Department of **Business e Management**

Bachelor's Degree in **Management and Computer Science**

Course of **Finance and Financial Technologies**

The Impact of Environmental and Social Scores on Stock Performance During COVID-19

Prof. Michela Altieri
SUPERVISOR

Petar Jelusic
CANDIDATE

Academic Year 2024/2025

Acknowledgements

First and foremost, I am grateful to my family for their constant love, support, and belief in me. Their unwavering support has been a source of strength throughout my academic career.

I would also want to thank LUISS University for providing me with a scholarship, which allowed me to continue my studies and perform this research with the required resources.

A particular thank you to my thesis supervisor, Professor Michela Altieri, for her invaluable direction, insightful feedback, and ongoing support throughout the research process.

Importantly, I'm grateful to my friends and peers for their support, talks, and companionship, which have made this journey more enriching and pleasurable.

Finally, I acknowledge all the professors and staff at LUISS who contributed to my academic development over the years.

Contents

1 Introduction

The COVID-19 epidemic triggered a rapid and far-reaching economic shock in the whole world and one of the biggest in modern history, causing turmoil in global financial markets (Ramelli Wagner, 2020). Stock prices fell at a historic rate as investors reacted to extraordinary uncertainty and disruption in industries and geographies (Albuquerque et al., 2020). However, the sell-off was not universal. Some businesses appeared to cope with the shock better than others, raising crucial issues regarding what underlying qualities contribute to corporate resilience during crises of this size (Ding et al., 2023).

Among the elements taken into account, Environmental and Social (ES) responsibilities received special consideration. Although ES policies were once thought to be a component of larger corporate responsibility objectives, they are now widely thought to have the capacity to affect financial performance (Ferrell, Liang, Renneboog, 2016; Amel-Zadeh Serafeim, 2018). Hence, the debate over whether businesses with higher ES profiles were better equipped to withstand the market decline and maintain investor confidence was triggered by the early phases of the pandemic.

This query raises basic questions in financial economics. The traditional belief that markets primarily price financial and operational fundamentals is called into question if ES variables do provide protective benefits during times of market difficulties. Therefore, it implies that when uncertainty increases, investor behavior, risk perceptions, and stock price dynamics may be influenced by social and environmental metrics.

Nonetheless, despite the increased interest in ESG-related resilience, empirical evidence is unclear and divided among the scholars. While some research suggests that ES policies reduce downside risk (Lins, Servaes, Tamayo, 2017; Broadstock et al., 2020; Zhou et al., 2022), others emphasize the importance of other characteristics like liquidity, industry classification, or intangible assets (Demers et al., 2021; Marín et al., 2023). Furthermore, it is unclear whether the noted advantages in findings supporting the ES-related resilience of ES enterprises are due to root causes or more context-specific dynamics associated with specific industries or market conditions. Therefore, it results in some arguing that ES-oriented organizations benefited during the pandemic, resulting in more stable performance, while others believe that alternative factors, such as liquidity safeguards or industry characteristics, can better explain observed trends (Gianfrate, 2023; Ding et al., 2023). Whether ES commitments provide universal benefits or are relevant just in specific settings remains an open question.

To contribute to this debate, this thesis revisits and repeats a study that found favorable performance differences associated with ES variables during the COVID-19 sell-off. Businesses with higher ES ratings performed better than their peers in the early phases of the pandemic, according to research by Albuquerque et al. (2020), that is the basis for this thesis. These companies had greater trading volumes, reduced volatility, and higher stock returns, according to their findings. These results suggest that, in times of market difficulty, ES factors aside from more conventional business attributes like size or leverage do provide protective advantages. This study uses a similar methodology to an updated and separate dataset to test the reliability and generality of previous findings. By addressing these challenges, the thesis hopes to add to the existing discussion about the robustness and financial usefulness of ES policies in times of severe volatility.

2 Literature Overview

In the first quarter of 2020, Albuquerque et al. (2020) carried out a research study that examined American companies. According to their research, businesses with higher ES ratings saw greater trading volumes, reduced volatility, and higher stock returns than other companies with lower ratings. Therefore, the authors linked this resiliency to elements including investor confidence in businesses' social responsibility efforts and client loyalty.

In support of this view, Ding et al. (2023) looked at companies in five developed nations and discovered that during the COVID-19-induced market collapse, those with robust ES operations showed noticeably less stock price volatility. In a comparable manner, Pastor and Vorsatz (2020) found that throughout the crisis, mutual funds with higher sustainability ratings performed better than competitors and attracted more capital. This research supported the idea that, in part because investor tastes are evolving toward safer and more socially conscious investments, ESG-focused businesses may experience increased stability during times of market turmoil.

However, some academics doubt the preventive benefits of ESG, and the research is not always favorable. ESG scores did not offer much protection against the market downturn, according to Demers et al. (2021), who suggest that investments in intangible assets are important and effective for business resilience. Hence, it allows for the assessment of whether these results are valid with various company samples. In support of this argument, Takahashi and Yamada (2021) discovered no connection between abnormal returns among Japanese companies during the pandemic and ESG scores. The difference in results emphasizes that the advantages of ESG might not be consistent across markets and regions.

The influence of ESG performance on company resilience does appear to vary by sector and geography. According to Marín et al. (2023), the impact of ESG on stock resilience varies by industry, highlighting the significance of sector-specific factors. Gianfrate (2023) broadens this analysis globally, demonstrating that the resilience of ESG enterprises is stronger in North America, possibly due to differences in investor expectations, legislation, and cultural attitudes toward sustainability. Together, these findings indicate and further support the view that ESG advantages may be sample or context-dependent rather than globally universal.

Although there seem to be sectoral and geographical differences, other research has attempted to provide nuanced insights into ESG performance during the pandemic by examining different points of view. For example, Rubbaniy et al. (2021) examine whether ESG stocks served as safe heavens during market turbulence. Their analysis, which uses a statistical method called "wavelet coherence technique" (used to examine how two time series are related across both time and frequency), reveals that ESG stocks have safe-haven and hedging qualities, especially over medium-term investment horizons. However, the protective function of ESG equities did not apply to all risk indicators. For example, when utilizing the CBOE Volatility Index (VIX or "fear index") as a fear proxy, ESG stocks did not always act as safe havens. This means that, while ESG qualities may provide some protection, their ability to completely shield investors is dependent on market sentiment and individual risk indicators. Hence, if the general investor sentiment is fearful, as in times of COVID-19, ESG equities may not serve as a "safe haven".

The story of the banking sector is a little different from that of the general equities markets. The impact of banks' ESG practices on their stock performance and lending practices during the pandemic was examined by Dursun-de Neef et al. (2023). According to their findings, during the COVID-19 pandemic, banks with higher ESG ratings actually had poorer stock returns, especially those with a large retail investor base. Furthermore, throughout the crisis, institutions with robust ESG profiles seemed to implement more cautious lending practices.

Hoang et al. (2021) present a European perspective on market activity during COVID-19 by analyzing listed corporations and their ESG ratings. Their findings support the notion that ESG correlates to lower volatility, as highly ranked ESG enterprises experienced less price swings than others. However, they find no significant evidence that these firms received larger returns. Hence, they have found that ESG provides stability during crises, but it does not always improve short-term returns. Further investigating other markets and looking into the UK, Hoang et al. (2020) found that firms with higher ESG disclosure transparency showed lower stock volatility during the COVID-19 pandemic. Adding to this perspective, Yi and Ahn (2023) discovered that ESG scandals have a negative impact on business value, but firms with high ESG performance can offset these negative effects, implying that proactive ESG involvement can operate as a reputational risk barrier. Furthermore, Abdulla and Saba (2025) extended the focus to sovereign entities and showed that robust governance and superior ESG performance are linked to higher sovereign credit ratings. This suggests that ESG elements support resilience at both the business and national levels.

Furthermore, the evidence from China gives another perspective to the discussion, by further exploring additional markets, as previous findings from different markets provided different conclusions. Broadstock et al. (2020) investigate if ESG performance is relevant in China. Their research found that during the COVID-19 crisis, portfolios with higher ESG ratings outperformed those with lower ratings, mainly in terms of minimizing financial risks. However, they point out that ESG performance had a far lesser impact during normal periods; saying that ESG benefits may be especially important during periods of market turbulence.

Zhou et al. (2022) give additional evidence supporting ESG's function in risk reduction. Their research focuses on stock price volatility risk and discovers that good ESG performance was associated with lower volatility during the pandemic. Furthermore, also they reveal that this risk-mitigating effect varies by industry, implying that ESG's protective characteristics are not universal but rather dependent on sector-specific dynamics. When taken as a whole, this expanding collection of research highlights how contextual factors and ESG's impact in resilience are conditional. Supporting this view, the Hong Kong Institute for Monetary and Financial Research (2022), found that the ESG-weighted Hang Seng Index outperformed its standard counterpart in terms of returns and volatility.

