ERASMUS UNIVERSITY ROTTERDAM
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How are firms' ESG scores related to stock performance and resilience?

Author: Teresa Nicolau
Student number: 611451
Thesis supervisor: Dr. J.J.G. Lemmen
Second reader: Dr. R. Wang
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PREFACE AND ACKNOWLEDGEMENTS

Finishing my Master's thesis was challenging but very rewarding. I have developed a special interest in ESG investing and risk management.

I am thankful to my supervisor, Dr. J.J.G. Lemmen, for his support and guidance. I also want to express my gratitude to the professors at the Erasmus School of Economics and to my classmates, from whom I have learned so much over the past year.

Finally, on a personal note, special thanks go to my parents. Their constant support and encouragement throughout my studies and life have made all my achievements possible.

ABSTRACT

This thesis investigates the relationship between firms' Environmental, Social, and Governance (ESG) scores and stock robustness. We analyse 2,597 NASDAQ-listed American firms from January 2002 to July 2023, and categorize them into two groups based on their ESG scores. The results show firms with high ESG scores consistently outperform those with low ESG scores in the stock market. Specifically, they display higher returns, lower volatility, and reduced tail risk, and demonstrate enhanced resilience during market shocks, challenging well-established risk-return principles. Hence, we advocate for the integration of ESG factors into financial strategies to mitigate risks and promote long-term sustainable performance.

Keywords: ESG Scores, Stock Performance, Market Resilience, Volatility, Tail Risk

Jel Classification: G01, G11, G32, M14, Q01

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CHAPTER 1 Introduction

Over the past decade, there has been a growing focus on the integration of environmental, social, and governance (ESG) considerations in financial strategies. Yet, the pressing question remains whether compliance with ESG principles truly impacts financial performance. In this study, we address the question *‘How are firms’ ESG scores related to stock performance and resilience?’*

The field of sustainable finance has seen a significant rise, with an increasing number of stakeholders adopting ESG investing strategies. As a result, the role of ESG scores in evaluating a firm's financial robustness and potential for long-term success is becoming increasingly relevant. While views of shareholder primacy and profit maximization have long influenced the corporate world, this understanding is being challenged by evidence suggesting a positive link between ESG practices and financial robustness. Empirical studies have shown that firms with strong ESG engagement tend to have superior stock performance and stability. Furthermore, recent studies also indicate that firms with high ESG integration may outperform their low ESG counterparts, especially during market shocks. Still, most studies stress the need for more critical and comprehensive research.

Our study investigates how firms’ ESG scores relate to stock performance, volatility, and tail risk, and with stock resilience during market shocks. We analyse a dataset consisting of weekly observations of 2,597 American firms listed on NASDAQ and their associated ESG scores retrieved from Refinitiv, between January 2002 and July 2023. Moreover, we split the firms into two groups based on their ESG scores: group 1 consists of firms with high ESG scores, and group 2 includes firms with low ESG scores.

To examine financial robustness under different market conditions, we employed three distinct methodologies to compare the differences between the two ESG groups. We used the CAPM Approach to study firms' stock performance by comparing their stocks' excess return and systematic risk. In addition, we employed a Regression Approach that focuses on six target analyses related to return performance, volatility, asymmetry distribution assessment, and tail risk assessment. Finally, we study the firms’ stock resilience during market shocks by conducting a regression analysis with six dummy variables, each corresponding to a specific U.S. stock market shock, that we have identified.

After extensive analysis, we confirm the hypotheses that we formulated in the literature review (chapter 2) and thus, can answer our research question: Firms with higher ESG scores exhibit superior stock performance and resilience under various market conditions when compared to their low-scoring counterparts. This conclusion challenges modern portfolio and asset pricing theories that suggest a direct risk-return trade-off in investment decisions.

Our research contributes to the existing literature by providing a thorough analysis of how firms' ESG scores relate to stock endurance and, specifically, by investigating tail risk in the context of firms with high and low ESG scores.

In summary, the implications of our findings are substantial, offering practical insights for stakeholders committed to ethical practices and sustainable business models. The results advocate for the integration of ESG criteria into investment strategies and corporate decisions as a critical tool for mitigating tail risk and ensuring sustained long-term returns. Hence, we recommend that all stakeholders prioritize ESG principles, not only with a focus on corporate responsibility but also as a key strategy for effectively managing the complexities of today's financial markets. To conclude, we acknowledge the study's limitations and suggest avenues for future research.

CHAPTER 2 Literature Review

Sustainable finance approaches have boomed in recent years, which is evidenced by a rising number of investors, issuers, financial intermediaries, and institutions embracing Environmental, Social, and Governance (ESG) investment strategies. Consequently, the influence of ESG scores on a firm's financial health is becoming increasingly crucial, as ESG scoring and reporting can reveal insights into a firm's resilience, critical for long-term value creation.

Different rank providers measure sustainability aspects according to their frameworks and indicators. For instance, Refinitiv groups ESG metrics into ten distinct categories, which are then aggregated into the three core pillar scores (E, S and G). The "E" stands for environmental considerations, specifically related to emissions, innovation, and resource use. The "S" indicates social factors, focusing on community, human rights, product responsibility, and workforce. The "G" represents governance indicators, including corporate social responsibility (CSR) strategy, management, and shareholders. Each ESG category covers a total of 25 themes that are weighted to evaluate a firm's ESG score (see Appendix A1).

Interest in ESG investing and integration is driven by a variety of factors. It's not only about ethical and moral considerations but also about competing on improved risk-adjusted returns and risk management. Studies indicate that stakeholders believe firms with robust ESG performances are better positioned to achieve sustainable long-term success (Boffo, 2020). Investors use these ESG scores to assess corporate behaviour and to predict future financial performance that might not be fully captured by a traditional financial analysis. Hence, there is an increasing demand for ESG disclosures, which has led to a growing tendency for firms to incorporate ESG metrics into their annual reports. Indeed, ESG investing has witnessed exponential growth. A 2022 Bloomberg Intelligence Report argued that global ESG assets value could surpass USD 41 trillion that year and could reach USD 50 trillion by 2025, representing one-third of the projected total global assets under management (Bloomberg Intelligence, 2022).

However, despite this rising interest in ESG investing, the past decade's returns present a mixed picture. The differences in ESG metrics, ratings, and investment approaches have made it challenging for investors to manage ESG risk guidelines and pursue ESG objectives without a trade-off in financial performance. Historically, some scholars have argued that incorporating ESG factors into business operations and investment decisions could compromise financial outcomes. ESG initiatives could divert funds that would be better spent on direct revenue-generating activities. For example, Friedman's Doctrine (1970) argues that a business's primary social responsibility is to maximize its profits. According to Friedman, a firm has no social responsibility to the public or society, only to its shareholders. This shareholder primacy view in capital markets, often interpreted as treating sustainability issues as externalities, significantly influenced the corporate world. Yet, this perspective is increasingly being challenged.

Empirical studies have begun to draw connections between ESG excellence and enhanced financial performance and stability. For instance, a meta-analysis by Friede et al. (2015) compiled evidence from over 2,000 empirical studies and found a correlation between ESG and corporate financial performance (CFP). Of these studies, 90% indicated a non-negative, statistically significant ESG-CFP relationship, with the majority reporting positive findings that remained consistent over time. The research highlighted that ESG outperformance opportunities exist in several market sectors, particularly in North America, emerging markets, and non-equity asset classes. Their findings suggest that ESG and financial performance are more complementary than mutually exclusive.

Moreover, Eccles et al. (2014) observed that high-sustainability firms in the U.S., those that voluntarily adopted sustainability policies, consistently outperformed their low-sustainability counterparts in the long run, based on both stock market and accounting measures. They posited that these high-sustainability firms implemented unique governance mechanisms, in contrast to low-sustainability ones, which largely adhered to the traditional profit-maximization model, emphasizing short-term gains, and disregarding social and environmental concerns. Separately, Cunha et al. (2019) found that investments rooted in ESG criteria offer a potential advantage for investors seeking superior risk-adjusted returns in specific regions, such as Europe and emerging markets, when compared to traditional benchmarks. Despite the heterogeneity across regions, their study emphasizes the importance of sustainable investing for stakeholders.

Furthermore, Albuquerque et al. (2019) focused on U.S. firms and examined the impact of corporate social responsibility (CSR), a category of the governance pillar, on firm risk. They determined that when CSR aligns with consumer preferences and market demand, it reduces systematic risk and enhances firm value. They further suggested that stocks with higher CSR could reduce the overall risk profile of a portfolio. However, these benefits are contingent upon the proportion of firms already engaging in CSR. In relation to this topic, Gillan et al. (2021) conducted a comprehensive review of existing literature on ESG and CSR, with a focus on corporate finance. They noted that while many studies suggest ESG/CSR initiatives correlate with reduced risk and potential increases in firm value, there remains a degree of inconsistency and conflicting hypotheses within the current body of research.

Moreover, recent studies have indicated a positive correlation between stock performance and ESG scores during market shocks. A negative stock market shock refers to a sudden and often unexpected decline in stock prices, causing significant disruption in the market. Such shocks can arise from economic downturns, catastrophic events, or speculative behaviour, leading to increased uncertainty and potential market volatility. For instance, Lins et al. (2017) discovered that in times when trust becomes especially crucial, as was the case during the 2007-2008 crisis, firms with strong CSR values outperformed those with weaker CSR. Their results showed that the enhanced profitability of firms with high CSR suggests that such firm-specific social capital acts as an insurance policy through severe market shocks.

Additionally, recent literature has investigated the impact of the COVID-19 pandemic on firms' performance across various regions: Albuquerque et al. (2020) focused on the U.S., Broadstock et al. (2021) examined China, and Cardillo et al. (2022) studied Europe. Albuquerque et al. (2020) found that firms with robust environmental and social (ES) policies not only generated higher returns but also experienced reduced return volatility and increased operating profit margins, even in the face of declining sales. This underscores the role of customer and investor loyalty as a protective mechanism during market disruptions. Broadstock et al. (2021) noted that portfolios with high ESG scores typically outperformed those with lower scores, suggesting investors might see ESG performance as an indicator of both future stock potential and a tool for financial risk mitigation during uncertain times. Cardillo et al. (2022) emphasized that firms oriented towards sustainability were better equipped to face the challenges of the pandemic, highlighting the critical role of solid ESG policies in comprehensive risk management strategies. In contrast, Kick et al. and Rottmann (2022) examined the impact of the Russian invasion of Ukraine on European stock returns, with a particular focus on the effects of Refinitiv ESG ratings and carbon dioxide intensity. While the ecological dimension of Refinitiv's ESG rating showed a positive effect on cumulative abnormal stock returns, its magnitude was not of significant economic importance. Nevertheless, they stress the need for further research in the context of different types of crises.

The ongoing debate on the impact of ESG practices on financial performance and the different significant results from prior research emphasize the need for a more extensive and critical analysis. Hence, we will address the question *'How are firms' ESG scores related to stock performance and resilience?'* by testing the following four hypotheses.

