiment impact on different time horizons

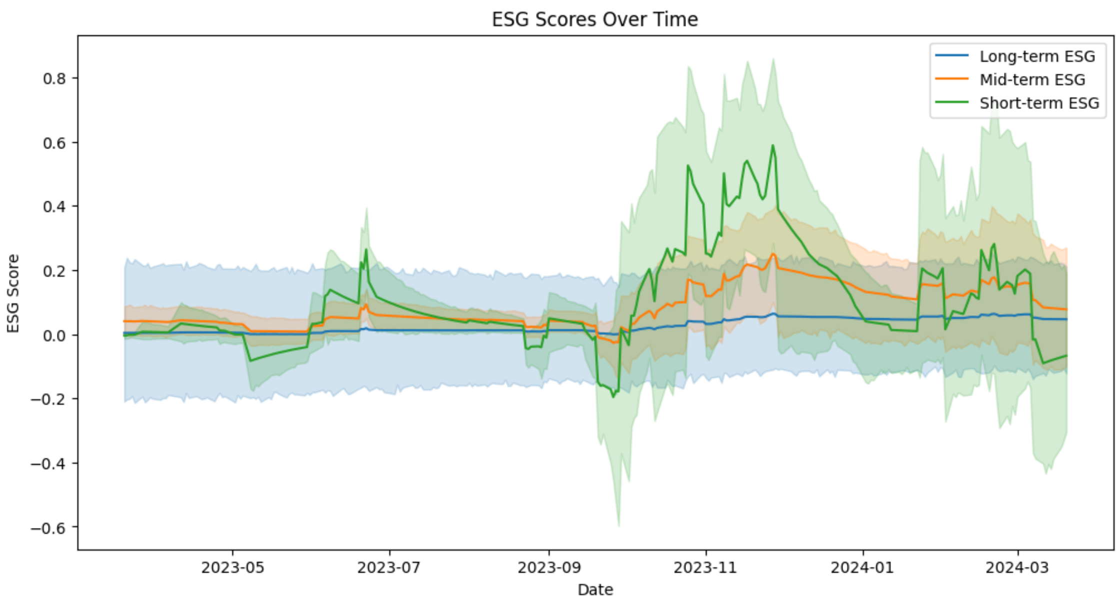

Figure 3.4: Evolution of ESG Scores Over Time for Companies Listed on the DAX Index

4

Hypothesis development

While preparing this paper, we decided to take a slightly different approach of not testing our ESG on each company like in Luo (2022), or each stock market as one variable like in Gavrilakis and Floros (2023) but as an investment portfolio built on a selected range of recommendations of best and worst scores calculated from average and adjusted to stock values. We believe it is worthwhile to test the approach used in creating portfolios of companies that are engaged best or worst in their ESG performance. This competitive advantage can be tested with the Granger causality test to determine whether it is true that grouped company portfolios matter and whether we can get better predictive results, which can be used for things like optimizing investor portfolios. The Granger method is a good research start for us and future leading projects for investors operating on DAX and researchers trying to discover the possible existing or lack of relation between ESG and stock market prices. The decision of the Granger causality test choice was made after a higher popularity growth of papers using this technique in stock price predictions (Comincioli, 1996).

Hypothesis 1: The average ESG performance of the grouped companies is a significant predictor of their share prices, as shown by Granger causality analysis. This relationship suggests that market participants respond to sustained ESG excellence among leading companies by contributing to price dynamics in the DAX equity market.

Some studies show that investing in companies with solid ESG performance becomes correlated with higher returns and unique portfolio attributes Xiaoke Zhang and He (2022) noted that equally high and low ESG-scored portfolios have the potential to deliver better returns, showing a multi-faced correlation between ESG performance and financial return. This shows that ESG-focused portfolios can show differences in the outcomes in comparison to conventional investment portfolios, potentially outperforming them.

Furthermore, Schmidt (2022) noted that portfolios with higher ESG values tend to be more concentrated and show a lower Sharpe ratio, indicating a possible bargain between good social responsibility standards and achieving traditional risk-return metrics.

To effectively broaden the analytical framework used in this study, we turned our attention to the Gini coefficient that was traditionally used to measure income inequality; now, it has also been adapted in financial markets to assess the distribution of returns and risk within portfolios. Wang et al. (2023) highlights its use in 'uncertain portfolio selection problems' where it serves as an important measure, particularly in assessing the dispersion between securities in a portfolio. This capability makes it a tool for investors who prioritize ESG performance, as it allows for a more in-depth analysis of homogeneity within their investments.

Insights mentioned above collectively show the important role of the Gini coefficient in financial analysis, particularly in the context of portfolios with high ESG. Its ability to show the homogeneity of stock value and ESG performance provides a powerful tool for investors looking for balanced and sustainable portfolios.

This wider application of the Gini coefficient underlines the growing understanding that we need better tools to analyze a socially responsible investment. This is why we formulated the following hypothesis after analyzing the above.

Hypothesis 2: Portfolios that prioritize high ESG-score companies across different periods exhibit higher returns and lower homogeneity in ESG scores and stock values, as measured by Gini coefficients, compared to portfolios that allocate fewer resources to such companies.

After a deeper look into the literature, more nuanced findings around ESG factors and financial performance emerge. For example, Kumar et al. (2016) discusses how companies that consider ESG factors show lower volatility in their stock performances, which could imply a differential impact of ESG scores on prediction accuracy. They highlight that industries are affected differently by ESG factors, suggesting that comprehensive, collective analysis might be particularly effective with companies with high ESG scores as the impacts of ESG factors are more pronounced.

Although we did not find studies that explicitly compare the highest and lowest ESG rankings with forecast accuracy, nor have such results been reported, the findings by Kumar et al. (2016) suggest that higher ESG scores, which are often associated with more comprehensive management and sustainability practices, may lead to more stable and predictable financial results. This insight forms the logical basis to hypothesize that the collective analysis of ESG factors might lead to more accurate financial predictions in high ESG-ranked companies.

Hence, the hypothesis is proposed as:

Hypothesis 3:Analysis using multiple ESG factors simultaneously results in more accurate predictions of financial performance than analysis conducted with separate ESG factors, particularly for companies in the top ESG rankings within the DAX Index, while companies with lower ESG scores show increased prediction errors across both analytical methods.

Three-dimensional analysis: By combining these three approaches, the analysis explores not only the direct impacts but also the indirect consequences of ESG performance on the stability and predictability of portfolios. This approach will reinforce ESG-based investment theory and provide practical guidance on how to construct portfolios that can minimize risk and increase potential returns. In this way, the study transcends traditional statistical methods by providing a comprehensive view of the impact of ESG on the management of investment portfolios.

5

Pre-processing

In preparing to examine our data, we had to decide on models and methods for time series analysis. In many research studies on the financial and ESG market, such as the one from D'Amato et al. (2021) or Capelle-Blancard and Petit (2019), we could observe situations where stationarity and its characteristics were not presented, i.e., were bypassed or not tested at all. This phenomenon appeared frequently in academic papers and reports from the companies we encountered. The intentional or unintentional oversight we encountered was why we decided to take an in-depth look at the stationarity of our data and devote this chapter to presenting our findings and observations.

Our dependent data, such as share prices, are characterized by trends and have non-stationary, or so-called unit root, characteristics. Also, independent variables such as ESG indices at different time horizons (long, mid, short) do not exhibit a constant mean and do not have a mean reversion feature, making them non-stationary with a unit root. However, we checked their stationarity using the Augmented Dickey-Fuller test to avoid basing our analysis on a visual chart inspection. Additionally, we conducted the Phillips-Perron (PP) test to support the ADF result. By adjusting these two characteristics for serial correlation and heteroskedasticity in the data, we could fully reject or accept the null hypothesis based on a p-value <0.05.