Now if we look beyond returns and volatility, other scholars have investigated additional aspects of ESG investing during crises, focusing on investor behavior, capital allocation, and reputational risk. Cornell (2021) investigates the link between ESG preferences, risk, and return. The study reveals that while investor preferences for ESG-compliant enterprises can reduce capital costs, they may also result in lower expected returns. This trade-off demonstrates the complexities of ESG investment, in which ethical considerations may not necessarily coincide with short-term financial goals. Furthermore, Cornell discusses the current dispute over whether ESG is a distinct risk element in financial models. Similarly, Berkman and Tirodkar (2024) found that during financial crises, such as the Global Financial Crisis and the COVID-19 pandemic, stocks with higher ESG scores had lower expected returns, implying that investors may accept lower returns in exchange for perceived stability during turbulent times.

Bouslah et al. (2018) provide additional insights by investigating the effect of social performance on corporate risk during the global financial crisis. Their findings show that enterprises with excellent social performance experienced lower volatility during the crisis, with the risk reduction benefit being driven mostly by active social measures. This shows that genuine ESG commitments, particularly those involving social responsibility, can act as a hedge against unfavorable economic situations. In the German context, Neuenroth and Zureck (2024) discovered that enterprises with higher ESG ratings during the COVID-19 crisis had superior financial performance, notably in terms of EBITDA.

Meanwhile, the validity of ESG ratings has been questioned. Berg et al. (2020) report widespread historical variations in ESG scores by Refinitiv ESG (an important element to note given that thesis data is taken from Refinitiv), raising questions about the consistency and openness of ESG data. Yang et al. (2022) brought upon the importance of ESG materiality by demonstrating that firms that focused on material ESG issues (defined by the Sustainability Accounting Standards Board (SASB)) had better financial performance and lower risk, putting a focus on prioritizing financially relevant ESG factors.

Investor perspectives on ESG information confuse the matter even more. Yarwood (2024) examined ESG fund flows and found that investors in ESG index funds were more resilient during market downturns, with less significant withdrawals than non-ESG funds, showing stronger investor adherence to ESG principles even in the face of financial stress. Amel-Zadeh and Serafeim (2018) conducted a global study and discovered that investors predominantly use ESG data to analyze investment performance potential, followed by customer demand and product strategy. Nonetheless, they highlight issues such as variable reporting standards and varying information quality, which may prevent the effective incorporation of ESG aspects into investing processes.

In the end, Mackintosh (2020) offers a critical viewpoint, claiming that the outperformance of ESG funds during the pandemic was mostly due to sectoral allocations and lucky circumstances rather than ESG elements themselves. This viewpoint cautions against overestimating the relevance of ESG criteria in driving financial performance, instead advocating for a more balanced and complex assessment of ESG investment outcomes. Together, these papers contribute to the ongoing debate about ESG and resilience. While some data suggests that ESG ratings provide stability and may act as a buffer during crises, other research shows that the impacts are conditional and not necessarily connected with better stock performance.

This conflicting evidence emphasizes the need for additional empirical work that replicates the research findings using a different sample. This thesis thus seeks to duplicate and test the findings of Albuquerque et al. (2020), evaluating their robustness in a new setting. By evaluating both stock returns and trading volumes during the COVID-19 shock, this study hopes to provide a more nuanced and comprehensive understanding of the significance of ES variables in improving business resilience.

3 Data and Methodology

3.1 Overview of Dataset Construction

To investigate whether companies with stronger Environmental and Social (ES) practices demonstrated greater resilience in their stock performance during the initial COVID-19 market shock, I created a firm-level panel dataset that combines financial characteristics, sustainability scores, and high-frequency market data. Company-level data were sourced from Moody's Orbis, while stock-based and ESG data were sourced from Refinitiv.

3.2 Sample Selection

The initial firm set was designed to provide wide market representation and adequate ESG data coverage. This sample included companies listed on the NYSE Composite Index, NASDAQ Composite Index, and SP 500, totaling 4596.

This was done due to need to create a big dataset that could withstand numerous filtering stages, given the limitations in ESG data availability. While broader indices like the SP 1500, which can be accessed directly through Refinitiv, were also evaluated, many of its components lacked consistent disclosure of environmental and social measures or lacked complementing firm-level financial information required for control variables. Expanding the sample to include NYSE and NASDAQ listings reduced the chance of having an underpowered final sample. As a result, I began by compiling a comprehensive list of U.S.-listed firms from Orbis and then gradually removed companies depending on data availability.

During data extraction, it became clear that many publicly listed corporations had incomplete or absent ES pillar scores in the Refinitiv ESG database. A manual investigation revealed that the gaps were attributable to non-reporting or coverage limits, not technical faults. Firms with missing data were excluded from the working sample. Additional exclusions were applied while integrating Moody's Orbis firm-level accounting data. In other situations, crucial financial data such as total assets, advertising expenditure, and book equity were lacking, requiring further sample size reductions. Furthermore, to ensure correct estimate of CAPM beta coefficients, firms that had not been consistently listed since at least January 1, 2017, were omitted. This guaranteed that daily return data for the whole estimation window was continuously available.

Despite these adjustments, the final sample had a significant overlap with the SP 500 constituents, ensuring comparison with previous research such as Albuquerque et al. (2020). The resulting group makes a balance between representativeness, data quality, and sound methodology, setting the groundwork for the empirical study to follow.

3.3 ESG and Market Data from Refinitiv

As previously stated, the Refinitiv database serves as the key source of both sustainability and high-frequency market data. Refinitiv ESG compiles and standardizes data from corporate filings, sustainability reports, news sources, and non-governmental organizations. The Environmental and Social Pillar Scores used in this study measure business performance relative to sector peers in categories such as emissions, resource consumption, workplace norms, and product responsibility. These scores are pooled, materiality-adjusted, and expressed on a 0–1 scale. For this research, a firm's ES profile is defined as the average of its Environmental and Social Pillar Scores. Governance scores are deleted in accordance with the methodology used by Albuquerque et al. (2020).

Firms with incomplete ES pillar scores were eliminated to ensure data accuracy and internal consistency. After filtering, the ESG dataset contained 2,365 enterprises with complete environmental and social data.

Refinitiv's Excel Workspace also provided access to daily market data, such as stock returns, trade volume, and intraday high-low price ranges. The sample period runs from January 1, 2017, to March 31, 2020, giving enough pre-crisis data for CAPM beta estimation while also allowing for observation of market dynamics during the COVID-19 shock. Price range data were standardized to yield a non-parametric measure of daily volatility. Volume data were adjusted to millions, and abnormal returns were estimated using the CAPM model's residuals.

Table 1: Summary statistics for ESG and stock return variables
This table reports the summary statistics (number of observations, mean, standard deviation, 25^{th}, 50^{th} (median), and 75^{th} percentiles) for all variables. The Appendix provides the definition and data sources for all variables.

Variable	**Obs.**	**Mean**	**Std. Dev.**	**25%**	**Median**	**75%**
Abn Return_cum (%)	1330	−6.734	30.179	−22.369	−4.824	10.643
ES	1330	0.347	0.236	0.155	0.279	0.520
Volatility	1330	0.054	0.018	0.042	0.049	0.061
Idiosyncratic Volatility	1330	0.042	0.020	0.037	0.040	0.050
Abnormal Return (Daily, %)	81 130	−0.110	4.658	−1.500	−0.079	1.209
Daily Price Range	82 229	0.056	0.057	0.020	0.037	0.073
Trading Volume (in millions)	82 331	3.131	21.157	0.220	0.659	1.893

3.4 Firm Fundamentals and Accounting Data

The study uses accounting-based control variables that are taken from the Moody's Orbis database in order to account for firm-level variation in performance and structure. The factors that were chosen are Tobin's Q, firm size (log of total assets), cash holdings (cash-to-assets ratio), leverage (total debt-to-assets ratio), return on equity (ROE), and advertising intensity (advertising expenditures scaled by total assets), as in Albuquerque et al. (2020), the final full year before the COVID-19 pandemic, fiscal year 2019, is used to measure all factors. After filtering missing values, excluding Other and Oil Industries from Fama French, the sample resulted in 1330 companies with all required features (some companies with negative ROE were filtered as well).

Furthermore, to decrease the influence of outliers, each control variable is winsorized at the 1st and 99th percentiles. This increases the robustness of regression results and reduces the impact of extreme values.

Table 2: Summary statistics for firm fundamentals

This table reports the summary statistics (number of observations, mean, standard deviation, 25^{th}, 50^{th} (median), and 75^{th} percentiles) for firm-level control variables. The Appendix provides the definition and data sources for all variables.

