State Ownership and the Value of Sustainability: Evidence from China *

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Abstract**:** This study examines the impact of state ownership on the performance of environmental and social (ES) stocks in China's stock markets. Using the COVID-19 market crash as an exogenous shock, we find that ES positively impacts stock returns for non-state-owned enterprises (non-SOEs); however, this effect is absent for state-owned enterprises (SOEs). The ES effect in non-SOEs concentrates on firms with strong employee relations and is more pronounced in those with high institutional ownership, financial constraints, and bankruptcy risk. In the long term, we also find that ES performance boosts stock returns for non-SOEs, but not for SOEs. These results suggest that ES investments by SOEs may be driven by non-economic motivations.

Keywords**:** State Ownership; Environmental & Social Performance; COVID-19

JEL classification**:** G12, G32, M14

1 Introduction

With the rise in state capitalism worldwide, state-owned enterprises (SOEs) have attracted renewed attention (Economist, 2014; Hsu et al., 2023). In 2020, the World Bank reported that "State-owned enterprises account for 20 percent of investment, 5 percent of employment, and up to 40 percent of domestic output in countries around the world. They deliver critical services in key economic sectors, including utilities, finance, and natural resources."[1] Although private firms dominate many developed economies, some of the largest listed firms, such as EDF Group in France, have now been nationalized. In China, SOEs significantly contribute to the economy; they comprise approximately one-third of publicly listed firms and two-thirds of stock market capitalization in recent years. In contrast to non- SOEs, SOEs have multiple objectives such as social and political purposes, along with shareholder–wealth maximization (Shleifer, 1998). For example, as an agile tool of the government, SOEs are established to address market failures and externalities, including unemployment and pollution reduction. Therefore, the two types of firms may have different motivations for environmental, social, and governance (ESG) strategies.

A fundamental question is whether ESG activities create value for firms and shareholders, as theoretical analysis to date provides conflicting perspectives. The predominant view holds that ESG practices benefit shareholders by potentially maximizing their welfare, which is known as "doing well by doing good." However, the opposite view considers ESG policies agency-driven (Friedman, 1970), suggesting that managers pursue ESG for their personal gains (e.g., reputation) at shareholders' expense, thereby reducing firm value. Despite these conflicting theoretical predictions, practitioners widely believe that ESG activities are crucial for sustainable development (Hou et al., 2024; Yi et al., 2024) and can create value for firms (Albuquerque et al., 2020). Numerous investors now incorporate ESG into their investment decision-making process (Wan et al., 2024), making it a dominant theme in the business world. According to Bloomberg Intelligence statistics, global ESG assets rose from US$22.8 trillion in 2016 to US$37.8 trillion in 2021, with an average annual growth rate of approximately 10.64%, and are projected to reach US$53 trillion by 2025. The academic literature also highlights the positive effect of ESG on shareholder value. For instance, ESG activities improve corporate financial performance (Albuquerque et al., 2020; Broadstock et al., 2021; Lins et al., 2017), reduce the cost of debt financing (Alves & Meneses, 2024; Apergis et al., 2022; Lian et al., 2023), and increase investment efficiency (Bilyay-Erdogan et al., 2024; Su & Xue, 2023). While ESG benefits likely vary between SOEs and non-SOEs because of their different

[1] https://thedocs.worldbank.org/en/doc/739371594131714315-0130022020/original/15444WBSOEWEB.pdf

motivations for ESG practice. For example, as an agile tool of the government, SOEs conduct ESG activities for social welfare objectives in addition to corporate sustainable development. However, to the best of our knowledge, the role of state ownership in the relationship between ESG and stock performance remains unexplored, despite its growing importance. This study addresses this open question with the outbreak of the Coronavirus disease 2019 (COVID-19) pandemic as an unparalleled shock and a unique dataset on long-term ESG performance covering the entire cross-section of Chinese listed firms.

Our study focuses on the Chinese stock market for three key reasons. First, SOEs in China significantly influence the economy and environment, representing one-third of listed firms and two-thirds of total stock market capitalization in China. According to Clark and Benoit (2022), carbon dioxide emissions from Chinese SOEs comprise most carbon emissions from global SOE emissions and exceed those of any other country, including the U.S. However, less is known about how ESG affects the financial performance of Chinese SOEs, an issue that has important implications for understanding the growing ESG investment by SOEs worldwide (Hsu et al., 2023). Second, the Chinese economy is transitioning toward sustainable development, with a growing emphasis on environmental and social (ES) awareness (Wang et al., 2023). The Chinese government has adopted a top-down framework to enforce various policies and regulations for the development of ESG. For example, seven ministerial agencies (including the People's Bank of China and the Ministry of Finance) released the *Guidelines for Establishing the Green Financial System*, which is the first systematic green finance policy framework in the world. The government-led ESG initiatives could make it more likely for SOEs to adopt ESG policies than non-SOEs. Third, ESG practices in China are nascent (Sun & Wang, 2025), and ESG performance varies significantly among listed firms. This variation allows us to investigate how ESG influences financial performance. Fourth, although not yet mandatory, the Chinese financial regulators are developing guidance to encourage all listed firms to disclose corporate social responsibility (CSR) reports[2], providing an opportunity for better data on the ESG performance of Chinese listed firms.

Testing the relationship between ESG and firm value is challenging, as causality may run from firms' financial performance to their ESG performance. Therefore, we use stock returns, rather than operating performance, as our dependent variable, as suggested by Edmans (2011). Moreover, we leverage the COVID-19 pandemic as an exogenous shock to examine the causal link between ESG and stock performance. First, COVID-19 represents an exogenous shock

[2] The Shanghai Stock Exchange (SSE) mandates the disclosure of CSR reports for firms in the SSE Corporate Governance Panel, firms issuing overseas-listed foreign shares, and financial firms. The Shenzhen Stock Exchange (SZSE) mandates the disclosure of CSR reports for firms that are constituents of the SZSE 100 Index.

driven by public health concerns rather than economic conditions. Second, the outbreak and subsequent lockdown were unexpected disruptions to the Chinese stock market. Third, the pandemic led to a stock market crash. The stock market experienced considerable declines in five trading days, with the CSI300 Index[3] plunging from 4185.83 on January 20 to 3688.36 points on February 3. The unexpected and exogenous shock suggests that firms had limited ability to respond in time to an unfolding crisis, making stock performance during this period an indicator of each firm's pre-crisis resilience. Therefore, the COVID-19 pandemic presents a unique context to estimate the causal effect of ESG on stock performance in China's stock market.

We examine all Chinese listed firms using a novel and comprehensive ESG dataset specific to China. To the best of our knowledge, this is the first study to analyze Chinese ESG issues covering the entire cross-section of China's stock markets. Following Lins et al. (2017) and Albuquerque et al. (2020), we focus on the ES aspects of ESG to avoid capturing governance effects because governance is typically not part of a firm's social capital remit. To assess the effect of state ownership on the relationship between ES and stock returns, we conduct a difference-in-difference-in-differences analysis. Specifically, we identify high- and low-ES firms according to firms' ES ratings in 2019. The event dummy equals one between January 20 and February 3, 2020, and zero between January 1 and January 19, 2020. We use raw and abnormal returns as primary proxies for corporate stock performance. We document a significantly higher stock return for high ES-rated non-SOEs relative to other non-SOEs during the COVID-19 market crisis. Economically, the high ES-rated non-SOEs have daily stock returns that are 0.4 to 0.5 percentage points on average higher than other non-SOEs between January 20 and February 3, 2020, with a cumulative effect of 2–2.5 percentage points. While we do not find a significant effect of ES on stock returns in SOEs, the evidence confirms the value of ES on stock returns in pandemic-induced market crises for non-SOEs rather than SOEs. Our findings are robust after several endogeneity and robustness tests.

We further examine whether it is overall ES performance or specific components of ES that drive returns during crisis periods. Lins et al. (2017) suggest that firms can build social capital through some ES-related activities, which may enhance the trust between firms and their stakeholders. For example, investors may prefer to invest in firms that demonstrate a stronger commitment to environmental issues. If this holds, some ES aspects could be more significant to investors in building trust with firms. To explore this, we re-estimate the difference-in-difference-in-differences model using nine secondary indicators available across industries,

[3] The CSI300 Index consists of the 300 largest and most liquid A-share stocks.

including all the secondary indicators in one regression. We find that for non-SOEs, the value of ES during crises is concentrated in employee relations.

Moreover, we perform various cross-sectional analyses. First, if the COVID-19 shock changes investors' risk attitudes, we would expect institutional investors to show significant loyalty to ES stocks. As expected, we find that the effect of ES on non-SOEs' stock returns is more pronounced in firms with higher institutional ownership. Second, if ES can act as a risk buffer during a market crisis, we would expect a stronger positive relationship between ES and stock returns of non-SOEs in risky firms. Consistent with this expectation, our findings suggest that the value of ESG on non-SOEs' stock returns is more pronounced in firms with stronger financial constraints and higher bankruptcy risk.

To identify the mechanism behind the outperformance of high-ES-rated non-SOEs, we investigate firms' operating performance during the COVID-19 pandemic. As accounting numbers are slower to incorporate the worsening economic situation than stock returns, we measure the change in operating performance from 2019–2020. We find that ES predicts higher returns on assets and net operating margins for non-SOEs. However, the positive effect is not present in SOEs. The evidence shows that for non-SOEs only, ES contains information on operating performance.

Finally, we examine the long-term impact of ES on stock returns with the asset pricing model. Our sample covers the entire A-shares from the year 2016–2020. We construct five industry-neutral, ES-based portfolios and find that the positive effect of ES is present in non-SOEs rather than in SOEs, further confirming that state ownership reduces the value of ES.

