The Impact of Natural Disasters on Stock Prices in China: A Comparative Analysis of State-Owned and Privately Owned Enterprises

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ABSTRACT

The Impact of Natural Disasters on Stock Prices in China: A Comparative Analysis of State-Owned and Privately Owned Enterprises

Shurui Liu

This paper examines the impact of natural disasters on corporate stock price performance in China, with a particular focus on state-owned enterprises (SOEs) and privately owned enterprises (POEs). Utilizing an event study methodology, we analyze the stock price reactions of Chinese companies to large-scale tropical cyclones from 2000 to 2022. Our findings indicate that these natural disasters have a significant negative impact on stock prices, particularly during the immediate impact period. SOEs, however, demonstrate greater resilience compared to POEs during the post-disaster recovery period, suggesting that political connections and government support provide advantages in mitigating market volatility. Cross-sectional regression analyses reveal that firms with high leverage, low profitability, smaller size, and low market valuation experience higher abnormal returns in the recovery phase, indicating a faster recovery rate. An industry-specific analysis further shows that the financial services sector performs better following natural disasters, potentially due to increased demand for financial products, access to government aid, and favorable investor sentiment.

Keywords: Natural Disasters, Political Connections, Chinese Stock Market, Event Study, Abnormal Returns, Cross-Sectional Analysis

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Table of Contents

List of Tables

List of Figures

1. Introduction

Natural disasters resulting from natural hazard events can significantly impact human communities (Federal Emergency Management Agency, n.d.). Since 1990, natural disasters have resulted in more than 1.6 million fatalities worldwide, with economic losses averaging between US$260 to 310 billion annually (UNDRR, 2015a). In 2013, the World Bank estimated that disasters between 1980 and 2012 resulted in economic losses totaling US$3.8 trillion, with 74% of these losses attributed to extreme weather events (World Bank, 2013). Further, the World Bank (2016) reported that extreme natural disasters result in an estimated global loss of $520 billion in annual consumption and push approximately 26 million people into poverty each year (see also Walker et al., 2023). In the latest report by the World Bank (2023), since 1980, natural hazard-related disasters have resulted in the loss of over 2.5 million lives and caused nearly $6 trillion in damages, adjusted for inflation. This marks a 350 percent rise in annual damages, increasing from $52 billion in the 1980s to $232 billion in the early 2020s. In addition, Hallegatte et al. (2017) argue that natural disasters have the potential to exacerbate global poverty, with their impact on overall well-being surpassing the direct losses of physical assets.

Han et al. (2016) claim that China is highly prone to natural disasters due to its expansive territory, varied climate zones, complex geographical characteristics, and fragile ecological systems. The country has also faced an increase in natural disasters over the past three decades. Similarly, Zhou et al. (2013) indicate that China experienced a significant increase in natural disasters over the 32-year period from 1980 to 2011, with an average rate of 7.3 events per decade. The total direct economic losses caused by natural disasters in China between 1980 and 2011 amounted to US$109.16 billion, with an annual average of US$3.41 billion. In another study based on natural disasters in China from 1900 to 2011, Chen et al. (2013) show that China suffered 12 million deaths from natural disasters that affected a total population of 3 billion individuals. The estimated damage costs reached US$350 million. Moreover, they point out that floods, storms, and droughts are the three most extensive disaster types, each affecting more than 450 million people. Natural disasters in China have a profound impact, both socially and economically.

Natural disasters impact stock market performance in two primary ways: at the macroeconomic level and the stock valuation level. On a macroeconomic scale, regions affected by natural disasters typically encounter significant negative consequences. Botzen et al. (2019) point out that such events result in considerable direct economic losses, including extensive property damage in developed countries and high casualty rates in developing nations. Moreover, net macroeconomic (indirect) losses tend to be generally negative. Walker et al. (2023) also note that, following a natural disaster, countries or regions bear substantial costs for infrastructure reconstruction, employment support, medical aid, and various other expenses. At the stock valuation level, Seetharam (2017) reports that stocks impacted by natural disasters often experience negative abnormal returns in the post-disaster period. Additionally, firms exposed to environmental disasters generally have lower market valuations compared to those not affected, as observed in the U.S. market. Similarly, Mishra et al. (2021) identify a negative stock market reaction in India following the Uttarakhand disaster, underscoring the adverse effects of natural disasters on stock performance.