Variable	**Obs.**	**Mean**	**Std. Dev.**	**25%**	**Median**	**75%**
Tobin's Q	1330	2.395	1.833	1.243	1.747	2.841
Size	1330	7.975	1.788	6.662	7.902	9.171
Cash	1330	0.116	0.137	0.023	0.069	0.157
Leverage	1330	0.261	0.199	0.077	0.267	0.399
ROE	1282	0.125	0.534	0.044	0.140	0.251
Advertising	1330	0.037	0.085	0.000	0.000	0.030

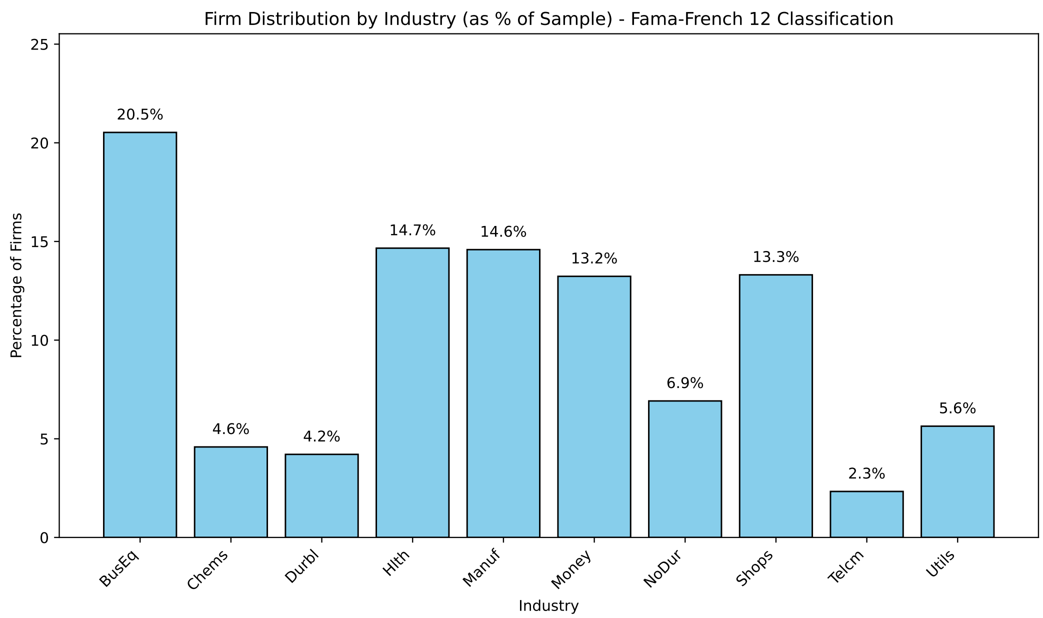
The dataset's firms were classified according to the Fama-French 12-industry categorization (French, 2024). To ensure cross-sector comparability and reduce bias from industry-specific shocks, enterprises in the "Energy" and "Other" categories were omitted from the main sample.

This choice is further supported by the observation that the steep drop in oil prices during the first quarter of 2020 disproportionately affected the energy sector, which is also correlated with poor ES scores. Particularly, the COVID-19 pandemic-induced decline in demand, combined with an oil price war, generated historic volatility and momentarily sent oil futures into negative territory (Investopedia, 2020).

The instability had a significant impact on energy companies, with the SP 500 Energy Sector index posting one of its worst performances in recent history (SP Global Market Intelligence, 2021). The COVID-19 outbreak and major fiscal policy announcements were chosen as events because they caused substantial and unexpected disruptions to the global economy and financial markets, furthermore the pandemic led to widespread uncertainty and shifts in investor behavior, while fiscal responses such as government stimulus measures influenced risk perceptions.

Excluded industries are reintroduced in the robustness checks to assess the sensitivity of the results. The distribution of firms by industry is presented in the Figure 1.

Figure 1: Distribution of firms by industry (as a percentage of the sample)
distribution of firms in the sample across Fama-French 12 industry classifications. The height of each bar reflects the percentage share of total firms belonging to each industry. Firms classified under “Energy” and “Other” were excluded from the main sample and are not shown in the chart.



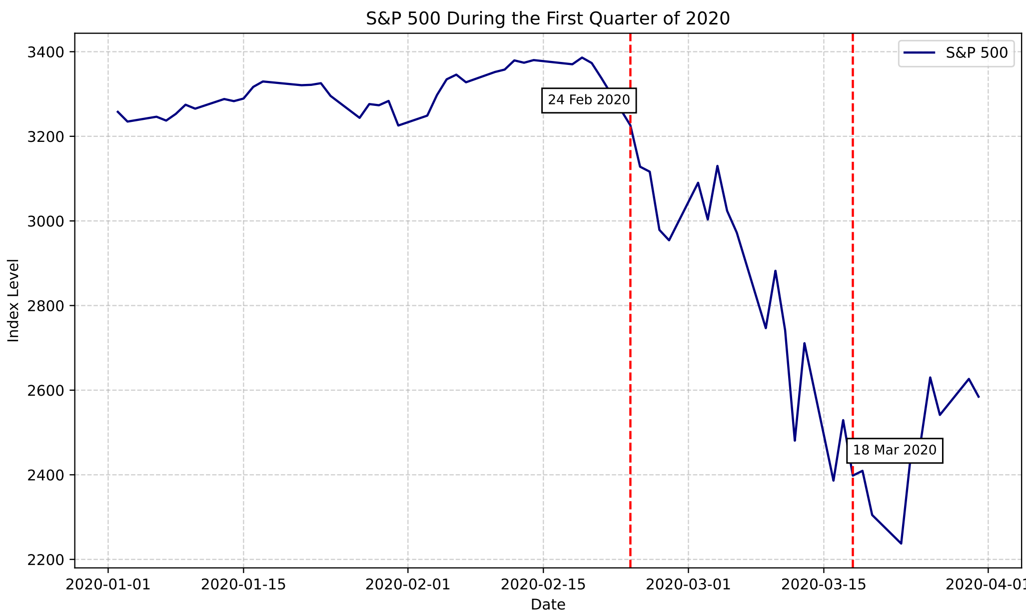
3.5 Empirical Methodology

To determine whether enterprises with stronger environmental and social (ES) policies displayed more resilience during the COVID-19 crisis, this study employs a two-pronged empirical design based on Albuquerque et al.’s (2020). We conduct a cross-sectional regressions to examine firm-level volatility and cumulative abnormal returns in the first quarter of 2020, and difference-in-differences (DiD) regression based on firm-day panel data. All regressions are estimated with robust standard errors and include firm-level control variables that are weighted at the 1st and 99th percentiles to reduce the impact of outliers, as is common practice in the ESG-finance literature (Lins, Servaes, Tamayo, 2017; Cornett, Erhemjamts, Tehranian, 2016).

The DiD methodology is used to analyze three firm-day datasets: abnormal returns, daily price ranges, and trading volume. Each regression examines whether firms classified as ES-High (those in the top quartile of the ES distribution) had different stock market outcomes before and after two key treatment dates: February 24, 2020, the start of the COVID-19 sell-off (Vanity Fair, 2020), and March 18, 2020, when the US Congress passed a major fiscal stimulus package (U.S. News, 2020). In figure 2 we can observe behavior of SP 500 during Q1 with labeled treatment dates.

Figure 2: S&P 500 Index During the First Quarter of 2020

This figure shows the evolution of the S&P 500 index from January 1 to March 31, 2020. The vertical dashed lines indicate two key event dates: February 24, 2020, marking the start of the COVID-19 market sell-off, and March 18, 2020, corresponding to the U.S. fiscal stimulus announcement.



To test these trends, we estimate the following general model:

$$
\begin{aligned}
Y_{it} = \alpha + \beta_1 \cdot \text{Dummy\_COVID}_t + \beta_2 \cdot \text{Dummy\_Fiscal}_t \\
+ \beta_3 \cdot \text{Dummy\_ES\_High}_i + \beta_4 \cdot \text{COVID\_ES}_{it} + \beta_5 \cdot \text{Fiscal\_ES}_{it} + \varepsilon_{it}
\end{aligned}
$$

In this equation, the dependent variable Y reflects either firm i's abnormal return, price range, or trading volume on the given day. The regression includes indicator variables for the COVID period, the fiscal announcement period, and whether the firm is in the ES-High category, as well as interaction factors that capture the combined effect of high ESG status and each treatment period. The coefficients for the interaction terms, particularly COVID ES and Fiscal ES, indicate whether high-ES enterprises performed differently throughout the crisis. To account for unobserved heterogeneity and time-varying market shocks, a second specification includes company and day fixed effects:

$$Y_{it} = \alpha_i + \delta_t + \beta_1 \cdot \text{COVID\_ES}_{it} + \beta_2 \cdot \text{Fiscal\_ES}_{it} + \varepsilon_{it}$$

These panel regressions are estimated with standard errors clustered by both firm and date, consistent with the original study and related literature (Ramelli Wagner, 2020; Gianfrate, 2023). The general model for firm-level cross-sectional regressions examining cumulative abnormal returns during the first quarter of 2020 is given by:

$$\text{AbnReturn\_cum}_i = \alpha + \delta_1 \cdot \text{ES}_i + \gamma' X_i + \varepsilon_i$$

This regression is run in three variations: (1) ES score only, (2) ES plus industry fixed effects based on the Fama-French 12-industry classification, and (3) ES with industry fixed effects and full firm-level controls including Tobin's Q, firm size, cash holdings, leverage, ROE, and advertising.