Stationarity means that the mean and variance will be constant, even if there are shifts and movements over time. Based on the above results (ADF, PP test), we can conclude that most time series are stationary only at the difference. Of course, looking at the amount of data the 38 companies have, we can see 3 cases where the original data were stationary. Still, for the purposes of the full analysis, we have ignored this fact and extracted the difference.

Our first approach for this data was to check cointegration between non-stationary variables with the Engle-Granger cointegration test. The alternative approach to the analysis of "long-run" (equilibrium) relationships would be to analyze the relationships between the differences of the series, i.e., among the non-stationary series (Ibrahim, 2000). However, this approach is only concerned with short-run movements and throws useful long-run information. We decided to check this step during our preparation of this paper, and we saw a lot of visible correlations in the data that could possibly be spurious results.

Before approaching the topic of cointegration testing, we find the optimal lag value from the overall data set. We checked ADF and the optimal lag based on the

Akaike information criterion (AIC) and Bayesian information criterion (BIC). The output shows that the optimal lag to be used is around 3. The lower the value, the better for the VAR model. Cointegration was checked at each successive step for latency = 1,2,3 because we wanted to be sure of the correctness of the output. With such a large dataset, we couldn't decide on a specific one, but we knew we wanted these lags to be low. Testing the value of each company's stock with each ESG index (long, medium, short) with the selected lags showed a lack of cointegration for almost all of our cases. The cointegration was only visible for the long-term ESGs and at different lags, such as Henkel at lags 2 and 3, E.ON at lags 1 and 2, and Adidas at lag 1. We can see that the decision to choose and present on 3 delays was good, as their cointegration appears simultaneously on different delays for different companies. Therefore, we will continue our later processes on three lags simultaneously to discover as many features as possible.

For our research, three companies are not enough to continue with unit root—non-stationary data. That's why we decided to take the first difference and develop our research into stationary data. We found out during our thesis preparation that researchers, most of the time, continue with unit root data without checking possible Engle-Granger tests, and that is what we want to avoid. A cointegrating approach can catch long-run co-movements or equilibria between two variables, particularly implied by the portfolio approach to determining the exchange rate.

The next step is to calculate stationarity, starting by checking the dependence of our dependent and independent elements (see Figure 5.1). We hope that this particular movement will contribute to already existing research.

Theoretically, taking logarithms from stationary variables wouldn't have a meaningful effect because the goal of differencing is to remove trends (La Torre et al., 2020). So their properties should not change much, but it can improve noise reduction and possibly the model simplification.

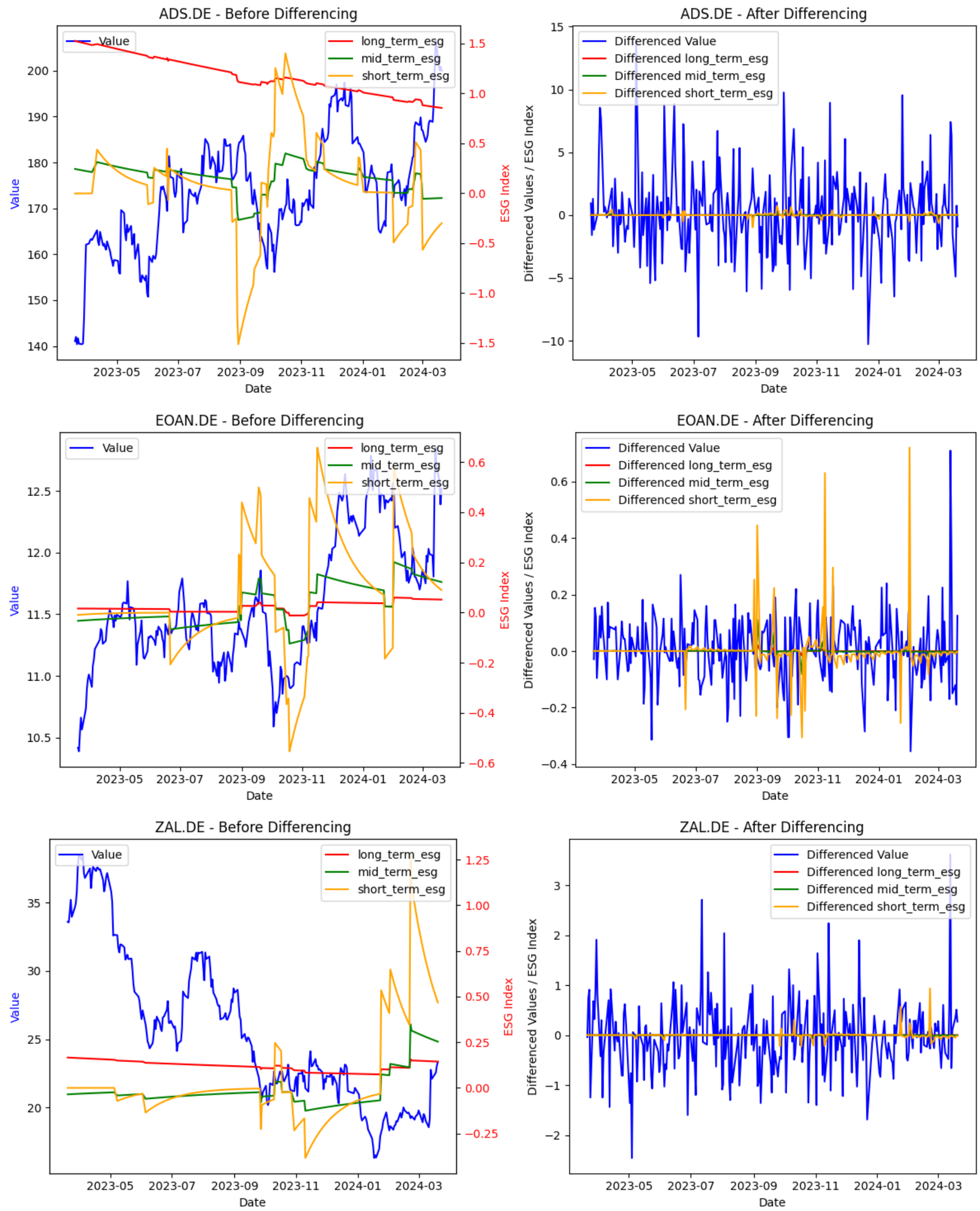

Figure 5.1: First, middle, and last examples of companies, their original series stationarity, and difference series stationarity with individual ESG factors to visualize the visible change.

With all of this knowledge, we will continue to pursue and develop our hypotheses 1 and 3 on the first difference stationary data. As shown in Figure 5.1 on the right, the new logarithmic stock market prices and ESG return to the mean. We can also see the characteristic fluctuations at the ESG only for the short term. This confirms our earlier discussion about disturbances and deviations in the mostly short-term ESG in the Explanatory data section.

6

Methodology

6.1 Hypothesis 1

Our methodology for testing the first hypothesis consists of two parts. In the first part, we tested Granger causality for each company, and in the second, we tested Granger causality for the grouped portfolios. With this methodology, we aim to determine whether the grouped companies and their average performance yield better results, i.e., more causality, and whether these results will exhibit characteristics of the best or worst companies

Groups were formed by calculating the best and worst ESG scores see in Appendix B. The Granger method determines our causality's direction and checks if it exists. It gives us better results than the cointegration test in the Pre-Processing section. Granger causality will be applied to the three lags reselected by the AIC and BIC information criterion tests. In our case, as we have a considerably short period (12 months), the limit of a maximum number of lags is required. Too big a lag choice would lead us to overfitting the model. As the results of the trial-and-error method differed for each of the three delays, we decided to show all three.