> **H1:** Firms with higher ESG scores display superior stock performance compared to those with lower ESG scores.

> **H2:** Firms with higher ESG scores exhibit lower stock price volatility, suggesting superior stock stability, compared to those with lower ESG scores.

> **H3:** Firms with higher ESG scores present reduced tail risk, indicating greater robustness to extreme events that result in financial losses, compared to those with lower ESG scores.

> **H4:** During market shocks, firms with higher ESG scores demonstrate enhanced stock resilience compared to those with lower ESG scores.

CHAPTER 3 Data

The data we use in this paper are obtained from Refinitiv[1]. We have opted for Refinitiv as our data source as it is worldwide recognized as a premier source for ESG data, offering a database that covers over 85% of global market capitalization.

The data obtained includes weekly stock prices and ESG scores for American firms listed at NASDAQ from January 2002 to July 2023. We use weekly data because Refinitiv updates the ESG score on a weekly basis. Furthermore, from all the firms initially available, only a subset of 2,597 had accessible ESG scores and were included in our analysis.

Our goal is to compare the performance and resilience of stocks from firms with higher ESG scores to those with lower ESG scores. For this purpose, we divided the 2,597 firms into two distinct groups based on their ESG scores, employing the classifications provided by Refinitiv, as follows.

We calculated the weekly ESG median for each firm for the sample period. We decided to use the median as a central tendency measure as it is a more robust measure to deal with outliers compared to the sample mean. Group 1 – classified as high ESG score firms – includes all the firms whose median exceeds the score of 50. Likewise, group 2 – classified as low ESG score firms – comprises all the firms whose median is less than the score of 50. The threshold of 50 was selected because according to the Refinitiv methodology, scores higher than 50 indicate good or excellent relative ESG performance. Similarly, scores lower than 50 specify satisfactory or poor relative ESG performance.

This division of firms into group 1 and group 2, based on their ESG scores, establishes the data basis for the subsequent analyses: CAPM Approach; Regression Approach; and Stock Resilience during Market Shocks.

3.1 Descriptive Statistics

In this section, we present key descriptive statistics on the distribution of the ESG scores in our sample. Figure 1 illustrates the overall indicators of ESG scores for the 2,597 firms, and Table I. offers a detailed snapshot of the five firms with the lowest ESG scores as well as the five firms with the highest ESG scores in the sample. We will briefly discuss the general trends observed in the sample.

[1] The data from Refinitiv (formerly Thomson Reuters Financial & Risk business) incorporate more than 630 distinct ESG metrics from 210 countries and trace back to 2002. Refinitiv uses a proprietary model to calculate ESG scores based on industry and country benchmarks. Based on this assessment, it assigns each firm a score that ranges from 0, indicative of poor ESG practices, to 100, indicative of exceptional ESG performance (for a detailed description of the ESG score range, please refer to Appendix A2). Further information regarding scores and methodology can be found at Refinitiv's ESG Scores.

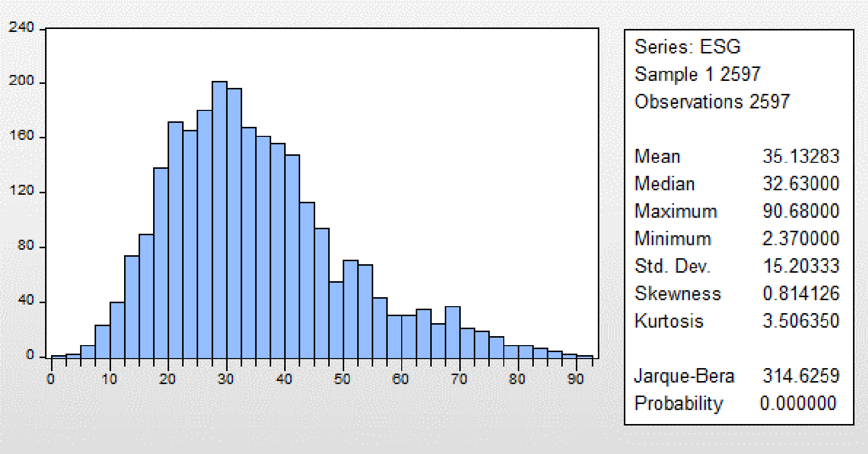

Figure 1. Distribution of ESG Scores in our Sample. This figure illustrates the distribution of ESG scores and key statistics, for the 2,597 firms in the sample. The x-axis refers to the range of ESG scores, while the y-axis represents the frequency of these scores.

On average, firms in our sample have an ESG score of around 35.13, which represents ESG grade C (see Appendix A2) and suggests "satisfactory relative ESG performance and a moderate degree of transparency in reporting material ESG data publicly". The scores vary significantly across firms, as indicated by the standard deviation of 15.20. This shows a wide range of ESG performance. The ESG scores range from 2.37 to 90.68, showing significant discrepancies in ESG performance across firms.

Furthermore, the positive skewness indicates a right-skewed distribution, this reveals that in our sample there are more firms with lower ESG scores. Additionally, the kurtosis value is slightly higher than 3, which implies a distribution leptokurtic, as there is more data in the tails and peak than what a normal distribution would have. Finally, the Jarque-Bera test statistic is significantly larger than 0, and the probability is close to 0, hence, the distribution of ESG scores is not normal.

Table I.
Snapshot: Key Descriptive Statistics for Selected Firms in the Sample

This table provides key descriptive statistics for the four firms with the lowest ESG scores and the four firms with the highest ESG scores in our sample.

	Firms with the lowest ESG score in the sample					Firms with the highest ESG score in the sample					
Stats	**CASSAVA_SCIENCES**	**REMARK_HOLDINGS**	**NATIONAL_BEVERAGE**	**SLM**	**PRIMEENERGY_RESOURCES**	**_3M**	**OWENS_CORNING**	**ALCOA**	**INTEL**	**MICROSOFT**	**S&P 500**
Median score	2.37	3.68	4.70	5.05	5.43	86.49	86.80	87.66	88.25	90.68	-
Group j (j=1,2)	2	2	2	2	2	1	1	1	1	1	
Mean	-0.0010	-0.0080	0.0017	0.0005	0.0002	0.0005	0.0020	0.0013	0.0001	0.0021	0.0012
Median	-0.0038	-0.0106	0.0014	0.0016	0.0000	0.0017	0.0040	0.0027	0.0012	0.0029	0.0036
Maximum	1.0485	1.0938	0.3345	0.4462	0.5145	0.1159	0.3187	0.2384	0.2228	0.1504	0.1237
Minimum	-1.3781	-1.0068	-0.1870	-0.8308	-0.4349	-0.1469	-0.3611	-0.3346	-0.3075	-0.1753	-0.1577
Std. Dev.	0.1339	0.1463	0.0517	0.0640	0.0705	0.0289	0.0565	0.0762	0.0441	0.0347	0.0236
Skewness	-1.4313	0.7855	0.2656	-1.8413	0.5681	-0.4888	-0.5848	-0.5177	-0.6334	-0.2997	-0.9431
Kurtosis	33.4230	15.4257	6.2102	34.3632	13.3916	5.4963	9.1495	5.1791	7.3529	5.5456	8.8265
Jarque-Bera	43730.68	5379.15	495.85	46702.74	5117.74	336.61	1431.88	85.37	962.55	320.31	1756.51
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	1124	823	1124	1124	1124	1124	877	352	1124	1124	1124

Regarding mean returns, firms with the lowest ESG score, such as CASSAVA and REMARK, show negative average returns. In contrast, all firms with higher ESG scores display positive mean returns.

Regarding volatility (standard deviation - Std. Dev.), CASSAVA and REMARK, both from the low ESG score group, have higher standard deviations than any of the stocks from the high ESG score group, which indicates they might be riskier.

The skewness indicates the asymmetry of the return distributions. A negative skewness suggests that the left tail is longer, that is, the probability of extremely negative returns is higher. Stocks like CASSAVA and SLM, have the lowest values of skewness, which indicates potential for higher negative returns.

The kurtosis is a statistical measure of the distribution's tails and reflects the frequency of extreme deviations from the return mean. High kurtosis values, such as those of CASSAVA and SLM, suggest their returns distribution have fat tails and are thus, susceptible to extreme values, either positive or negative. On the other hand, stocks like NATION-AL and MICROSOFT have relatively lower kurtosis, which indicates fewer extreme returns.

The Jarque-Bera statistic tests the null hypothesis that the data is normally distributed. A higher value of this statistic indicates that the returns are less likely to be normally distributed. Given the high values across all stocks and a probability of 0, we can infer that returns for all these firms are not normally distributed. Particularly, firms with the lowest scores appear to deviate more significantly from normality.

In summary, the stocks from firms with the lowest ESG scores exhibit varying degrees of return and risk. Some have negative average returns and others show high volatility. Firms with higher ESG scores, on the other hand, generally display positive average returns with relatively less volatility. This suggests that higher ESG scores might be correlated with better stock performance.

CHAPTER 4 CAPM Approach

In this approach, our purpose is to compare stock performance between firms with high ESG scores and those with low ESG scores. Therefore, we will test our first hypothesis:

> **H1:** Firms with higher ESG scores display superior stock performance compared to those with lower ESG scores.

4.1 Methodology

To test **H1**, we run the CAPM regression:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{f,t}\right) + \varepsilon_{i,t} \,,$$

for the 2597 firms. Where $R_{i,t}$ represents the stock 'i' return at time t, $R_{f,t}$ stands for the risk-free rate of return at time t, $R_{m,t}$ indicates the return of the market portfolio at time t measured by a benchmark index, α_i measures the excess return of a stock 'i' relative to the return of the benchmark index, adjusted for its level of risk, β_i measures the systematic risk of stock 'i' in comparison to the market. It reflects how responsive the stock is to market fluctuations. Finally, $\varepsilon_{i,t}$ is the error term at time t. It captures the idiosyncratic risk of the stock's return that is not explained by the relationship with the market's return.

We used the index S&P500[2] as a benchmark and the three-month treasury US bill from the Federal Reserve Bank of St. Louis[3] as the risk-free rate R_f. All the variables obtained were annualized.

In this model, we assume that the error term $\varepsilon_{i,t}$, follows a normal distribution with conditional heteroskedasticity characterized by the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Tsay, 2014). We opt for this approach because incorporating conditional heteroskedasticity into our model significantly increases the estimation efficiency (via Maximum likelihood) compared to the Ordinary Least Squares (OLS) estimation. This is a crucial step as our target estimation is the parameter α, as we discuss below. OLS assumes that the variance of the error terms is constant across time, which is often unrealistic in financial data and other time series data exhibiting volatility clustering. The GARCH model, on the other hand, allows for time-varying volatility, capturing the changing variances in the error terms across different time periods. This is especially crucial in the modelling of financial data where volatility is a common phenomenon.