I next estimate a series of cross-sectional regressions with measures of volatility as dependent variables to assess whether ESG performance is associated with lower stock risk. Two types of volatility are used: the standard deviation of raw daily returns and the standard deviation of CAPM-adjusted residual returns (idiosyncratic volatility). Each specification is estimated with and without controls and industry fixed effects. The general form of this regression is shown below:

$$\text{Volatility}_i = \alpha + \theta_1 \cdot \text{ES}_i + \gamma' X_i + \varepsilon_i$$

These models are estimated using heteroskedasticity-consistent standard errors (HC3). Together, they assess whether ESG performance is predictive of lower total or idiosyncratic risk in volatile markets, supporting the hypothesis that credible ES policies can mitigate downside exposure by stabilizing investor expectations.

All cross- sectional regression models include industry dummies based on Fama-French classifications to ensure that findings are not driven by sectoral heterogeneity. Lastly, to avoid bias stemming from industry-specific shocks, particularly the collapse of oil prices, I exclude companies classified in the Energy and "Other" sectors from the main specification. These exclusions are repeated in robustness checks to ensure that the results are not sensitive to sample composition (Gianfrate, 2023; Hoang, Segbotangni, Lahiani, 2020).

4 Results

4.1 Cross Sectional Regression on Abnormal Returns

Table 3 reports the results from three cross-sectional regressions examining the relationship between firms' Environmental and Social (ES) scores and their abnormal returns during the first quarter of 2020.

In Specification (1), the ES score is the only explanatory variable. The coefficient is positive (2.128), but statistically insignificant (t = 1.48), hence there is no strong evidence that higher ES scores alone are associated with higher abnormal returns when we do not control for any other factors.

In Specification (2), industry fixed effects are added to control for differences across sectors that could influence both ES scores and performance during the crisis. After inclusion of FE, the ES coefficient increases to 3.330 and becomes statistically significant at the 5 percentage level (t = 2.60). Hence, once we account for sectoral differences, firms with stronger ES performance did in fact experience higher abnormal returns. The adjusted R squared improves to 0.147, showing a better fit of the model.

In Specification (3), the model adds a full set of firm-level financial controls, including Tobin's Q, firm size, cash holdings, leverage, return on equity (ROE), and advertising intensity. With these additional variables, the coefficient on ES rises further to 5.502 and remains statistically significant at the 1 percentage level (t = 5.24). This tells us that after accounting for financial characteristics that influence performance, the independent contribution of ES to abnormal returns strengthens. Some of the performance that appeared to be due to other firm fundamentals in specification (2) is captured by the ES variable in this final model.

Looking at the control variables in specification (3), Tobin's Q and firm size both have positive and highly significant coefficients, indicating that firms with better growth opportunities and larger scale performed better during the crisis. Cash holdings are also strongly positive and significant, suggesting that liquidity was an important cushion during the uncertainty of the pandemic. In contrast, leverage has a negative and significant coefficient, further adding that firms with higher debt were more vulnerable to market shocks. ROE and advertising intensity are not statistically significant, implying that profitability and marketing efforts were less relevant in explaining short-term return differences.

The progression from specification (1) to (3) shows that the relationship between ES and abnormal returns becomes more robust as we introduce more controls. Therefore, ES appears to be a distinct and meaningful contributor to resilience, even after accounting for financial fundamentals.

Table 3: Cross-sectional regressions of abnormal returns on ES ratings

*This table reports the results of regressions of first-quarter 2020 abnormal returns on firms' ES ratings. Column (1) includes only ES scores, column (2) adds industry fixed effects, and column (3) adds firm-level controls (with size adjusted to address multicollinearity). Figures in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1) Abn Return_cum	(2) Abn Return_cum	(3) Abn Return_cum
ES	2.128	3.330***	5.502***
	(1.48)	(2.60)	(5.24)
Tobin's Q			2.841***
			(4.06)
Size			3.353***
			(3.72)
Cash			21.337***
			(4.16)
Leverage			–16.202**
			(–2.11)
ROE			–2.027
			(–0.52)
Advertising			–5.499
			(–1.45)
Industry FE	No	Yes	Yes
Number of firms	1282	1282	1282
Adj. R^2	0.000	0.147	0.230

4.2 Difference-in-Differences Analysis of Abnormal Returns

The cross-sectional regressions in Table 3 provided initial insights into how Environmental and Social (ES) scores relate to stock performance during the COVID-19 crisis, but they offer only a static view in one point of time, averaging firm characteristics over a fixed period. Table 4 presents Difference-in-Differences (DiD) regressions using firm-day level panel data.

The models examine whether firms in the top quartile of ES scores (ES High) experienced different daily abnormal return patterns around two critical events: (1) the start of the COVID-19 market sell-off on February 24, 2020, (Vanity Fair, 2020) and (2) the announcement of major U.S. fiscal stimulus on March 18, 2020 (U.S. News, 2020).

In Specification (1), which excludes firm and day fixed effects, the interaction term between ES High and the COVID period (COVID * ES High) is positive (0.264) but not statistically significant ($t = 1.35$). Similarly, the interaction term for the fiscal period (Fiscal * ES High) is negative and insignificant (–0.645, $t = -0.92$). These results suggest no robust differential return pattern for high ES firms during these windows when controlling only for the treatment structure but not for firm-level or time-specific heterogeneity.

The main effect for the COVID period (–0.584, $t = -2.51$) is negative and statistically significant, indicating that on average, firms experienced abnormal return declines during the COVID shock window. However, ES High firms do not appear to have been significantly shielded from these losses in this initial model.

In Specification (2), firm and day fixed effects are included to absorb unobserved heterogeneity across firms (e.g., size, sector, financial structure) and market-wide shocks on specific days (e.g., coordinated investor reactions). After adding these controls, the COVID * ES High interaction remains positive (0.264) but stays statistically insignificant ($t = 1.34$). The fiscal interaction again shows no meaningful effect. The adjusted R squared increases from 0.006 in model (1) to 0.070 in model (2), showing improved explanatory power (although the ES interactions themselves still do not reach statistical significance as mentioned).

The lack of a strong ES effect in the DiD framework despite some positive patterns in the cross-sectional setting suggests that the timing of abnormal return advantages for high-ES firms may be limited or driven by other firm-level traits. While high ES scores may be linked to resilience, they do not consistently lead to better returns during times of market stress once we account for firm and day effects. Here, resilience also means how stable a stock is and how much it is traded, something we explore further by looking at volatility, daily price range, and trading volume in the next sections.

From my findings ES strength alone does not guarantee return resilience. Rather, ES may operate alongside deeper firm fundamentals like cash reserves and low leverage to support stability, but not necessarily outperform in return terms during crisis-specific time windows.

Table 4: Difference-in-Differences regressions for abnormal returns

*This table reports the results of DiD regressions examining the effect of ES scores on daily abnormal returns during the first quarter of 2020. Column (1) shows results without fixed effects, while column (2) includes both firm and day fixed effects (that control for firm-specific unobservables and common macroeconomic factors). The variable COVID × ES High captures the interaction between the COVID sell-off period and high ES firms. Fiscal × ES High captures the interaction during the fiscal stimulus window. Figures in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1) Abn Return	(2) Abn Return
COVID × ES High	0.264	0.264
	(1.35)	(1.34)
Fiscal × ES High	–0.645	–0.645
	(–0.92)	(–0.92)
ES High	0.016	
	(0.39)	
COVID period	–0.584**	
	(–2.51)	
Fiscal period	1.245	
	(1.08)	
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	81,130	81,130
R^2 adjusted	0.006	0.070

