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Does sustainability activities performance matter during financial crises? Investigating the case of COVID-19

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ABSTRACT

As a market for sustainability investing is growing rapidly, understanding the impact of environmental, social, and governance (ESG) activities on firms’ financial performance is becoming increasingly important. In this study, we examine the effect of ESG performance on stock returns and volatility during the financial crisis resulting from the coronavirus (COVID-19) pandemic. To quantify the impact, we use company-level daily ESG score data and United Nations Global Compact (GC) score data. In our dataset, ESG scores indicate ESG performance that is deemed important to financial materiality, and the GC score indicates the firm reputation for following UN rules. Our results indicate that during the pandemic, an increase in the ESG score, especially the E score component, is related to higher returns and lower volatility. Conversely, increasing GC scores is correlated with lower stock returns and higher volatility. In addition, we find that firms in lower return groups benefit more than other firms. Focusing on energy sector impacts, we show that although the non-energy sector benefits more than the energy sector from increasing E scores, energy sector firms can still reduce their stock price volatility by increasing these scores. Our study offers significant implications for ESG investment strategies during financial crises.

1. Introduction

The rapid spread of coronavirus-19 (COVID-19) has resulted in more than 37,740,227 cases and 1,081,408 deaths worldwide as of October 12, 2020 (World Health Organization, 2020). Furthermore, COVID-19 has had negative impacts on financial and stock markets as countries have halted economic activities as a result of social distancing requirements and lockdowns. For example, the market value of the Standard & Poor 500 index has dropped around 30% since the outbreak of COVID-19 (Shehzad et al., 2020). Many countries, including the US, UK, China (Ashraf, 2020; Zhang et al., 2020; Al-Awadhi et al., 2020), and the emerging markets (Topcu and Gulal, 2020) have suffered from falls in stock values. On average, stock values have fallen around 10%–30%, meaning the falls are even more substantial than during the 2008–2009 global financial crisis (Shehzad et al., 2020). In addition, the rapid spread of COVID-19 has resulted in a significant impact on energy investment, with capital spending in this sector expected to decline by around 20% (or USD 400 billion) compared with 2019 (IEA, 2020).

The following questions then arise: what kinds of firms are more resilient toward financial crises triggered by disaster events such as the COVID-19 pandemic, and how can firms reduce the risk of their financial performance declining during such crises? Some existing studies highlight that firms pursuing green finance, and therefore demonstrating high “social capital” levels, are more resilient in times of crisis, as this gives them the capacity to reduce the risks (see Albuquerque et al., 2019 and Servaes and Tamayo, 2017). As mentioned in Sachs et al. (2019) and Ng (2019), green finance involves ensuring sustainability through firmly established institutions and systems. Thus, it encompasses environmental, social, and governance (ESG) attributes and firms’ financial performance.1 Sachs et al. (2019) and Ng (2019), among others, demonstrate the importance of green finance from a macroeconomic perspective.

Along with the growth of the green finance market, there is an increasing number of studies exploring how to facilitate green finance more effectively. Fostered by top-down changes—including the European Union’s sustainable finance taxonomy and Hong Kong’s compulsory reporting framework—and increasing investor and consumer interest in ESG performance and transparency, the market for ESG

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1 Therefore, in this work, we regard ESG as closely related to green finance, as both seek to ensure firm sustainability.
investments has almost doubled over the last 4 years, and more than tripled over the last 8 years. ESG criteria are a set of standards for a firm’s operations that socially conscious investors use to screen potential investments. In 2020, the market size reached $40.5 trillion in assets under management (Baker, 2020). The UN Principles for Responsible Investment (PRI) consider the incorporation of ESG into credit ratings and analysis by credit rating agencies and fixed income investors as the key to further facilitating green finance. Led by the UN PRI, more than 160 investors (with around US$30 trillion in collective assets under their management) and 23 credit rating agencies have signed the “Statement on ESG in credit risk and ratings” (PRI, 2020).

With the growing ESG investment market, there is an increasing number of studies supporting the view that firms with high ESG performances experience lower downside risk and are more resilient during both normal times and turbulent times. In recent studies, a theoretical framework developed by Albuquerque et al. (2020) illustrated that firms’ sustainability activities increase product differentiation and provide product portfolio diversification. Hoepner et al. (2019) investigated the relationship between ESG performances and financial risk using data covering the period between January 2005 and April 2018, and showed that engagement with ESG issues reduces downside risk. Similarly, Mendiratta et al. (2020) examined the relationship between financial risk and performance characteristics of ESG score percentiles (high, medium and low ESG ratings) using monthly data covering 2014 to 2020, and found that the upper percentiles had improved risk characteristics and showed better risk-adjusted returns than the lower tercile. Other similar recent empirical studies include Ilhan et al. (2019) and Jacobsen et al. (2019). Although these studies provide valuable evidence to deepen our understanding on the impact of firms’ ESG performance on their financial performance in general, there is still limited research on the effects of ESG performance during financial crises. Lins et al. (2017) investigated the case of the 2008-09 global financial crisis, and showed that US firms with higher ESG scores have better financial performance than other firms during this period. Cornett et al. (2016) found that the financial performance of banks in the US is positively related to their ESG scores during the 2008-09 global financial crisis, and Nofsinger and Varma (2014) showed that ESG funds outperformed other funds during the market crisis.

The recent market-wide financial crisis triggered by the rapid spread of COVID-19 provides an opportunity to test the resilience of ESG and responsible investment solutions, yet there are only few studies investigating the impact of ESG activities during the recent market fallout. Broadstock et al. (2020) investigated the role of ESG performance in China during the market-wide financial crisis triggered by the rapid spread of COVID-19. They showed that higher ESG performance lowered financial risk in this situation. However, the role of ESG performances during the stock market crisis brought about by the rapid spread of COVID-19 has yet to be explored thoroughly. Thus, this study aims to fill this gap by utilizing daily, worldwide, company-level ESG score data to examine the relationship between financial performance and ESG attributes during the recent market crisis. In addition, we employ the United Nations Global Compact (GC) score to investigate to what extent a firm’s reputation for following the UN’s rules influences financial performance during the crisis. To this end, we estimate a model to investigate the relationship between daily ESG and GC scores, and the stock returns and volatility of all firms in our data set. In addition, we conduct a further analysis focusing on the energy sector, which is expected benefit from a large amount of green finance flow.