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[2] https://www.spglobal.com/spdji/en/indices/equity/sp-500/

[3] https://fred.stlouisfed.org/

The above regression was applied to all available firms under study. The purpose was to estimate the α and β_i parameters. α measures the performance of an investment against a benchmark market index. It indicates the amount by which a fund has overperformed or underperformed relative to the benchmark on a risk-adjusted basis. β_i measures the systematic risk of stock 'i' in comparison to the market. It reflects how responsive the stock is to market fluctuations.

As a second step, we divided the estimates α_i (i = 1,…,2597) into group 1 – high ESG score firms, and group 2 – low ESG score firms), according to the procedure we explained in Chapter 3 Data.

The comparison between the alphas in groups 1 and 2 was based on the Kernel Density Estimation (KDE) which allows us to assess the differences between both probability density functions. The KDE allows us to create a smoothed version of a histogram without requiring a predetermined bin size. We use the Gaussian (normal) kernel and the bandwidth (h) Silverman's rule of thumb, which is given by:

$$h = \left(\frac{4\sigma^5}{3n}\right)^{\frac{1}{5}},$$

where σ is the standard deviation of the data and n is the number of data points (Simonoff, 2012).

4.2 Results

In this section we examine the probability density functions of alpha (Figure 2) and beta (Figure 3) across the two groups, to address **H1:** Firms with higher ESG scores display superior stock performance compared to those with lower ESG scores.

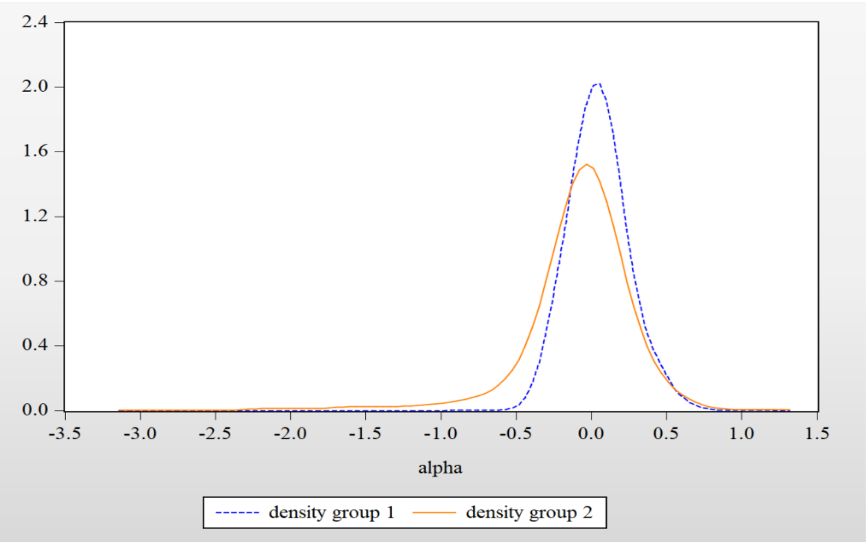

Figure 2. Probability Density Function of Alpha in the Two Groups. The probability density function of alpha of group 1, relative to that of group 2, exhibits a shift towards the right and a significantly higher peak around the mean.

The probability density function of alpha of group 1, relative to that of group 2, exhibits a noticeable shift towards the right and a significantly higher peak around the mean. This implies that the mean alpha of group 1 is higher than that of group 2, while also displaying less variability. Additionally, it is observed that the distribution for group 2 exhibits a pronounced skewness towards the left tail, indicating a substantially higher likelihood of extreme negative alpha values. In summary, the alpha values for group 1 suggest that firms with a superior ESG score (above 50) not only yield higher profitability but also exhibit lower variability in comparison to firms with lower ESG scores.

Furthermore, we analysed the linear association between α_i and the ESG score (Appendix B1). Our data indicates a positive linear relationship between alpha and ESG scores. The estimated correlation coefficient is 0.238, suggesting a positive association, and this correlation is statistically significant (p-value=0). This means that higher values of alpha tend to correspond to higher ESG scores.

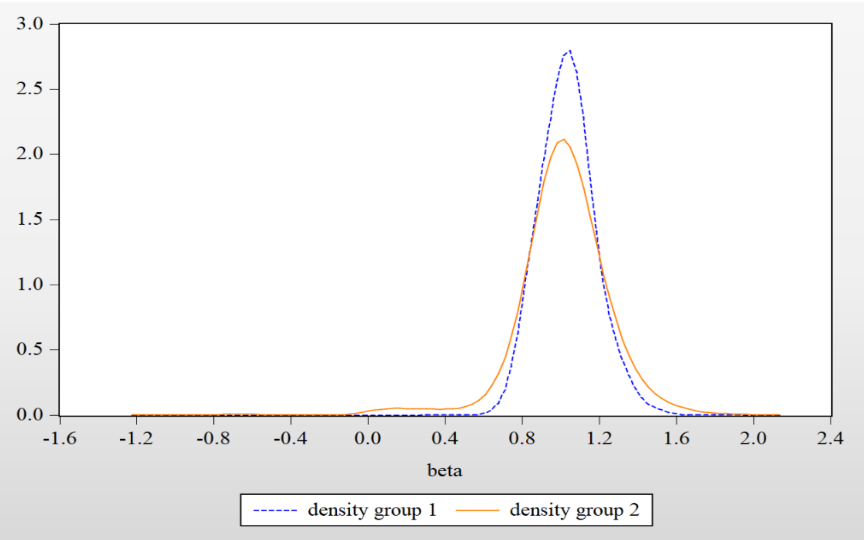

Figure 3. Probability Density Function of Beta in the Two Groups. The probability density function of the beta of group 1, relative to that of group 2, presents a significantly higher peak around the mean. However, it seems that both groups have approximately the same mean.

The probability density function of the beta of group 1, relative to that of group 2, presents a significantly higher peak around the mean. This implies that the beta values from group 1 are more concentrated around the mean, which implies they have less systematic risk variability. However, it seems that both groups have approximately the same mean.

Additionally, we analysed the linear association between β_i and the ESG score (Appendix B2). The estimated correlation coefficient is 0.058 and it is only significant at a 10% confidence level (p-value=0.051). The relatively low magnitude and the p-value suggest that there is no strong evidence of a correlation between both variables. We further analyse this topic in the next section, employing a different methodology.

CHAPTER 5 Regression Approach

In this approach, our aim is to compare stock returns, volatility, and tail risk between firms with high ESG scores and those with low ESG scores. Hence, we will introduce a new methodology to confirm that the results from our first hypothesis are robust and to test our second and third hypotheses:

> **H1:** Firms with higher ESG scores display superior stock performance compared to those with lower ESG scores.
>
> **H2:** Firms with higher ESG scores exhibit lower stock price volatility, suggesting superior stock stability, compared to those with lower ESG scores.
>
> **H3:** Firms with higher ESG scores present reduced tail risk, indicating greater robustness to extreme events that result in financial losses, compared to those with lower ESG scores.

5.1 Methodology

To test **H1**, **H2** and **H3**, we employ the same dataset comprising 2,597 firms, and divided into group 1 and group 2. We explain below the theoretical statistical framework of our regression analysis.

We assume that the stock returns of group j, where *j*=1,2, are governed by a conditional density $f_{it,j}$ where i (i=1,…,2597) refers to the specific stock return *i*; *t* refers to time, and *j* is the group. Likewise, the moments of $f_{it,j}$ are also characterized by the 3 indices, *i*, *t* and *j*, with the same meaning. We assume that although different assets can have different moments, depending on *i* and *t*, dynamics in the group *j* are the same for all assets because they are driven by common processes. Kelly and Jiang (2014) applied this idea to estimate the common processes of the tail risk, which refers to the potential for rare and extreme events to significantly deviate from the mean. In particular, they call the common process "tail risk" at time *t*, say λ_t, a "dynamic power law". This parameter at time *t* is estimated from the cross-section of returns (i.e., with *t* fixed and *i* varying).

In this thesis we generalize this approach. Specifically, we assume that there are several common processes associated with each of the various moments of our time series model. We examine the indicators listed in Table II.

Table II.

Description of the Conditional Moments and Risk Parameters

This table presents the conditional moments, specifically the mean, standard deviation, and skewness, and risk parameters, namely the quantile, expected shortfall, and tail index, for group 1 (j=1) and group 2 (j=2) over time, denoted as t. These statistical indicators assist in analysing the distributional characteristics and risk measures over time, for both groups over the sample period.

Statistical Indicator	Description
$\mu_{t,j}$	Mean at time t of group j; j=1,2
$\sigma_{t,j}$	Standard deviation at time t of group j; j=1,2
$skew_{t,j}$	Skewness at time t of group j; j=1,2
$Q(0.05)_{t,j}$	Quantile of order 0.05 at time t of group j; j=1,2
$ES(0.01)_{t,j}$	Expected shortfall of order 0.05 at time t of group j; j=1,2
$\lambda_{t,j}$	Tail Risk at time t of group j; j=1,2

As in Kelly and Jiang (2014), we use cross-section returns to estimate the parameters of interest. For example, we obtain an estimate of $\mu_{t,j}$ using the following statistics:

$$\hat{\mu}_{t,j} = \sum_{i=1}^{N_{t,j}} r_{it,j} \ ,$$

where $N_{t,j}$ represents the number of returns of all firms in group *j* in period *t*.

Therefore, at each period *t* we have an estimate of the conditional mean $\mu_{t,j}$ using all available cross-section stock returns. As *t* goes from 1 to T, we obtain a time-varying measure. The estimation of the other parameters is done in a similar way, with the necessary adjustments. For example[4],

$$ES(0.05)_{t,j} = -\frac{\sum_{i=1}^{N_{t,j}} r_{it,j} I(r_{it,j} < Q(0.05)_{t,j})}{\sum_{i=1}^{N_{t,j}} I(r_{it,j} < Q(0.05)_{t,j})} \ ,$$

gives the average of the highest 5% losses (Chen, 2008). This measure averages the magnitude of losses that could occur below $Q(0.05)_{t,j}$. Basically, this is an average loss that an investor can expect to incur (for every euro invested) if the portfolio's returns fall beyond a given percentile level, in our case $Q(0.05)_{t,j}$ (the negative sign is defined in the expression just for the sake of convenience, so that the value of ES comes out positive and indicates the magnitude of the losses). Another example is the estimate of $\lambda_{t,j}$, which is given in Kelly and Jiang (2014):

$$\hat{\lambda}_{t,j} = \frac{1}{K_{t,j}} \sum_{i=1}^{K_{t,j}} \ln\left(\frac{r_{it,j}}{u_{it,j}}\right),$$

[4] In the formula below I(A) is an indicator function that takes the value 1 if event A is true, and zero otherwise.

where $r_{it,j}$, is the return that falls below an extreme value threshold, $u_{t,j}$, say a quantile or order q, $Q(q)$, where q is typically 0.01 or 0.05 and $K_{t,j}$ is the total number of such exceedances. To indicate the order of the quantile that was used, we write the lambda $\lambda(q)$ where q is 0.01 or 0.05.