4.3 Evolution of Coefficients During Q1 2020

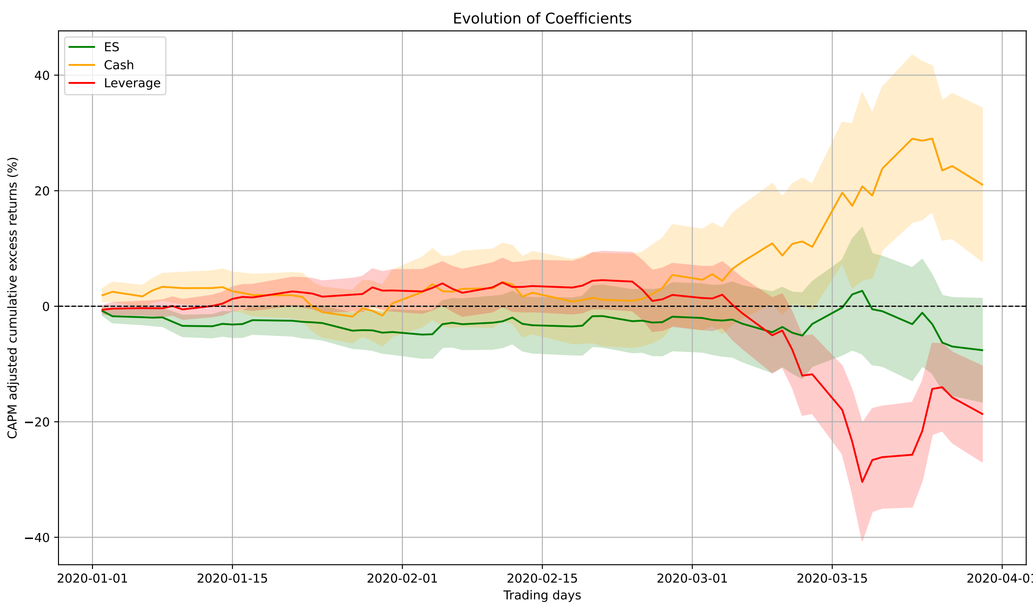
Now, I estimate daily cross-sectional regressions of cumulative returns on ES scores, firm fundamentals (Tobin's Q, size, cash, leverage, ROE, advertising), and industry fixed effects, to better understand how firm characteristics influenced returns over time. Figure 2 plots the daily coefficients for ES, cash-to-assets, and leverage, along with two-standard-error bands.

Figure 3 shows how the influence of key firm characteristics on cumulative stock returns evolved over the first quarter of 2020. The graph plots the estimated daily coefficients on Environmental and Social (ES) scores, cash-to-assets, and financial leverage from rolling cross-sectional regressions, with all other firm controls and industry fixed effects included. Here we want to observe whether certain firm attributes gained or lost importance as the COVID-19 crisis developed.

The coefficient on cash-to-assets displays a clear upward trend beginning in late February and continuing into March. As uncertainty and risk aversion increased, investors rewarded firms with better liquidity. In contrast, the leverage coefficient decreases during the same time span, demonstrating that highly leveraged companies were increasingly penalized as financial instability became a major worry.

Figure 3: Evolution of coefficients during Q1 2020

This figure plots the evolution of coefficients from daily cross-sectional regressions of cumulative stock returns on firm-level characteristics during the first quarter of 2020. The lines represent the estimated coefficients for ES scores, cash-to-assets, and leverage, with two-standard-error bands.



Furthermore, the coefficient on ES scores remains relatively stable throughout the quarter, with no visible trend or significant fluctuations. This suggests that, in this sample, ES performance did not become a more influential determinant of cumulative returns as the crisis developed. While ES may still contribute to firm reputation or long-term value, the evidence from this time-varying regression does not indicate that it played a prominent role in driving investor behavior during the peak of the COVID-19 sell-off. However, financial fundamentals such as cash liquidity and leverage appear to have been the drivers of cross-sectional return differences during this period.

4.4 Cross-Sectional Regressions for Volatility and Idiosyncratic Volatility

Cross-sectional regression for volatility and idiosyncratic volatility are present in Table 5.

In Specifications (1), (2), (4), and (5), ES ratings are strongly and significantly associated with reduced volatility and idiosyncratic volatility. The coefficients are negative and statistically significant at the 1 percentage level, indicating that high-ES firms experienced lower risk during the crisis.

Importantly, in Specifications (3) and (6), where a full set of firm-level financial controls is included, the coefficients on ES remain negative and statistically significant (at the 1 percentage level). Hence, even after accounting for firm fundamentals ES performance continues to contribute independently to risk reduction.

Looking at the control variables in Specification (3) for raw volatility and (6) for idiosyncratic volatility, firm size and ROE are negatively and significantly related to risk, implying that larger and more profitable firms were perceived as less risky. Leverage is positively and significantly associated with both measures of volatility, noting its role as an important risk cushion. Strangely, cash holdings do not show a meaningful effect, while advertising intensity has a modest positive relationship with idiosyncratic volatility.

These findings indicate that ES scores are consistently associated with lower volatility even when controlling key firm characteristics and provide independent explanatory power for understanding which firms weathered the crisis more stably.

Table 5: Cross-sectional regressions for volatility and idiosyncratic volatility

*This table presents cross-sectional regressions of stock return volatility and idiosyncratic volatility during Q1 2020 on ES scores and firm characteristics(size is adjusted to address multicollinearity). Columns (1)–(3) use raw volatility as the dependent variable, and columns (4)–(6) use idiosyncratic volatility. Specifications (1) and (4) include ES scores only; (2) and (5) add industry fixed effects; (3) and (6) include full firm-level controls and industry fixed effects. Figures in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1) Vol	(2) Vol	(3) Vol	(4) Idio	(5) Idio	(6) Idio
ES	-1.838*** (-5.04)	-1.779*** (-4.71)	-1.962*** (-5.11)	-2.558*** (-7.28)	-2.512*** (-7.57)	-2.626*** (-7.15)
Tobin's Q			-0.031 (-0.52)			-0.022 (-0.40)
Size			-0.422*** (-7.49)			-0.528*** (-10.01)
Cash			-0.006 (-0.01)			-0.099 (-0.14)
Leverage			2.039*** (5.74)			1.891*** (5.28)
ROE			-0.289*** (-3.18)			-0.363*** (-5.23)
Advertising			0.346 (0.55)			1.153* (1.77)
Industry FE	No	Yes	Yes	No	Yes	Yes
Number of firms	1282	1282	1282	1282	1282	1282
Adj. R^2	0.056	0.098	0.231	0.090	0.143	0.296

4.5 Other Measures of Resiliency

While the previous sections examined returns as the primary indicator of crisis performance, resilience can also be reflected through stock price stability and trading volumes. In this section, I analyze two complementary dimensions: daily price range, which captures short-term volatility, and trading volume, which reflects the level of market activity and investor interest, following the approach of Albuquerque et al. (2020).

4.5.1 Difference-in-Differences Analysis of Daily Price Range

As mentioned, resilience can also be analyzed through stock price stability and to explore this dimension, I estimate a set of Difference-in-Differences (DiD) regressions using daily price range a nonparametric proxy for return volatility as the dependent variable, which allows us to test whether firms with stronger Environmental and Social (ES) performance experienced lower intraday volatility during the COVID-19 shock.

The results are presented in Table 6. In Specification (1), which does not include firm or day fixed effects, the interaction term between the COVID period and ES High firms (COVID * ES High) is negative and statistically significant (–0.005, t = –3.07) (firms in the top quartile of ES scores experienced lower daily price fluctuations during the initial pandemic market disruption). Similarly, the interaction between the fiscal stimulus period and ES High firms (Fiscal * ES High) is also negative and significant at 10 percent (–0.007, t = –1.96), indicating that volatility reductions for these firms may have persisted into the policy response phase.

Importantly, the standalone effect of being a high-ES firm is strongly negative (–0.010, t = –13.97), confirming that these companies tended to exhibit lower intraday price swings even outside the crisis periods. Moreover, the COVID and Fiscal period dummy variables are both positively and significantly associated with higher price range, consistent with the elevated market uncertainty during those windows.

In Specification (2), which incorporates both firm and day fixed effects that control for firm-specific unobservables and common macroeconomic factors, the key interaction terms remain negative and significant at the 1 percent and 10 percent levels, respectively. This builds up to the idea that high-ES firms had more stable trading during the COVID-19 shock, even after considering firm-specific traits and overall market trends. Although the effects are not

Table 6: Difference-in-Differences Regressions for Daily Price Range

*This table reports the results of DiD regressions examining the effect of ES scores on daily price range during the first quarter of 2020. Column (1) shows results without fixed effects, while column (2) includes both firm and day fixed effects (that control for firm-specific unobservables and common macroeconomic factors). The variable COVID × ES High captures the interaction between the COVID sell-off period and high ES firms. Fiscal × ES High captures the interaction during the fiscal stimulus window. Figures in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1) Daily Range	(2) Daily Range
COVID × ES High	–0.005***	–0.005***
	(–3.07)	(–2.93)
Fiscal × ES High	–0.007*	–0.007*
	(–1.96)	(–1.88)
ES High	–0.010***	
	(–13.97)	
COVID period	0.051***	
	(5.80)	
Fiscal period	0.042***	
	(2.85)	
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	82,329	82,329
R^2 adjusted	0.384	0.636

large, they are consistent and statistically significant, which strengthens the view that strong ESG performance can help reduce stock price swings during times of stress.