In this study, we examine the impact of natural disasters on the abnormal stock price performance of Chinese enterprises, with a specific focus on the differential effects between state-owned enterprises (SOEs) and privately owned enterprises (POEs). The Chinese market, characterized by a unique blend of both SOEs and POEs, offers a valuable context to investigate how environmental risks intersect with political connections. By analyzing the stock price responses to natural disasters, this research aims to uncover the varying degrees of resilience and risk associated with different corporate ownership forms. Furthermore, understanding these dynamics is essential for investors, policymakers, and corporate managers in formulating risk management strategies and enhancing market stability.

By employing an event study methodology, this research examines stock market reactions to natural disasters, specifically tropical cyclones, in China from 2000 to 2022. This approach provides a framework for assessing the impact of these events on the stock price performance of Chinese state-owned enterprises and privately owned enterprises. The findings indicate that tropical cyclones result in significant declines in stock prices across the market. Further analysis using cross-sectional OLS regression reveals that while SOEs and POEs are similarly affected during the disaster, SOEs demonstrate superior performance in the post-disaster recovery period. Additionally, our results indicate that firms with higher leverage, lower profitability, lower market valuation, and smaller size experience higher abnormal returns during the recovery phase, suggesting a faster recovery rate. Moreover, companies impacted by tropical cyclones that cause less damage exhibit a quicker recovery trajectory. These insights contribute to a deeper understanding of market dynamics in the face of natural disasters and can inform risk management strategies for different types of enterprises.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive literature review and the development of our research hypotheses. Section 3 describes the sample selection process, data sources, and key variables utilized in the study. Section 4 outlines our research methodology. Section 5 discusses the empirical findings derived from the study. Section

6 includes robustness checks and supplementary analyses. Finally, Section 7 provides the concluding remarks and examines the implications of our research.

2. Literature Review and Hypothesis Development

2.1. Literature Review

2.1.1. The Impact of Natural Disasters on the Economy and the Stock Market

Natural disasters have profound macroeconomic impacts, affecting key indicators such as GDP growth, balance of trade, public deficits, and national indebtedness (Mechler, 2003). They often result in extensive losses, including significant mortality rates, destruction of private infrastructure such as homes and manufacturing facilities, and damage to public goods such as roads, water supply systems, electricity grids, and public buildings. These disruptions can have long-lasting consequences on both economic stability and development (Johar et al., 2002; Navrud & Magnussen, 2013). Moreover, natural disasters can adversely affect local communities in both the short and long term, hindering recovery and resilience (Xiao, 2011).

Kousky (2014) observes that natural disasters, especially severe or recurring events, can lead to long-term negative consequences. This adverse impact is found to be more pronounced in developing countries and nations with smaller geographical areas. In contrast, higher-income countries, those with elevated education levels, and those with stronger institutional quality tend to experience less significant negative effects. Furthermore, the study highlights that the most substantial impact of natural disasters is often distributional. While certain groups and sectors may suffer considerable losses, others can potentially benefit from the reconstruction activities that follow the disaster. Shabnam (2014), utilizing a comprehensive panel dataset of 187 countries from 1960 to 2010, demonstrates that floods have a significant negative impact on economic growth. The study specifically finds that an increase in the total number of people affected by floods is associated with a notable decline in the annual GDP per capita growth rate. However, the death toll from floods does not appear to have a substantial impact on the annual GDP per capita growth rate.

Several prior studies have shown that natural disasters often lead to stock market volatility. For instance, Pagnottoni et al. (2022) examine the effects of natural disasters on international capital markets using an event study methodology, covering 104 countries and 27 global market indexes. They categorize disasters into five types—biological, climatological, geophysical, hydrological, and meteorological—and find that market reactions vary by disaster type. Climatological events typically result in negative market impacts, while biological events often trigger positive responses. In another study, Malik et al. (2020), employing an event study methodology, analyze industry-based stock price performance in the U.S. market from 1960 to 2015. Their findings indicate that industries exhibit varying reactions to the same disaster, with responses that are not always negative. Additionally, the study shows that different industries do not respond uniformly to various types of disasters, highlighting the nuanced and sector-specific nature of market reactions to such events. Similarly, Cao et al. (2020) conduct an event study on the Chinese stock market, revealing that meteorological disasters significantly impact market volatility. Their results show that domestic climatic events have a stronger effect on market fluctuations. Additionally, the impact varies by industry, with the same event affecting different industries differently, and different events having varying effects on the same industry. Liu et al. (2021) employ an event study methodology to assess the impact of the most economically damaging hurricanes in the North Atlantic on the stock returns of major U.S. energy companies over the four decades preceding the Paris Agreement. Their findings reveal a significant negative impact on stock returns, with variations across companies depending on their carbon intensity.