To analyse whether the difference between the two groups with respect to returns, volatility and tail risk is statistically significant we ran six regressions of type:

$$\Delta_t = \beta_k + \varepsilon_t ,$$

where Δ_t is the difference between the variables under analysis for the two groups, k refers to the six variables displayed in Table II (e.g., β_μ, β_σ). The parameter β_k represents the expected value of Δ_t (i.e., $\beta_k = E(\Delta_t)$). Therefore, $\beta_k \neq 0$ means that the moments/parameters between the two groups are different. We will consider a two-tailed test, $\beta_k = 0$ against $\beta_k \neq 0$, although a one tailed test was also possible. So, when the null hypothesis is rejected, we will also study the sign and magnitude of β_k.

For example, to analyse whether the difference between $\mu_{t,1}$ *and* $\mu_{t,2}$ is statistically significant we ran the following regression:

$$\mu_{t,1} - \mu_{t,2} = \beta_\mu + \varepsilon_t ,$$

The OLS estimate of β_μ is simply the average mean of $\mu_{t,1} - \mu_{t,2}$ and conventional inference, with robust standard errors allows us to test $\beta_\mu = 0$ against $\beta_\mu \neq 0$.The same reasoning was applied to the other five variables. Finally, ε represents the error term.

5.2 Results

In this section, we review the findings presented in Table III to address our three first hypotheses: **H1:** Firms with higher ESG scores display superior stock performance compared to those with lower ESG scores; **H2:** Firms with higher ESG scores exhibit reduced stock price volatility, suggesting superior stock stability compared to those with lower ESG scores; **H3:** Firms with higher ESG scores present reduced tail risk, indicating greater robustness to extreme events that result in financial losses, compared to those with lower ESG scores.

Table III.

Summary of Regression Results: Conditional Moments and Risk Parameters

This table exhibits the regression results for the six core financial metrics centered on the conditional moments and risk parameters between group 1 and group 2, for the period 2002 to 2023. The analyses include return performance, volatility, asymmetry, and tail risk assessments. Each dependent variable represents $\Delta = k_1 - k_2$, where Δ_t is the difference between the variables under analysis for the two groups and k_1 and k_2 refer to the six variables displayed in Table II, from group 1 and group 2, respectively. For each dependent variable, we provide the OLS coefficient, a robust standard error (corrected for heteroskedasticity), and the associated p-value. For detailed statistics, please refer to Appendix B.

Analysis	**Dependent Variable** $\Delta = k_1 - k_2$	**Coefficient**	**Robust std.err.**	**p-value**
Return performance	$\mu_{t,1} - \mu_{t,2}$	0.0008	0.0003	0.0053
Volatility assessment	$\sigma_1 - \sigma_2$	-0.0301	0.0006	0.0000
Asymmetry assessment	$skew_1 - skew_2$	-0.0195	0.1382	0.8877
Tail risk assessment	$Q(0.05)_1 - Q(0.05)_2$	0.0291	0.000654	0.0000
	$ES(0.05)_1 - ES(0.05)_2$	-0.0612	0.0011	0.0000
	$\frac{1}{\lambda_1(0.05)} - \frac{1}{\lambda_2(0.05)}$	0.4120	0.0279255	0.0000

Return Performance

The Figure 4 presents $\mu_{t,1} - \mu_{t,2}$ over the period under analysis. It is not clear from this figure whether the difference is statistically significant. However, the sign and significance of β_μ allows us to answer the previous question (Appendix B3). According to Table III, $\widehat{\beta_\mu}$ = 0.0008 suggests that, on average, firms with higher ESG scores tend to produce higher stock returns. The t-statistic of 2.90 (p-value: 0.005) implies that this positive return is statistically significant at conventional levels. To get an annualized value, we multiply the coefficient by 52, which results in a difference of 0.039 or 3.9% higher annual stock return than firms with low ESG scores. This value is economically very relevant when comparing both groups.

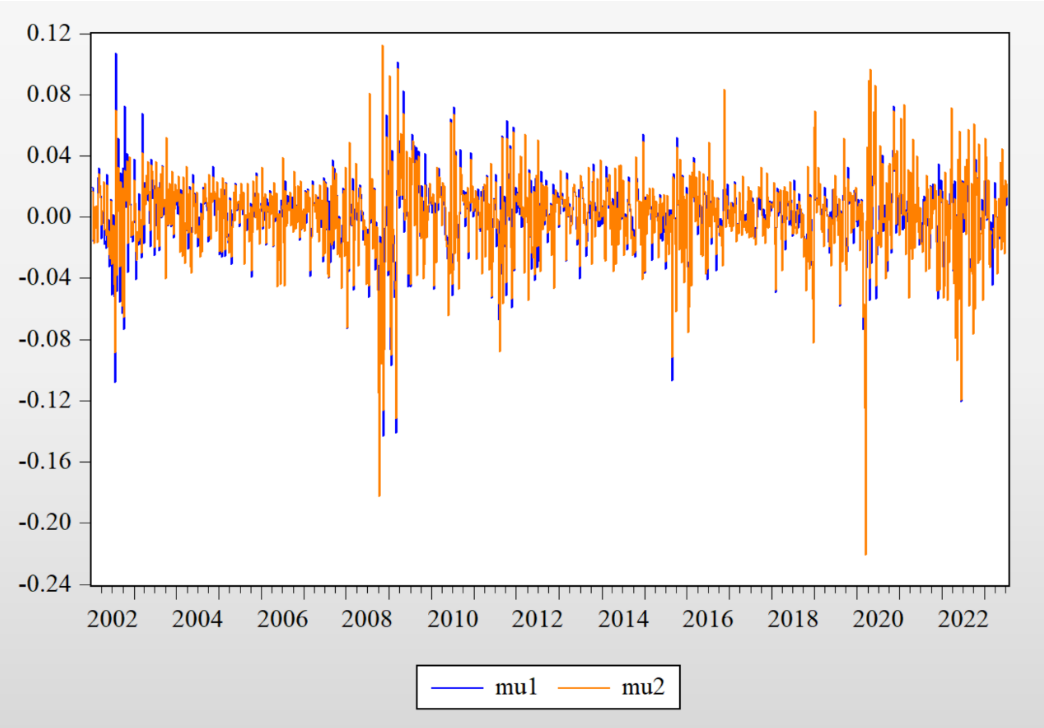

Figure 4. Time-Series Analysis of Return Performance: Comparison of the Two ESG Groups. This figure illustrates the time-series results of the returns (μ) for the two ESG groups, ranging from 2002 to 2023. The x-axis represents the years, while the y-axis indicates the magnitude of the drift. The blue line, labelled as mu1 refers to μ_1, and denotes the drift for group 1. The orange line, labelled as mu2 refers to μ_2, and signifies the drift for group 2.

Volatility Assessment and Symmetry Assessment

The Figure 5 shows that σ_2 is in general, higher than σ_1 over almost all the periods. This is confirmed by the regression analysis results (Appendix B4). The negative coefficient $\widehat{\beta_\sigma}$ = -0.0301 indicates that stocks with higher ESG scores tend to have lower volatility than stocks with lower ESG scores. This suggests that firms with higher ESG scores might be seen as less risky in terms of price fluctuations. This volatility measure assesses the fluctuation in the price of a security or an entire market over a specific period. It is a measure of the dispersion of returns for a given security or market index.

Given the p-value of 0, this negative association between ESG scores and volatility is statistically significant by prevalent academic standards. This implies that the difference in volatility between stocks with high and low ESG scores is not due to random chance but is a consistent pattern.

We observed in Chapter 4 (CAPM approach) that the market betas of groups 1 and 2 are approximately equal. However, the data indicates that firms with higher ESG scores have lower variance, possibly because these companies are subject to less idiosyncratic risk. This illustrates how ESG factors can play a critical role in an asset's risk profile, beyond what is captured by beta alone.

Finally, regarding the asymmetry distribution assessment, given the p-value of 0.87 (Appendix B5), there is no evidence that suggests the distributions of the two groups present different asymmetries.

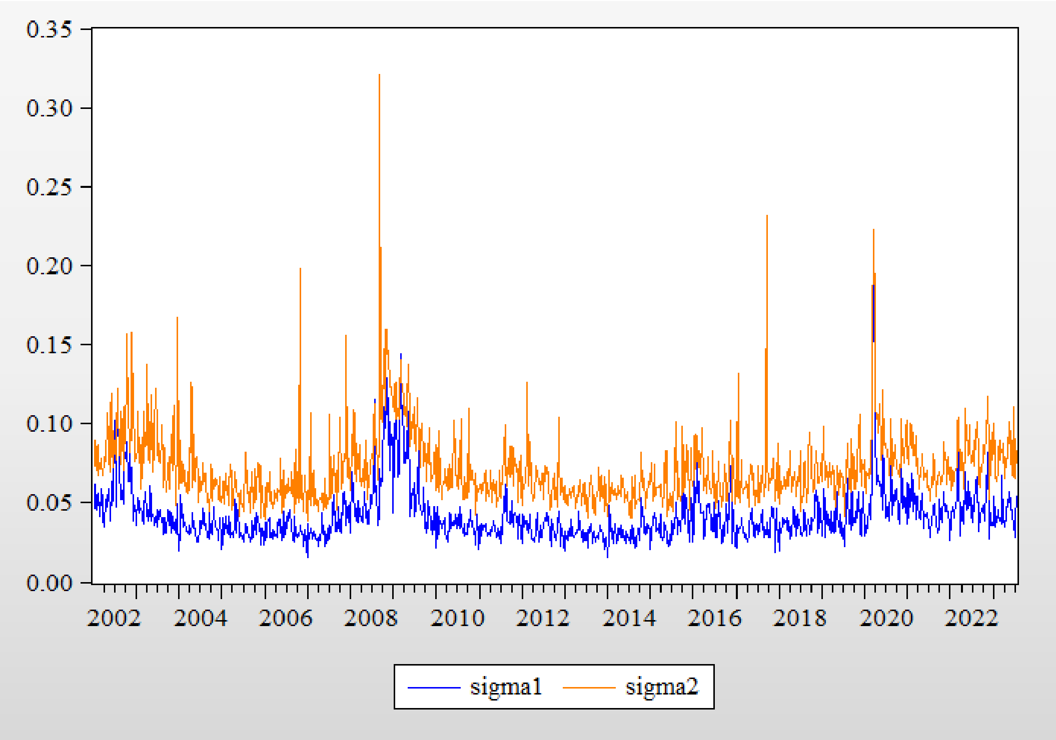

Figure 5. Time-Series Analysis of Volatility: Comparison of the Two ESG Groups. This figure shows the time-series results of the volatility (σ) for the two ESG groups, ranging from 2002 to 2023. The x-axis denotes the years, while the y-axis represents the magnitude of the volatility. The blue line, labelled as sigma1 refers to σ_1, indicating the volatility for group 1. The orange line labelled as sigma2 refers to σ_2, representing the volatility for group 2.