These findings complement the patterns observed in the abnormal return regressions (Section 3.1). While ES strength did not robustly shield firms from return losses in the initial specification, the final model shows that ES is significantly associated with abnormal return performance when firm fundamentals are considered. Together with the lower intraday volatility, this reinforces the view that a strong ESG performance contributed to greater market stability during the crisis.

4.5.2 Difference-in-Differences Analysis of Trading Volume

Higher trading volume during periods of market stress may indicate that investors continue to transact with confidence, rather than abandoning a firm's stock due to uncertainty or illiquidity concerns (Investopedia, n.d.). I conduct a Difference-in-Differences (DiD) regression on firm-day trading volume, following the same structure as in the previous analyses.

The results are presented in Table 7. In Specification (1) without Day and Firm fixed effects, the interaction between high ES status and the COVID period is positive and statistically significant (4.200, t = 3.80). This shows that during the peak of the market sell-off, high-ES firms had a significant rise in trading volume relative to their peers. A similar pattern is observed throughout the fiscal stimulus period, with the interaction term similarly positive and significant (0.753, t = 3.81). These findings indicate that high-ES firms remained actively traded even as market conditions worsened and later recovered. The effect remains in Specification (2) when unobserved heterogeneity across firms and market-wide shocks on the specific day are absorbed. For the COVID * ES High interaction as it stays statistically significant (4.194, t = 3.29), indicating that high-ES firms experienced higher trading volumes during the initial market crash. However, the Fiscal * ES High term becomes statistically insignificant (0.758, t = 1.35) once fixed effects are included. This drop tells that the earlier observed increase in trading volume around the fiscal stimulus may have been driven by firm-level traits or overall market movements.

Table 7: Difference-in-Differences Regressions for Daily Trading Volume

*This table reports the results of DiD regressions examining the effect of ES scores on daily trading volume during the first quarter of 2020. Column (1) shows results without fixed effects, while column (2) includes both firm and day fixed effects (that control for firm-specific unobservables and common macroeconomic factors). The variable COVID × ES High captures the interaction between the COVID sell-off period and high ES firms. Fiscal × ES High captures the interaction during the fiscal stimulus window. Figures in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

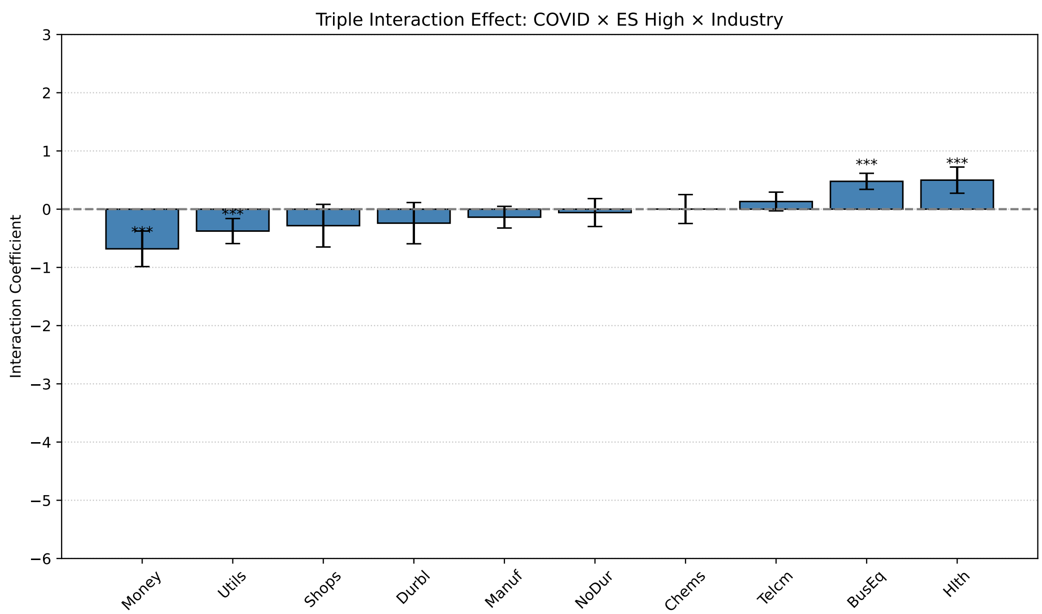
	(1) Volume	(2) Volume
COVID × ES High	4.200***	4.194***
	(3.80)	(3.29)
Fiscal × ES High	0.753***	0.758
	(3.81)	(1.35)
ES High	5.610***	
	(3.59)	
COVID period	0.671***	
	(7.09)	
Fiscal period	0.143	
	(1.06)	
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	82,331	82,331
R^2 adjusted	0.028	0.810

5 Robustness

Now I perform several robustness checks, firstly, to evaluate whether the results are driven by sector-specific dynamics, I begin by re-estimating the main regression using industry-specific triple interaction terms between the COVID period, high ES score, and industry dummies. This analysis is conducted on the same dataset used throughout the core of this thesis, which excludes firms classified in the Energy and Other sectors based on the Fama-French 12-industry classification. These two sectors were omitted in the main specification due to concerns over interpretability and potential structural shocks unrelated to ES performance such as oil price decline for energy sector (Investopedia, 2020; SP Global Market Intelligence, 2021). The estimated coefficients for each industry are displayed in Figure 4.

Figure 4: *

This figure plots the estimated coefficients from a difference-in-differences regression allowing for triple interactions between *Dummy_COVID*, *Dummy_ES_High*, and industry dummies, excluding "Energy" and "Other." The bars represent point estimates with two-standard-error bands.

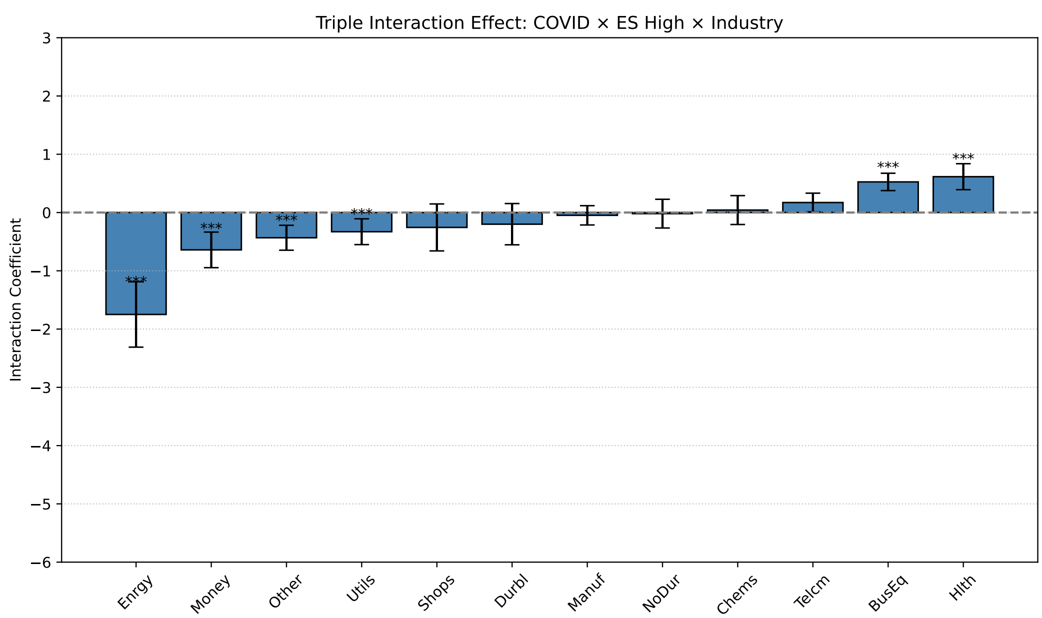


The results reveal that only two industries, Business Equipment and Health, display statistically significant positive interaction, indicating that high-ES firms in these sectors experienced better abnormal returns during the COVID-19 shock. In contrast, Money and Utilities exhibit statistically significant negative coefficients, suggesting that ES strength did not shield firms in those sectors from crisis-related underperformance. The remaining industries show mostly negative but statistically insignificant effects. This distribution implies that the ESG-performance relationship is not uniformly positive and may depend on sector-specific characteristics.

To further investigate, I now include Energy and Other sectors for the first time and re-estimate the regression with the full industry coverage. The results are presented in Figure 5. The inclusion of Energy and Other adds important nuance to the analysis. Both sectors have large and statistically significant negative coefficients, with Energy showing the most negative effect among all industries. This suggests that even firms with high ES scores in these sectors experienced substantial underperformance during the crisis, likely due to the oil price collapse in the case of Energy (Investopedia, 2020), and the mixed or ambiguous classification of firms within the Other category. Therefore, these results indicate that while high ES performance appears to offer resilience in certain industries, its effects are not uniform.