The Granger causality test allows for a rigorous analysis of the relationship between ESG performance and share prices. By posing a null hypothesis and a test hypothesis, we can test causality in the chosen direction in which the ESG response causes the average market prices of the stocks calculated for the constructed portfolios.

6.2 Hypothesis 2

In our initial hypothesis, we utilized the Granger causality test on differenced data to explore the predictive relationship between ESG scores and stock performance. In this subsequent hypothesis, we must change our approach to the raw, undifferenced data to compute ROI and the Gini index to explore predictive power and the impact on economic equity and profitability across the DAX. Working with raw indifference data was an essential step to accurately capture variations and true value relationships within the data, which are often obscured in differenced data, thereby providing a more precise basis for calculating both ROI and the Gini Index

As in Hypothesis 1, companies were categorized based on their ESG scores into top and bottom performers for different scores (long-term ESG, mid-term ESG, and short-term ESG).

This classification made it possible to focus on how the top ESG-performing companies differ in stock market performance compared to their lower-scoring equivalents (Components of the groups are listed in the Appendix B).

The analysis examines the Return On Investment (ROI) in share values. ROI is chosen as it provides a direct measure of an investment's profitability performance, enabling us to measure the financial returns connected with ESG scores. ROI is calculated for each portfolio, ensuring that the analysis captures specific performance and equity distribution within each group of companies. This approach allows us to aggregate the data at the portfolio level and analyze each portfolio independently better to understand ESG scores' impact on economic equity. Our analysts use the Gini coefficient to assess the distribution of values, providing insight into the equality of the distribution of values between all groups of companies with different ESG scores.

The ROI is calculated to check the relative change between the initial and final value in the dataset, expressed as a proportion of the initial value, being calculated with this formula:

$$ROI = \left(\frac{LastValue - FirstValue}{FirstValue} \right) \times 100\%$$

That provided the percentage increase or decrease from the initial value to the final value, showing growth or decline over time.

The Gini coefficient, denoted as G, is a statistical measure used to express inequality within the distribution and is discussed more in a paper about economic disparities by Yitzhaki (1997), the Gini coefficient rangefrom 0 to 1. A Gini coefficient of 0 expresses perfect equality (all values are the same), and a Gini coefficient of 1 indicates maximal possible inequality among values. In our context, it assesses the distribution of values based on the adjusted value price and ESG scores among portfolios. In our analysis, we decided to calculate the Gini coefficient in two ways: one will calculate equality for each group in terms of ESG data, and the second will be calculated to evaluate equality in Stock data.

The Gini coefficient is calculated using this formula:

$$G = \frac{\sum_{i=1}^{n} (2i - n - 1) \cdot x_i}{n \sum_{i=1}^{n} x_i}$$

Where:

- n represents the number of companies within each portfolio.
- x_i is calculated based on the individual company's adjusted value price and its ESG score, ordered from smallest to largest.
- i s the rank of a company's adjusted value price and ESG score within the portfolio, ranging from 1 to n.

This methodology subsection presents a detailed approach for evaluating the influence of ESG performance on the financial outcomes of DAX index companies through the lens of Gini coefficients and ROI; using these specific metrics, the research aims to understand the behavior of groups categorized by ESG scores and offer insights into the variations inside the groups.

6.3 Hypothesis 3

Building on the first two hypotheses, which used the Granger causality test to establish a causality framework and estimated ROI and Gini coefficients to gain more insights into equality and profitability, this hypothesis aims to refine further our predictive capabilities regarding the impact of ESG on stock performance. While first hypothesis outcomes provide initial insights into directional influences between ESG outcomes and stock market behavior, it is unfortunately limited by its linear assumption and the complexity of financial markets. To address those limitations and increase the robustness of our forecasts, we decided to introduce ensemble methods in the next part of our analysis. Although non-linear Granger causality tests could address some of those limitations, we specifically chose ensemble methods because they combine multiple models to reduce the variance of the outcomes, avoid overfitting, and improve accuracy, especially in our case, which seems like a non-linear and complex scenario. Ensemble methods are particularly effective in capturing relationships that a single model might miss. This approach is not a rejection of the utility of the first hypothesis but an extension that will give us a better understanding of the underlying patterns in the data, not only their direction and strength.

This part of our research starts with acquiring and initially processing the dataset and categorizing the companies based on their ESG scores as in the previous hypotheses. This step is followed by transforming the data to suit analytical needs. This transformation involves aggregating the data by date to calculate average values for each group of companies and subsequently applying a differencing transformation (as mentioned in Chapter 5). The data is then normalized using standard scaling to ensure uniform scale.

Our study employs three advanced ensemble machine learning models: *Random Forest, Gradient Boosting and Extremely Randomized Trees (Extra-Trees)*, this choice is riven by their complementary strengths in handling complex, non-linear relationships, *Random Forest* for its robustness and good performance on diverse datasets (https://builtin.com/data-science/random-forest-algorithm), *Gradient Boosting* for its ability to optimize by combining weak predictive models into a strong learner (https://www.geeksforgeeks.org/ml-gradient-boosting/) and *Extra-Trees* to introduce additional randomization into the splits of the decision tree in *Random Forest* (https://pro.arcgis.com/en/pro-app/latest/tool-reference/geoai/how-extra-tree-classification-and-regression-works.htm).

Each model is evaluated using two distinct approaches. The first approach assesses each ESG term (long, mid, and short) separately within each group, allowing for a detailed analysis of each term's impact. The second approach evaluates the combined effect of all ESG terms simultaneously within each group, providing insights into the cumulative influence of ESG factors.

A time series-specific cross-validation method, maintaining the data's chronological integrity. Model performance is quantified using Mean Squared Error (MSE) and Mean Absolute Error (MAE).

To be sure that our analysis is carried out with the best possible settings, the selection of model parameters is conducted through a grid search to minimize prediction errors. Each potential set of parameters is tested using a designated cross-validation method in both analytical approaches—testing ESG terms individually and in combination. The optimal parameters are identified based on their ability to achieve the lowest MSE.

Method	Hyperparameters
Random Forest	n_estimators: 50, 100, 200 max_depth: 5, 10, 15
Gradient Boosting	n_estimators: 50, 100, 200 max_depth: 3, 5, 7 learning_rate: 0.01, 0.1, 0.5
Extra-Trees	n_estimators: 50, 100, 200 max_depth: 5, 10, 15

Table 6.1: Hyperparameters for Different Methods

6.3.1 Ensemble methods

Ensemble methods in machine learning are advanced techniques that improve the predictive performance of models by training multiple models and combining their predictions. These methods use diverse models to gain better accuracy and robustness than a single model, mitigating their weaknesses. Such strategies are beneficial in solving complex machine learning challenges in different domains, proving their effectiveness in real-world application (Sagi and Rokach, 2018), (Mienye and Sun, 2022). Each model is pivotal in enhancing prediction accuracy and robustness in our context.

Random Forest, uses bagging to form an ensemble of decision trees which are trained on a random subset of data and features, promoting model diversity and reducing variance, as noted in the Table 6.1 important such as "n_estimators" (that refer to the number of trees in the forest) and "max_depth" (that determine maximum depth of each tree) are crucial for tuning the model. **Gradient Boosting** builds an ensemble in a sequential manner where each new model incrementally reduces the error, it is highly responsive to "n_estimators," "max_depth"(with the same meanings as in Random Forest), and "learning_rate" (that control the rate at which algorithm adapts to the complexity of the problem). **Extra-Trees** increase randomness in comparison to Random Forest by selecting random thresholds for each feature rather than the best split; similarly to Random Forest, it uses "n_estimators" and "max_depth" (with the same meaning as in two previous methods) (Pedregosa et al., 2011), (https://scikit-learn.org/stable/modules/ensemble.htmlrandom-forests-and-other-randomized-tree-ensembles).