Risk assessment

While volatility provides a measure of general fluctuations in prices, tail risk focuses on the extreme events that can result in significant financial losses. Both contribute to market risk, but they represent different aspects and require different strategies for risk management.

Figure 6 illustrates that, for the sample period, $Q(0.05)_1$ tends to be greater than $Q(0.05)_2$. The regression analysis results (Appendix B6) further support this observation. The positive coefficient of 0.0291 for $Q(0.05)_1 - Q(0.05)_2$ indicates that, on average, the 5% worst returns (i.e., the returns at the far-left tail of the distribution) for the firm group with high ESG scores are higher by approximately 0.0291 units compared to the same quantile of returns for the firm group with low ESG scores. With a p-value of 0, the difference in the 5% tail values between the two groups is clearly statistically significant.

Higher values at the 5% worst returns for the high ESG score group suggest that these firms, even in their worst-case scenarios (the most unfavourable 5% of times), tend to perform better than the firms in the low ESG score group. This difference is an indicator of resilience and suggests that firms with high ESG scores may be better positioned to withstand adverse market conditions, exhibiting less severe downturns in their most negative returns compared to firms with lower ESG scores.

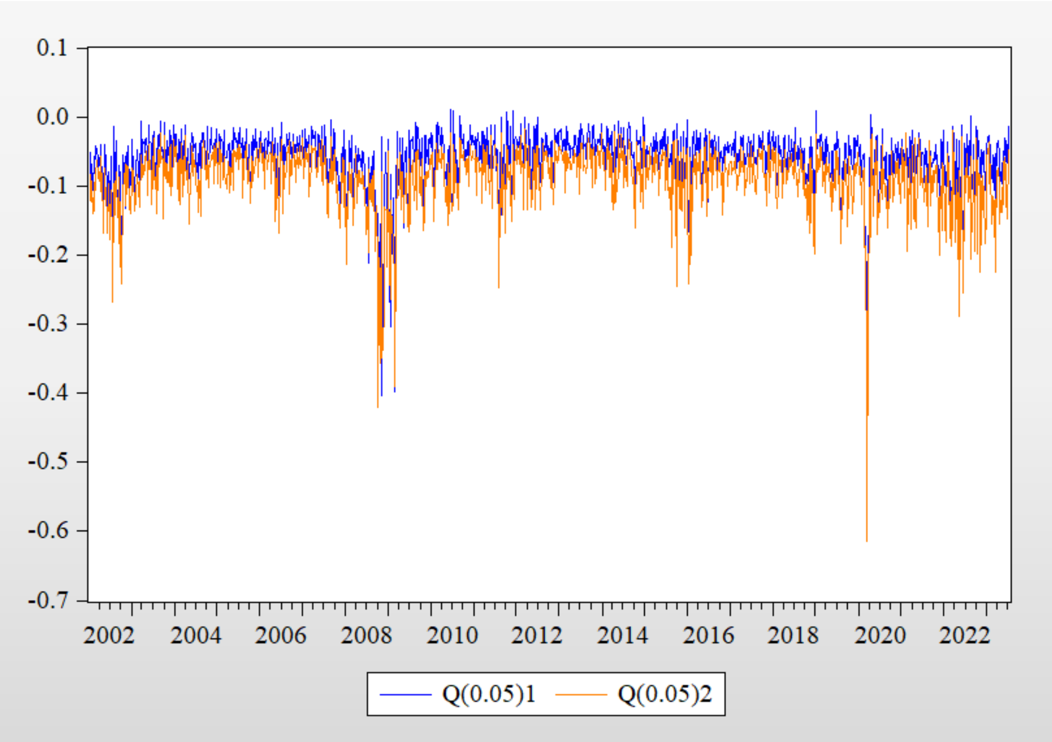

Figure 6. Time-Series Analysis of Quantile: Comparison of the Two ESG Groups. This figure displays the time-series results of the quantile of order 0.05 (Q(0.05)j) for the two ESG groups, covering the period from 2002 to 2023. The x-axis refers to the years, while the y-axis represents the magnitude of the quantile measure. The blue line, labelled as Q(0.05)1, indicates the quantile measure for group 1. The orange line, labelled as Q(0.05)2, presents the results for group 2.

The coefficient of −0.0612 for $ES(0.05)_1 - ES(0.05)_2$ (Appendix B7) implies that, on average, the expected shortfall (a measure of tail risk) for the firm group with high ESG scores is lower by approximately 0.06 units compared to that of the firm group with low ESG scores. The p-value of 0.00 indicates that this observed difference in the expected shortfall between the two groups is statistically significant at the usual conventional threshold.

A lower expected shortfall for the high ESG score group suggests that these firms have a reduced risk of experiencing large losses compared to the firms in the low ESG score group. In essence, the potential extreme losses (or "worst-case scenarios") are, on average, less severe for firms with higher ESG scores than for those with lower scores. Figure 7 supports what the regression analysis indicates.

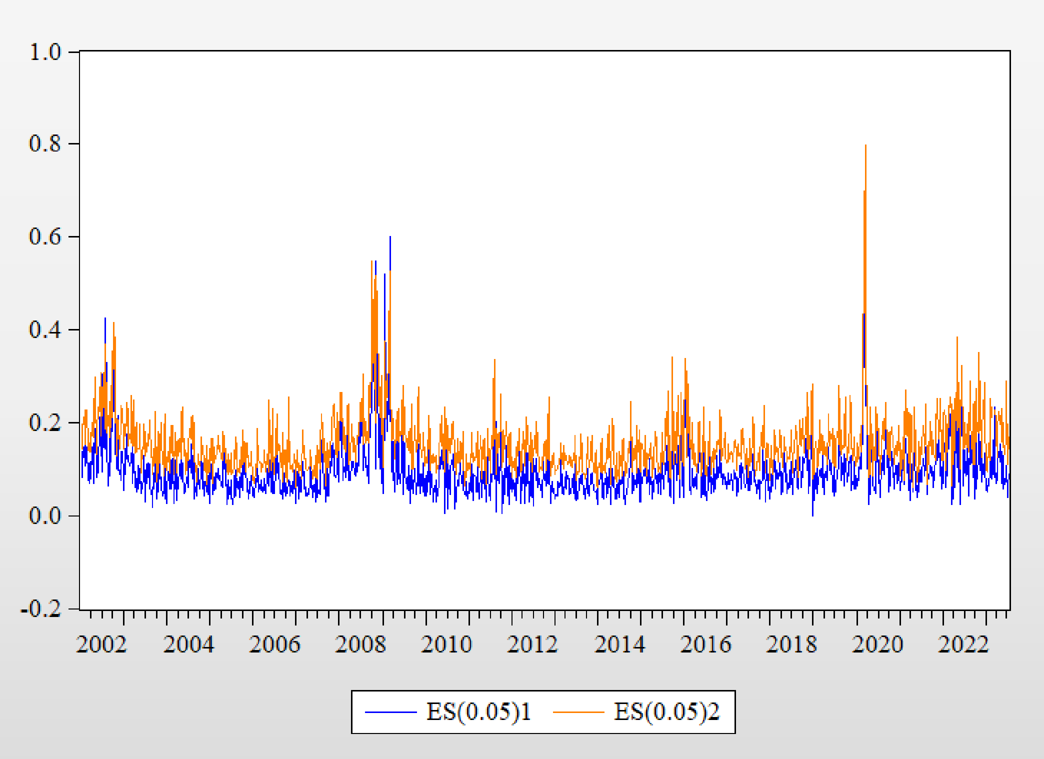

Figure 7. Time-Series Analysis of Expected Shortfall: Comparison of the Two ESG Groups. This figure details the time-series results of the expected shortfall measures for the two ESG groups, spanning from 2002 to 2023. The x-axis indicates the years, while the y-axis outlines the magnitude. The blue line labelled ES(0.05)1, indicates the expected shortfall measure for group 1. The orange line labelled ES(0.05)2, presents the results for group 2.

λ is a parameter of Pareto-type distributions, representing tail risk, as noted in Table II. Its reciprocal, 1/λ, called the tail index, also measures the behaviour of extreme values in the distribution's tails, although with an inverse interpretation. Specifically, a smaller tail index implies thicker or fatter tails, signifying a greater likelihood of extreme events than those expected in a normal distribution.

The coefficient of 0.412 for $\frac{1}{\lambda_1} - \frac{1}{\lambda_2}$ (Appendix B8) indicates that the tail index, a measure of the thickness of the left tail of the distribution, for the firm group with high ESG scores is on average higher by approximately 0.41 units compared to that of the firm group with low ESG scores. The below Figure 8 confirms this result. There is evidence that the observed difference in the tail index between the two groups is statistically significant at conventional levels (p-value =0).

A higher tail index for the high ESG score group means these firms have a lighter tail in their return distributions compared to those with low ESG scores. Typically, a thicker left tail suggests a higher probability of negative extreme outcomes compared to a standard normal distribution. In the context of this analysis, firms with low ESG scores may have a higher potential for extreme bad returns, compared to firms with high ESG scores.

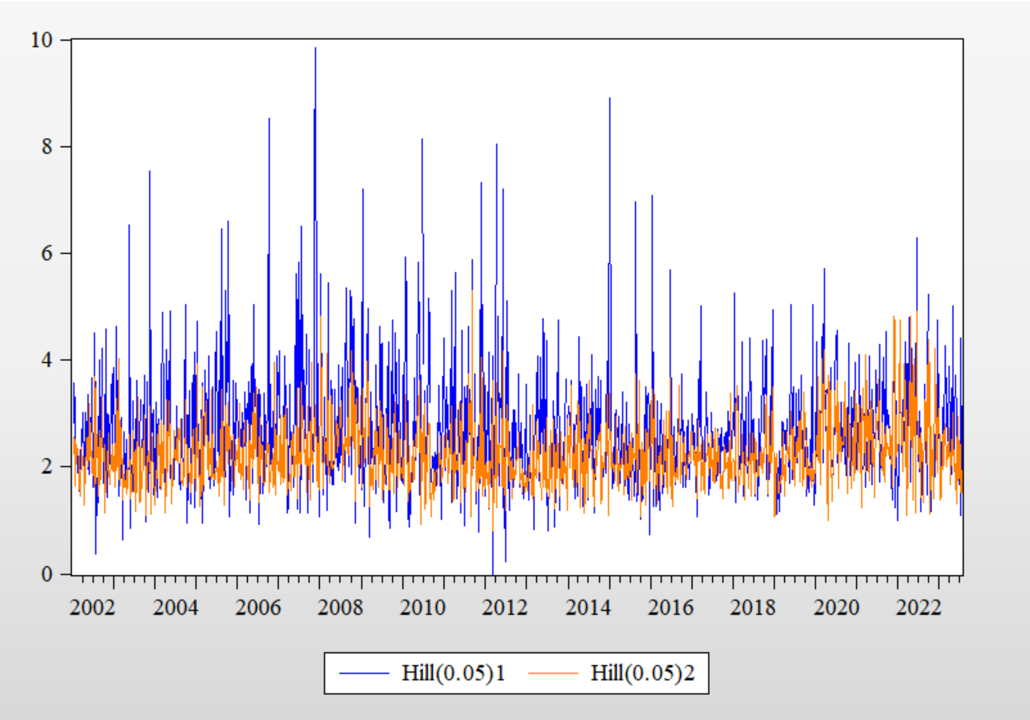

Figure 8. Time-Series Analysis of Tail Risk: Comparison of the Two ESG Groups. This figure presents the time-series results of the tail index $\left(\frac{1}{\lambda}\right)$ measures for the two ESG groups, covering the period from 2002 to 2023. The x-axis represents the years, while the y-axis highlights the magnitude. The blue line, labelled as Hill(0.05)1, refers to $\frac{1}{\lambda_1}$ for group 1. The orange line, labelled as Hill(0.05)2, refers to $\frac{1}{\lambda_2}$ for group 2.