The overall ESG score consists of separate environmental (E), social (S), and governance (G) scores. The scores enable us to identify sustainable companies that are better positioned to outperform others over the long term, based on the principles of financial materiality. The GC score serves as an indication of the reputational risk that companies are exposed to in relation to the four core principles of the UN GC, which is composed of the human rights (GC_HR), anti-corruption (GC_AC), labor rights (GC_LR), and environment (GC_E) scores. The GC score allows us to investigate whether firms are pursuing higher reputations in relation to these four core principles of the UN GC. Our estimation results confirm that a higher E score is correlated with higher returns and lower volatility, whereas increasing GC_E scores are related to a reduction in returns and higher volatility. Although the E and GC_E scores were the dominant factors for stock returns and volatility, we find less evidence of their relationship to other social and governance aspects. Finally, as noted above, we conducted an analysis focusing on the energy sector. The estimation results show that although the non-energy sector would benefit more from increasing E scores compared with the energy sector in terms of both stock returns and volatility, firms belonging to the energy sector can still reduce their stock price volatility by increasing their E scores.

Our findings contribute to the literature by providing quantitative evidence of the role of ESG performance during financial crises. Our results are in line with the results obtained by Broadstock et al. (2020) that investigated the role of ESG performance focusing on China uring the recent market crisis triggered by the rapid spread of COVID-19, and supports the argument made by preceding studies that examine the impact of ESG activities on financial performances during the 2008-09 global financial crisis by providing empirical evidence that higher ESG performance lower financial risk during financial crises. In addition, we shed light on the importance of separating the financial performance benefits into those gained from ESG activities (ESG scores) and those from ESG-related reputations (GC scores), which may be an important direction for future research.

The remainder of this paper is structured as follows. Section 2 describes the data and the empirical model used in the study. Section 3 provides the empirical results, conducts robustness tests of the models, and discusses the results. Finally, Section 4 concludes.

2. Methodology

In this section, we first describe the data used in this study in Section 2.1 by providing descriptive statistics and confirming the trend between ESG metrics and stock returns. Then, we present our empirical model in Section 2.2.

2.1. Data

We collate data on firms’ daily ESG and GC scores from the Arabesque S-Ray to construct our data sample of over 2887 companies from October 2019 to June 2020. S-Ray’s ESG scores are calculated after a sector-specific analysis of corporate ESG performance. First, the ESG score shows whether firms earn profits because of consideration of their ESG behavior. Second, the GC score provides a normative assessment of companies based on the four UN GC core principles (human rights, labor rights, the environment, and anti-corruption, as noted above). Table 1 explains the components included in the scores, with score names and notations. Whereas the ESG scores represent the corporate performance derived from ESG activities, GC scores are indicative of the firm’s reputation for following the UN GC norms. Thus, the analysis in this study shows whether investments that consider the firm’s reputation or their long-term profitability related to ESG are beneficial for the firm’s financial performance.

To calculate the scores, S-Ray collects a wide range of data from three types of sources. First, it collects data from the reports on a company’s sustainability performance from non-financial disclosures (released on an annual basis). Second, S-Ray scans over 30,000 daily public news sources for sustainability-related controversies, using natural language processing. In this process, S-Ray mainly collects news on “controversies”, that is, negative or unfavorable news. To be specific, S-Ray aggregates news-based controversies using a proprietary present

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2 We present the list of sectors and industries in Table A1 in the Appendix.
news value, which is a function of the article’s controversy level, how long it has taken, and the impact of the source. Then, S-Ray deducts the points calculated from the controversies from those gained as a result of the annual report calculations. Third, S-Ray tracks nongovernmental organizations’ campaigns on sustainability on a regular basis. After collecting the data, S-Ray computes the long-term trends by aggregating firms’ long-term performance trends by topic based on ESG considerations according to the expert opinions. In short, S-Ray corrects the long-term trends by updating them on a short-term basis.

Therefore, one unique characteristic of the S-Ray data is that it reflects the firms’ daily commitment to ESG-related activities, whereas other sources mainly use annual reports. As stock prices are likely to respond quickly to daily score updates, our data enable us to examine the relationship between ESG-related activities and stock prices more closely and accurately.

We merge the S-Ray data with the monthly stock price data, provided from two different sources, Quick’s Quick FactSet Workstation and Refinitiv Eikon, which contains the monthly stock prices of 2884 firms worldwide. Using the stock prices, we calculate the monthly raw return (%), the abnormal returns (the raw returns minus the expected returns), and volatility for our study period. Hereafter, we use the term “returns” to refer to the raw returns for simplicity. All of the variables were estimated from October 2019 to June 2020. As our scores are measured on a daily basis, we take a monthly average of the daily scores when merging our data with the stock price data. This merging does not dilute the benefit of using daily data. Our score data still efficiently capture the daily score trends, as we sum the daily scores to obtain monthly values rather than using data measured every month.

Table 2 displays descriptive statistics. The upper column of Table 2 shows the variables before the COVID-19 outbreak, and the lower column displays the variables after the COVID-19 outbreak. The first to fourth rows of each column shows variables related to stock prices, including stock prices (Million USD), returns, abnormal returns, and volatility. (We henceforth use the term ‘returns’ which indicate ‘raw returns’ for simplicity.) We find that all of these values decreased after the COVID-19 outbreak compared to the pre-COVID-19 period, indicating that investors and other stakeholders were likely quite concerned about the market prospects of many of the firms they held in their portfolios, worked for, or interacted with in business transactions after COVID-19.