Joint analysis techniques: By structuring the analysis in this manner, it not only builds a logical basis and progression from simple, complex analyses but also explores factors with different measurements of ESG impact on financial performance, from causality and distribution effects to predictive modeling. This tiered approach allows for a thorough examination of ESG factors through different statistical lenses, offering a richer, more nuanced insight into their implications.

7

Empirical Analysis

7.1 Analysis of Hypothesis 1

7.1.1 Analysis overview

Starting from our Granger causality test for each company, we consider both ways, which is ESG (long, mid, short) causing stock value prices of our DAX companies and the reverse. The outcome was predictable as it was ESG that was causing stock value prices. The model results were better than the previous random walk cointegration process. What this means is that the test identified more statistically significant companies than the previous result, which included only 3 companies with meaningful Granger causation. Our analysis shows a significant Granger causality in 12 out of 38 companies. The output inform us that the three different ESG indicators, long, mid, and short, behave differently relative to the peer companies. From the results, we can conclude that 4 companies—Allianz, Deutsche Börse, Heidelberg Materials, and Symrise—demonstrate effects where the time series influences the present values of another stationary time series. It is clear that these companies, among the 38 studied, exhibited a noticeable Granger causation across all ESG durations (long, mid, short). Notably, significant statistical evidence was found particularly in the long ESGs for companies such as Allianz, Deutsche Börse, Heidelberg Materials, Symrise, Deutsche Bank, Commerzbank, Henkel, Merck, Munich Re, and Zalando. However, the results were also fairly positive for the 5 companies with medium-term ESG and the 5 companies with short-term strategies.

With this knowledge, we will process further. But this time, we want to check if the relationship between the specific variable groups of our choice will perform better with portfolios than with the singular companies. This analysis aims to understand our dataset and the relationship between the DAX index companies and their ESG indicators as best as possible.

In constructing these groups, we obviously took the first difference again and checked the direction of the relationship. The results in Table 7.1 below show our test results after applying the logarithm to change stationarity. All the top groups except the top 10 short-term groups show a significant p-value < 0.05. This rejects our null hypothesis of no causality between the variables and allows us to accept the alternative hypothesis of unilateral causality between share price value and ESG at different dates. In contrast, there is no single casualty between the bottom groups. We can see that this method is quite effective, looking at the possibilities and the clarity it has given us.

Group	Orginal ADF	ADF after log	GC:lag=1	GC:lag=2	GC:lag=3
Top 5 LT ESG	0.8702	2.091103e-27		0.0172	0.0058
Top 10 LT ESG	0.5123	1.042128e-27	0.0093	0.0333	0.0151
Top 15 LT ESG	0.9968	7.407598e-28	0.0471		
Bottom 5 LT ESG	0.6848	1.441639e-28	No significant results		
Bottom 10 LT ESG	0.6889	5.404830e-25	No significant results		
Bottom 15 LT ESG	0.872	1.087398e-20	No significant results		
Top 5 MT ESG	0.848	5.103676e-29	0.0103	0.0039	0.0039
Top 10 MT ESG	0.823	2.185058e-28	0.0091	0.0229	0.0335
Top 15 MT ESG	0.9722	8.005542e-29	0.0091	0.0265	
Bottom 5 MT ESG	0.6418	5.862002e-26	No significant results		
Bottom 10 MT ESG	0.7161	6.897952e-21	No significant results		
Bottom 15 MT ESG	0.9177	5.050396e-21	No significant results		
Top 5 ST ESG	0.848	5.103676e-29		0.0190	0.0457
Top 10 ST ESG	0.8197	3.330291e-28			
Top 15 ST ESG	0.9981	3.376778e-28	0.0484		
Bottom 5 ST ESG	0.658	1.674185e-25	No significant results		
Bottom 10 ST ESG	0.7233	4.266874e-21	No significant results		
Bottom 15 ST ESG	0.9259	4.125454e-21	No significant results		

Table 7.1: Granger causality results. Analysis of all given groups with their stationarity level before and after taking first difference and their Granger causality test for 3 lags. For Long term (LT), Mid term (MT), Short term (ST) ESG Groups. GC stands for Granger causality test outputs

7.1.2 Causality between changes in build portfolios and ESG

The visible Granger causality is observed at the top but not at the bottom groups. We see that the top ones are not always notable in each of our 3 selected lags. That can happen if we have data that share values that can vary over time. A dynamic relationship is observed in this case, which indicates the possibility of being subject to shifts in market conditions, trader sentiment, or other external factors. Significant Granger causality at some lags may reflect periods of increased sensitivity or responsiveness to ESG-related changes, while the absence of significant effects at other lags may indicate periods of reduced market sensitivity or other factors influencing share value. We also see no apparent Granger causality results for each bottom group. This strongly occurring relationship may suggest that bottom-performing companies may have weaker ESG profiles dispersed across the market.

7.1.3 Conclusion on the analysis

Firstly, creating group portfolios helped us to better understand the research question. Granger causation alone for individual companies showed 12 out of 38 statistically significant companies, but this was at different levels of duration. However, the grouped and calculated average prices for the companies gave us a clear answer in the form of a strongly statistical result for the Top portfolios. This means that the portfolios that have the best ESG scores best explain their occurrence through their past events. A potential investor could use this data to group portfolios and base their decisions on specific groups of companies with the best ESG performance.

The performance data would best explain the current share market prices of these companies.

Secondly, using clustering and averaging techniques relatively helps reduce noise in our model. This is a correlation to the better performance from the result above. Thanks to the collective data set, the fluctuations previously visible in individual companies have disappeared. The ability to pick out clear patterns was more helpful than the individual analysis. The new clear results and statistically significant p-value showed that using portfolios helped optimize the models.

A final conclusion is that selecting the best and worst-performing companies helped us consistently predict significantly the stays of the relationship for environmental well-being, government, and society, creating relationships between prices and ESG performance. Investors building portfolios have their own specific perceptions of market behavior and tend to generalize the performance of the best companies influencing market values. Therefore, our chosen method confirmed the correct application of the portfolio construction method.

Our result reporting a lack of correlation for companies with worse mean annual ESG scores (bottom 5,10,15) shows that these companies do not have ESG factors significantly affecting their share prices or their market performance is affected by more diverse or less measurable factors than those included in the ESG scores. Further investigation of the relationship with other groups of companies, such as the segregation of their shareholdings by economic sectors, is recommended.

7.2 Analysis of Hypothesis 2

Group	ROI	Gini ESG	Gini Stock
Top 5 LT ESG	35.41%	0.18	0.29
Top 10 LT ESG	22.26%	0.32	0.38
Top 15 LT ESG	32.73%	0.44	0.42
Bottom 5 LT ESG	-6.21%	0.16	0.26
Bottom 10 LT ESG	-1.25%	0.17	0.36
Bottom 15 LT ESG	13.17%	0.16	0.43
Top 5 MT ESG	20.78%	0.28	0.33
Top 10 MT ESG	21.56%	0.26	0.41
Top 15 MT ESG	36.62%	0.25	0.45
Bottom 5 MT ESG	-8.70%	0.06	0.30
Bottom 10 MT ESG	-2.72%	0.05	0.36
Bottom 15 MT ESG	12.45%	0.04	0.42
Top 5 ST ESG	20.78%	0.23	0.33
Top 10 ST ESG	20.38%	0.20	0.40
Top 15 ST ESG	31.45%	0.17	0.45
Bottom 5 ST ESG	-6.52%	0.06	0.26
Bottom 10 ST ESG	-1.91%	0.05	0.36
Bottom 15 ST ESG	13.11%	0.04	0.42

Table 7.2: Comparative Analysis of ROI and Gini Coefficients for Long Term (LT), Mid Term (MT), and Short Term (ST) ESG Groups (Appendix B)

7.2.1 ROI in different groups

ROI provides valuable insights into how ESG performance may affect share price movements over time across different groups (Table 7.2). It is worth noting that the Top 5 Long Term ESG group showed a significant positive ROI (35.41%). What is even more impressive is that if we check the annual returns on the DAX index, we can see that the annual return on the entire index is around 20.3% (https://curvo.eu/backtest/en/market-index/dax?currency=eur) - some of our results show returns much higher. This can indicate that other factors may be at play in improving share performance.