CHAPTER 6 Stock Resilience During Market Shocks

We have established that, on average, stocks with higher ESG scores tend to yield higher returns, experience lower price volatility, and have lower tail risk compared to stocks with lower ESG scores. In particular, these stocks consistently outperform even in the 1% worst return scenarios, bear a smaller risk of experiencing significant losses and are less likely to incur extreme negative returns.

In this chapter, our goal is to further investigate whether our previous findings hold for specific periods of market shocks, that is, if firms with higher ESG scores are, indeed, more resilient to endure adverse market conditions. We have analysed six market shocks, as listed in Table IV. Finally, we will test our fourth hypothesis:

> **H4:** During market shocks, firms with higher ESG scores demonstrate enhanced stock resilience compared to those with lower ESG scores.

6.1 Methodology

To investigate **H4**, we run six regressions of type:

$$\Delta = \beta_0 + \beta_1 c_1 + \beta_2 c_2 + \beta_3 c_3 + \beta_4 c_4 + \beta_5 c_5 + \beta_6 c_6 + \varepsilon ,$$

where Δ represents the difference between the variables under analysis for the two groups. Specifically, $\Delta = \{\mu_1 - \mu_2 \,;\, \sigma_1 - \sigma_2 \,;\, Q(0.05)_1 - Q(0.05)_2 \,;\, ES(0.05)_1 - ES(0.05)_2 \,;\, \frac{1}{\lambda(0.05)_1} - \frac{1}{\lambda(0.05)_2} ; \frac{1}{\lambda(0.01)_1} - \frac{1}{\lambda(0.01)_2}\}$. The term β_0 is the intercept, β_1 to β_6 are the coefficients corresponding to each dummy variable c_i, i = 1 to 6. They measure the impact of each of the six shocks (Table IV) on the variable under analysis Δ. ε represents the error term.

The section focuses on the analysis of return performance, volatility, and tail risk, in line with the methodology outlined in the previous section 5.1, Chapter 5 (refer to Table II). For the analyses, we use six dummy variables, denoted as c_i, where i = 1 to 6, each representing one of the major shocks in the U.S. stock market. By employing regressions with dummy variables, we can isolate and understand the different impact that each shock has on the dependent metrics under study. The coefficient of each dummy variable reflects the average change in the dependent variable attributed to that shock while keeping other factors constant.

Table IV enumerates the market shocks under study and the corresponding sample period considered. These specific six events were chosen due to the significant stress they exerted on the U.S. stock market and the instability and fluctuations they created. To ensure a thorough analysis of each shock effect, we have narrowed our sample period to those specific months or weeks during which each event had the worst impact on the U.S. stock market.

Table IV.
List of the Major Shocks in the U.S. Stock Market (2002-2023)

This table enumerates six major shocks that exerted significant stress on the U.S. stock market between 2002 and 2023. These shocks range from bear markets and market crises to market corrections. Based on S&P 500 data from Yahoo Finance, these specific events were selected due to the pronounced instability and fluctuations they introduced to the market. For each shock, the ID represents the corresponding dummy variable, denoted as c_i. The sample period specifies the event and narrows down to the specific time interval when the shock had its most adverse effect on the U.S. stock market. Finally, the description provides a brief context about each event and how it impacted the U.S. stock market.

ID	Market Shock	Sample Period ▼	Description
c_1	**Russo-Ukrainian war**	March (29) 2022 – June (14) 2022	The Russian invasion of Ukraine raised macroeconomic concerns and politic instability which introduced significant uncertainty.
c_2	**COVID-19 pandemic**	February (18) 2020 – March (24) 2020	This health crisis generated economic disruptions and market volatility. S&P 500 fell 34%.
c_3	**2018 Stock Market Correction:** - FED hikes rates - China-US trade war	October 2018 – December 2018	The S&P 500 plummeted more than 10% due to America trade war with China, global economy growth slowdown concerns, and sharp market reactions to interest rate increase.
c_4	**2015 Stock Market Selloff**	August 2015	China's economic slowdown, unexpected yuan devaluation, oil prices drop, and anticipated U.S. IR hikes, let to global market selloffs and a decline in stock values.
c_5	**2011 Bear Market:** - U.S. debt ceiling crisis - European debt crisis	July (26) 2011 – October (4) 2011	The U.S. debt ceiling crisis rose political uncertainty, spiking volatility and dropping the S&P 500 by 19%. In the same period, concerns about the European sovereign debt crisis further intensified instability.
c_6	**Global Financial Crisis**	December 2007 – June 2009	Global banking crisis that generated a bear market; S&P 500 plummeted by 56.8%

6.2 Results

In this section, we review the findings presented in Table V to address our last hypotheses: **H4:** During market shocks, firms with higher ESG scores demonstrate enhanced stock resilience compared to those with lower ESG scores.

Table V.

Summary of Regression Results: Stock Resilience Across Six Market Shocks

This table presents the regression results for the six core financial metrics, incorporating dummy variables to control for different market shocks, and analyses the conditional moments and risk parameters between group 1 and group 2 for the period 2002 to 2023. Analyses include return performance, volatility, asymmetry, and tail risk assessments, in accordance with the methodology detailed in section 5.1, Chapter 5. The columns labelled c_i, where i= 1,...,6, represent the six dummy variables. For each dependent variable, we provide the OLS coefficient and the robust standard error (corrected for heteroskedasticity and autocorrelation using the HAC method). These standard errors (std. error) are presented in brackets below the respective coefficients. Significance on a 10% (*), 5% (**), or 1% level (***) is indicated. For detailed statistics, please refer to Appendix B.

Analysis	**Dependent variable**	**c1**	**c2**	**c3**	**c4**	**c5**	**c6**
Return Performance	$\mu_{t,1} - \mu_{t,2}$	0.0061** (0.0024)	0.0054 (0.0043)	0.0052** (0.0024)	-0.0015 (0.0043)	0.0016 (0.0026)	-0.0008 (0.0029)
Volatility Assessment	$\sigma_1 - \sigma_2$	-0.0023 (0.0045)	-0.0086 (0.0080)	0.0045 (0.0045)	-0.0032 (0.0080)	-0.0007 (0.0049)	-0.0034 (0.0054)
Tail risk assessment	$Q(0.05)_1 - Q(0.05)_2$	0.0165*** (0.0049)	0.0277*** (0.0087)	0.0091* (0.0049)	0.0095 (0.0087)	-0.0013 (0.0053)	0.0031 (0.0058)
	$ES(0.05)_1 - ES(0.05)_2$	-0.0226*** (0.0086)	-0.0392** (0.0155)	-0.0036 (0.0086)	-0.0049 (0.0155)	-0.0025 (0.0094)	-0.0061 (0.0104)
	$\frac{1}{\lambda(0.05)_1} - \frac{1}{\lambda(0.05)_2}$	-0.0380 (0.2595)	0.3553 (0.4658)	-0.0295 (0.2595)	0.2137 (0.4658)	0.0623 (0.2954)	0.2129 (0.3113)
	$\frac{1}{\lambda(0.01)_1} - \frac{1}{\lambda(0.01)_2}$	1.9148* (1.1072)	0.5879 (1.9876)	-1.5476 (1.1072)	-1.5717 (1.9876)	2.7921** (1.2025)	2.3759* (1.3282)

Return Performance

The positive coefficient β_1 (Appendix B9) suggests that, during the Russo-Ukrainian war (c1), stocks with higher ESG scores (group 1) performed better than those with lower ESG scores (group 2) by an average of 0.0061 units per week, at a 10% level of confidence. This translates to a 6.7% better stock performance, during this 11-weeks geopolitical conflict, which would be equivalent to a substantial 31,7% annual increase. Furthermore, during the 2018 market correction period (c3), high-ESG stocks outperformed low-ESG stocks by an average of 0.0052 units (p-value <5%), which means they had 2.6% higher returns during this 5-week event, representing 27% higher annual return. For the other shocks (c2, c4, c5, c6), the coefficients are not statistically significant, therefore we cannot confidently assert a difference in the returns of high-ESG and low-ESG groups during these periods based on this analysis.

Volatility Assessment

Regarding stock volatility, results (Appendix B10) present a negative coefficient for most of the six crises (with the exception for c3). This negative difference could imply a lower stock volatility of firms with higher ESG scores. However, there is no coefficient that is statistically significant at the common levels

(10%, 5%, or 1%). Hence, we cannot verify if this negative difference in volatility between group 1 and group 2, for the periods analysed, can be attributed to firms' ESG performance.

Tail Risk Assessment

The quantile of order 5 is a particularly helpful resilience metric during crises, because it reflects the tangible and immediate potential extreme losses during these periods of market distress. For instance, higher and statistically robust weekly values for group 1 during the three market shocks c1 ($\beta_1 = 0.0165$ p-value<1%), c2 ($\beta_2 = 0.0277$, p-value<10%), and c3 ($\beta_3 = 0.0091$, p-value<), imply that high ESG scoring firms demonstrated, on average, a better ability to limit extreme losses through the Russo-Ukrainian War, the COVID-19 pandemic crisis and the 2018 market correction period, respectively. The results (Appendix B11) suggest that these firms might have more structural robustness to endure market shocks, when comparing with low ESG scoring firms.

Regarding the expected shortfall metric, the significant negative coefficients (Appendix B12) for c1 (0.0226 units at a confident level of 1%) and c2 (0.0392 units at a confident level of 1%), indicate that during the Russo-Ukrainian War and the COVID-19 pandemic, respectively, high-ESG-score firms had significantly lower expected shortfalls, so they were expected to lose less relative to their low-ESG counterparts in extreme-risk scenarios. These results strengthen the idea that high-ESG firms can offer more protection against extreme market downturns.