We choose to aggregate our daily ESG/GC score data to monthly data. Whether it is better to use daily or monthly data depends on our research objectives. Using daily data would have implications based on high-frequency data; for example, if we want to investigate ‘instant’ changes after a particular event, using daily data would be better. On the other hand, using monthly data would provide insights on relatively long-term trends, focusing less on noises and fluctuations daily.

Another reason why we choose monthly data is due to the primary benefit of using monthly returns data over daily data. With monthly information, returns are at least approximately normally distributed (or, at the very least, the simplifying assumption of normality is much less fluctuating for monthly returns than it is for daily returns). As our research is more focused on investigating long-term trends and providing insights into rational portfolio decisions, we choose to use monthly data.

To capture the changing trends in stock returns and the scores, we define January 2020 as the start of the COVID-19 period and examine the impacts of ESG-related activities from then. Before conducting the analysis, Fig. 1 shows the time trend for the average monthly stock price returns and ESG scores in Panel (A) and GC scores in Panel (B).

First, we confirm that in both panels, the stock returns start to slowly fall from January 2020 (from around 2.89% in January 2020 to -2.91% in February 2020), the time when the COVID-19 outbreak started, and fall rapidly, by ~19%, until March 2020, before recovering from April 2020. Second, Panel (A) indicates that the E, S, and G scores increase from December 2019. However, the G score begins to fall around January 2020, followed by the E and S scores in February 2020, and all three fall further again in May 2020. While the stock returns show an increasing trend from April 2020, the ESG scores fall rapidly from May 2020, then dramatically increase. Third, the GC scores show a falling trend from January 2020, increase rapidly again from February 2020, fall again in March 2020, and then increase from May to June 2020.

From the time series data alone, we can see that the scores move together with a time lag of approximately one month, and that they share symmetric patterns: a reduction in the stock price return is followed by falls in the scores. That is, the stock return decreases slightly from November to December 2019, then the scores decrease around December 2019 to January 2020. Similarly, the stock return falls around January to February 2020, with the scores following suit in around February to March 2020. Finally, when the stock return falls dramatically in March 2020, the scores show significant decreases around May 2020.

Thus, the time series data suggest that changes in stock returns and ESG activities scores move together with a time lag after the COVID-19 outbreak. Thus, when we present our model in Section 3.2, we take into account the ESG activity scores post-COVID-19, and consider whether ESG activity scores are crucial to the stock prices returns.

2.2. Empirical strategy

As we are interested in investigating whether ESG activities are
Table 2
Descriptive statistics.

|                      | Before COVID-19                | After COVID-19                |
|----------------------|--------------------------------|------------------------------|
|                      | Obs.  | Mean  | Std. Dev. | 25% Percentile | Median  | 75% Percentile |
| Stock Price (Million USD) | 8568  | 60.326| 206.190   | 8.470          | 25.440  | 57.400         |
| Return               | 8556  | 0.074 | 3.534     | -0.045         | 0.001   | 0.035          |
| Abnormal Return      | 8556  | 0.484 | 4.701     | -3.796         | 2.416   | 2.897          |
| Volatility           | 8558  | 1.149 | 12.279    | 0.106          | 0.251   | 0.560          |
| E score              | 8495  | 50.678| 13.866    | 36.910         | 49.527  | 62.505         |
| S score              | 8495  | 52.920| 8.716     | 45.970         | 52.785  | 59.720         |
| G score              | 8495  | 50.133| 13.208    | 40.597         | 50.850  | 59.648         |
| GC HR score          | 8587  | 51.318| 9.825     | 43.595         | 51.396  | 59.088         |
| GC LR score          | 8589  | 53.234| 9.362     | 46.023         | 53.515  | 60.587         |
| GC E score           | 8589  | 50.324| 12.542    | 37.050         | 48.970  | 61.936         |
| GC AC score          | 8589  | 54.666| 5.435     | 51.869         | 54.763  | 58.155         |
| Stock Price (Million USD) | 19,951| 59.332| 214.950   | 7.270          | 22.590  | 55.150         |
| Return               | 19,925| -0.014| 1.389     | -0.037         | 0.004   | 0.038          |
| Abnormal Return      | 11,396| 2.296 | 1.672     | 1.770          | 2.505   | 3.006          |
| Volatility           | 19,967| 0.294 | 1.361     | 0.036          | 0.062   | 0.123          |
| E score              | 19,722| 50.750| 13.846    | 36.931         | 49.678  | 62.520         |
| S score              | 19,722| 52.936| 8.694     | 46.025         | 52.773  | 59.649         |
| G score              | 19,722| 50.135| 13.322    | 40.499         | 50.767  | 59.794         |
| GC HR score          | 19,998| 51.330| 9.784     | 43.643         | 51.428  | 59.022         |
| GC LR score          | 19,999| 53.206| 9.326     | 46.037         | 53.460  | 60.516         |
| GC E score           | 19,999| 50.362| 13.513    | 37.074         | 49.133  | 61.888         |
| GC AC score          | 19,999| 54.680| 5.410     | 51.854         | 54.783  | 58.131         |

Note: Returns, abnormal returns, and volatility are measured in monthly terms.

Fig. 1. Time Trends of the stock Return and ESG scores and GC scores.
positively correlated to the stock returns and volatility during the COVID-19 outbreak, we estimate the model shown in Equation (1):

\[ Y_t = \beta_0 + \beta_1 ESG_t + \beta_2 COVID_t + \beta_3 GC_t + \epsilon_t \]

(1)

where \( Y_t \) is represents each dependent variable (returns, abnormal returns, and volatility) and \( ESG_t \) is a vector of the ESG scores of company \( i \) at time \( t \) (i.e. of the E, S, and G scores), \( GC_t \) is a vector of the GC scores of company \( i \) at time \( t \) (the GC_HR, GC_LR, GC_AC, and GC_E scores). \( COVID_t \) is a dummy variable set to 1 in the period from January 2020.

We include firm fixed controls control for the differences between individual firms. Additionally, we add country and sector dummies to control for the country and region in which each company is located. Finally, \( \epsilon_t \) is an error term.