Our study contributes to the related literature from two aspects. First, our findings deepen the understanding of the effect of state ownership in the capital market. On the one hand, some studies note that SOEs have poor corporate governance and are economically inefficient. Politicians use SOEs to pursue political goals and personal benefits (Karolyi & Liao, 2017; Li et al., 2020), leading to corruption, reduced innovation, and poor resource distribution (Shleifer, 1998). On the other hand, some other studies suggest that SOEs help economies more efficiently (Bosek et al., 2024; Boubakri et al., 2018; Carney & Child, 2013; Hart & Zingales, 2017). For example, Hsu et al. (2023) and Liu et al. (2024) find that SOEs engage significantly more in ES issues relative to non-SOEs. Complementary to these studies, we examine the effect of state ownership in the ES–financial performance link. We find a positive relationship between ES and stock returns for non-SOEs but not for SOEs. The evidence generates immediate implications for investors and financial analysts to understand how state ownership influences the value of ES in the capital market.

Second, our study adds to the large literature on the effect of ESG on financial performance. Although there are opposing views in the literature, abundant emerging literature asserts a positive causal link between ESG activities and corporate financial performance. For instance, Lins et al. (2017) reveal that firms with high CSR ratings performed better during the Great Recession of 2008–2009 due to the trust between firms and their stakeholders. Meanwhile, the recent literature uses the outbreak of the COVID-19 pandemic as an unparalleled shock to examine the effect of ESG on stock performance. Different from the Great Recession, the COVID-19 pandemic is an unpredictable public health shock rather than an economic shock (Albuquerque et al., 2020). These studies document a positive effect of ESG on stock performance during the COVID-19 market crash (Albuquerque et al., 2020; Broadstock et al., 2021; Garel & Petit-Romec, 2021; Pástor & Vorsatz, 2020; Xu et al., 2023). We extend this line of literature by focusing on the role of state ownership in the ESG–financial performance link. Our findings support the view of "doing well by doing good" and further document that only private ownership affects the value of ES in China.

The remainder of this paper is organized as follows: Section 2 develops the hypotheses. Section 3 describes the data and methodology. Section 4 presents the evidence on the impact of state ownership on the performance of ES stocks. Sections 5 and 6 investigate operating performance and long-term stock performance, respectively. Section 7 conducts robustness analyses. Section 8 concludes the paper.

2 Hypothesis Development

Firms' social capital, driven by ES activities, can help build trust between firms and stakeholders (Lins et al., 2017). From investors' perspective, they will place a valuation premium on ES stocks that are deemed to be more trustworthy during market crises, such as COVID-19. Therefore, the price of ES stocks should not decline as much as other stocks. ES can offer insurance-like protection for firms in negative shocks (Albuquerque et al., 2020; Godfrey et al., 2009; Lins et al., 2017). Based on this risk buffer conjecture, state ownership might influence the value of ES on stock returns, particularly in times of market downturns, from two aspects.

First, SOEs and non-SOEs operate in different financing environments. SOEs are backed by national resources and preferential policies. Particularly, the Chinese government has "deep pockets" that could support the firms they own (Ding et al., 2021). Moreover, SOEs have advantages in the credit market as Chinese banks have different lending practices for two types of firms in that they prefer lending to SOEs rather than to non-SOEs (Cull et al., 2015; Firth et al., 2008). Therefore, in contrast to non-SOEs, SOEs are expected to have fewer financial constraints and have sufficient external funds to support both operating activities and debt obligations. During the COVID-19 pandemic, SOEs were less likely to experience financial distress and exhibited lower firm risk. If ES can act as a risk buffer, we expect the effect of ES on stock returns to be more pronounced in non-SOEs relative to SOEs.

Second, SOEs are more likely to have well-known agency issues with their managers investing in ES for personal tastes (Jiang & Kim, 2015), social reputation (Hsu et al., 2023; Jiang & Kim, 2020) and political capital. For example, politicians have incentives to use SOEs to win votes in elections (Li et al., 2020). If risk buffer is one of the important incentives for investors to consider ESG when constructing portfolios, the potential agency problems will reduce the benefits of ES in SOEs. We thus predict that the positive effect of ES on stock returns is more pronounced in non-SOEs than SOEs, as investors are more likely to use ES to screen high-quality firms in non-SOEs rather than SOEs. We posit a hypothesis below to test the role of state ownership in the relationship between ES and stock performance.

Hypothesis 1: The positive relationship between ES and stock returns is more pronounced in non-SOEs than in SOEs.

We investigate the effect of institutional ownership on the benefit of ES in non-SOEs. The previous literature documents that, relative to individual investors, institutional investors are more likely to have a long-term investment horizon (Dyck et al., 2019) and care more about firms' ES strategies (Bolton & Kacperczyk, 2021; Chava, 2014; Hong & Kacperczyk, 2009). Furthermore, they are more sophisticated and rational (Black, 1986; Kyle, 1985) and less sensitive to pandemic-induced market pessimism. If the COVID-19 market crash changes investors' attitude towards risk, with many investors choosing to sell their holdings, institutional investors are expected to be more loyal to ES stocks, thus enhancing the resiliency of ES stocks (Albuquerque et al., 2020). In this vein, we expect to observe a stronger effect in firms with high institutional ownership. To test this conjecture, we posit the following hypothesis:

Hypothesis 2: The positive effect of ES on stock returns of non-SOEs is more pronounced in firms with high institutional ownership.

Furthermore, we examine the effect of firm risk on the benefit of ES in non-SOEs. With the increasing social awareness of sustainable development in recent years, more and more investors and lenders have incorporated social responsibility into their investment decisions (Alves & Meneses, 2024; Bolton & Kacperczyk, 2021; Raimo et al., 2021). For example, the Chinese Central Bank issued the green credit guidelines in 2012 to incorporate ES risks into the loan decision-making process for commercial banks. Therefore, social responsibility firms could benefit from moral capital (Godfrey, 2005; Godfrey et al., 2009; Lins et al., 2017), which is particularly important for firms with strong financial constraints and high bankruptcy risk, known as risky firms. These high-risk firms are more likely to experience financial difficulties. Moral capital can help attract investors, providing them with funds to support operational needs and debt obligations. Therefore, it is reasonable to predict that the benefit of ES is more pronounced in high-risk firms. To test this conjecture, we posit the following hypothesis:

Hypothesis 3: The positive effect of ES on stock returns of non-SOEs is more pronounced in high-risk firms.

3. Data and Methodology

3.1 Sample and summary statistics

To construct our sample, we gather data on firms' ES performance from a novel and comprehensive ESG information dataset constructed by the International Institute of Green Finance (IIGF)[4] in China, covering the entire cross-section of China's stock markets. This database is based on a localized ESG evaluation system[5] and incorporates international standards and Chinese characteristics to create a "1+1" ESG rating system. Specifically, it considers development paths and patterns of Chinese listed companies (e.g., SOEs) and incorporates negative behaviors and risk exposures to identify potential ESG risks for firms. To quantify ESG performances, IIGF's analysts rely on publicly available information gathered through manual collection and artificial intelligence. One important source is firms' ESG, CSR, and annual reports. The analysts single out information that is relevant to firms' ESG process and performance. Another two important sources of information are news releases and penalty information disclosed by the governments. Examples of news releases include negative news stories about pollution, illegal discharges, poor product quality, poor stakeholder relations, or weak corporate governance. If information is considered relevant to ESG, IIGF's analysts will

[4] IIGF is based at Central University of Finance and Economics (CUFE) and is the first international green finance research institute in China. It works with the People's Bank of China, the Chinese Ministry of Finance, the National Development and Reform Commission, the Chinese Ministry of Environmental Protection, and many national, regional, and local government institutions, financial institutions, and research organizations to promote green finance in China. Internationally, IIGF conducts many joint research projects on green finance with international organizations, such as UNEP, UN PRI, the European Investment Bank, Cambridge University, and the International Institute for Sustainable Development. More information on IIGF can be obtained from the following link: http://iigf.cufe.edu.cn/.

[5] Based on the IIGF ESG evaluation system and IIGF ESG database, IIGF has compiled the CSI CUFE SH-SZ 100 ESG leading index, CSI300 Green Leading Stock Index, CUFE-CNI SZ-HK Connect Green Selection Index, SINA Beautiful China ESG 100 Stock Index, JD Digital ESG Industry Series Index, CUFE-SZRCB Suzhou Green Development Index, and CUFE-Suzhou Yangtze River Delta Integrated Green Development Bond Index. In the international capital markets, the IIGF ESG database is live on Deutsche Börse and is the first Chinese ESG database to be included. In addition, IIGF and Qontigo Indices jointly developed the STOXX-IIGF China A-share ESG Index, which is the first international ESG index based on a Chinese ESG database.

record and classify it based on pre-determined criteria, as presented in Table A1 in the appendix. The IIGF develops a comprehensive ESG scoring form that includes both quantitative and qualitative indicators. For qualitative indicators, the IIGF defines a set of binary indicator variables, which are either positive (1 score) or neutral (0 score). Under three primary indicators, the IIGF first aggregates all qualitative indicators and then normalizes the aggregated scores based on industry averages. For quantitative indicators, each indicator is normalized to the industry average. Quantitative indicators can be positive, zero, or negative. Then, the IIGF constructs a net environment (social, governance) pillar score by adding the aggregated qualitative indicator and positive quantitative indicators and subtracting negative quantitative indicators. In this study, The ES score is the average between the environment pillar score and the social pillar score.