Finally, focusing on tail index at 5%, the results (Appendix B13) do not indicate a statistically significant difference between high and low ESG score firms, for any variable across the six market shocks. However, when analysing tail index results at 1%, we obtained interesting findings (Appendix B14). This metric of order 1, focuses on even more extreme, tough less likely events. By studying these extremes, we might increase the results bias because these "black swan" events provide a smaller sample. Yet, the metric also increases result efficiency by capturing the potential severe impacts that can be overlooked by a broader metric. Indeed, we obtained statistically significant coefficients for crises c1, c5 and c6. The positive values in the Russo-Ukrainian War (1.91 units significant at 10% level), the 2011 Bear Market (2.79 significant at 5% level), and the Financial Crisis (2.38 significant at 10% level), indicate that the high ESG-score firms' loss distributions exhibited, on average, thinner tails for these events, suggesting a lower likelihood of suffering extreme losses. These findings reinforce the superior stock resilience of firms with high ESG scores.

An interesting observation we can retrieve from the data is that the recent crises c1, c2, and to a lesser extent, c3, presented more statistically significant results across the six dependent variables, than the other crises. This pattern could be attributed to the specific nature of each crisis. Yet, it is also possible that the findings reflect the evolving emphasis on ESG factors over the years. Indeed, the Russo-Ukrainian War

(2022), the COVID-19 pandemic (2020), and the 2018 stock market correction are the most recent U.S. market shocks from our data and occurred in periods where ESG considerations were becoming increasingly more important to investor decision-making and corporate strategy. As such, the statistically significant results could indicate that the impact of ESG frameworks, is becoming, over the years, more relevant for firms' superior stock performance and resilience.

CHAPTER 7 Discussion

In this study, we investigate the relationship between firms' ESG scores and their stock performance and resilience. We analysed a dataset consisting of weekly observations of 2,597 American firms listed on NASDAQ and their associated ESG scores retrieved from Refinitiv between January 2002 and July 2023, and categorized the firms into two groups based on their ESG scores: group 1 consists of firms with high ESG scores, and group 2 includes firms with low ESG scores. To examine return performance and assess volatility, asymmetry, and risk under different market conditions, we employed three distinct methodologies. First, we used the CAPM Approach to study firms' stock performance by comparing their stocks' excess return (measured by alpha) and systematic risk (measured by beta). The study reveals that group 1, on average, exhibits higher mean alpha values with less variability compared to group 2, indicating higher profitability. This conclusion is supported by the significant positive correlation between alpha and ESG scores. In contrast, beta values indicate minimal differences between the groups. Although the betas of group 1 showed less variability, both groups exhibited similar mean values. Moreover, the weak correlation between beta and ESG scores did not provide sufficient evidence to establish a compelling association between the two variables, which motivated further analysis.

Second, we employed a Regression Approach that focused on six target analyses related to return performance (measured by the mean), volatility assessment (measured by the standard deviation), asymmetric distribution (measured by skewness), and tail risk assessment (measured by quantile, shortfall, and index tail using the lowest 5% observations from the left tail). The study reaffirms that firms with higher ESG scores generally yield a higher average stock return of approximately 3.9% annually. In contrast, there is no evidence that suggests the distributions of the two groups present different asymmetries. Furthermore, the study reveals that these firms exhibit lower volatility and reduced tail risk compared to their low-ESG counterparts. Specifically, high ESG-scoring firms demonstrate higher returns in the 5^{th} quantile, implying that even in their 5% worst-case scenarios, these firms outperform others. Additionally, they display a lower expected shortfall, indicating that their potential extreme losses tend to be less severe. Finally, the tail index analysis underscores that firms with high ESG scores, having a lighter tail in return distribution, are less susceptible to extreme negative financial outcomes. In summary, the findings clearly demonstrate the greater financial resilience of firms with high ESG scores when compared to their low-ESG-score counterparts.

Third, we assessed the stock resilience of the two groups during market shocks by conducting a regression analysis with six dummy variables, each corresponding to a specific U.S. stock market shock (Table IV). Our goal was to determine whether any of these market disturbances could significantly impact the differences in returns, volatility, and tail risk between group 1 and group 2. The analysis reveals that during the market crashes of 2022, triggered by the Russo-Ukrainian war, and the 2018 market correction, firms with high ESG scores demonstrated superior stock performance, evidenced by annual stock returns that were 31.7% and 27% higher, respectively, compared to those of firms with low ESG scores. However, the analysis of volatility during the six market shocks did not present statistically significant results to confirm the role of ESG in reducing volatility in adverse market periods. On the other hand, high-ESG firms demonstrated lower tail risk during the most recent market downturns, including the COVID-19 pandemic, as they exhibited a reduced potential for losses and a lower risk of extreme outcomes in the worst 5% scenarios of market shocks. Lastly, the tail index assessment at the 1% level revealed that high-ESG-score firms were less susceptible to extreme losses in half of the U.S. market shocks analysed.

Overall, the consistent results across the three analyses reinforce the profile of high-ESG firms as stable and resilient investments in different market conditions, which allows us to confirm the hypotheses raised in our thesis, as follows.

Table VI.
Thesis Hypotheses and Results

This table presents the four hypotheses raised in the literature review chapter and their respective outcomes.

#H	Hypothesis	Outcome
1	Firms with higher ESG scores demonstrate superior stock performance compared to those with lower ESG scores.	Accepted
2	Firms with higher ESG scores exhibit lower stock price volatility, suggesting superior stock stability, compared to those with lower ESG scores.	Accepted
3	Firms with higher ESG scores present reduced tail risk, indicating greater robustness to extreme financial events, compared to those with lower ESG scores.	Accepted
4	During market shocks, firms with higher ESG scores demonstrate enhanced stock resilience compared to those with lower ESG scores.	Accepted

Our methodological approach, inspired by Kelly and Jiang (2014), allowed for a comprehensive examination of the conditional moments and parameters in our analysis. By extending this methodology, we were able to thoroughly investigate the common processes associated with each characteristic of the distribution. Indeed, our research introduces an analytical perspective by investigating these aspects in the context of firms with high and low ESG scores. Specifically, our study contributes to the existing literature by emphasizing tail risk, an area not extensively explored in previous research on ESG impacts. Tail risk events, that represent extreme market downturns and are considered rare and unpredictable, have the potential to severely impact portfolios. The correlation between lower tail risks and high-ESG firms is groundbreaking because it provides empirical evidence that sustainable business practices contribute to financial robustness, even in the face of market shocks.

Another key insight from our research is how high-ESG-score firms, compared to low-ESG-score firms, tend to achieve higher returns at lower risk, challenging well-established principles of the risk-return trade-off. (Markowitz, 1952; Sharpe,1964; Fama & French, 2015). This suggests a shift in market dynamics, where qualitative factors such as strong governance, social responsibility, and sustainability efforts have become crucial in determining a firm’s financial stability and attracting investor interest. It emphasizes the need for an integrated approach to evaluating a firm's financial health, one that reflects the growing impact of sustainability in modern investment decisions.

Moreover, we identified an interesting pattern in our results. Our research found that the most recent market shocks, including the Russian-Ukrainian war, the COVID-19 pandemic, and, with a relatively smaller impact, the 2018 market correction, exhibited statistical significance across a greater number of dependent variables compared to earlier periods.

On the one hand, this pattern could be explained by the specific nature of each crisis. Geopolitical tensions usually increase market sensitivity to global supply chains, energy resources, and international trade stability. Thus, the Russian-Ukrainian war may have prompted a preference for firms with ethical business practices, as investors sought safer options during times of intense uncertainty. The COVID-19 pandemic, a global health crisis, generated economic disruptions and market volatility, stressing the importance of firms with solid corporate social responsibility practices, particularly focused on employee welfare and supply chain resilience. The 2018 market correction, driven by trade tensions and changes in U.S. monetary policy, increased political uncertainty and intensified instability, which might have influenced investors to opt for firms with strong corporate governance measures.

On the other hand, these differences, when contrasted with earlier market shocks, could also suggest a growing emphasis on ESG investing over the years. This increasing awareness appears to have an impact on the market, as investors increasingly prefer firms that follow ESG practices, particularly during times of market uncertainty.

Overall, our study addresses the ongoing debate regarding the impact of ESG practices on financial performance, consistent with previous findings that identified positive correlations between sustainability initiatives and enhanced stock performance, while also providing an extensive and critical time-series analysis for different market conditions. In short, we strongly recommend that investors consider firms' ESG scores in their strategic planning to optimize risk-return profiles, especially when constructing portfolios designed to mitigate significant market fluctuations and extreme scenarios. Similarly, we encourage firms to adopt ESG practices and disclose their metrics to enhance long-term financial performance and resilience and refine risk management strategies.

CHAPTER 8 Limitations and Avenues for Further Research

Our study offers valuable insights into the relationship between firms' ESG scores and their stock performance and resilience. However, it's crucial to recognize some limitations of our research. One significant constraint comes from inconsistencies across ESG rating agencies. Different ESG data employ unique evaluation criteria and methods and use their own analytical tools and qualitative assessments (e.g., see Appendix A3). These disparities prevent the use of a universal benchmark for assessing ESG performance, potentially introducing biases in our comparative analysis. Moreover, our analysis is restricted by the firm's disclosure practices, which are critical for providing accurate information. Non-standardized or voluntary reporting limits the reliability of the ESG data, possibly leading to an underestimation of critical ESG-related metrics and, consequently, the firm's financial performance.

Furthermore, factors beyond ESG scores may influence firms' resilience and market performance. In this study, our focus was not on finding potential factors that could explain the observed differences between group 1 (firms with high ESG scores) and group 2 (firms with low ESG scores). Instead, we concentrated on estimating the average differences and assessing their statistical significance. In future research, it would be interesting to explore the underlying reasons for these disparities. Other potential explanatory factors could include firm size, economic downturns, inflation, liquidity and corporate governance, and investor sentiment among other variables. Notwithstanding, by examining the disparities between group 1 and group 2, some of these factors might cancel each other. However, the extent to which this happens remains an empirical question.

An intriguing topic for future discussion is the causal relationship between high ESG values and stock performance. It raises the question: do firms with high ESG values generally exhibit better stock performance, or does superior stock performance encourage firms to adopt higher ESG standards? There is also the possibility of a bidirectional relationship, where both phenomena influence each other reciprocally.

Additionally, further studies might consider expanding the Fama and French 5-factor model by introducing 'ESG scores' as a sixth factor. Incorporating ESG scores as an additional factor could enable researchers to determine whether high ESG scores truly lead to excess returns or if the observed differences are also influenced by other underlying factors.

Likewise, it would be interesting to validate our findings by comparing different metric providers, like Bloomberg and MSCI. Simultaneously, we encourage future research to broaden the scope of our sample to include other geographic regions, such as Europe and emerging markets. It is valuable to confirm if our results hold in markets with different trading dynamics, such as differences in liquidity or regulations. Besides, specific regional economic conditions, political climates, and cultural attitudes to investments might influence investor sentiment and impact the results for other regions.

Finally, examining the impact of firms' ESG scores on stock performance and resilience within specific industries might reveal insights into sector-specific trends, enabling investors to identify sectors where sustainable practices more strongly correlate with financial robustness.