The coefficients on the interaction between \( COVID_t \) and ESG scores (\( \beta_1 \)) and between \( COVID_t \) and GC scores (\( \beta_2 \)) capture the differential impact of ESG activities on monthly stock returns and volatility during the COVID-19 pandemic, after controlling for the firm’s factor loadings and financial characteristics over the entire estimation period, country-specific and region-specific effects (country and region fixed effects), and any time series pattern in overall returns (time fixed effects).

As shown in Fig. 1, there is a time lag between the movement of the stock prices and changes in the scores. Thus, to confirm the robustness of the result, we estimate Equation (1) with the time lag added in \( ESG_{it} \) and \( GC_{it} \) in Equation (1).

### 3. Results and discussion

In this section, we first present and discuss our results on the relationship between ESG activities and stock returns, abnormal returns, and volatility in Section 3.1. Then, we conduct multiple robustness tests to confirm our results in Section 3.2. We conduct an additional analysis focusing on the energy sectors in Section 3.3. Finally, we present sensitivity analysis results in Section 3.4.

#### 3.1. Main results

In this section, we present and interpret our main results, which are shown in Tables 3-5. Our models usually have R-squared of around 10–15%. However, the R-sq values are usually low when it comes to the repeated cross sectional data; it goes around 10%, according to (Klier and Linn, 2010), and the R-sq value of our main models were around 10–15%, which is acceptable. Overall, our results highlight that during the COVID-19 pandemic, a unit (1 point) increase in the E score is positively correlated with stock returns, which increase around 15%–16%, and negatively correlated with the returns’ volatility, with volatility falling by around 41% for firms that do increase their E score compared with firms that do not during COVID-19. However, increasing the GC_E score by one is negatively correlated to returns, which fall by around 16%, and negatively correlated with the returns and volatility, which increases by 40–41% compared with firms that do not increase their GC_E score during the COVID-19 period. This result indicates that focusing on increasing their E scores would enable firms to perform substantially better in terms of increasing returns and reducing volatility. Conversely, improving their reputation (GC_E score) is associated with a reduction in returns and an increase in volatility.

Table 3 shows the estimation results for the four model specifications. Models (1) and (3) take “Return” as a dependent variable, whereas models (2) and (4) take “Abnormal Return” (“Abnormal” in the table) as a dependent variable. Models (1) and (2) are full models, including all types of fixed effects, models (3) and (4) exclude COVID dummy. We focus on models (1) and (2), as they are the fully specified models that include all scores and indices. We note that the coefficients were largely consistent for all models, (1) to (4), which indicates the robustness of our estimation results. Given that the dependent variables are stock returns (in logarithmic form), a higher coefficient suggests that an increase in ESG metrics is positively correlated with an increase in stock returns, and vice versa.

Our first result in Table 3 is that the COVID* E score shows positive coefficients of around 0.150 to 0.157, indicating that an increasing E score during the COVID-19 period is positively correlated with a 15.0%–15.7% increase in returns and abnormal returns. Conversely, we find that the coefficients of the GC_E score during the COVID-19 period have negative coefficients of –0.145 to –0.149, which indicates that focusing on the firm reputation is negatively correlated with the raw returns, which decrease by around 15%. The rest of the parameters related to social and governance indicators are largely statistically insignificant. COVID shows negative coefficients around -2.5, indicating that Covid-19 pandemic has negatively correlated to stock returns.

| Table 3 | Relationship between ESG metrics and returns. |
|---------|-----------------------------------------------|
| Model (1) | Model (2) | Model (3) | Model (4) |
| Return | Abnormal Return | Abnormal Return | Abnormal Return |
| COVID * E score | 0.150** | 0.127 | 0.157** | 0.128 |
| (0.070) | (0.096) | (0.0705) | (0.0959) |
| COVID* GC-E score | -0.145** | -0.123 | -0.149** | -0.123 |
| (0.0732) | (0.0994) | (0.0731) | (0.0994) |
| E Score | -0.0426 | 0.228 | -0.0446 | 0.228 |
| (0.123) | (0.171) | (0.123) | (0.171) |
| GC-E Score | 0.0290 | -0.248 | 0.0277 | -0.249 |
| (0.128) | (0.179) | (0.128) | (0.179) |
| COVID* S score | -0.0260 | -0.0572 | -0.0436 | -0.0598 |
| (0.0521) | (0.0707) | (0.0515) | (0.0698) |
| COVID* GC HR score | -0.0312 | -0.00978 | -0.0255 | -0.000118 |
| (0.0452) | (0.0613) | (0.0451) | (0.0612) |
| COVID* GC HR score | 0.0135 | 0.00995 | 0.0202 | 0.0109 |
| (0.0315) | (0.0427) | (0.0313) | (0.0425) |
| S score | 0.0520 | 0.328** | 0.0648 | 0.330** |
| (0.0930) | (0.130) | (0.0928) | (0.130) |
| GC HR score | -0.0131 | -0.355*** | -0.0183 | -0.355*** |
| (0.0905) | (0.127) | (0.0905) | (0.127) |
| GC LR score | 0.00610 | 0.0834 | 0.00142 | 0.0828 |
| (0.0615) | (0.0861) | (0.0615) | (0.0860) |
| COVID* G score | 0.0110 | 0.0107 | 0.00665 | 0.0109 |
| (0.09824) | (0.0112) | (0.00789) | (0.0108) |
| COVID* GC AC score | 0.0735*** | 0.0759** | 0.0351** | 0.0702*** |
| (0.0251) | (0.0341) | (0.0174) | (0.0236) |
| G score | -0.0125 | -0.0126 | -0.00972 | -0.0123 |
| (0.0151) | (0.0207) | (0.0151) | (0.0207) |
| GC AC score | -0.0623 | -0.0211 | -0.0372 | -0.0180 |
| (0.0460) | (0.0647) | (0.0445) | (0.0633) |
| COVID | -2.494*** | -0.370 | (1.167) | (1.592) |
| (3.315) | (1.524) | (1.509) | (1.716) |
| Constant | 3.2815 | 1.524 | 1.509 | 1.716 |
| (13.99) | (9.930) | (13.97) | (9.896) |