We obtain daily stock returns from the China Stock Market & Accounting Research Database (CSMAR)[6]. As in Albuquerque et al. (2020), the daily abnormal return for each firm is the difference between the daily logarithm return of the stock and the CAPM beta multiplied by the daily logarithm return of the market based on the CAPM model. The CAPM beta is estimated using daily stock returns over three years between 2017 and 2019 and the CSI300 Index as the market index. To obtain more accurate estimates, we exclude stocks traded for less than 30 days during this period. Other firm data, such as firm size, financial leverage, Tobin's Q, cash holdings, return on asset, net profit margin, and asset turnover, are taken from the CSMAR database. To avoid problems with outliers, we winsorize all accounting variables at the 1st and 99th percentiles.

The data on state ownership comes from the CSMAR database, which provides the types of ultimate owners for Chinese listed firms. If the ownership pyramid exists, the ultimate owner is identified through an uninterrupted path of control rights. According to Article 84 of *Administrative Measures for the Takeover of Listed Companies*, the ultimate owner of Chinese listed firms should meet at least one of the conditions: (1) owning at least 50% of shares; (2) owning at least 30% of voting rights; (3) being able to decide the election of more than half of the members of the board of directors through voting. A firm is an SOE if its ultimate owner is one or more governments, government entities, or public authorities. For instance, the municipality of Beijing, the China State-Owned Assets Supervision and Administration Commission, and the China Development Bank. Under this definition, SOEs are set more stringently than in Hsu et al. (2023), who suggest that the most common example of an SOE is

[6] Abundant literature uses the CSMAR database to extract corporate fundamental information in China. For instance, Yu et al. (2015), Cui et al. (2018), Shan and Tang (2022), and He et al. (2024).

one in which the governments hold more than 25% of the outstanding shares. Meanwhile, we also manually check whether a firm is state-owned through its annual reports or other public sources.

After matching all databases, our sample consists of 3,704 A-share listed firms in 2019 with 62,842 firm-day stock return observations. The variables are described in Appendix A2 and their summary statistics are presented in Table 1. According to IIGF, firms' ES performance varies widely, with a 25^{th} percentile value of 0.294 and a 75^{th} percentile value of 0.657. For SOEs, the mean of the ES scores is 0.521, which is 10.85% higher than that of non-SOEs (0.470). This is in line with the argument that SOEs care more about social welfare and externalities (Hart & Zingales, 2017) and are ESG-oriented by design. Panel C presents a correlation matrix of the variables used in our main analyses. We find that the state ownership indicator is not highly correlated with other firm fundamental variables.

[Insert Table 1 about Here]

3.2 Methodology

To identify the effect of state ownership on the relationship between ES and stock returns during the COVID-19 outbreak, we extend the difference-in-differences regression in Lins et al. (2017) and Albuquerque et al. (2020) and employ a three-way interaction between the ES performance proxy, COVID-19 indicator, and state ownership indicator. We include both firm and day-fixed effects to control for any other unobservable effects. To alleviate the concern that some time-varying industrial shocks will drive the results, we also include the industry-day fixed effect in our regression model[7]. Standard errors are clustered by firm. The coefficient of the three-way interaction term captures the effect of state ownership on the ES–stock return link during the COVID-19 market crash period and is of interest. The formula is as follows:

$$\begin{aligned} Stock\ Return_{it} = \alpha &+ \beta_1 ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t} \\ &+ \beta_2 ES\ High_{i,t} \times Covid_{i,t} + \beta_3 Nsoe_{i,t} \times Covid_{i,t} + \delta X_{i,t} + \gamma_i \\ &+ \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

The two dependent variables we study are daily abnormal returns and daily raw returns of firm *i* on day *t*. $ES\ High_{i,t}$ is an indicator that equals one if the ES rating of firm *i* is in the top third in 2019 and zero otherwise. We relate firms' financial performance to their precrisis ES performance to guard against the possibility that firms have changed their ES policies in response to the unforeseen exogenous shock. Thus, our research design allows us to avoid the typical endogeneity issues that make it challenging to identify the effect of corporate ES performance on financial performance. $Covid_{i,t}$ is an indicator that equals one from January 20

[7] We use the one-digit industry classification issued by the China Securities Regulatory Commission in 2012.

to February 3, 2020, and zero from January 1 to January 19, 2020. There are five trading days in the post-event window as the stock market was closed from January 24 to February 2, 2020, for the Chinese New Year celebrations. To better understand the choice of the event window for $Covid_{i,t}$, Figure 1 plots the stock market path during the COVID-19 outbreak. As the figure shows, the stock markets did not react to COVID-19 until January 20, 2020, when Dr. Nanshan Zhong arrived in Wuhan and confirmed human-to-human transmission. The stock market experienced considerable declines with the CSI300 Index plunging from 4185.83 on January 20 to 3688.36 points on February 3. The market then rebounded as panic waned due to the effective prevention and control by the Chinese government. On February 24, the WHO announced that the peak of the coronavirus outbreak in China had passed. The CSI300 Index regained 4132.84 points on that day. In March, COVID-19 became a global pandemic. Although the Chinese market further experienced declines in mid to late March, we do not include the March crash in our study. First, it is a global shock emerging from the epidemic spreading to countries worldwide and the oil price crash. Second, the outbreak in China has been effectively controlled, with most Chinese firms (approximately 70%) resuming production in March. Therefore, the March crash was more a result of international influences than a direct impact of COVID-19 on Chinese firms.

[Insert Figure 1 about Here]

To isolate the effect of state ownership from the known determinants of stock returns, we include a vector of control variables, denoted by $X_{i,t}$. Specifically, we construct a three-way interaction term between $ES\ High_{i,t}$, $Covid_{i,t}$ and each control variable. All other possible interaction terms are included. Control variables include: $Size_{i,t}$ is the logarithm of total assets; $Leverage_{i,t}$ is the ratio of total liabilities to total assets; $Tobin's\ Q_{i,t}$ is the ratio of book value of assets minus book value of equity plus market value of equity to book value of assets; return on assets ($ROA_{i,t}$) is the ratio of net profit to total assets, multiplied by 100; $Cash_{i,t}$ is the ratio of cash and cash equivalents to total assets; $Idiosyncratic\ Risk_{i,t}$ is the residual variance from the CAPM model, which is estimated with daily returns from 2017 and 2019 with the CSI300 Index as the market index. The detailed definitions of the variables are reported in Appendix A2.

4. State Ownership, ES, and Stock Returns

4.1 Effect of state ownership on the relationship between ES and stock returns

We first present a univariate analysis to examine the stock performance by groups. As shown in Figure 2, the raw returns of the four groups of firms are strongly negative during the

COVID-19 market crash between January 20 and February 3, 2020. It indicates that investors are likely to care more about the risk and survival prospects of firms they hold. Moreover, we find that non-SOEs with high ES ratings have the highest stock returns, with an abnormal return of -0.5% and a raw return of -11.1%. Importantly, the difference in stock returns between high-ES firms and other firms is larger for non-SOEs than for SOEs. Through the univariate analysis, we find that the benefit of ES is more significant for non-SOEs than SOEs during the market crash.

[Insert Figure 2 about Here]

We continue to conduct the regression estimation. As presented in Columns (1) and (2) of Table 2, we find that the coefficient of the interaction term $ES\ High_{i,t} \times Covid_{i,t}$ is positive and significant at the conventional level. Economically, high ES firms earn an average daily return of 0.2%–0.3% relative to other firms between January 20 and February 3, 2020, for a cumulative effect of 1%–1.5% (0.2%×5–0.3%×5). The evidence suggests that investors pay more for ES stocks during the market collapses following Lins et al. (2017) and Albuquerque et al. (2020). Further, we proceed to estimate the effect of state ownership on the relationship between ES and stock returns with a difference-in-difference-in-differences estimation. As presented in Columns (3) and (4) of Table 2, the coefficient of $ES\ High_{i,t} \times Covid_{i,t}$ is insignificant, indicating that high ES-rated SOEs cannot earn a higher stock return relative to the other SOEs during the COVID-19 market crisis. In comparison, the coefficient of the three-way interaction term is positive and significant at the conventional level for both stock return proxies. It suggests that the positive effect of ES on stock returns is driven by non-SOEs. Regarding economic significance, non-SOEs with high ES ratings earn an average daily return of 0.4%–0.5% relative to other non-SOEs during the pandemic-induced market crash, with a cumulative effect of 2%–2.5% (0.4%×5–0.5%×5). Moreover, the coefficient of $Nsoe_{i,t} \times Covid_{i,t}$ is significantly negative, suggesting that non-SOEs are more affected by COVID-19 than SOEs. It is consistent with our expectations. In addition, to mitigate the concern that the effect of state ownership on the ES-stock return link might be driven by some other firm fundamental characteristics, we construct a three-way interaction term between $ES\ High_{i,t}$, $Covid_{i,t}$ and each control variable and include all possible interaction terms. As presented in Columns (5) and (6) of Table 2, we find that the coefficient of the interaction term $ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$ remains positive and statistically significant at the conventional level for both stock return proxies using unrestricted regression models. The evidence suggests that the positive effect of ES on stock returns is more pronounced in non-SOEs than SOEs during the crisis, which supports Hypothesis 1's argument.

[Insert Table 2 about Here]

4.2 Dimensions of ES

Some aspects of ES are more important to risk aversion than others. Therefore, we re-estimate the model (1) by nine secondary indicators that are available across industries. Specifically, four indicators are under the environment pillar, including energy-saving and emission reduction, pollution treatment, publicity of greening and environmental protection, and green office. Five indicators are under the social pillar, including charity activities, consumer relations, supplier relations, community relations, and employee relations. For each of the nine indicators, we construct a dummy variable that equals one if a firm's rating is in the top third in 2019 and zero otherwise. Then, we conduct the regression model (1) with nine interaction terms included in a regression. As presented in Table 3, the coefficient associated with the interaction term of $Employee_{i,t}$, $Covid_{i,t}$ and $Nsoe_{i,t}$ is positive and statistically significant at the conventional level for both stock return proxies. The evidence confirms the value of employee relations during the crisis and aligns with Shan and Tang (2022). Therefore, we conclude that the benefit of ES activities in non-SOEs concentrates on employee relations.