Overall, natural disasters typically have a negative impact on stock market returns worldwide. However, the extent and nature of this impact can vary depending on factors such as the type of disaster, the industries affected, and the country's economic characteristics. Different disasters can trigger varied market responses, as some industries may suffer immediate losses, while others might benefit from post-disaster reconstruction efforts.

2.1.2. Political Connections

Political connections can create mutual benefits for both politicians and companies, potentially allowing shareholders to profit, if politicians do not appropriate all the gains from the collaboration (Wisniewski, 2016). Civilize et al. (2015), using a comprehensive dataset that includes both direct and subtle political connections of firms in Thailand, conduct a longitudinal study revealing that politically connected firms consistently achieve higher long-term stock returns, both in raw and risk-adjusted terms. The study finds that firms connected to higher-level politicians experience greater stock returns compared to those linked with lower-level officials. Additionally, the political connection premium is more pronounced when political entities hold shares in the company rather than simply occupying positions on the company's board of directors. Faraji et al. (2020), analyzing 1,146 firm-year observations from companies listed on the Tehran Stock Exchange (TSE) from 2005 to 2017, identify a positive association between political connections and firms' annual actual and abnormal returns. Moreover, this positive relationship is further intensified during presidential election periods, leading to higher cumulative abnormal returns for politically connected firms. Claessens et al. (2008), using innovative indicators of political connections derived from campaign contribution data, reveal that Brazilian firms that made contributions to elected federal deputies saw higher stock returns than those that did not, particularly around the 1998 and 2002 elections. Additionally, the study observes that these contributing firms substantially increased their bank financing in comparison to a control group post-election, indicating that improved access to bank finance is a crucial mechanism through which political connections impact firm performance.

In the Chinese market, Du and Girma (2010), using unique firm-level data from China, analyze the role of political connections in the post-entry performance of private start-up companies. Their findings indicate that political affiliation significantly enhances a firm's survival and growth prospects. However, the benefits of political connections are primarily limited to firms associated with local or top-level governments and are more pronounced in capital-intensive industries. Schweizer et al. (2020) examine the influence of political connections on the corporate bond market for privately owned enterprises in China, exploring both the zero-default myth and borrower channel theories. Using a dataset of Chinese POEs from 2007 to 2016, the study finds that politically connected firms are more likely to issue corporate bonds and benefit from lower coupon rates, indicating reduced refinancing costs, which supports the zero-default myth theory. Despite these advantages, the performance of these firms tends to decline post-issuance. Furthermore, the study shows that investors react favorably to bond issuance announcements from politically connected firms. However, it also uncovers that politically connected POEs exhibit weaker corporate governance and a surprisingly higher default probability than their non-connected counterparts. Fonseka et al. (2015) investigate the influence of political connections and ownership structures on firms' access to the private equity market. This study examines the role of political connections and ownership structures in Chinese firms' access to private-equity placements, focusing on how political ties influence the regulatory process. Their analysis reveals that while political connections do not influence a firm's decision to apply for private-equity placements, state-owned firms are more likely to pursue such opportunities. Additionally, both political connections and state ownership increase the likelihood of securing approval from the Chinese Securities Regulatory Commission (CSRC) and result in more favorable treatment compared to firms without such connections. He et al. (2022) demonstrate that state ownership, political connections, and institutional ownership are key drivers that enhance CSR activities in disaster-affected areas. Moreover, enterprises with these characteristics tend to receive both accounting and stock market benefits in the post-disaster period.

2.2. Hypothesis Development

The existing literature emphasizes the substantial economic impact that natural disasters have on affected regions, particularly in terms of stock market returns. It is also well-documented that political connections can confer economic benefits to firms, enhancing their financial performance and access to capital. However, there remains a significant gap in understanding how environmental risks, such as natural disasters, intersect with political connections, especially within the Chinese market. This study aims to address this gap by exploring the differential impact of natural disasters on the stock returns of state-owned enterprises and privately owned enterprises in China. Given the unique nature of China's economic and political landscape, it is essential to investigate how political affiliation and ownership structures influence firms' resilience and recovery following environmental shocks. We hypothesize that:

1- Natural disasters have a negative impact on the Chinese stock market, resulting in negative cumulative abnormal returns (CARs) for companies headquartered in the provinces affected by the disaster during the event period.

This hypothesis is grounded in existing literature, which suggests that natural disasters typically cause significant economic losses and damage to the affected regions. These events increase stock market volatility, often leading to negative market reactions.

2- The stock price decline during the occurrence of natural disasters is anticipated to be less pronounced for state-owned enterprises (SOEs) compared to privately owned enterprises (POEs).
3- State-owned enterprises (SOEs) are expected to experience fewer negative impacts than privately owned enterprises (POEs) during the post-disaster recovery period.