Figure 5: *

This figure extends the previous analysis by including all Fama-French 12 industries. It adds the *Energy* and *Other* sectors to the triple interaction specification. Bars represent coefficients of *Dummy_COVID* × *Dummy_ES_High* × industry dummies with two-standard-error bands.



As the next robustness check, I modify the definition of the COVID period by setting the covid dummy variable equal to one starting from January 30, 2020, the date on which the World Health Organization declared COVID-19 a global public health emergency instead of February 24, 2020, as in the baseline specification (World Health Organization, 2020). This adjustment allows for the possibility that markets began reacting earlier to the escalating pandemic. The difference-in-differences regressions are then re-estimated for all initial regressions. The resulting tables 9,10, and 11 are in the appendix.

The results for abnormal returns remain largely consistent with the baseline findings. Although the COVID period dummy loses some magnitude and significance in the revised model, the core coefficient of interest remains stable.

Similarly, the results for daily price range (Tables 6 and 10) also remain robust, as similar results are obtained. The interaction between COVID * ES High is negative and significant level across all specifications. The fiscal * ES High coefficient remains significant in both models and becomes slightly stronger with the revised COVID definition.

The only noteworthy shift occurs in the analysis of daily trading volume (Tables 7 and 11). While the COVID * ES High coefficient remains large, positive, and statistically significant across both specifications, the fiscal * ES High interaction becomes significant at the 1 percentage level in the revised model, where it was previously insignificant. This can suggest that under the broader covid definition, market participants may have reallocated capital more decisively toward high-ES firms not just during the crisis sell-off, but also in the fiscal stimulus phase.

Overall, the results under the revised COVID timing confirm the robustness of the baseline findings.

As the last robustness check, I expand the sample to include firms from the Energy and Other sectors, which were excluded from the main analysis, and conduct repeat cross-sectional regressions from table 3 and 5.

The results in Table 12 show that including these sectors slightly alters the coefficient on ES in the simplest specification, where it turns negative. This likely reflects disruptions in the Energy sector during early 2020 as it was shown before, such as the oil price collapse (Investopedia, 2020).

The extended cross-sectional regressions of volatility and idiosyncratic volatility reported in Table 13 continue to show a strong, negative, and highly significant relationship with ES scores consistent with the original results.

6 Conclusion

This thesis examined whether firms with stronger Environmental and Social (ES) scores exhibited greater resilience in the face of the COVID-19 market shock. By replicating and extending the study by Albuquerque et al. (2020) on a new sample of companies and employing both cross-sectional and difference-in-differences (DiD) regressions, the analysis offers nuanced evidence on the role of ES performance in shaping stock behavior during a systemic crisis.

The findings indicate that ES scores are significantly associated with lower total and idiosyncratic volatility, as well as smaller daily price ranges, supporting the risk-mitigation potential of good ESG practices. Additionally, firms with high ES scores maintained higher trading volumes during the sell-off, indicating continued investor interest and liquidity in their stocks. In terms of stock returns, the correlation between ES performance and abnormal returns is more conditional. While no strong differential return pattern is revealed using the DiD regression, cross-sectional regressions indicate that firms with high ES scores experienced significantly higher returns but only after controlling for industry effects and firm-level factors.

However, the analysis also reveals that these benefits are not universally distributed across sectors, suggesting that the value of ESG resilience may be context specific.

Robustness checks including alternative COVID period definitions, full sample inclusion, and triple interactions by industry including all Fama-French 12 industries, support the validity of the core results, with minor differences.

This thesis concludes that ES scores do enhance firm resilience during periods of heightened uncertainty, especially by lowering risk exposure and sustaining investor confidence. However, the benefits of ES are neither uniform nor automatic. Since they interact with industry conditions and financial foundations, it is crucial to consider ESG as a component of a larger company profile rather than as a stand-alone cushion. These observations highlight the significance of context when assessing the financial materiality of ESG issues and add to the continuing discussion in sustainable finance with different conclusions and points of view.

References

Abdulla, S., Saba, Z., 2025. Governance, Resilience, and Sovereign Credit Ratings: Implications for ESG Investing Strategies. Asian Development Bank Working Paper.

Albuquerque, R., Koskinen, Y., Yang, S., Zhang, C., 2020. Love in the Time of COVID-19: The Resiliency of Environmental and Social Stocks. The Review of Corporate Finance Studies, 9(3), 593–621.

Albuquerque, R., Koskinen, Y., Zhang, C., 2019. Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence. Management Science, 65(10), 4451–4469.

Amel-Zadeh, A., Serafeim, G., 2018. Why and How Investors Use ESG Information: Evidence from a Global Survey. Financial Analysts Journal, 74(3), 87–103.

Barney, J., 1991. Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99–120.

Berg, F., Fabisik, K., Sautner, Z., 2020. Is History Repeating Itself? The (Un)Predictable Past of ESG Ratings. European Corporate Governance Institute – Finance Working Paper, 708/2020.

Berkman, H., Tirodkar, M., 2024. ESG Investing During Calm and Crisis: Implied Expected Returns. SSRN Electronic Journal.

Bouslah, K., Kryzanowski, L., M'Zali, B., 2018. Social Performance and Firm Risk: Impact of the Financial Crisis. Journal of Business Ethics, 149(3), 643–669.

Broadstock, D.C., Chan, K., Cheng, L.T.W., Wang, X.W., 2020. The Role of ESG Performance During Times of Financial Crisis: Evidence from COVID-19 in China. Finance Research Letters, 38, 101716.

Cornell, B., 2021. ESG Preferences, Risk and Return. European Financial Management, 27(1), 12–19.

Cornett, M.M., Erhemjamts, O., Tehranian, H., 2016. Greed or Good Deeds? An Examination of the Relation Between CSR and Financial Performance of U.S. Commercial Banks. Journal of Banking Finance, 70, 137–159.

Demers, E., Hendrikse, J., Joos, P., Lev, B., 2021. ESG Didn't Immunize Stocks During the COVID-19 Crisis, But Investments in Intangible Assets Did. Journal of Business Finance Accounting, 48(3–4), 433–462.

Ding, W., Levine, R., Lin, C., Xie, W., 2023. Corporate Immunity to the COVID-19 Pandemic. Journal of Financial Economics, 141(2), 802–830.

Dursun-de Neef, H.Ö., Forchieri, J., Gehrig, T., Schandlbauer, A., 2023. How Did Banks' ESG Conduct Affect Financial Performance and Lending During COVID-19? SSRN Electronic Journal.

Ferrell, A., Liang, H., Renneboog, L., 2016. Socially Responsible Firms. Journal of Financial Economics, 122(3), 585–606.

Freeman, R.E., 1984. Strategic Management: A Stakeholder Approach. Pitman.

French, K.R., 2024. Fama/French 12 Industry Classification Definitions. Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/DataLibrary/det12indport.html

Gianfrate, G., 2023. On the Resilience of ESG Firms During the COVID-19 Crisis: Evidence Across Countries and Asset Classes. Journal of International Business Studies, 54(1), 1–25.

Heinkel, R., Kraus, A., Zechner, J., 2001. The Effect of Green Investing on Corporate Behavior. Journal of Financial and Quantitative Analysis, 36(4), 431–449.

Hoang, T.-H.-V., Segbotangni, E.A., Lahiani, A., 2020. Does ESG Disclosure Transparency Help Mitigate the COVID-19 Pandemic Shock? An Empirical Analysis of Listed Firms in the UK. SSRN Electronic Journal.

Hoang, T.-H.-V., Segbotangni, E.A., Lahiani, A., 2021. ESG Performance and COVID-19 Pandemic: An Empirical Analysis of European Listed Firms. SSRN Electronic Journal.

Hong Kong Institute for Monetary and Financial Research (HKIMR), 2022. The Impact of ESG Rating on the Asymmetrical Volatility-Return Relationship: Early Evidence from a Weight-Tilted Hang Seng Index. Journal of Risk and Financial Management, 17(2), 57.

Investopedia, 2020. What Happened to Oil Prices in 2020. Retrieved from https://www.investopedia.com/articles/investing/100615/will-oil-prices-go-2017.asp

Investopedia, n.d. Why Trading Volume Is Important to Investors. Retrieved from https://www.investopedia.com/ask/answers/041015/why-trading-volume-important-investors.asp

Lins, K.V., Servaes, H., Tamayo, A., 2017. Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility During the Financial Crisis. Journal of Finance, 72(4), 1785–1824.

Mackintosh, J., 2020. ESG Investing in the Pandemic Shows Power of Luck. The Wall Street Journal, 15 July.

Marín, E., Nave, J.M., Toscano, D., 2023. ESG and Stock Market Resiliency During COVID-19: An Industry-Specific Approach. SSRN Electronic Journal.

Neuenroth, K., Zureck, A., 2024. The Influence of ESG Ratings on the Performance of Listed Companies in Germany During Crisis. SSRN Electronic Journal.