CHAPTER 9 Conclusion

In this study, we answer the question*: 'How are firms' ESG scores related to stock performance and resilience?'*. To address our research question, we analysed a dataset of 2,597 American firms and their associated ESG scores between 2002 and 2023, to test four hypotheses, specifically that firms with higher ESG scores 1) display superior stock performance, 2) exhibit lower stock price volatility, 3) present reduced tail risk, and 4) demonstrate enhanced stock resilience during market shocks, compared to firms with lower ESG scores. After extensive analysis, all hypotheses were confirmed. Firms with higher ESG scores exhibit superior stock performance and resilience in various market conditions when compared to their lower-scoring counterparts. Such evidence challenges modern portfolio and asset pricing theories, which instead suggest a direct risk-return trade-off in investment decisions. These findings not only affirmatively answer our initial research question but also underscore the substantial financial impact of ESG investing on the stock market.

Overall, the research significantly emphasizes the superior financial adaptability of high-ESG firms across several market conditions. This conclusion is not just academically interesting; it holds substantial implications for different stakeholders who value corporate responsibility and long-term sustainability. Nevertheless, there are still unanswered questions that need further investigation. Our study primarily focused on estimating the average differences in financial performance metrics between groups of high and low-ESG-scoring firms, evaluating their statistical significance without exploring the underlying causal factors behind these observed disparities. Although our approach accounted for potential offsetting effects among these factors, the precise magnitude of their individual impacts remains an empirical question. Future studies should further investigate these complexities to provide deeper insights into causal relationships. Moreover, subsequent studies could corroborate our findings by examining various metric providers, regions, and distinct industries.

In conclusion, despite the avenues for future research, our study unequivocally supports the integration of ESG factors into corporate and investment strategies for risk mitigation and long-term sustainable performance. We recommend that investors and firms prioritize high ESG standards, not only as a mark of corporate responsibility but as a wise way to effectively manage the complexities of modern financial markets.

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APPENDIX

APPENDIX A: Overview of ESG Scores

Appendix A1: Refinitiv's ESG categories and themes

Pillars	Catagories	Themes	Data points	Weight method
Environmental	Emmission	Emissions	TR.AnalyticCO2	Quant industry median
		Waste	TR.AnalyticTotalWaste	Quant industry median
		Biodiversity*		
		Environmental management systems*		
	Innovation	Product innovation	TR.EnvProducts	Transparency weights
		Green revenues, research and development (R&D) and capital expenditures (CapEx)	TR.AnalyticEnvRD	Quant industry median
	Resource use	Water	TR.AnalyticWaterUse	Quant industry median
		Energy	TR.AnalyticEnergyUse	Quant industry median
		Sustainable packaging*		
		Environmental supply chain*		
Social	Community	Equally important to all industry groups, hence a median weight of five is assigned to all		Equally important to all industry groups
	Human rights	Human rights	TR.PolicyHumanRights	Transparency weights
	Product responsibility	Responsible marketing	TR.PolicyResponsibleMarketing	Transparency weights
		Product quality	TR.ProductQualityMonitoring	Transparency weights
		Data privacy	TR.PolicyDataPrivacy	Transparency weights
	Workforce	Diversity and inclusion	TR.WomenEmployees	Quant industry median
		Career development and training	TR.AvgTrainingHours	Transparency weights
		Working conditions	TR.TradeUnionRep	Quant industry median
		Health and safety	TR.AnalyticLostDays	Transparency weights
Governance	CSR strategy	CSR strategy	Data points in governance category and governance pillar	Count of data points in each governance category/all data points in governance pillar
		ESG reporting and transparency		
	Management	Structure (independence, diversity, committees)	Data points in governance category and governance pillar	Count of data points in each governance category/all data points in governance pillar
		Compensation		
	Shareholders	Shareholder rights	Data points in governance category and governance pillar	Count of data points in each governance category/all data points in governance pillar
		Takeover defenses		

*No data points available that may be used as a proxy for ESG magnitude/materiality

Source: Refinitiv
https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

Appendix A2: ESG Score Range and Grade

Score range	Grade	Description
0.0 <= score <= 0.083333	D -	'D' score indicates poor relative ESG performance and insufficient degree of transparency in reporting material ESG data publicly.
0.083333 < score <= 0.166666	D	
0.166666 < score <= 0.250000	D +	
0.250000 < score <= 0.333333	C -	'C' score indicates satisfactory relative ESG performance and moderate degree of transparency in reporting material ESG data publicly.
0.333333 < score <= 0.416666	C	
0.416666 < score <= 0.500000	C +	
0.500000 < score <= 0.583333	B -	'B' score indicates good relative ESG performance and above-average degree of transparency in reporting material ESG data publicly.
0.583333 < score <= 0.666666	B	
0.666666 < score <= 0.750000	B +	
0.750000 < score <= 0.833333	A -	'A' score indicates excellent relative ESG performance and high degree of transparency in reporting material ESG data publicly.
0.833333 < score <= 0.916666	A	
0.916666 < score <= 1	A +	

ESG laggards

ESG leaders

Source: Refinitiv
https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

Appendix A3: ESG Criteria – Major Index Providers Comparison

Pillar	Thomson Reuters	MSCI	Bloomberg
Environmental	Resource Use	Climate Change	Carbon Emissions
	Emissions	Natural resources	Climate change effects
	Innovation	Pollution & waste	Pollution
		Environmental opportunities	Waste disposal
			Renewable energy
			Resource depletion
Social	Workforce	Human capital	Supply chain
	Human Rights	Product liability	Discrimination
	Community	Stakeholder opposition	Political contributions
	Product Responsibility	Social opportunities	Diversity
			Human rights
			Community relations
Governance	Management	Corporate governance	Cumulative voting
	Shareholders	Corporate behaviour	Executive compensation
	CSR strategy		Shareholders' rights
			Takeover defence
			Staggered boards
			Independent directors
Key metrics and submetrics	186	34	>120

Source: Refinitiv, MSCI, Bloomberg, FTSE; OECD assessment. https://www.oecd.org/finance/ESG-Investing-Practices-Progress-Challenges.pdf
Note: Thomson Reuters is now known as Refinitiv.

APPENDIX B: Regression Analyses Outputs

Appendix B1: Correlation Analysis between Alpha and ESG scores

Covariance Analysis: Ordinary
Sample: 1 1125
Included observations: 1125

Correlation Probability	ALPHA	MED_SCORE
ALPHA	1.000000 -----	
MED_SCORE	0.238323 0.0000	1.000000 -----

Appendix B2: Correlation Analysis between Beta and ESG scores

Covariance Analysis: Ordinary
Sample: 1 1125
Included observations: 1125

Correlation Probability	BETA	MED_SCORE
BETA	1.000000 -----	
MED_SCORE	0.058253 0.0508	1.000000 -----

Appendix B3: Regression Approach Output - Returns

Dependent Variable: M1-M2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1123
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000750	0.000268	2.794520	0.0053

Appendix B4: Regression Approach Output - Volatility

Dependent Variable: SIGMA1-SIGMA2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1123
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.030127	0.000622	-48.42210	0.0000

Appendix B5: Regression Approach Output - Skewness

Dependent Variable: SK1-SK2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1123
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.019530	0.138210	-0.141307	0.8877

Appendix B6: Regression Approach Output - Quantile 0.05

Dependent Variable: Q05_1-Q05_2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1124
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.029056	0.000654	44.44139	0.0000

Appendix B7: Regression Approach Output – Expected Shortfall

Dependent Variable: ES_05_1-ES_05_2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1123
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.061173	0.001093	-55.98561	0.0000

Appendix B8: Regression Approach Output – Tail Index 0.05

Dependent Variable: HILL_05_1-HILL_05_2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1104
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.419993	0.029745	14.11966	0.0000

Appendix B9: Stock Resilience Output – Returns

Dependent Variable: M1-M2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1123
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000597	0.000264	2.256540	0.0242
C1	0.006096	0.002412	2.527258	0.0116
C2	0.005351	0.004330	1.235740	0.2168
C3	0.005164	0.002412	2.140776	0.0325
C4	-0.001528	0.004330	-0.352944	0.7242
C5	0.001608	0.002620	0.613946	0.5394
C6	-0.000787	0.002894	-0.271965	0.7857

Appendix B10: Stock Resilience Output – Volatility

Dependent Variable: SIGMA1-SIGMA2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1123
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed
bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.030076	0.000491	-61.24758	0.0000
C1	-0.002289	0.004480	-0.510934	0.6095
C2	-0.008617	0.008043	-1.071353	0.2842
C3	0.004498	0.004480	1.004003	0.3156
C4	-0.003211	0.008043	-0.399300	0.6897
C5	-0.000729	0.004866	-0.149915	0.8809
C6	-0.003371	0.005374	-0.627280	0.5306

Appendix B11: Stock Resilience Output – Quantile 0.05

Dependent Variable: Q05_1-Q05_2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1124
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed
bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.028616	0.000532	53.83543	0.0000
C1	0.016459	0.004852	3.392575	0.0007
C2	0.027743	0.008710	3.185243	0.0015
C3	0.009094	0.004852	1.874338	0.0611
C4	0.009514	0.008710	1.092262	0.2750
C5	-0.001348	0.005269	-0.255898	0.7981
C6	0.003086	0.005820	0.530213	0.5961

Appendix B12: Stock Resilience Output – Expected Shortfall 0.05

Dependent Variable: ES_05_1-ES_05_2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1123
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.060638	0.000948	-63.97009	0.0000
C1	-0.022641	0.008648	-2.618160	0.0090
C2	-0.039222	0.015525	-2.526368	0.0117
C3	-0.003592	0.008648	-0.415368	0.6780
C4	-0.004912	0.015525	-0.316361	0.7518
C5	-0.002537	0.009393	-0.270127	0.7871
C6	-0.006125	0.010374	-0.590423	0.5550

Appendix B13: Stock Resilience Output – Tail Index 0.05

Dependent Variable: HILL_05_1-HILL_05_2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1104
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.416426	0.028682	14.51888	0.0000
C1	-0.037971	0.259480	-0.146335	0.8837
C2	0.355311	0.465802	0.762795	0.4457
C3	-0.029492	0.259480	-0.113658	0.9095
C4	0.213655	0.465802	0.458682	0.6466
C5	0.062293	0.295435	0.210851	0.8330
C6	0.212904	0.311269	0.683985	0.4941

Appendix B14: Stock Resilience Output – Tail Index 0.01

Dependent Variable: HILL_01_1-HILL_01_2
Method: Least Squares
Sample: 8/01/2002 18/07/2023
Included observations: 1112
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.030494	0.121982	16.64586	0.0000
C1	1.914757	1.107181	1.729399	0.0840
C2	0.587864	1.987594	0.295767	0.7675
C3	-1.547604	1.107181	-1.397788	0.1625
C4	-1.571720	1.987594	-0.790765	0.4293
C5	2.792067	1.202508	2.321870	0.0204
C6	2.375866	1.328178	1.788816	0.0739