On the other hand, significant negative ROI was observed among the 5 worst ESG companies in the medium term (-8.70%) and the 5 worst ESG companies in the short term (-6.52%), highlighting that companies with poor ESG performance may suffer from share price declines.

This trend highlights the potential financial impact of ESG issues. Better ESG performance may protect against negative market volatility, while poor performance may exacerbate the declines (particularly in the short—to medium-term groups).

7.2.2 Gini Coefficients

Gini coefficients calculated for ESG and equity data across groups provided us with an understanding of the distributional characteristics in our dataset, showing divergence in ESG practices and equity value distribution among DAX index companies (Table 7.2).

Higher Gini coefficients observed in ESG performance, particularly in the top 15 groups across all categories (long-, medium- and short-term), suggest broader inequality in companies' ESG performance. For example, the Top 15 Long-term ESG group has scored a Gini Coefficient of approximately 0.44 for ESG performance, indicating significant variation in how companies manage their long-term practices. Such variation may be caused by different strategic priorities or capabilities in addressing ESG issues inside the group.

On the other hand, Gini coefficients for share values tend to be lower in groups with poor ESG performance, for example - bottom five and bottom ten across categories, with values of approximately 0.26 and 0.36, respectively, in the long-term ESG group. This trend indicates a more homogeneous share price performance among companies with low ESG performance. Interestingly, the bottom five of the mid-term ESG group showed an unusually low Gini coefficient for ESG (approximately 0.06) coupled with a negative ROI value, highlighting that an extremely poor ESG score can lead to a more homogeneous and negatively skewed share price distribution.

Moreover, the discrepancy of Gini coefficients between ESG scores and share values in the same groups also sheds some light on how ESG integration affects financial performance. For example, higher Gini coefficients in ESG scores, connected with lower Gini coefficients in share prices, can suggest that even when ESG practices vary widely, market response in terms of share price adjustment tends to converge, especially in scenarios where weak ESG practices are obvious.

Therefore, the analysis of Gini coefficients highlights the importance of considering both spread and central tendencies in ESG and stock performance. It reveals that while higher ESG scores generally correlate with better stock performance (in most cases), the degree of inequality in ESG practices may also play a vital role in shaping these scores. Observed trends suggest that markets may be more forgiving and even reward disparities in ESG performance among top-performing companies but are less tolerant of disparities in ESG practices among underperforming companies.

7.2.3 Conclusion on the analysis and hypothesis evaluation

Examining ROI offers key insights into the dynamics of ESG scores and their impact on the financial ratios of DAX index companies. Data reveals significant differences across different ESG performance groups, highlighting potential financial consequences linked to the ESG ratings. In particular, the differences between the highest and the lowest ESG scores show how ESG practices can affect how much a company is worth and how well it does in the market.

In addition, Gini coefficient analysis provided a deeper understanding of the distributional characteristics in our dataset, showing higher inequality in ESG practices among the top groups and more uniform stock price performance among companies with poorer ESG performance. This can indicate that while ESG integration can lead to better stock market performance, the spread of this performance across groups can vary widely.

Hypothesis number two evaluation

Analysis of ROI and Gini coefficients for ESG scores offered complex evidence regarding the hypothesis. While portfolios with a high ESG score over long-term, medium-term, and short-term achieve higher returns than those with lower scores, the distribution of ESG scores and stock values represents a complex picture

Looking into details, high ESG score groups such as Top 5, 10, and 15 in the long-term (LT), medium-term (MT), and short-term (ST)groups consistently show positive returns, with significant increases such as 35.41%, 36.62% and 31.45% in the top groups in each period, respectively. On the other hand, the bottom groups in these periods had either negative returns, such as -6.21%, -8.70%, and -6.52%, or minimal positive returns, highlighting a stark contrast in performance.

However, Gini coefficients for ESG performance in the top ESG performance in the top groups are consistently higher (0.44, 0.25, and 0.17 in the Top 15 LT, MT, and ST, respectively) compared to those in the bottom groups (0.16, 0.04, and 0.04 in Bottom 15 LT, MT and ST respectively), indicating greater variation in ESG performance in the top-ranked companies. This can suggest that while the top ESG companies perform better financially, there is a wider range of ESG scores across their groups, indicating variability in how these scores are achieved.

In addition, Gini coefficients for share values often show a similar pattern, with higher coefficients in the top groups, indicating higher variation in share values among these companies compared to more uniform values among the bottom-ranked group.

These results support the hypothesis regarding both financial returns and the lower homogeneity of ESG performance among the top-performing groups.

7.3 Analysis of Hypothesis 3

Analysis Type	Group	Term	Model	MSE	MAE
Separate	Top 5 Long Term ESG	Long	Extra-Trees	1.508	0.947
Separate	Top 5 Long Term ESG	Long	Random Forest	1.344	0.914
Separate	Top 10 Mid Term ESG	Short	Gradient Boosting	1.818	1.117
Separate	Top 10 Mid Term ESG	Short	Extra-Trees	1.502	0.977
Separate	Bottom 5 Mid Term ESG	Long	Extra-Trees	2.495	1.082
Separate	Bottom 5 Mid Term ESG	Long	Random Forest	2.962	1.168
Collective	Top 5 Short Term ESG	-	Gradient Boosting	1.057	0.810
Collective	Bottom 15 Short Term ESG	-	Gradient Boosting	0.967	0.698
Separate	Bottom 15 Short Term ESG	Mid	Gradient Boosting	2.503	1.210
Collective	Top 10 Mid Term ESG	-	Extra-Trees	1.122	0.827
Collective	Bottom 10 Short Term ESG	-	Random Forest	1.311	0.803
Separate	Bottom 10 Short Term ESG	Mid	Gradient Boosting	2.673	1.207
Separate	Bottom 5 Long Term ESG	Short	Extra-Trees	1.231	0.847
Separate	Bottom 10 Mid Term ESG	Mid	Extra-Trees	1.861	0.985
Collective	Top 5 Long Term ESG	-	Gradient Boosting	1.098	0.820
Collective	Bottom 5 Long Term ESG	-	Gradient Boosting	0.982	0.718

Table 7.3: Important outcomes of ESG Factor Analysis on Financial Performance Prediction that are mentioned in the analysis part, all of the outcomes are listed in Appendix C (The primary metric for choosing the best parameters and ESG term is MSE).

7.3.1 Separate Analysis Outcomes

In separate terms analysis, results varied across models, conditions, and groups, revealing quite complex dynamics between ESG factors and predictive accuracy (Table 7.3). For example, using long-term data, the Extra-Trees model applied to the Top 5 Long-Term ESG group showed an MSE of 1.508 and MAE of 0.947. When the same group was analyzed using the Random Forest model, using long-term data too, the MSE dropped slightly to 1.344, with an MAE of 0.914, suggesting that Random Forest may be slightly more effective for the highest-ranked groups over longer periods.

Focusing on medium-term analysis, the Top 10 Mid-Term ESG group, assessed using Gradient Boosting on short-term data, showed an MSE of 1.818 and MAE of 1.117. However, when the same group was assessed using the Extra-Trees model (again with a medium-term perspective), the MSE improved to 1.502, and the MAE improved to 0.977, showing how the length of the scoring period can significantly affect the predictive accuracy of the model.