Pastor, L., Vorsatz, M.B., 2020. Mutual Fund Performance and Flows During the COVID-19 Crisis. The Review of Asset Pricing Studies, 10(4), 791–833.

Ramelli, S., Wagner, A.F., 2020. Feverish Stock Price Reactions to COVID-19. Swiss Finance Institute Research Paper, No. 20-12.

Rubbaniy, G., Khalid, A.A., Rizwan, F., Ali, S., 2021. Are ESG Stocks Safe-Haven During COVID-19? Studies in Economics and Finance, 39(2), 239–255.

SP Global Market Intelligence, 2021. SP 500 posted 2020 gains as COVID-19, oil price crash obliterated energy sector. Retrieved from https://www.spglobal.com/market-intelligence/en/news-insights/articles/2021/1/s-p-500-posted-2020-gains-as-covid-19-oil-price-crash-obliterated-energy-sector-61975042

Shiller, R.J., 2003. From Efficient Markets Theory to Behavioral Finance. Journal of Economic Perspectives, 17(1), 83–104.

Spence, M., 1973. Job Market Signaling. The Quarterly Journal of Economics, 87(3), 355–374.

U.S. News, 2020. Senate Passes Coronavirus Relief as Congress Crafts 1 Trillion Stimulus. Retrieved from https://www.usnews.com/news/politics/articles/2020-03-18/senate-passes-coronavirus-relief-as-congress-crafts-1-trillion-stimulus

Vanity Fair, 2020. The Dow Dropped 1,000 Points as Trump Bashed the Media, Ignored the Coronavirus. Retrieved from https://www.vanityfair.com/news/2020/02/donald-trump-coronavirus-stock-market

World Health Organization, 2020. Statement on the second meeting of the International Health Regulations (2005) Emergency Committee regarding the outbreak of novel coronavirus (2019-nCoV), 30 January 2020. [online] Retrieved from https://www.who.int/news/item/30-01-2020-statement-on-the-second-meeting-of-the-international-health-regulations

Yang, S.S., Huang, J.-W., Chen, H.-Y., 2022. Detecting Corporate ESG Performance: The Role of ESG Materiality in Corporate Financial Performance and Risks. SSRN Electronic Journal.

Yarwood, G., 2024. Are ESG Investors More Resilient? An Examination of ESG Fund Flows. SSRN Electronic Journal.

Yi, J., Ahn, T.-W., 2023. ESG Controversies and Firm Value: Moderating Role of ESG Performance. SSRN Electronic Journal.

Zhou, G., Lin, H., Luo, S., 2022. COVID-19 Impact, ESG Performance and Stock Price Volatility Risk. SSRN Electronic Journal.

APPENDIX

Table 8: Summary statistics for all variables

This table reports the summary statistics (number of observations, mean, standard deviation, 25th, 50th (median), and 75th percentiles) for all variables used in the analysis. The Appendix provides the definition and data sources for all variables.

Variable	**Obs.**	**Mean**	**Std. Dev.**	**25%**	**Median**	**75%**
Abn Return_cum (%)	1330	−6.734	30.179	−22.369	−4.824	10.643
ES	1330	0.347	0.236	0.155	0.279	0.520
Volatility	1330	0.054	0.018	0.042	0.049	0.061
Idiosyncratic Volatility	1330	0.042	0.020	0.037	0.040	0.050
Abnormal Return (Daily, %)	81 130	−0.110	4.658	−1.500	−0.079	1.209
Daily Price Range	82 229	0.056	0.057	0.020	0.037	0.073
Trading Volume (in millions)	82 331	3.131	21.157	0.220	0.659	1.893
Tobin's Q	1330	2.395	1.833	1.243	1.747	2.841
Size	1330	7.975	1.788	6.662	7.902	9.171
Cash	1330	0.116	0.137	0.023	0.069	0.157
Leverage	1330	0.261	0.199	0.077	0.267	0.399
ROE	1282	0.125	0.534	0.044	0.140	0.251
Advertising	1330	0.037	0.085	0.000	0.000	0.030

Table 9: Difference-in-Differences Regressions for Abnormal Returns

*This table reports the results of DiD regressions examining the effect of ES scores on daily abnormal returns during the first quarter of 2020. COVID period equals one from 30th January to 31st March 2020, and zero before this period, in contrast to the baseline model, which measures from 24th February, everything else is the same. Column (1) reports results without fixed effects, while column (2) includes both firm and day fixed effects. Figures in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

	(1) AbnRet	(2) AbnRet
COVID × ES High	0.189	0.189
	(1.67)	(1.66)
Fiscal × ES High	-0.536	-0.536
	(-0.79)	(-0.79)
ES High	-0.017	
	(-0.40)	
COVID period	-0.282*	
	(-1.78)	
Fiscal period	0.955	
	(0.84)	
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	81,130	81,130
R^2 adjusted	0.004	0.070

Table 10: Difference-in-Differences Regressions for Daily Price Range

*This table reports the results of DiD regressions examining the effect of ES scores on daily price range during the first quarter of 2020. COVID period equals one from 30th January to 31st March 2020, and zero before this period, in contrast to the baseline model, which measures from 24th February, everything else is the same. Column (1) shows results without fixed effects, while column (2) includes both firm and day fixed effects. Figures in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

	(3) Range	(4) Range
COVID × ES High	-0.003**	-0.003**
	(-2.66)	(-2.48)
Fiscal × ES High	-0.009***	-0.009***
	(-2.85)	(-2.75)
ES High	-0.010***	
	(-13.56)	
COVID period	0.029***	
	(4.55)	
Fiscal period	0.066***	
	(4.96)	
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	82,329	82,329
R^2 adjusted	0.288	0.636

Table 11: Difference-in-Differences Regressions for Daily Trading Volume

*This table reports the results of DiD regressions examining the effect of ES scores on daily trading volume during the first quarter of 2020. COVID period equals one from 30th January to 31st March 2020, and zero before this period, in contrast to the baseline model, which measures from 24th February, everything else is the same. Column (1) shows results without fixed effects, while column (2) includes both firm and day fixed effects. Figures in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

	(5) Volume	(6) Volume
COVID × ES High	3.049***	3.046***
	(3.02)	(2.84)
Fiscal × ES High	2.466***	2.468***
	(5.89)	(3.17)
ES High	5.048***	
	(3.97)	
COVID period	0.383***	
	(4.33)	
Fiscal period	0.454***	
	(3.02)	
Firm FE	No	Yes
Day FE	No	Yes
Number of firm-days	82,331	82,331
R^2 adjusted	0.027	0.809

Table 12: Cross-sectional regressions of abnormal returns on ES ratings

*This table reports the results of regressions of first-quarter 2020 cumulative abnormal returns on firms' ES ratings with all Fama-French 12 industries included. Column (1) includes only ES scores, column (2) adds industry fixed effects, and column (3) adds firm-level controls. Figures in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1) Abn Return_cum	(2) Abn Return_cum	(3) Abn Return_cum
ES	–0.329 (–0.20)	1.138 (0.70)	3.266*** (3.39)
Tobin's Q			3.402*** (4.18)
Size			3.395*** (6.19)
Cash			18.751*** (3.73)
Leverage			–18.956*** (–3.83)
ROE			–0.584 (–1.61)
Advertising			–4.040 (–0.57)
Industry FE	No	Yes	Yes
Number of firms	1619	1619	1619
Adj. R^2	–0.001	0.224	0.314

Table 13: Cross-sectional regressions of volatility and idiosyncratic volatility on ES ratings

*This table presents cross-sectional regressions of total and idiosyncratic volatility on firms' ES ratings during Q1 2020 with all Fama-French 12 industries included. Each specification adds more controls sequentially. Columns (1)–(3) use total volatility as the dependent variable, while columns (4)–(6) use idiosyncratic volatility. Figures in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

	Vol (1)	Vol (2)	Vol (3)	Idio (1)	Idio (2)	Idio (3)
ES	–1.762***	–1.741***	–2.056***	–2.452***	–2.447***	–2.682***
	(–7.54)	(–6.60)	(–6.99)	(–9.89)	(–8.77)	(–9.18)
Tobin's Q			–0.031			–0.024
			(–0.82)			(–0.63)
Size			–0.427***			–0.543***
			(–8.65)			(–11.41)
Cash			0.059			0.254
			(0.12)			(0.41)
Leverage			2.374***			2.088***
			(6.07)			(6.87)
ROE			–0.004			–0.018
			(–0.15)			(–0.63)
Advertising			0.476			0.982**
			(1.16)			(2.16)
Industry FE	No	Yes	Yes	No	Yes	Yes
Number of firms	1619	1619	1619	1619	1619	1619
Adj. R^2	0.043	0.260	0.302	0.072	0.170	0.302