[Insert Table 3 about Here]

4.3 Effect of institutional ownership

Previous literature documents that institutional investors are rational and sophisticated (Black, 1986; Kyle, 1985) and have a long-term ESG investment horizon (Bolton & Kacperczyk, 2021; Chava, 2014; Dyck et al., 2019; Hong & Kacperczyk, 2009). We expect the positive relationship between ES and stock returns for non-SOEs to be more pronounced in firms with high institutional ownership. We assign firms into two groups according to the sample median level of institutional ownership percentage in 2019. As presented in Panel A of Table 4, the coefficient of the three-way interaction term is significantly positive, about 0.005 - 0.006, in firms with high institutional ownership, which is significantly higher than in firms with low institutional ownership. Additionally, following Cleary (1999), we use the bootstrapping resampling method to examine the statistical difference between the coefficients of the interaction term between groups. We find that the difference between the coefficients is statistically different from zero at the conventional level. The evidence supports Hypothesis 2's argument.

4.4 Effect of firm risk

We continue to examine the risk-buffering value of ES. Although it is hard to measure directly, we consider that if the risk buffer conjecture holds, the value would be more pronounced in risky firms. To gain further insight into the influence of firm risk on the ES effects in non-SOEs, we employ two proxies from a financial perspective: external financial constraints and bankruptcy risk. First, we use the KZ index constructed by Kaplan and Zingales (1997) to measure the degree of external financial constraints. We split our full sample into two subsamples according to the median of the KZ index in 2019. As reported in Panel B of Table 4, the coefficient of the three-way interaction term is significantly positive in the high financially constrained subsample and statistically insignificant in the low financially constrained subsample. The difference between the coefficients is statistically different from zero at the conventional level. This empirical evidence supports Hypothesis 3's argument.

Alternatively, we use bankruptcy risk to reflect firm risk from a different perspective. We use the probability of bankruptcy estimated using the methodology of Ohlson (1980) to reflect firm bankruptcy risk and assign the firms into two subsamples according to the median value of the probability of bankruptcy in 2019. As presented in Panel C of Table 4, the coefficient of the three-way interaction term is significantly positive in firms with a high probability of bankruptcy for both stock return proxies, while it is statistically insignificant in firms with a low probability of bankruptcy. The difference between the coefficients is statistically different from zero at the conventional level. The empirical evidence further strengthens the risk-buffering value of ESG.

[Insert Table 4 about Here]

5 State ownership, ES, and operating performance

To conduct a preliminary look at the possible sources of the excess returns earned by high-ES-rated non-SOEs during the COVID-19 market crash, we follow Lins et al. (2017) and Albuquerque et al. (2020) and study firms' operating performance during the pandemic and surrounding periods. As accounting numbers are slower to incorporate the worsening economic situation than stock returns, we measure the change in operating performance from 2019 to 2020. The regression formula is as follows:

$$\Delta Performance_i = \alpha + \beta_1 ES_i + \beta_2 Firm\ Controls_i + \beta_3 Industry\ FE + \varepsilon_i \qquad (2)$$

where the dependent variables are changes in ΔROA_i, net profit margin (ΔNPM_i), and asset turnover (ΔAT_i) from 2019 to 2020. The independent variable is the firms' ES ratings in 2019. We include firm size, Tobin's Q, cash holding, and leverage as control variables and add industry-fixed effects to control for any other unobservable effects. Standard errors are clustered by industry.

As presented in Columns (1), (4), and (7) of Table 5, firms with high ES ratings exhibit significantly higher return on assets and net profit margins at the conventional level. It is consistent with the work of Lins et al. (2017). However, we do not find a significant influence of ES on the change in asset turnover ratio from 2020 to 2019. Our results suggest that firms with high ES ratings increase their profitability even as sales remain constant. Furthermore, we examine the impact of ES on operating performance by state ownership. As presented in Columns (2), (5), and (8) of Table 5, ES policies do not have a significant impact on operating performance for SOEs. In comparison, as reported in Columns (3), (6), and (9) of Table 5, ES activities have a significant and positive influence on return on assets and net profit margin for non-SOEs. We do not observe a significant impact of ES on the asset turnover ratio between 2020 and 2019 for non-SOEs. Overall, the operating performance results suggest that one of the channels through which non-SOEs with high ES ratings earn excess returns in the market crash is the risk-buffering value of ES, as reflected in higher profitability during the crisis.

[Insert Table 5 about Here]

6 State ownership, ES, and long-term stock returns

We further examine the long-term impact of ES activities on stock performance with the asset pricing model. Our long sample covers the entire A-shares from 2016 to 2020. Based on firms' ES ratings, we develop five industry-neutral, annually re-balanced investment portfolios. Specifically, we assign stocks in each year to four ES-sorted portfolios: low, median-low, median-high, and high ES portfolios. We also form a high-minus-low portfolio, which is equivalent to going long on the high ES portfolio and short on the low ES portfolio. Since IIGF updates firms' ES ratings for the previous year at the end of June each year, we refresh the portfolios every August. The sample period runs from August 2016 to December 2020. Portfolio returns are calculated every month with value weights based on firms' market value at the end of July every year. To better assess the four portfolios' stock performance, we analyze the monthly risk-adjusted return (alpha) relative to the four-factor model (Carhart, 1997)[8]. The formula is as follows:

$$Return_t = \alpha + \beta_1 mkt\_rf_t + \beta_2 smb_t + \beta_3 hml_t + \beta_4 umd_t + \varepsilon_t \quad (3)$$

where $Return_t$ is the value-weighted portfolio return in month t in excess of the risk-free rate. α is the intercept that captures the monthly risk-adjusted return. The explanatory variables are the market risk premium factor (mkt_rf_t), size factor (smb_t), value factor (hml_t), and momentum factor (umd_t). Standard errors are adjusted for heteroscedasticity.

[8] The four-factor model includes market risk premium factor (*mkt_rf*), size factor (*smb*), value factor (*hml*), and momentum factor (*umd*). We obtain factor data from the Center for China Asset Management Research at CUFE.

Table 6 lists the monthly returns of stocks sorted into five portfolios based on their ES ratings. As presented in Panel A of Table 6, the high ES portfolio can generate a significant excess return of 3.6% annually; conversely, the low ES portfolio has a significant and negative risk-adjusted return of -2.4% annually. We also estimate the return difference between the high and low ES portfolios in the right-most column. The results show that a portfolio that longs high ES-rated stocks and shorts low ES-rated stocks can generate a significant excess return of 4.8% annually. Consequently, our findings further suggest that ES can create value for firms in the long run.

We continue to estimate the monthly returns of ES-sorted portfolios for SOEs and non-SOEs, respectively. For brevity, we do not report coefficients for risk factors in the sub-sample analysis. As presented in Panel B of Table 6, the high ES portfolio cannot generate a significant excess return for SOEs. The return difference between high and low ES portfolios is also insignificant, indicating that ES activities cannot create value for SOEs in the long run. For non-SOEs, a high ES portfolio earns a significant excess return of 6% annually, while a low ES portfolio has a significant and negative risk-adjusted return of -3.6% annually. A portfolio constructed by longing high ES-rated non-SOEs and shorting low ES-rated non-SOEs earns a significant excess return of 8.4% annually, as reported in Panel C of Table 6. Overall, the empirical findings further support the argument that the value of ES on stock returns is driven by non-SOEs.

[Insert Table 6 about Here]

7 Robustness Analyses

First, firms with ES information disclosure are more likely to be identified with their ES activities; we use ES information disclosure to replace ES ratings to mitigate the concern that our main results are sensitive to ES rating estimation. As presented in Panel A of Table 7, the coefficients of the three-way interaction term are positive and statistically significant for both stock return proxies. The evidence is in line with our main finding and further strengthens the significant impact of state ownership on the ES-stock return link.

Second, to eliminate the possibility that our findings are driven by the grouping methods, we re-examine the model (1) with alternative grouping approaches. Specifically, we construct the high ES group with firms whose ES ratings are in the top quartile and top half of the whole sample in 2019, respectively. As presented in Panel B of Table 7, the results remain consistent with our main findings and are of similar statistical and economic significance.

Third, to answer the question of whether the benefit of ES activities in non-SOEs during the market crash is for all firms in China or is limited to those with close linkage to the coronavirus, we investigate the possibility that such an effect could vary with firms' location. As the COVID-19 pandemic was first identified and broke out in Wuhan[9], we exclude firms in this city to explore whether the value of ES in non-SOEs is a general pattern. As presented in Columns (1) and (2) of Panel C in Table 7, the coefficient of the three-way interaction term is positive and statistically significant for both stock return proxies. The evidence confirms that the value of ES in non-SOEs holds for firms outside of Wuhan. Moreover, we continue to exclude firms in Hubei province[10] and find consistent results, as reported in Columns (3) and (4) of Panel C in Table 7. We thus conclude that the benefit of ES activities in non-SOEs during the COVID-19 market crash is not unique to firms in Wuhan or Hubei but represents a general influence on all listed firms in China.