Moving to the lowest-ranked groups, the Extra-trees model showed some robustness. For example, the ESG Bottom 5 Mid-Term Group analyzed with Extra-Trees and a long-term setting showed an MSE of 2.495 and MAE of 1.082, which was an improvement on the Random Forest model, which gave an MSE of 2.962 and MAE of 1.168 under similar conditions. This shows us the differential performance of the model based on the ESG group and the term used.

7.3.2 Collective Analysis Outcomes

During our collective-terms analysis, we observed an overall improvement in prediction accuracy across all groups and models (Table 7.3). For example, the collective application of Gradient Boosting for the Top 5 Short-Term ESG group resulted in a lower MSE of 1.057 and MAE of 0.810 compared to the results of a separate analysis. This improvement was even more pronounced for the Bottom 15 Short Term ESG Group, where gradient Boosting reduced the MSE to 0.967 and MAE to 0.698, a significant decrease from the 2.503 and 1.210 observed in the separate analysis for the same model.

Furthermore, when we used the Extra-Trees model collectively on the top 10 Mid-Term ESG group, the MSE dropped to 1.122 and MAE to 0.827 from 1.502 and 0.977 using similar settings in the 'Separate' model.

A detailed exploration of the short-term ESG using Random Forest for the Bottom 10 Short-Term ESG group revealed an MSE of 1.311 and MAE of 0.803, significantly better than the 2.673 and 1.207, respectively, observed in separate analyses using Gradient Boosting. This shows that collective analysis can significantly reduce prediction errors in the lower-ranked groups.

7.3.3 Comparative Insights: Model efficacy across terms and groups

Empirical results highlight the varying effectiveness of different models applied to different ESG terms and groups (Table 7.3). Random Forest generally performed well in the long-term scenarios, especially for the highest-ranked groups.

Extra-Trees, on the other hand, showed adaptability in medium-term analyses, often outperforming other models in the lowest-ranked groups. This suggests its availability to fit into more complex, diverse scenarios.

Gradient Boosting consistently showed its strength in short-term analysis in both the top and bottom groups when applied to a collective approach. It often achieved the lowest error rates and illustrated its ability to adapt to integrated ESG factors.

7.3.4 Comparative Insights: of predictive Accuracy - Top vs. Bottom ESG Rankings

Separate Analysis Insight

In a separate analysis setting, the divergence of results is visible (Table 7.3). For example, using the Extra-Trees model, the Top 5 Long Term ESG Group recorded an MSE of 1.508 and MAE of 0.947. In contrast, the opposite Bottom 5 Long Term ESG group in the same model and term showed a higher error with n MSE of 1.231 and MAE of 0.847. While the errors are not dramatically higher in this case, the trend in other models and terms shows increased variability.

Another example can be seen in the mid-term analysis, where the Top 10 Mid Term ESG group, analysed separately using Extra-Trees gave outcome - MSE 1.502 and MAE 0.977. In comparison, the Bottom 10 Mid-Term ESG group showed an MSE of 1.861 and MAE of 0.985

Collective Analysis Insight

In the collective analysis, predictive accuracy is generally improved. Still, the relative difference in performance between the highest and lowest ESG rankings remains as consistent as in the separate case (Table 7.3). For example, the collective application of Gradient Boosting for the Top 5 Long Term ESG group resulted in an MSE of 1.098 and MAE of 0.820. Meanwhile, the Bottom 5 Long Term ESG group with the same model showed an MSE of 0.982 and MAE of 0.718. Although the MSE appears lower for the Bottom group, it primarily reflects lower variability rather than improved predictive power.

7.3.5 Conclusion on the analysis and hypothesis evaluation

This comprehensive analysis supported our hypothesis that a collective approach to ESG factors analysis significantly improves the accuracy of financial performance forecasts, particularly among companies with higher ESG rankings. While companies with lower rankings benefit from collective analysis, they are inherently subject to higher errors. These results show the importance of using ESG factors in predictive models and highlight the role of choosing the right model and scoring timeframes of the ESG data. Such a mixed approach enables a more tailored, effective predictive strategy, essential for making informed decisions in the financial sector.

7.4 Recommendations

For a more comprehensive analysis, a longer time frame than just one year is recommended. We initially focused on one year to avoid periods of significant market shocks and changes, such as the addition and removal of companies from the DAX. However, extending the analysis over several years will allow us to visualise the performance of the DAX and examine its volatility and behaviour during crises such as the COVID-19 pandemic.

Furthermore, we recommend comparing our analysis of Sanctify's ESG performance with the sustainability product DAX50, an index of environmental indicators for the German market. This comparison is necessary because previous analyses by other researchers, such as Gavrilakis and Floros (2023), may have been influenced by corporate manipulation and government preferences. The comparative analysis will provide a clearer insight into the quality of our research and the reliability of Sanctify's databases.

8

Conclusion

Our thesis explored the relationship between ESG metrics and investment strategies inside the DAX Index, revealing several key insights.

Our findings confirmed that Granger causality is a more significant method than the cointegration test. The first hypothesis output showed that developed portfolios produce more relevant and realistic results than predictive influence on individual companies. Additionally, the ESG scores across various periods (long, mid, and short) demonstrate a clear temporal dependency on portfolios composed of the average stock prices of top-performing companies while showing no such dependency on those of the lowest ESG performers.

Portfolios prioritizing companies with high ESG performance achieved higher returns. However, Gini coefficient analysis showed higher inequality not only in ESG practices but also in stock prices within top ESG groups where companies with poorer ESG performance exhibited more uniform stock performance.

Furthermore, we have shown that collective ESG analysis using ensemble methods provides a more accurate earning forecast for the highest-ranked ESG companies in the DAX index.

In summary, our research contributes significantly to understanding the impact of ESG on investment strategies in equity markets. By highlighting the predictive power of ESG performance and the concrete benefits of ESG-focused portfolios, this study provides valuable insights for investors who want to integrate alternative data, such as ESG criteria, into their decision-making processes.

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Appendix A

Companies used in the analysis and their tickers

Table A.1: Companies used in the analysis and their tickers

Order Number	Company Symbol	Company Name
1	1COV.DE	Covestro AG
2	ADS.DE	adidas AG
3	ALV.DE	Allianz SE
4	BAS.DE	BASF SE
5	BAYN.DE	Bayer Aktiengesellschaft
6	BEI.DE	Beiersdorf Aktiengesellschaft
7	BMW.DE	Bayerische Motoren Werke Aktiengesellschaft
8	BNR.DE	Brenntag AG
9	CBK.DE	Commerzbank AG
10	CON.DE	Continental Aktiengesellschaft
11	DB1.DE	Deutsche Börse AG
12	DBK.DE	Deutsche Bank Aktiengesellschaft
13	DHL.DE	Deutsche Post AG
14	DTE.DE	Deutsche Telekom AG
15	ENR.DE	Siemens Energy AG
16	EOAN.DE	E.ON SE
17	FRE.DE	Fresenius Medical Care AG & Co. KGaA
18	HEI.DE	HeidelbergCement AG
19	HEN3.DE	Henkel AG & Co. KGaA
20	HNR1.DE	Hannover Rück SE
21	IFX.DE	Infineon Technologies AG
22	MBG.DE	Daimler AG
23	MRK.DE	MERCK Kommanditgesellschaft auf Aktien
24	MTX.DE	MTU Aero Engines AG
25	MUV2.DE	Münchener Rückversicherungs-Gesellschaft Aktiengesellschaft
26	P911.DE	Dr.Ing. h. c. F. Porsche AG
27	PAH3.DE	Porsche Automobil Holding SE
28	QIA.DE	QIAGEN N.V.
29	RHM.DE	Rheinmetall AG
30	RWE.DE	RWE Aktiengesellschaft
31	SAP.DE	SAP SE
32	SHL.DE	Siemens Healthineers AG
33	SIE.DE	Siemens Aktiengesellschaft
34	SRT3.DE	Sartorius Aktiengesellschaft
35	SY1.DE	Symrise AG
36	VNA.DE	Vonovia SE
37	VOW3.DE	Volkswagen AG
38	ZAL.DE	Zalando SE