These two hypotheses are based on the premise that SOEs, owing to their political connections and potential government support, may experience a less severe impact on stock returns during and after natural disasters compared to POEs. In contrast, POEs are likely to encounter greater market volatility and a slower recovery due to their limited access to government resources and support.

By examining these dynamics, this research aims to provide a more nuanced understanding of how natural disasters, political connections, and ownership structures influence firm performance in the Chinese stock market. The findings of this study have the potential to contribute to both academic literature and practical applications. Academically, it expands the existing body of knowledge on the impact of environmental risks on financial markets, particularly in the context of an emerging economy like China. Practically, it can offer valuable insights for investors, policymakers, and company executives on how political affiliations and government support can mitigate the financial repercussions of natural disasters, ultimately informing investment strategies, corporate risk management, and policy formulation.

3. Data

3.1. Sample Construction

Our natural disaster events data are sourced from the International Disaster Database (EM-DAT). To ensure accuracy, we cross-referenced and adjusted the event dates and identified the affected provinces in China using additional information from Wikipedia and Baidu Baike (the Chinese equivalent of Wikipedia). The International Disaster Database (EM-DAT) is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain (CRED, 2024).

Our sample construction begins by selecting large-scale natural disasters, focusing on floods, droughts, storms, extreme temperatures, and earthquakes, which are the most prevalent types in China (Chen et al., 2013). However, determining the exact event dates for floods, droughts, and extreme temperatures is challenging due to their prolonged durations. Therefore, we decided to exclude these events from our sample. For earthquakes, different industries exhibit varying responses (Zhou et al., 2019), and these events predominantly affect the Sichuan province and its surrounding areas, where relatively few companies are headquartered. Consequently, this limitation leads to an insufficient dataset for each industry, making it challenging to achieve statistical significance in our analysis (see also Tao, 2014). Thus, we have decided to exclude earthquakes from our sample. Ultimately, our sample focuses solely on large-scale tropical cyclones occurring between 2000 and 2022, specifically those that caused the most significant economic damage and affected the largest populations. Table 1 presents a comprehensive overview of the natural disasters included in our study. It outlines details such as the disaster name, event date, affected provinces, and the total recorded damage.

Insert Table 1 about here

The Chinese publicly traded companies included in our study are identified by matching the selected natural disasters with the Chinese publicly traded company database provided by the China Stock Market & Accounting Research (CSMAR) database. A company is classified as affected if it is headquartered in a province that has been significantly impacted by a natural disaster. Our sample consists of 1,678 publicly traded companies between 2000 and 2022, including 618 state-owned enterprises (SOEs) and 1,060 privately-owned enterprises (POEs). Table 2 provides a detailed breakdown of the number of affected companies in each industry, along with their corresponding CSRC industry codes.

Insert Table 2 about here

3.2. Variables

Table 3 details the variables used in our regression analysis. The dependent variable is the cumulative abnormal returns (CARs) of Chinese publicly traded companies' stock. This metric, derived from the event study methodology, captures the deviation in stock price reactions within a specified event window surrounding the natural disaster. By analyzing CARs, we can assess investor sentiment and market volatility in response to the event.

The key independent variable in our study is the SOE dummy, which is set to 1 if the enterprise is a state-owned enterprise and 0 otherwise. This dummy variable allows us to distinguish and analyze the differing magnitudes of a natural disaster's impact on the stock returns of publicly traded companies, comparing state-owned enterprises to privately owned enterprises.

The firm-specific independent variables include leverage, defined as the ratio of net total debt to total shareholders' equity. This metric indicates the extent to which a company relies on borrowed funds compared to the owners' capital, providing insight into the firm's financial risk and stability. Moreover, the return on assets (ROA) ratio, calculated as net profit divided by total assets, illustrates how efficiently a company utilizes its assets to generate income, serving as an indicator of its overall profitability. The liquidity ratio, calculated as cash and cash equivalents divided by total current liabilities, assesses a company's ability to meet its short-term obligations using its most liquid assets. It indicates how effectively a company can quickly convert its assets into cash to cover its current liabilities. Firm size is measured as the natural logarithm of total assets, providing a standardized way to compare companies of different scales. Additionally, the price-to-book ratio, calculated as the market value of equity divided by the book value of equity, indicates how the market values the company relative to its accounting value. A higher ratio suggests that the market expects strong future performance, while a lower ratio might signal potential undervaluation or concerns about the firm's prospects. Tobin's Q is another market valuation variable, defined as the ratio of the market value of a company's assets to the replacement cost of those assets. This measure provides insights into market expectations. We source these financial variables from the China Stock Market & Accounting Research (CSMAR) database.