N 28,125 19,714 28,125 19,714
R-sq 0.101 0.145 0.101 0.145

Note: Standard errors are shown in parentheses. * p < 0.1; ** p < 0.05; *** p < 0.01; ***.
Focusing on the returns and abnormal returns requires that volatility is investigated because returns hinge significantly on volatility, and pandemics (or other shocks) are likely to increase stock return uncertainties among investors. Therefore, we examine the relationship between ESG metrics and volatility and present the results in Table 4, based on models (1) to (2). As in Table 3, we focus on model (1), which is the full specification. The results indicate that the E score during the pandemic is negatively correlated with volatility (a unit increase results in a decrease of volatility of 41.3%), whereas the GC_E score is positively correlated with volatility, which increases by 40.8%. These results indicate that firms with higher E scores during pandemics and other crises are likely to have more stable returns, whereas those that focus on increasing their GC_E scores experience more volatile returns compared with the firms with lower GC_E scores during the COVID-19 period.

Other variables concerning the social and governance aspects of firms generally show negative coefficients. For example, the COVID*G score coefficients indicate that an increase in the G score during the pandemic would be correlated to the reduction of stock return volatility by 2.85%. The positive coefficient of COVID indicates that the volatility increases during COVID-19 outbreak, which is quite natural.

In Table 5, we re-estimate the models of Tables 3 and 4, but with the returns, abnormal returns, and volatility categorized into two groups: high and low. High indicates the firms in the upper 25% for returns/abnormal returns/volatility, whereas low indicates firms in the bottom 25% for returns/abnormal returns/volatility. For example, model (1) shows the results for firms with returns in the upper 25%, and model (6) presents the results for firms with volatility in the bottom 25%. This approach allows us to examine whether our results and findings hold for firms with higher financial capacity or higher volatility.

Table 5 presents the results. Models (1) and (3) estimate the returns, abnormal returns, and volatility for firms in the high returns group (upper 25%), and models (2) and (4) do so for firms in the low returns group (bottom 25%). Models (1) and (2) show the estimation results for returns, models (3) and (4) shows those for abnormal returns, and models (5) and (6) presents the results for volatility. We include all types of fixed effects, as in model (1) in Table 3.

In general, we find that the results are similar to those in Tables 3 and 4 and that the implications are consistent. However, there are some differences. First, models (1) and (2) show that when the firms’ profits are high (in the top 25%), their E and GC_E scores during COVID-19 are not likely to have positive (or negative) coefficients on their stock returns, as all of the coefficients are statistically insignificant. Conversely, when a firm belongs to the low returns group and during the pandemic, increasing the E score is correlated with higher returns (which increase by 16.7% for a unit increase in the E score), whereas increasing the GC_E score has a negative correlation, leading to a 16.4% reduction in returns. In addition, scores related to governance are positively correlated with returns and abnormal returns, and the coefficients are more statistically significant for the firms belonging to the low return group.

As for the abnormal returns (Models (3) and (4)), firms in the high abnormal returns group have a negative coefficient (-2.83%) in the GC_E score and a positive coefficient (3.19%) in the E score. In contrast, the low abnormal returns group has a positive coefficient and abnormal returns increase 16.6% when an E score increases during the COVID-19 era, while the coefficients are negative in the GC_E score and abnormal returns decrease by 16.4%.

Interpretation of the volatility results requires a careful approach, yet these results continue to support our argument that an increase of the E score would benefit firms more than would an increase in the GC_E score. For firms in higher volatility groups (in Model (5)), increasing E scores during the pandemic would reduce volatility by 40.9%, whereas increasing the GC_E score is positively correlated with volatility, which would increase by approximately 40.5%. This indicates the need to focus on E scores rather than GC_E scores. Increasing the E score would also make firms with lower volatility (Model (6)) better off, as it is negatively correlated to volatility (which falls 0.04%), whereas increasing the GC_E score implies an increase in volatility of 0.06%. As for the volatility, we find other score metrics (i.e., G score during pandemic, of high volatility group) also show statistical significance. Hence, for the magnitude of the coefficients, we still find that the E score (-40.9%) and GC_E scores’ coefficients (40.5%) were larger than other score metrics, such as GC_LR score (-5%) during pandemic.

Again, this result highlights the importance of increasing E scores rather than GC_E scores. Further, it suggests that firms belonging to low returns groups in particular would benefit from investing in E score-related activities during crises. The result supports the conclusions of Tables 3 and 4 that investing in E and GC_E scores can significantly influence firms’ returns and volatility. If the financial strategies of firms in the lower returns group are not carefully designed, the reduction in their returns may be substantially larger than that experienced by firms in the high returns group, as the negative coefficients are larger for the former group. For example, as indicated by the results of models (1) and (2), shown in Table 5, increasing the GC_E score by 1 point would be negatively correlated to returns for these firms by 16.4%, whereas the returns of firms in the high returns group would not change.

Our findings are straightforward. They suggest that during the COVID-19 pandemic, the E score is negatively correlated with volatility and higher returns, whereas the GC_E score shows a positive correlation with volatility and lower returns. Combining the results in Tables 3 and 4 suggests that, for firms aiming for higher returns and lower volatility, strategically investing in E score-related activities would benefit them more than investing in GC_E scores. The benefits of improving environmental performances have been well discussed in preceding studies: for example enhancing energy efficiency generally improves financial performance (Fan et al., 2017). Horváthová (2010) conducts meta
a society, we would prefer the former firms. Therefore, there is still a need for firms to develop financial strategies to enhance their reputations; or strategies that can increase their GC_E scores.