Appendix B

Composition of the groups used in the analysis

Table B.1: Company Groups Based on ESG Rankings

Group	**Term**	**Companies**
Top 5	Long Term	BAS.DE, SIE.DE, ADS.DE, SAP.DE, RWE.DE
	Mid Term	BAS.DE, BAYN.DE, SAP.DE, SIE.DE, RWE.DE
	Short Term	BAYN.DE, BAS.DE, SAP.DE, SIE.DE, RWE.DE
Top 10	Long Term	BAS.DE, SIE.DE, ADS.DE, SAP.DE, RWE.DE, HEN3.DE, BAYN.DE, 1COV.DE, IFX.DE, ENR.DE
	Mid Term	BAS.DE, BAYN.DE, SAP.DE, SIE.DE, RWE.DE, IFX.DE, HEN3.DE, ALV.DE, VOW3.DE, CBK.DE
	Short Term	BAYN.DE, BAS.DE, SAP.DE, SIE.DE, RWE.DE, IFX.DE, ALV.DE, HEN3.DE, VOW3.DE, ENR.DE
Top 15	Long Term	BAS.DE, SIE.DE, ADS.DE, SAP.DE, RWE.DE, HEN3.DE, BAYN.DE, 1COV.DE, IFX.DE, ENR.DE, BEI.DE, MRK.DE, ALV.DE, ZAL.DE, RHM.DE
	Mid Term	BAS.DE, BAYN.DE, SAP.DE, SIE.DE, RWE.DE, IFX.DE, HEN3.DE, ALV.DE, VOW3.DE, CBK.DE, QIA.DE, ADS.DE, 1COV.DE, ENR.DE, RHM.DE
	Short Term	BAYN.DE, BAS.DE, SAP.DE, SIE.DE, RWE.DE, IFX.DE, ALV.DE, HEN3.DE, VOW3.DE, ENR.DE, QIA.DE, CBK.DE, MBG.DE, DB1.DE, RHM.DE
Bottom 5	Long Term	MBG.DE, VOW3.DE, P911.DE, PAH3.DE, DBK.DE
	Mid Term	MRK.DE, PAH3.DE, P911.DE, DHL.DE, DBK.DE
	Short Term	PAH3.DE, P911.DE, DHL.DE, BMW.DE, DBK.DE
Bottom 10	Long Term	VNA.DE, MTX.DE, DHL.DE, CBK.DE, BMW.DE, MBG.DE, VOW3.DE, P911.DE, PAH3.DE, DBK.DE
	Mid Term	BMW.DE, ZAL.DE, MTX.DE, VNA.DE, SY1.DE, MRK.DE, PAH3.DE, P911.DE, DHL.DE, DBK.DE
	Short Term	DTE.DE, MTX.DE, VNA.DE, MRK.DE, SY1.DE, PAH3.DE, P911.DE, DHL.DE, BMW.DE, DBK.DE
Bottom 15	Long Term	BNR.DE, MUV2.DE, CON.DE, FRE.DE, HNR1.DE, VNA.DE, MTX.DE, DHL.DE, CBK.DE, BMW.DE, MBG.DE, VOW3.DE, P911.DE, PAH3.DE, DBK.DE
	Mid Term	HEI.DE, MUV2.DE, CON.DE, FRE.DE, HNR1.DE, BMW.DE, ZAL.DE, MTX.DE, VNA.DE, SY1.DE, MRK.DE, PAH3.DE, P911.DE, DHL.DE, DBK.DE
	Short Term	HEI.DE, MUV2.DE, CON.DE, FRE.DE, HNR1.DE, DTE.DE, MTX.DE, VNA.DE, MRK.DE, SY1.DE, PAH3.DE, P911.DE, DHL.DE, BMW.DE, DBK.DE

Appendix C

Full results of the analysis carried out in hypothesis three

Group	Term	MSE	MAE	Best Parameters
Top 5 Long Term ESG	Long Term	1.344	0.914	{'max_depth': 5, 'n_estimators': 100}
Top 10 Long Term ESG	Long Term	1.366	0.917	{'max_depth': 5, 'n_estimators': 50}
Top 15 Long Term ESG	Long Term	1.410	0.957	{'max_depth': 5, 'n_estimators': 100}
Bottom 5 Long Term ESG	Short Term	1.291	0.868	{'max_depth': 5, 'n_estimators': 200}
Bottom 10 Long Term ESG	Mid Term	1.403	0.850	{'max_depth': 5, 'n_estimators': 200}
Bottom 15 Long Term ESG	Long Term	1.522	0.933	{'max_depth': 5, 'n_estimators': 50}
Top 5 Mid Term ESG	Mid Term	1.382	0.930	{'max_depth': 5, 'n_estimators': 100}
Top 10 Mid Term ESG	Short Term	1.305	0.923	{'max_depth': 5, 'n_estimators': 50}
Top 15 Mid Term ESG	Mid Term	1.421	0.896	{'max_depth': 5, 'n_estimators': 50}
Bottom 5 Mid Term ESG	Long Term	1.844	0.928	{'max_depth': 5, 'n_estimators': 100}
Bottom 10 Mid Term ESG	Mid Term	1.513	0.894	{'max_depth': 5, 'n_estimators': 200}
Bottom 15 Mid Term ESG	Mid Term	1.521	0.924	{'max_depth': 5, 'n_estimators': 50}
Top 5 Short Term ESG	Mid Term	1.347	0.921	{'max_depth': 5, 'n_estimators': 100}
Top 10 Short Term ESG	Long Term	1.265	0.901	{'max_depth': 5, 'n_estimators': 200}
Top 15 Short Term ESG	Long Term	1.528	0.965	{'max_depth': 5, 'n_estimators': 50}
Bottom 5 Short Term ESG	Mid Term	1.553	0.841	{'max_depth': 5, 'n_estimators': 100}
Bottom 10 Short Term ESG	Mid Term	1.635	0.929	{'max_depth': 5, 'n_estimators': 100}
Bottom 15 Short Term ESG	Mid Term	1.658	0.973	{'max_depth': 5, 'n_estimators': 200}

Table C.1: Separate Analysis - Random Forest Outcomes for Different Terms and Best Parameters

Group	Term	MSE	MAE	Parameters
Top 5 Long Term ESG	Long Term	1.897	1.067	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Top 10 Long Term ESG	Long Term	1.943	1.100	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Top 15 Long Term ESG	Long Term	2.235	1.156	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 5 Long Term ESG	Short Term	1.824	1.051	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 10 Long Term ESG	Long Term	2.488	1.172	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 15 Long Term ESG	Long Term	2.295	1.165	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Top 5 Mid Term ESG	Long Term	1.726	1.005	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Top 10 Mid Term ESG	Short Term	1.818	1.117	'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 50
Top 15 Mid Term ESG	Long Term	2.411	1.217	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 5 Mid Term ESG	Long Term	2.962	1.168	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 10 Mid Term ESG	Mid Term	2.483	1.171	'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 50
Bottom 15 Mid Term ESG	Mid Term	2.393	1.182	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Top 5 Short Term ESG	Long Term	1.726	1.005	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Top 10 Short Term ESG	Short Term	2.042	1.126	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Top 15 Short Term ESG	Long Term	2.190	1.135	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 5 Short Term ESG	Long Term	3.363	1.248	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 10 Short Term ESG	Mid Term	2.673	1.207	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50
Bottom 15 Short Term ESG	Mid Term	2.503	1.210	'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50