[Insert Table 7 about Here]

Fourth, the effect of state ownership on the ES-stock return link may be driven by firms' other characteristics or latent variables. We employ a re-sampling method by randomly allocating the "wrong" SOEs and non-SOEs among firms. If the effect of state ownership is not driven by other unobserved factors, we expect to observe insignificant results when we perform the regression model (1) using the "wrong" indicators. We repeat 2000 times and report the distribution of *t*-statistics of the three-way interaction term between ES performance, COVID-19 indicator, and state ownership. As shown in Figure 3, the distribution of *t*-statistics estimates is centered around zero for both stock return proxies. The cumulative probability of insignificant positive *t*-statistics at a 10% significance level is 93.8% for abnormal returns and 93.4% for raw returns, respectively (the shaded area in Figure 3). When we correctly assign the state ownership indicator in our baseline regression, the value of *t*-statistics is 3.72 for abnormal returns and 2.97 for raw returns. Both of them are beyond the 99^{th} percentile of the 2000 wrong estimates. Therefore, the results of the placebo test suggest that the significant effect of state ownership on the relationship between ES and stock returns is unlikely to be driven by some unobserved factors.

[Insert Figure 3 about Here]

Fifth, we match SOEs and non-SOEs with a nearest neighbor propensity score matching method to eliminate the possibility that the different value of ES in the two groups is driven by some firm fundamental and industry factors. Specifically, for each SOE, a non-SOE with the

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[9] Wuhan had the largest number of infected people in the first quarter of 2020.
[10] Wuhan is the capital city of Hubei province.

closest propensity score is matched without replacement based on firm size, leverage, Tobin's Q, ROA, cash holdings, idiosyncratic risk, and industry fixed effect. We eventually obtain 1,098 pairs after the matching procedure. As presented in Panel A of Table 8, the coefficients of the three-way interaction term of $ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$ are statistically significant for both stock return proxies. The findings are consistent with our main findings and lend credence to the significant effect of state ownership on the ES-stock return link.

We continue to use the entropy balancing method in Hainmueller (2012) to achieve covariate balance in SOEs and non-SOEs. Specifically, we adjust the unit weights to make sure that the non-SOEs and reweighted SOEs match exactly the covariate means and variances. We include firm size, leverage, Tobin's Q, ROA, cash holdings, and idiosyncratic risk as the covariates. As presented in Panel B of Table 8, the coefficients of $ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$ remain positive and statistically significant at the conventional level for both stock return proxies when taking endogeneity into account.

[Insert Table 8 about Here]

Finally, we examine the natural question of whether the positive effect of ES on stock returns is temporary or permanent. If the higher stock return of ES firms during the COVID-19 market crash is due to investors' mispricing, then such misconduct should not be maintained for long. We extend our event window to 10 and 30 trading days from January 20, 2020, respectively. We do not go beyond 30 trading days, as new confounding events may contaminate the initial effect. As presented in Table 9, the coefficients of the interaction term $ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$ are positive and statistically significant in the case of both event windows. The evidence suggests that the outperformance of high-ES-rated non-SOEs is not subsequently reversed. The possible reason is that investors did not update their ES beliefs and incorporate ES into valuation until a shock such as the COVID-19 pandemic hit.

[Insert Table 9 about Here]

8 Conclusion

This study uses the outbreak of the COVID-19 pandemic in China as a quasi-natural experiment to investigate the effect of state ownership on the relationship between ES and stock returns. We find that firms with high ES ratings have significantly higher stock returns relative to others during the market collapse. The positive effect of ES on stock returns is insignificant for SOEs but significantly positive for non-SOEs, suggesting that state ownership reduces the value of ES in China. Our findings are robust under a series of endogeneity and robustness tests. Additionally, we show that the value of ES in non-SOEs concentrates on employee relations and is more pronounced in firms with high institutional ownership, strong financial constraints, and high bankruptcy risk. We also find that high ES stocks exhibit significantly higher return on assets and net profit margin firms in non-SOEs, while we do not find that ES policies affect operating performance in SOEs. Additionally, we document that a portfolio that longs high ES-rated stocks and shorts low ES-rated stocks can generate a significant excess return for non-SOEs but not for SOEs from 2016 to 2020. Overall, our findings suggest that the value of ES on stock returns is driven by non-SOEs.

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Table 1: Summary statistics

The table presents the summary statistics of variables in our sample. In Panel A, we report the summary statistics of the variables employed in our main analyses. In Panel B, we compare the mean of the variables between SOEs and non-SOEs. Panel C presents a correlation matrix of the variables. The definitions of all variables are reported in Appendix A2.

Panel A: Full sample						
Variable	Obs.	Mean	SD	25%	Median	75%
$ES_{i,t}$	62842	0.485	0.234	0.294	0.446	0.657
$ES\ high_{i,t}$	62842	0.334	0.472	0.000	0.000	1.000
$Nsoe_{i,t}$	62842	0.698	0.459	0.000	1.000	1.000
$Abnormal\ return_{i,t}$	62842	0.000	0.028	-0.012	-0.002	0.009
$Raw\ return_{i,t}$	62842	-0.005	0.035	-0.017	-0.002	0.011
$Cash_{i,t}$	62842	0.144	0.114	0.063	0.112	0.188
$Idiosyncratic\ risk_{i,t}$	62842	0.124	0.640	0.041	0.060	0.091
$Leverage_{i,t}$	62842	0.439	0.216	0.268	0.421	0.588
$ROA_{i,t}$	62842	0.019	0.117	0.011	0.034	0.066
$Size_{i,t}$	62842	22.388	1.452	21.368	22.154	23.117
$Tobin's\ Q_{i,t}$	62842	1.854	1.207	1.150	1.476	2.044

Panel B: SOEs vs Non-SOEs						
Variable	SOEs		Non-SOEs		Diff	*p-value*
	Obs.	Mean	Obs.	Mean		
$ES_{i,t}$	18979	0.521	43863	0.470	0.051***	0.000
$Abnormal\ return_{i,t}$	18979	-0.001	43863	0.001	-0.002***	0.000
$Raw\ return_{i,t}$	18979	-0.006	43863	-0.004	-0.002***	0.000
$Cash_{i,t}$	18979	0.146	43863	0.143	0.003***	0.001
$Idiosyncratic\ risk_{i,t}$	18979	0.068	43863	0.149	-0.081***	0.000
$Leverage_{i,t}$	18979	0.502	43863	0.412	0.090***	0.000
$ROA_{i,t}$	18979	0.023	43863	0.017	0.006***	0.000
$Size_{i,t}$	18979	23.163	43863	22.053	1.110***	0.000
$Tobin's\ Q_{i,t}$	18979	1.578	43863	1.973	-0.395***	0.000

Continuation of Table 1

Panel C: Correlation Matrix									
	$ES_{i,t}$	$Nsoe_{i,t}$	$Abnormal\ Return_{i,t}$	$Cash_{i,t}$	$Idiosyncratic\ Risk_{i,t}$	$Leverage_{i,t}$	$ROA_{i,t}$	$Size_{i,t}$	$Tobin's\ Q_{i,t}$
$ES_{i,t}$	1								
$Nsoe_{i,t}$	-0.101	1							
$Abnormal\ Return_{i,t}$	0.015	0.034	1						
$Cash_{i,t}$	-0.009	-0.013	0.010	1					
$Idiosyncratic\ Risk_{i,t}$	-0.055	0.058	0.012	0.107	1				
$Leverage_{i,t}$	0.094	-0.192	-0.030	-0.355	-0.114	1			
$ROA_{i,t}$	0.047	-0.025	0.043	0.208	0.034	-0.351	1		
$Size_{i,t}$	0.296	-0.351	-0.017	-0.191	-0.073	0.495	0.068	1	
$Tobin's\ Q_{i,t}$	-0.052	0.151	0.030	0.210	0.005	-0.219	-0.014	-0.408	1

Table 2: State ownership, ES and stock returns

This table reports the difference-in-difference-in-differences estimation of daily returns from January 1 to February 3, 2020. *ES High*$_{i,t}$ equals one if the ES rating of firm *i* is in the top third in 2019 and zero otherwise. *Covid*$_{i,t}$ equals one from January 20 to February 3, 2020, and zero from January 1 to January 19, 2020. *Nsoe*$_{i,t}$ equals one for non-SOEs and zero for SOEs. In Columns (1), (3), and (5), the dependent variable is the daily abnormal return estimated as the difference between the daily logarithm return of the stock and the CAPM beta multiplied by the daily logarithm return of the market based on the CAPM model. The CAPM beta is estimated using daily stock returns over 3 years between 2017 and 2019 and the CSI300 Index as the market index. In Columns (2), (4), and (6), the dependent variable is the daily raw return. All models include firm, day, and industry times day fixed effects and cluster standard errors by the firm. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Nsoe*$_{i,t}$			0.005***	0.004***	0.005***	0.004***
			(3.39)	(2.98)	(3.72)	(2.97)
ES High$_{i,t}$ × *Covid*$_{i,t}$	0.003***	0.002***	-0.001	-0.001	-0.017	-0.022**
	(4.30)	(3.73)	(-0.25)	(-0.29)	(-1.40)	(-1.97)
Nsoe$_{i,t}$ × *Covid*$_{i,t}$			-0.004***	-0.003***	-0.004***	-0.003***
			(-4.44)	(-3.57)	(-4.21)	(-3.20)
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Size*$_{i,t}$					0.001	0.001**
					(1.38)	(2.08)
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Leverage*$_{i,t}$					-0.005	-0.006
					(-1.06)	(-1.28)
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Tobin's Q*$_{i,t}$					0.001	0.001
					(0.91)	(1.15)
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *ROA*$_{i,t}$					0.006	0.007
					(0.88)	(1.01)
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Cash*$_{i,t}$					0.003	-0.016**
					(0.40)	(-2.46)
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Idiosyncratic Risk*$_{i,t}$					-0.013***	0.001
					(-2.97)	(0.29)
Size$_{i,t}$ × *Covid*$_{i,t}$					0.001	0.001
					(0.81)	(0.19)
Leverage$_{i,t}$ × *Covid*$_{i,t}$					0.001	0.001
					(0.38)	(0.52)
Tobin's Q$_{i,t}$ × *Covid*$_{i,t}$					0.001***	0.001***
					(3.44)	(2.72)
ROA$_{i,t}$ × *Covid*$_{i,t}$					0.003	0.005
					(0.80)	(1.22)
Cash$_{i,t}$ × *Covid*$_{i,t}$					-0.015**	0.003
					(-2.48)	(0.76)
Idiosyncratic Risk$_{i,t}$ × *Covid*$_{i,t}$					-0.002	-0.002***
					(-0.56)	(-3.52)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
# of observations	62842	62842	62842	62842	62842	62842
Adj. R-sq	0.085	0.509	0.085	0.509	0.091	0.510