Our estimates are larger in terms of the magnitudes of coefficients, and smaller in the negative terms, than those of Servaes and Tamayo (2017), who found that firms with higher corporate social responsibility would experience returns that were 4%–7% higher than those of firms with lower corporate social responsibility. We conjecture that the difference in magnitude between our study and theirs arises from the frequency of our data. For example, Servaes and Tamayo (2017) investigated a more extended time period (2006–2009) and examined annual returns, whereas we focus on monthly returns with daily updated scores. In most cases, monthly (or daily) returns fluctuate more than yearly returns and volatilities. The greater the frequency of data, the more prone they are to reflect seasonal or stochastic changes in stock returns. By contrast, using yearly differences would result in smoothing of economic shocks and seasonal cycles. Our results, therefore, the more prone they are to reflect seasonal or stochastic changes in stock returns. By contrast, using yearly differences would result in smoothing of economic shocks and seasonal cycles.

### 3.2. Results for the energy sector

In this section, we compare the estimation results across the energy and non-energy sectors. In the energy sector, we include the closely related industries, utilities and energy minerals (and they are excluded from the non-energy sector data). The energy sector accounts for 28% of the S&P 500. We find that firms in the energy sector experience returns that are 4%–7% higher than those of firms in the non-energy sector. In the energy sector, we include the closely related industries, utilities and energy minerals (and they are excluded from the non-energy sector data). The energy sector accounts for 28% of the S&P 500. We find that firms in the energy sector experience returns that are 4%–7% higher than those of firms in the non-energy sector. In the energy sector, we include the closely related industries, utilities and energy minerals (and they are excluded from the non-energy sector data). The energy sector accounts for 28% of the S&P 500. We find that firms in the energy sector experience returns that are 4%–7% higher than those of firms in the non-energy sector.
non-energy sector models separately over including energy sector dummy due to the possible concerns of multicollinearity as we have already included energy sector dummys in forms of industry and sector fixed effects.

Table 6 shows the estimation results. In models (1), (3), and (5), we present the results for the energy sectors, whereas models (2), (4), and (6) show the results for the non-energy sectors. We use a full specification of the model, which includes COVID dummy, country, sector, time, and company fixed effects. Models (1) and (2) show the results on returns, models (3) and (4) show those on abnormal returns, and models (5) and (6) presents the results on volatility.

The results indicate that the non-energy sector would benefit more from investing in the environmental aspect of ESG scores compared with the energy sector. To be more specific, the interpretation of the non-energy sector’s returns is similar to that of our main findings: during the COVID-19 period, increasing the E score (GC_E score) is positively (negatively) correlated with returns. Therefore, increasing the E score would benefit the non-energy sectors. Conversely, the energy sector has statistically insignificant coefficients on E and GC_E scores, both on returns and abnormal returns. For example, the GC_E score (E score) in the COVID-19 period, increasing the E score (GC_E score) is positively (negative) correlated with volatility, as shown in both sectors have statistically insignificant coefficients on E and GC_E scores, both on energy sector and company fixed effects. Models (1) and (2) show the results on returns, whereas models (2), (4), and (6) show the results for the non-energy sectors. We use a full specifica
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The result in Table 7 suggests that investors should exercise caution when designing ESG-related investment strategies as the E score and GC_E score are highly correlated. Therefore, distinguishing them

### Table 6

| Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) |
|----------|----------|----------|----------|----------|----------|
| Return   | Return   | Abnormal | Abnormal | Volatility | Volatility |
| Energy   | Energy   | Energy   | Energy   | Energy    | Energy    |
| COVID* E score | 0.0838 | 0.148** | 0.161 | 0.123 | -0.395*** |
|          | (0.181) | (0.0743) | (0.257) | (0.101) | (-0.139) |
| COVID* GC_E score | -0.0962 | -0.140* | -0.176 | -0.116 | 0.340**  |
|          | (0.180) | (0.0773) | (0.256) | (0.105) | (0.138)  |
| E Score  | -0.334  | -0.0171 | -0.472 | 0.273  | 0.524*** |
|          | (0.241) | (0.130) | (0.345) | (0.181) | (0.114)  |
| GC_E Score | 0.282   | 0.050997 | 0.458 | -0.294 | -0.421** |
|          | (0.246) | (0.136) | (0.353) | (0.190) | (0.119)  |
| COVID* S score | -0.0892 | -0.0219 | -0.0645 | -0.0581 | -0.0856 |
|          | (0.0737) | (0.0567) | (0.105) | (0.0768) | (0.0566) |
| COVID* GC HR score | 0.0844  | 0.0439 | 0.0753 | -0.0107 | 0.181*** |
|          | (0.0781) | (0.0484) | (0.111) | (0.0656) | (0.0600) |
| COVID* GC LR score | -0.0533 | 0.0209 | -0.0797 | 0.0193 | -0.157*** |
|          | (0.0486) | (0.0341) | (0.0691) | (0.0463) | (0.0374) |
| S score  | 0.211   | 0.0449 | 0.364* | 0.330** | -0.111 |
|          | (0.149) | (0.0999) | (0.217) | (0.139) | (0.114) |
| GC HR score | -0.267* | 0.00464 | -0.534* | -0.342** | -0.0653 |
|          | (0.154) | (0.0964) | (0.229) | (0.136) | (0.119) |
| GC LR score | 0.130   | -0.00512 | 0.301** | 0.0639 | 0.161** |
|          | (0.0867) | (0.0667) | (0.130) | (0.0930) | (0.0665) |
| COVID* G score | 0.0132  | 0.0113 | 0.00936 | 0.0110 | 0.00167 |
|          | (0.0154) | (0.00873) | (0.0220) | (0.0118) | (0.0119) |
| COVID* GC AC score | 0.0929* | 0.0746** | 0.116* | 0.0759** | 0.129*** |
|          | (0.0485) | (0.0269) | (0.0690) | (0.0365) | (0.0373) |
| G score  | -0.0372 | -0.0118 | -0.0307 | -0.0122 | 0.00851 |
|          | (0.0295) | (0.0160) | (0.0425) | (0.0219) | (0.0227) |
| GC AC score | -0.0725 | 0.0637 | -0.0610 | -0.0212 | -0.107** |
|          | (0.0822) | (0.0490) | (0.121) | (0.0687) | (0.0634) |
| COVID   | -2.087  | -2.638* | -0.344 | -0.454 | -1.268 |
|          | (2.395) | (1.256) | (3.417) | (1.703) | (1.845) |
| Constant | 7.757   | 4.543 | -0.615 | -0.462 | 1.428 |
|          | (6.38)  | (13.96) | (5.397) | (16.30) | (5.288) |
| N       | 2009    | 26116 | 1407  | 18307 | 2016 |
| R-sq    | 0.109   | 0.101 | 0.162 | 0.428 | 0.310 |

Note: Standard errors are shown in parentheses. * p < 0.1; *p < 0.05; **p < 0.01; ***.
carefully and focusing more on the financial strategies that are intended to enhance financial materiality rather than reputation would help firms survive during crises.