Table C.2: Separate Analysis - Gradient Boosting Outcomes for Different Terms and Best Parameters

Group	Term	MSE	MAE	Parameter
Top 5 Long Term ESG	Long Term	1.508	0.947	{'max_depth': 5, 'n_estimators': 100}
Top 10 Long Term ESG	Short Term	1.843	1.072	{'max_depth': 5, 'n_estimators': 100}
Top 15 Long Term ESG	Long Term	1.625	0.983	{'max_depth': 5, 'n_estimators': 100}
Bottom 5 Long Term ESG	Short Term	1.231	0.847	{'max_depth': 5, 'n_estimators': 100}
Bottom 10 Long Term ESG	Mid Term	1.555	0.864	{'max_depth': 5, 'n_estimators': 50}
Bottom 15 Long Term ESG	Long Term	1.746	1.000	{'max_depth': 5, 'n_estimators': 200}
Top 5 Mid Term ESG	Short Term	1.887	1.088	{'max_depth': 5, 'n_estimators': 200}
Top 10 Mid Term ESG	Short Term	1.502	0.977	{'max_depth': 5, 'n_estimators': 100}
Top 15 Mid Term ESG	Short Term	1.821	1.057	{'max_depth': 5, 'n_estimators': 200}
Bottom 5 Mid Term ESG	Long Term	2.495	1.082	{'max_depth': 5, 'n_estimators': 100}
Bottom 10 Mid Term ESG	Mid Term	1.861	0.985	{'max_depth': 5, 'n_estimators': 50}
Bottom 15 Mid Term ESG	Mid Term	1.810	0.998	{'max_depth': 5, 'n_estimators': 100}
Top 5 Short Term ESG	Short Term	1.844	1.075	{'max_depth': 5, 'n_estimators': 200}
Top 10 Short Term ESG	Long Term	1.368	0.900	{'max_depth': 5, 'n_estimators': 100}
Top 15 Short Term ESG	Long Term	1.739	1.024	{'max_depth': 5, 'n_estimators': 200}
Bottom 5 Short Term ESG	Mid Term	1.876	0.896	{'max_depth': 5, 'n_estimators': 50}
Bottom 10 Short Term ESG	Mid Term	2.233	1.095	{'max_depth': 5, 'n_estimators': 50}
Bottom 15 Short Term ESG	Mid Term	1.829	1.027	{'max_depth': 5, 'n_estimators': 50}

Table C.3: Separate Analysis - Extra-Trees Outcomes for Different Terms and Best Parameters

Group	MSE	MAE	Parameter
Top 5 Long Term ESG	1.145	0.833	{'max_depth': 5, 'n_estimators': 200}
Top 10 Long Term ESG	1.143	0.828	{'max_depth': 5, 'n_estimators': 100}
Top 15 Long Term ESG	1.123	0.835	{'max_depth': 5, 'n_estimators': 200}
Bottom 5 Long Term ESG	1.054	0.769	{'max_depth': 5, 'n_estimators': 50}
Bottom 10 Long Term ESG	1.275	0.815	{'max_depth': 5, 'n_estimators': 50}
Bottom 15 Long Term ESG	1.243	0.844	{'max_depth': 5, 'n_estimators': 200}
Top 5 Mid Term ESG	1.149	0.834	{'max_depth': 5, 'n_estimators': 50}
Top 10 Mid Term ESG	1.005	0.795	{'max_depth': 5, 'n_estimators': 50}
Top 15 Mid Term ESG	1.094	0.835	{'max_depth': 5, 'n_estimators': 50}
Bottom 5 Mid Term ESG	1.444	0.822	{'max_depth': 5, 'n_estimators': 50}
Bottom 10 Mid Term ESG	1.291	0.818	{'max_depth': 5, 'n_estimators': 50}
Bottom 15 Mid Term ESG	1.183	0.797	{'max_depth': 5, 'n_estimators': 100}
Top 5 Short Term ESG	1.154	0.841	{'max_depth': 5, 'n_estimators': 50}
Top 10 Short Term ESG	1.059	0.803	{'max_depth': 5, 'n_estimators': 50}
Top 15 Short Term ESG	1.132	0.831	{'max_depth': 5, 'n_estimators': 100}
Bottom 5 Short Term ESG	1.533	0.862	{'max_depth': 5, 'n_estimators': 200}
Bottom 10 Short Term ESG	1.311	0.803	{'max_depth': 5, 'n_estimators': 200}
Bottom 15 Short Term ESG	1.151	0.782	{'max_depth': 5, 'n_estimators': 50}

Table C.4: Collective Analysis - Random Forest Outcomes for Best Parameters

Group	MSE	MAE	Parameter
Top 5 Long Term ESG	1.098	0.820	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top 10 Long Term ESG	1.030	0.796	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top 15 Long Term ESG	0.978	0.787	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 5 Long Term ESG	0.982	0.718	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 10 Long Term ESG	0.999	0.704	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 15 Long Term ESG	0.960	0.726	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top 5 Mid Term ESG	1.057	0.810	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top 10 Mid Term ESG	0.944	0.760	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top 15 Mid Term ESG	0.951	0.794	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 5 Mid Term ESG	1.096	0.681	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 10 Mid Term ESG	1.038	0.710	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 15 Mid Term ESG	0.967	0.697	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top 5 Short Term ESG	1.057	0.810	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top Short Term ESG	0.962	0.760	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Top 15 Short Term ESG	0.992	0.792	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 5 Short Term ESG	1.031	0.670	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 10 Short Term ESG	1.064	0.713	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
Bottom 15 Short Term ESG	0.967	0.698	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}

Table C.5: Collective Analysis - Gradient Boosting Outcomes Best Parameters

Group	**MSE**	**MAE**	**Parameter**
Top 5 Long Term ESG	1.220	0.848	{'max_depth': 5, 'n_estimators': 100}
Top 10 Long Term ESG	1.172	0.829	{'max_depth': 5, 'n_estimators': 50}
Top 15 Long Term ESG	1.286	0.876	{'max_depth': 5, 'n_estimators': 100}
Bottom 5 Long Term ESG	1.018	0.739	{'max_depth': 5, 'n_estimators': 100}
Bottom 10 Long Term ESG	1.356	0.792	{'max_depth': 5, 'n_estimators': 100}
Bottom 15 Long Term ESG	1.220	0.778	{'max_depth': 5, 'n_estimators': 200}
Top 5 Mid Term ESG	1.214	0.856	{'max_depth': 5, 'n_estimators': 50}
Top 10 Mid Term ESG	1.122	0.827	{'max_depth': 5, 'n_estimators': 200}
Top 15 Mid Term ESG	1.183	0.846	{'max_depth': 5, 'n_estimators': 50}
Bottom 5 Mid Term ESG	1.440	0.738	{'max_depth': 5, 'n_estimators': 100}
Bottom 10 Mid Term ESG	1.400	0.803	{'max_depth': 5, 'n_estimators': 100}
Bottom 15 Mid Term ESG	1.287	0.796	{'max_depth': 5, 'n_estimators': 100}
Top 5 Short Term ESG	1.217	0.862	{'max_depth': 5, 'n_estimators': 50}
Top 10 Short Term ESG	1.177	0.821	{'max_depth': 5, 'n_estimators': 200}
Top 15 Short Term ESG	1.234	0.837	{'max_depth': 5, 'n_estimators': 50}
Bottom 5 Short Term ESG	1.620	0.813	{'max_depth': 5, 'n_estimators': 100}
Bottom 10 Short Term ESG	1.466	0.814	{'max_depth': 5, 'n_estimators': 50}
Bottom 15 Short Term ESG	1.308	0.803	{'max_depth': 5, 'n_estimators': 100}

Table C.6: Collective Analysis - Extra-Trees Outcomes for Best Parameters