Table 3: Dimensions of ES and crisis-period returns

This table reports the difference-in-difference-in-differences estimation of daily abnormal returns by secondary indicators. Energy-saving and emission reduction ($ESER_{i,t}$), pollution treatment ($PT_{i,t}$), publicity of greening and environmental protection ($EP_{i,t}$), green office ($GO_{i,t}$), charity activities ($Charity_{i,t}$), consumer relations ($Consumer_{i,t}$), supplier relations ($Supplier_{i,t}$), community relations ($Community_{i,t}$) and employee relations ($Employee_{i,t}$) equal one if the rating is in the top third in 2019. We control for the effect of firm size, leverage, Tobin's Q, ROA, cash holdings and idiosyncratic risk on ES value. All models include firm, day and industry times day fixed effects and cluster standard errors by the firm. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent Variables	$Abnormal\ Return_{i,t}$	$Raw\ Return_{i,t}$
$ESER_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	-0.001	-0.001
	(-0.30)	(-0.72)
$PT_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	-0.003*	-0.001
	(-1.66)	(-0.28)
$EP_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	-0.001	-0.001
	(-0.52)	(-0.63)
$GO_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.003	0.003
	(1.46)	(1.59)
$Charity_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.001	0.001
	(0.09)	(0.03)
$Consumer_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	-0.001	-0.001
	(-0.14)	(-0.28)
$Supplier_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.001	0.001
	(0.12)	(0.19)
$Community_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.001	0.001
	(0.66)	(0.47)
$Employee_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.004**	0.003*
	(2.51)	(1.91)
All other possible interactions included	Yes	Yes
Control variables	Yes	Yes
Firm FE	Yes	Yes
Day FE	Yes	Yes
Industry × Day FE	Yes	Yes
# of observations	62842	62842
Adj. R-sq	0.091	0.510

Table 4: Cross-sectional analysis

The table reports the results of cross-sectional analyses using subsamples. In Panel A, we split the sample into two subsamples according to the median of institutional ownership in 2019. The institutional investors include funds, brokers, banks, pension funds, insurance companies, trust companies, finance companies, non-finance companies, and qualified foreign institutional investors. In Panel B, we split the sample into two subsamples according to corporate financial constraints proxied by KZ index. A firm has high financial constraints if its KZ index is above the sample median in 2019, and *vice versa*. In Panel C, we split the sample into two subsamples according to the median probability of bankruptcy in 2019. The probability of bankruptcy is estimated with the methodology in Ohlson (1980). We control for the effect of firm size, leverage, Tobin's Q, ROA, cash holdings and idiosyncratic risk on ES value. All models include firm, day, and industry times day fixed effects and cluster standard errors by the firm. We conduct the difference test with the null hypothesis that the coefficients of the interaction term are the same in the two subgroups and calculate the empirical p-value with an 800-times bootstrapping procedure to estimate the likelihood of obtaining the null hypothesis. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of institutional ownership				
	(1)	(2)	(3)	(4)
	High IO	Low IO	High IO	Low IO
Dependent variables	$Abnormal\ Return_{i,t}$	$Abnormal\ Return_{i,t}$	$Raw\ Return_{i,t}$	$Raw\ Return_{i,t}$
$ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.006***	0.004*	0.005***	0.002
	(3.26)	(1.81)	(3.14)	(1.06)
Empirical p-values	0.060*		0.000***	
All other possible interactions	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Industry × Day FE	Yes	Yes	Yes	Yes
# of observations	31406	31351	31406	31351
Adj. R-sq	0.094	0.099	0.503	0.518
Panel B: Effect of financial constraints				
	(1)	(2)	(3)	(4)
	High financial constraints	Low financial constraints	High financial constraints	Low financial constraints
Dependent variables	$Abnormal\ Return_{i,t}$	$Abnormal\ Return_{i,t}$	$Raw\ Return_{i,t}$	$Raw\ Return_{i,t}$
$ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.004**	0.003	0.005**	0.002
	(2.02)	(1.28)	(2.26)	(0.94)
Empirical p-values	0.098*		0.016**	
All other possible interactions	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Industry × Day FE	Yes	Yes	Yes	Yes
# of observations	29292	29085	29292	29085
Adj. R-sq	0.107	0.088	0.504	0.517
Panel C: Effect of probability of bankruptcy				

	(1)	(2)	(3)	(4)
	High bankruptcy risk	Low bankruptcy risk	High bankruptcy risk	Low bankruptcy risk
Dependent variables	$Abnormal\ Return_{i,t}$	$Abnormal\ Return_{i,t}$	$Raw\ Return_{i,t}$	$Raw\ Return_{i,t}$
$ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$	0.005**	0.001	0.006***	0.001
	(2.36)	(0.52)	(2.58)	(0.06)
Empirical *p*-values	0.000***		0.000***	
All other possible interactions	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Industry × Day FE	Yes	Yes	Yes	Yes
# of observations	28651	28910	28651	28910
Adj. R-sq	0.103	0.092	0.508	0.514

Table 5: State ownership, ES and operating performance

This table reports the results of regressions of operating performance's change on firms' ES performance. The dependent variables are the change of return on assets, net profit margin, and asset turnover between 2019 and 2020 for Columns (1)–(3), (4)–(6), and (7)–(9), respectively. The independent variable is the firms' ES ratings in 2019. The control variables are firms' size, leverage, Tobin's Q, and cash holding. All models include industry fixed effect and cluster standard errors by industry. We conduct the difference test with the null hypothesis that the coefficients of *ES* are the same for SOEs and non-SOEs and calculate the empirical *p*-value with an 800-times bootstrapping procedure to estimate the likelihood of obtaining the null hypotheses. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample	SOEs	Non-SOEs	Full sample	SOEs	Non-SOEs	Full sample	SOEs	Non-SOEs
Dependent Variables	ΔROA_i	ΔROA_i	ΔROA_i	ΔNPM_i	ΔNPM_i	ΔNPM_i	ΔAT_i	ΔAT_i	ΔAT_i
ES_i	1.369*	-0.509	1.974*	8.725**	4.542	10.197**	0.073	0.320	-0.214
	(1.71)	(-0.58)	(1.80)	(2.41)	(1.01)	(2.26)	(0.07)	(0.19)	(-0.15)
Empirical *p*-values		0.000***			0.015**			0.205	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of observations	3687	1108	2568	3686	1108	2567	3687	1108	2568
Adj. R-sq	0.067	0.056	0.070	0.038	0.054	0.035	0.073	0.171	0.051

Table 6: Four-factor alpha of ES-sorted portfolios

This table reports the monthly returns of ES-sorted portfolios using Carhart's (1997) four-factor model. Panels A, B and C present results for the full sample, SOEs and non-SOEs, respectively. Since the IIGF updates firms' ES scores for the previous year at the end of June each year. We refresh the portfolios every August. The sample period runs from August 2016–December 2020. The stocks are ranked in ascending order based on their ES scores and grouped into four portfolios. The rightmost column reports the returns of portfolios that long the high ES portfolio and short the low ES portfolio. The formula is:

$$Return_t = \alpha + \beta_1 mkt\_rf_t + \beta_2 smb_t + \beta_3 hml_t + \beta_4 umd_t + \varepsilon_t$$

where $Return_t$ denotes the portfolio returns over the risk-free rate. We compute portfolio returns every month with value weights based on firms' market value at the end of July. α is the intercept in a time-series regression of monthly excess return, calculated based on the 4-factor model. The explanatory variables are the market risk premium factor (mkt_rf_t), size factor (smb_t), value factor (hml_t), and momentum factor (umd_t). Standard errors are adjusted for heteroscedasticity. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full sample					
Portfolio	P1 (Low)	P2 (ML)	P3 (MH)	P4 (High)	P5 (High-Low)
α	-0.002*	0.001	-0.002	0.003**	0.004*
	(-1.68)	(0.18)	(-1.21)	(2.11)	(2.01)
mkt_rf_t	1.028***	1.044***	0.942***	0.873***	-0.155***
	(39.36)	(24.35)	(29.50)	(21.25)	(-2.93)
smb_t	0.372***	0.200***	-0.147*	-0.292***	-0.664***
	(6.85)	(2.89)	(-1.75)	(-4.04)	(-6.91)
hml_t	-0.009	0.038	0.193***	0.204***	0.214***
	(-0.23)	(0.93)	(3.89)	(3.79)	(3.07)
umd_t	-0.103***	-0.110**	-0.025	-0.135***	-0.032
	(-2.84)	(-2.67)	(-0.55)	(-3.05)	(-0.61)
# of months	53	53	53	53	53
Adj. R-sq	0.974	0.960	0.945	0.942	0.705
Panel B: SOEs					
Portfolio	P1 (Low)	P2 (ML)	P3 (MH)	P4 (High)	P5 (High-Low)
α	0.001	-0.001	0.001	0.002	0.001
	(0.12)	(-0.38)	(0.14)	(0.84)	(0.04)
# of months	53	53	53	53	53
Adj. R-sq	0.926	0.907	0.883	0.888	0.527
Panel C: Non-SOEs					
Portfolio	P1 (Low)	P2 (ML)	P3 (MH)	P4 (High)	P5 (High-Low)
α	-0.003**	-0.002	-0.002	0.005**	0.007***
	(-2.04)	(-1.60)	(-1.43)	(2.34)	(3.09)
# of months	53	53	53	53	53
Adj. R-sq	0.969	0.979	0.969	0.928	0.691