On the other hand, while the ESG scores show the corporate performances derived from ESG activities, GC scores are indices of the firm’s reputations for following the UN GC norms. Therefore, results in this study show whether investments that consider the firm’s reputation or their long-term profitability related to ESG are beneficial for the firm’s financial performance. In this case, if there is a logistical relationship between ESG scores, GC scores and stock performances, it would not be reasonable to include ESG and GC scores in the same regression. Therefore, we check whether ESG performance in the past is correlated to firm’s reputations.

Table 8 shows the correlation matrix of lagged ESGs and GC scores. As seen from table 8, we see a very low correlation of around 1%, therefore we can conclude that ESG performances do not show a significant level of correlations with firm reputations.

4. Conclusion

Owing to the increased demands that firms pursue green finance, the market for ESG investments has been growing exponentially, and the capital catalyzed through ESG investments is expected to help fill the capital gap required for the transition to a sustainable energy system. Thus, it is critically important to deepen our understanding of the impact of firms’ ESG performance on their financial performance. Although the existing studies that explore the relationship between ESG performance and stock prices generally support the argument that enhancing ESG performance leads to an increased stock price, the role of ESG performance during financial crises has been relatively unexplored. Therefore, we investigated the effect of ESG performance on stock returns and volatility, with a focus on the time period covering the financial crisis brought by the rapid spread of COVID-19.

We employed company-level daily score data on the ESG and the UN GC scores provided by Arabesque S-Ray. The ESG score represents aspects of ESG performance that are deemed important in the light of financial materiality, and the GC score indicates a firm’s reputation for following UN GC norms. Our results indicate that during the financial crisis brought about by the COVID-19 pandemic, an increase in the ESG score, especially the E score, leads to higher returns and lower volatility, whereas an increase in the GC score is correlated with lower stock returns and higher volatility. In addition, we find that firms belonging to lower returns groups benefit more from increasing their E scores than firms in higher returns groups. An additional analysis focusing on the energy sector shows that although the non-energy sector would benefit more from increasing E scores than the energy sector in terms of both stock returns and volatility, energy sector firms can still reduce their stock price volatility by increasing their E scores.

These results contribute to the literature by providing quantitative evidence of the role of green finance by investigating the relationship between ESG performance and stock returns and volatility during financial crises. Our results support the argument made by preceding studies that higher ESG performance lower financial risk during financial crises, which was asserted by studies that examine the impact of ESG activities on financial performances during the 2008-09 global financial crisis. In addition, we shed light on the importance of separately identifying the impact of each aspect of ESG performance (environmental, social, and governance) on stock returns and volatility. In future research, it would be useful to expand the time period of analysis to, for example, five years or more, which would provide longer-term implications than our study, which focuses on a period of less than one year.

Another possible issue that can be addressed is the reverse causality; stock price return causes ESG and GC scores to move. Such issues can be addressed/minimised through using instrumental variables approach or two-stage least squares approach. However, we would like to stress that our findings do not suggest causation; rather, they indicate associations between stock returns and ESG ratings. Rather than a single ESG ranking, stock prices are influenced by various factors such as time patterns and macroeconomic factors. Examining causality (and reverse causality) would be fruitful future research, but it would require careful examinations, therefore conducting additional analyses such as GMM and 2SLS may be required. Running a Difference-in-Difference (DID) regression will also be good for future research to examine whether firms with ESG investments perform financially better than firms without ESG investments in times of COVID-19. Such analysis would require data on firms that do not invest in ESGs, and unfortunately, our data limitation does not allow us to investigate such an aspect, which is worth looking at in future research.

Although conducting additional analysis would be ideal, we decided to add correlation analysis rather than adding additional analysis. This is because adding the other analysis would contain sizable results and requires detailed background explanations, model settings, and some preliminary tests/post-estimations would divert our research objective. Therefore, examining reverse causality would be a fruitful future research. Furthermore, increasing the frequency of our stock price data to daily data would allow us to explore whether investors determine strategies to recover, or change their investment strategies in response to crises. Finally, researchers could consider whether seasonal effects impact stock prices in the longer term.

Declaration of competing interest

The authors declare that they have no known competing financial

| E score | GC-E score | S score | GC-HR score | GC-LR score | G score | GC-AC score |
|---------|------------|---------|-------------|-------------|---------|-------------|
| 1       | 0.994      | 1       | 0.763       | 0.782       | 0.698   | 0.413       |
|         |            |         | 0.769       | 0.788       | 0.703   | 0.416       |
|         |            |         | 1           | 0.964       | 0.921   | 0.548       |
|         |            |         |             | 1           | 0.909   | 0.506       |
|         |            |         |             |             | 1       | 0.571       |
|         |            |         |             |             |         | 0.092       |
|         |            |         |             |             |         | 1           |

| (lagged) E score | (lagged) S score | (lagged) G score | GC-HR score | GC-LR score | G score | GC-E score | GC-AC score |
|------------------|------------------|------------------|-------------|-------------|--------|------------|-------------|
| 1                | 0.7631           | 0.0055           | 0.006       | 0.0041      | 0.0025 | 0.4158      | 0.5062      |
| (lagged) S score |                  | 0.0305           | 0.0037      | 0.0034      | 0.0024 | 0.5706      | 1           |
| (lagged) G score|                  |                  | 1           | 0.0058      | 0.0073 | 0.7882      | 1           |
|                 |                  |                  |             | 1           | 0.7032 | 0.9087      | 1           |
|                 |                  |                  |             |             |        |            |             |
interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
The list of sectors and their mean scores

| Sectors               | N     | Portion (%) | E score | S score | G score | GC_HR score | GC_LR score | GC_E score | GC_AC score |
|-----------------------|-------|-------------|---------|---------|---------|-------------|-------------|-------------|-------------|
| Commercial Services   | 954   | 3.34        | 48.04   | 53.78   | 49.58   | 52.04       | 54.96       | 47.90       | 55.41       |
| Communications        | 360   | 1.26        | 55.55   | 53.63   | 46.47   | 53.37       | 54.53       | 54.63       | 55.51       |
| Consumer Durables     | 1004  | 3.51        | 55.84   | 53.55   | 50.81   | 52.27       | 54.07       | 55.13       | 54.24       |
| Consumer Non-Durables  | 1232  | 4.31        | 55.23   | 56.82   | 51.28   | 56.51       | 56.78       | 55.08       | 54.57       |
| Consumer Services     | 1449  | 5.07        | 47.70   | 51.92   | 49.21   | 50.47       | 52.14       | 46.83       | 54.17       |
| Distribution Services | 715   | 2.5         | 53.87   | 54.93   | 48.50   | 53.91       | 55.81       | 53.61       | 54.75       |
| Electronic Technology | 1893  | 6.62        | 55.50   | 55.28   | 51.76   | 54.03       | 54.90       | 54.46       | 55.17       |
| Energy Minerals       | 1113  | 3.89        | 52.73   | 54.98   | 50.39   | 51.13       | 55.72       | 52.38       | 57.62       |
| Finance               | 4745  | 16.6        | 44.80   | 50.05   | 47.42   | 50.17       | 44.55       | 53.95       |             |
| Health Services       | 443   | 1.55        | 44.75   | 53.06   | 45.61   | 51.83       | 55.25       | 44.17       | 53.87       |
| Health Technology     | 3065  | 10.72       | 42.24   | 47.35   | 48.72   | 45.41       | 47.82       | 42.07       | 52.58       |
| Industrial Services   | 1250  | 4.37        | 51.49   | 52.05   | 52.22   | 50.52       | 52.70       | 50.86       | 55.05       |
| Miscellaneous         | 30    | 0.1         | 56.14   | 49.61   | 39.55   | 48.03       | 53.74       | 54.14       | 56.39       |
| Non-Energy Minerals   | 1539  | 5.38        | 55.32   | 55.26   | 50.96   | 53.30       | 56.64       | 54.66       | 56.53       |
| Process Industries    | 1459  | 5.1         | 60.27   | 57.48   | 49.81   | 56.72       | 56.81       | 59.98       | 56.09       |
| Producer Manufacturing | 2369 | 8.29        | 56.68   | 55.57   | 49.99   | 55.16       | 55.28       | 56.23       | 55.06       |
| Retail Trade          | 1257  | 4.4         | 50.37   | 54.92   | 52.15   | 53.39       | 54.84       | 50.51       | 54.22       |
| Technology Services   | 1763  | 6.17        | 45.12   | 52.08   | 49.64   | 50.07       | 52.06       | 45.65       | 53.29       |
| Transportation        | 1010  | 3.53        | 53.98   | 53.26   | 50.15   | 51.73       | 53.64       | 53.00       | 54.47       |
| Utilities             | 940   | 3.29        | 59.29   | 54.72   | 51.68   | 54.03       | 56.08       | 59.48       | 58.08       |

Table A2 shows the Welch’s T test results, which shows that there was not a statistically significant difference in means between all variables as all of the variables reject the hypothesis that there is a significant difference, and Table X shows the test result. As we confirm that there was not a significant difference between the means, we conduct the regressions analysis.

Table A2
Welch’s T test result

| Variable               | T-test value | [95. % Conf. Interval of differences between pre-post COVID-19] |
|------------------------|--------------|-------------------------------------------------------------|
| Return                 | -0.6624      | -0.42 to 0.21                                              |
| Volatility             | 6.018        | 0.65 to 1.28                                               |
| E score                | -0.390       | -0.42 to 0.28                                              |
| S score                | -0.1411      | -0.24 to 0.21                                              |
| G score                | 0.007        | -0.34 to 0.34                                              |
| GC_EN score            | -0.2174      | -0.38 to 0.30                                              |
| GC_HR score            | -0.0942      | -0.26 to 0.24                                              |
| GC_AC score            | -0.1850      | -0.15 to 0.12                                              |
| GC_LR score            | 0.2372       | -0.21 to 0.26                                              |

Table A3 shows the correlation between lagged stock returns and ESG/GC scores. We do not find a significant correlation between lagged stock return and each score.

Table A3
Correlation Analysis of Lagged Stock Return and ESG/GC Scores

| Lagged Stock Return | E score | S score | G score | GC_E score | GC_HR score | GC_LR score | GC_AC score |
|--------------------|---------|---------|---------|------------|-------------|-------------|-------------|
| Lagged Stock Return | 1       | 1       | 1       | 1          | 1           | 1           | 1           |
| E score            | -0.001  | 0.763   | 0.03    | 1          | 1           | 1           | 1           |
| S score            | -0.004  | 0.994   | 0.769   | -0.002     | 1           | 1           | 1           |
| GC_E score         | -0.002  | 0.782   | 0.964   | 0.011      | 0.788       | 1           | 1           |
| GC_HR score        | -0.004  | 0.698   | 0.921   | 0.019      | 0.703       | 0.909       | 1           |
| GC_LR score        | -0.006  | 0.413   | 0.548   | 0.092      | 0.416       | 0.506       | 0.571       |