Table 7: Robustness analysis

The table presents the regression results of robustness analyses. Panel A reports the results with an alternative ES estimation. *ES Disclosure*$_{i,t}$ equals one for firms with ES information disclosure in 2019, and zero otherwise. Panel B reports the results with alternative grouping methods. High ES-rated firms are defined as firms with ES ratings in the top quartile and top half in 2019 in the IIGF ESG database, respectively. Panel C reports the results excluding firms located in Wuhan City and Hubei province, respectively. We control for the effect of firm size, leverage, Tobin's Q, ROA, cash holdings and idiosyncratic risk on ES value. All models include firm, day and industry times day fixed effects and cluster standard errors by the firm. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Alternative proxies for ES performance		
Dependent variables	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$
ES Disclosure$_{i,t}$ × *Covid*$_{i,t}$ × *Nsoe*$_{i,t}$	0.004***	0.002*
	(2.67)	(1.87)
All other possible interactions	Yes	Yes
Control variables	Yes	Yes
Firm FE	Yes	Yes
Day FE	Yes	Yes
Industry × Day FE	Yes	Yes
# of observations	62842	62842
Adj. R-sq	0.090	0.510

Panel B: Alternative grouping methods				
	Top 1/4		Top 1/2	
Dependent variables	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Nsoe*$_{i,t}$	0.006***	0.004***	0.003**	0.002*
	(3.61)	(2.78)	(2.18)	(1.67)
All other possible interactions	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Industry × Day FE	Yes	Yes	Yes	Yes
# of observations	62842	62842	62842	62842
Adj. R-sq	0.090	0.510	0.089	0.510

Panel C: Excluding firms in Wuhan and Hubei				
	Excluding firms in Wuhan		Excluding firms in Hubei	
Dependent variables	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Nsoe*$_{i,t}$	0.006***	0.004***	0.006***	0.004***
	(3.74)	(2.97)	(3.85)	(3.01)
All other possible interactions	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Industry × Day FE	Yes	Yes	Yes	Yes
# of observations	61873	61873	61074	61074
Adj. R-sq	0.091	0.510	0.091	0.511

Table 8: Matched sample analysis

This table presents the results after addressing possible endogeneity concerns. In Panel A, we adopt a one-to-one nearest neighbor matching method based on firm size, leverage, Tobin's Q, ROA, cash holdings, idiosyncratic risk and industry fixed effect without replacement. Panel B reports the regression results using the entropy balancing method (Hainmueller, 2012). We create balanced samples by adjusting the differences between the two groups in covariate means and variances. The covariates include firm size, leverage, Tobin's Q, ROA, cash holdings and idiosyncratic risk. All models include firm, day and industry times day fixed effects and cluster standard errors by the firm. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Propensity score matching		
	(1)	(2)
Dependent variables	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Nsoe*$_{i,t}$	0.004***	0.004**
	(2.64)	(2.46)
All other possible interactions	Yes	Yes
Control variables	Yes	Yes
Firm FE	Yes	Yes
Day FE	Yes	Yes
Industry × Day FE	Yes	Yes
# of observations	37253	37253
Adj. R-sq	0.114	0.546
Panel B: Entropy balancing method		
	(1)	(2)
Dependent variables	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Nsoe*$_{i,t}$	0.005***	0.004***
	(3.72)	(2.97)
All other possible interactions	Yes	Yes
Control variables	Yes	Yes
Firm FE	Yes	Yes
Day FE	Yes	Yes
Industry × Day FE	Yes	Yes
# of observations	62842	62842
Adj. R-sq	0.091	0.510

Table 9: Longer event windows

This table reports the difference-in-difference-in-differences estimation of daily returns with longer event windows. *ES High*$_{i,t}$ equals one if the ES rating of firm *i* is in the top third in 2019 and zero otherwise. *Covid*$_{i,t}$ equals zero from January 1 to January 19, 2020, and one from January 20, 2020, to 10- and 30-trading days after, respectively. *Nsoe*$_{i,t}$ equals one for non-SOEs and zero for SOEs. We control for the effect of firm size, leverage, Tobin's Q, ROA, cash holdings and idiosyncratic risk on ES value. All models include firm, day and industry times day fixed effects and cluster standard errors by the firm. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	10-trading days		30-trading days	
Dependent variables	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$	*Abnormal Return*$_{i,t}$	*Raw Return*$_{i,t}$
ES High$_{i,t}$ × *Covid*$_{i,t}$ × *Nsoe*$_{i,t}$	0.003***	0.002**	0.001**	0.001*
	(2.64)	(2.19)	(2.07)	(1.78)
All other possible interactions	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Industry × Day FE	Yes	Yes	Yes	Yes
# of observations	81357	81357	155391	155391
Adj. R-sq	0.144	0.454	0.135	0.410

Figure 1: Stock market path during COVID-19 outbreak

This figure plots the stock market path of the CSI300 Index during the COVID-19 outbreak in 2020. The vertical lines represent the stock market crash periods.

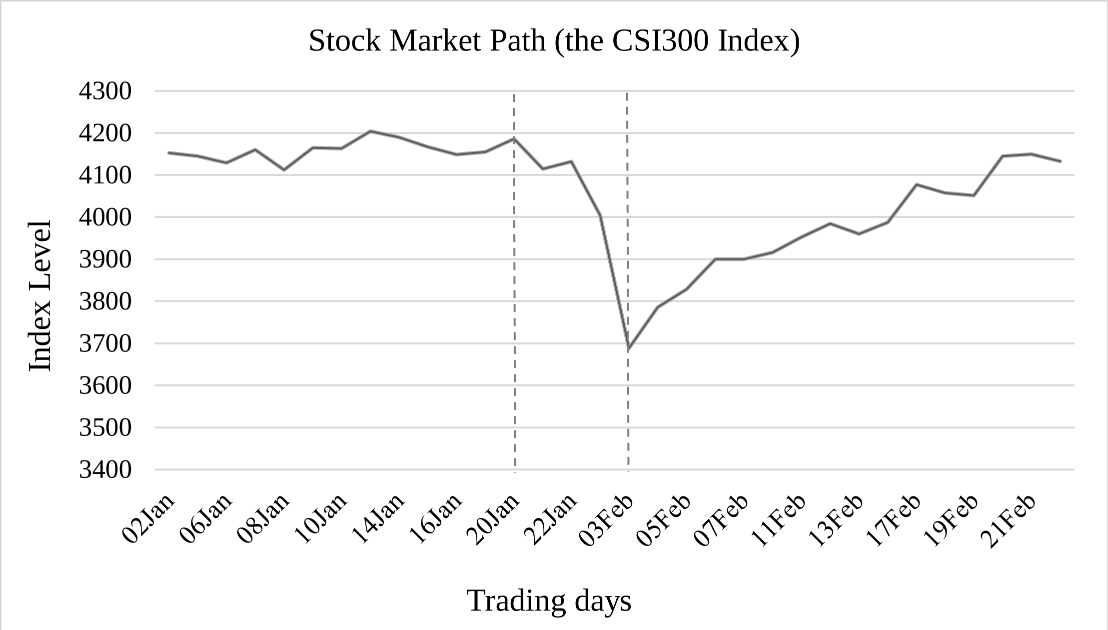


Figure 2: Stock returns by SOEs and ES groups during COVID-19 outbreak

This figure plots the equal-weighted abnormal and raw returns for the four subgroups from January 20 to February 3, 2020. The four groups are high ES non-SOEs, other non-SOEs, high ES SOEs, and other SOEs. *p*-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

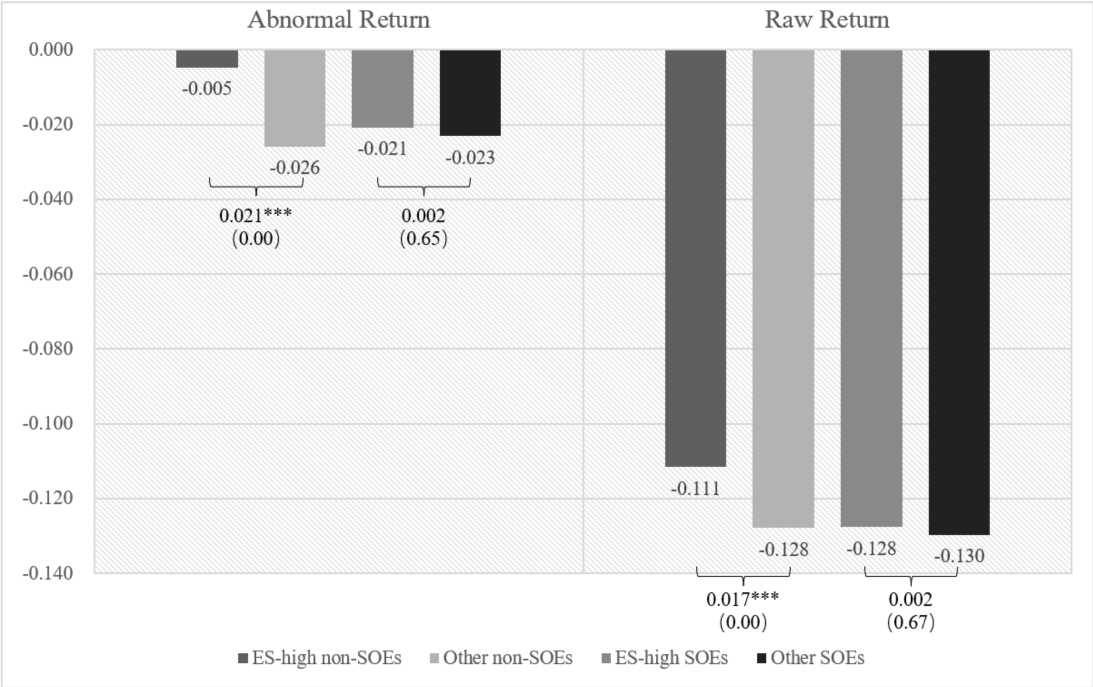
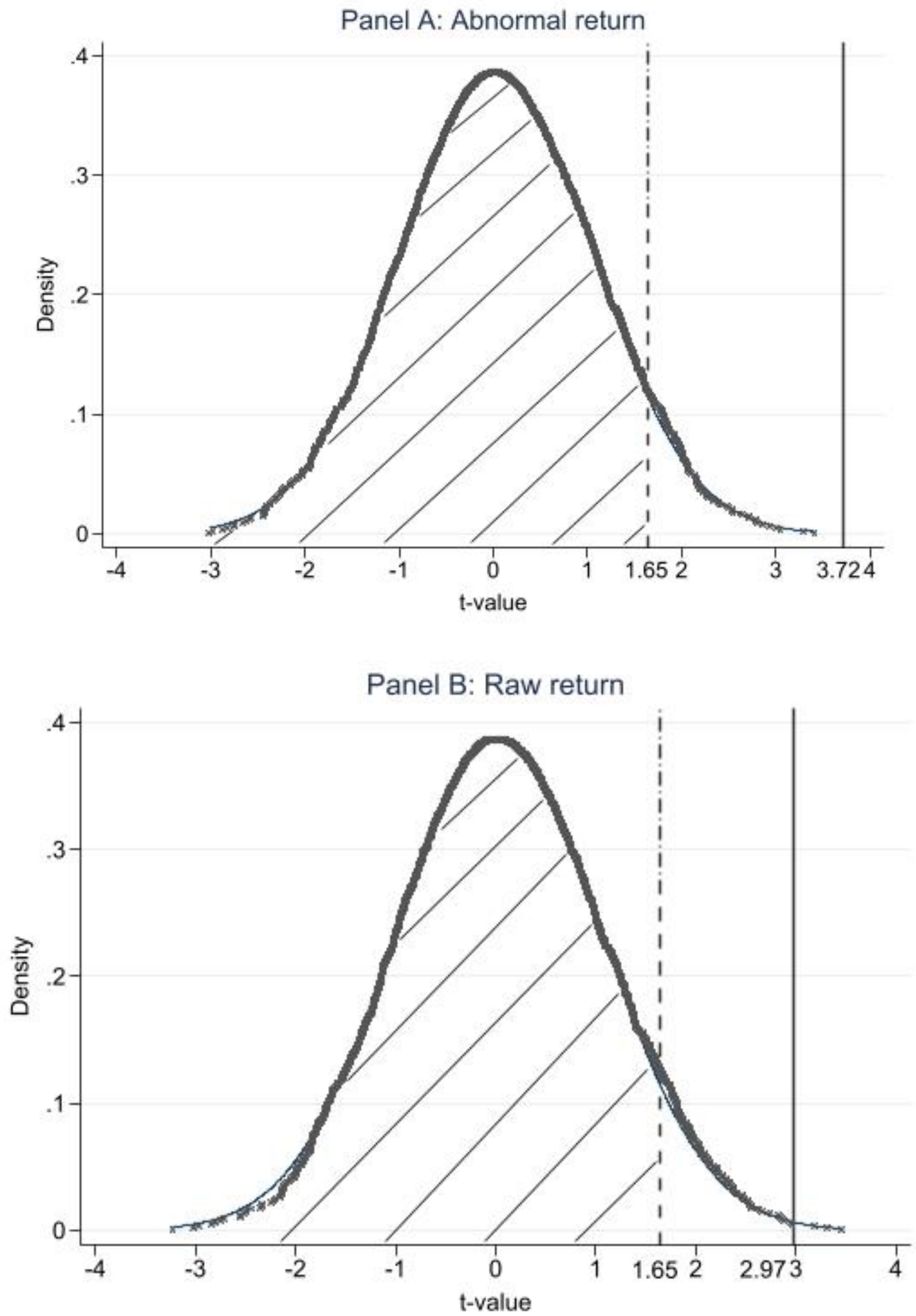


Figure 3: Placebo tests

The figure depicts the distribution of estimated *t*-statistics of the three-way interaction terms between high ES firm, COVID-19 and state ownership indicators of placebo tests. We randomly identify non-SOEs and perform the difference-in-difference-in-differences regression in Columns (5) and (6) of Table 2, respectively. We repeat the exercise 2000 times and plot the resulting estimated *t*-statistics. The vertical solid lines in Panels A and B present *t*-statistics of the interaction term $ES\ High_{i,t} \times Covid_{i,t} \times Nsoe_{i,t}$ in Columns (5) and (6) of Table 2, respectively. The vertical dashed line presents a *t*-statistic of 1.65. Shaded areas indicate the cumulative probability of a non-significant positive relationship at a 10% significance level.



Appendix

Table A1: IIGF ESG indicators

This table reports detailed information on ESG indicators in the IIGF ESG rating system. Secondary indicators marked with an asterisk represent industry-specific indicators.

Primary indicator	Secondary indicator	Qualitative/Quantitative
Environment	Energy-saving and emission reduction	Qualitative
	Pollution treatment	Qualitative
	Publicity of greening and environmental protection	Qualitative
	Green office	Qualitative
	Green design*	Qualitative
	Green technology*	Qualitative
	Green supply*	Qualitative
	Green production*	Qualitative
	Green financial products*	Qualitative
	Green revenue*	Quantitative
	Negative news	Quantitative
	Penalty	Quantitative
Social	Charity activities	Qualitative
	Community relations	Qualitative
	Employee relations	Qualitative
	Consumer relations	Qualitative
	Supplier relations	Qualitative
	Negative news	Quantitative
Governance	Organization structure	Qualitative
	Investor relations	Qualitative
	Information transparency	Qualitative
	Technical innovation	Qualitative
	Risk management	Qualitative
	Negative news	Quantitative
	Penalty	Quantitative

Table A2: Definitions of main variables

Variable	Definition
$ES_{i,t}$	Average between IIGF environment pillar score and social pillar score.
$ES\ High_{i,t}$	It is an indicator that equals one for firms in the top third of ES ratings in 2019, and zero otherwise.
$ES\ Disclosure_{i,t}$	It is an indicator that equals one for firms that released ESG reports in 2019, and zero otherwise.
$ESER_{i,t}$	It is an indicator that equals one for firms whose rating in energy-saving and emission reduction is in the top third in 2019, and zero otherwise.
$PT_{i,t}$	It is an indicator that equals one for firms whose rating in pollution treatment is in the top third in 2019, and zero otherwise.
$EP_{i,t}$	It is an indicator that equals one for firms whose rating in publicity of greening and environmental protection is in the top third in 2019, and zero otherwise.
$GO_{i,t}$	It is an indicator that equals one for firms whose rating in green office is in the top third in 2019, and zero otherwise.
$Charity_{i,t}$	It is an indicator that equals one for firms whose rating in charity activities is in the top third in 2019, and zero otherwise.
$Consumer_{i,t}$	It is an indicator that equals one for firms whose rating in consumer relations is in the top third in 2019, and zero otherwise.
$Supplier_{i,t}$	It is an indicator that equals one for firms whose rating in supplier relations is in the top third in 2019, and zero otherwise.
$Community_{i,t}$	It is an indicator that equals one for firms whose rating in community relations is in the top third in 2019, and zero otherwise.
$Employee_{i,t}$	It is an indicator that equals one for firms whose rating in employee relations is in the top third in 2019, and zero otherwise.
$Covid_{i,t}$	It is a dummy variable that equals one between January 20 and February 3, 2020, and zero between January 1 and January 19, 2020.
$Nsoe_{i,t}$	It is an indicator that equals one if the firm's controlling shareholder is not a government agency, and zero otherwise.
$Abnormal\ Return_{i,t}$	The daily abnormal return is the difference between the daily logarithm return of the stock and the CAPM beta multiplied by the daily logarithm return of the market. The CAPM beta is estimated with daily returns from 2017 and 2019, where the market index is the CSI300 Index.
$Raw\ Return_{i,t}$	Firms' daily stock return.
$Cash_{i,t}$	The ratio of cash and cash equivalents holdings to total assets.
$Idiosyncratic\ Risk_{i,t}$	The residual variance from the CAPM model. It is estimated with daily returns from 2017 and 2019 with the CSI300 Index as the market index.
$Leverage_{i,t}$	The ratio of total liabilities to total assets.
$ROA_{i,t}$	The ratio of net profit to total assets, multiplied by 100.
$Size_{i,t}$	The natural logarithm of book assets.
$Tobin's\ Q_{i,t}$	The ratio of book value of assets minus book value of equity plus the market value of equity to book value of assets.
ΔROA_i	It is the yearly change (2020 value minus 2019 value) for return on assets (ROA). ROA is net profit over book assets multiplied by 100.

ΔNPM_i	It is the yearly change (2020 value minus 2019 value) for net profit margin (NPM). NPM is net profit over sales multiplied by 100.
ΔAT_i	It is the yearly change (2020 value minus 2019 value) for asset turnover (AT). AT is sales over book assets multiplied by 100.