The provincial GDP index is defined as the annual percentage change in a province's GDP, measuring the economic growth rate of the province compared to the previous year. Provincial GDP per capita, calculated as the natural logarithm of the gross domestic product per capita of the affected province, provides insight into the region's economic development level and overall wealth, which may influence how companies within the province respond to natural disasters.

These provincial macroeconomic variables are obtained from the Chinese National Bureau of Statistics.

Adjusted damage represents the natural logarithm of total economic loss caused by a given natural disaster in China, in US dollars, adjusted for inflation using China's Consumer Price Index (CPI) with 2015 as the base year (CPI = 100). This variable serves as a disaster-specific control in the analysis to account for the varying severity of different events and was collected from Wikipedia. Lastly, industry dummies are binary variables that take a value of 1 if the enterprise belongs to the specified industry and 0 otherwise. These variables provide insights into industry-specific effects, allowing for a more nuanced understanding of how different sectors are impacted by natural disasters.

We draw the financial data utilized in our regression analysis from the quarterly reports immediately preceding the occurrence of each natural disaster. This approach allows us to capture the most accurate and current financial performance of the affected companies at the time of the disaster, providing insight into their financial health and resilience prior to the event.

Insert Table 3 about here

4. Methodology

4.1. Event Study

We use the event study methodology to perform our empirical analysis to access the stock market performance around natural disasters. An event study measures the impact of a specific event on the value of a firm, typically by analyzing the changes in its stock price around the event window. The primary goal is to determine whether the event had a statistically significant effect on the firm's market value and, if so, the direction and magnitude of that impact. The abnormal return is calculated as the actual return of a specific stock minus its expected return, estimated using a specific pricing model. The cumulative abnormal return (CAR) is the sum of these abnormal returns over a defined event window, capturing the total impact of the event on the stock's performance. To gain a broader market perspective, we then compute the cumulative average abnormal returns (CAARs) by averaging the CARs across all firms in the sample, offering an overall measure of how the market, on average, responds to the event (MacKinlay, 1997). By analyzing the abnormal return (residual), we can identify the portion of the stock's return that is not explained by the pricing model. This unexplained component provides an estimate of the impact that the event, such as a natural disaster, has on the company's stock returns (Corrado, 2011).

In our sample, the event date for a tropical cyclone is defined as the day it makes landfall. Since the National Meteorological Center of CMA typically issues warnings three days in advance and tropical cyclones often take several days to dissipate after landfall, we identify the period from -3 to +3 trading days relative to the event date (day 0) as the duration during which the tropical cyclone is actively occurring. To assess the overall impact of the tropical cyclone, we select an extended event window from -10 to +15 trading days relative to the event date. This window allows us to measure the market impact before, during, and after the event. For the estimation period, we set the endpoint to 20 days before the event date, with a minimum and maximum length of 150 and 400 days, respectively. This approach allows us to capture the unique characteristics of the Chinese market more accurately through a longer estimation period. We then normalized the abnormal stock return by the standard deviation of returns during the estimation period, helping to control for volatility. This normalization also facilitates comparisons across different periods and various stocks, providing a more standardized measure of the event's impact. Specifically, the abnormal return is calculated using the following equation:

$$AR_{i,t} = R_{i,t} - E\left(R_{i,t}\right) \tag{1}$$

Where $AR_{i,t}$ is the abnormal return for stock i on day t, $R_{i,t}$ is the actual return of stock i on day t, $E\left(R_{i,t}\right)$ is the expected return for stock i on day t, estimated using a chosen model.

We adopt the one-factor market model, which assumes that a stock's return is primarily driven by overall market movements (Brenner, 1979). In this study, we use the equally weighted returns of the SSE and SZSE A-share markets as the market index to represent market performance. The model is mathematically represented as:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{2}$$

Where $R_{i,t}$ is the return of stock i at time t, α_i is a constant term for stock i, β_i is the market beta for stock i that measures the sensitivity of the stock's return to changes in the market return, $R_{m,t}$ is the market return at time t, and $\varepsilon_{i,t}$ is the error term.

After estimating the expected return using the one-factor market model, we calculate the abnormal return (AR) by subtracting the expected return from the actual return, as shown in the following equation:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t}) \tag{3}$$

We aggregate the abnormal returns to compute the cumulative abnormal return (CAR) in order to measure the total impact of the event over the entire event window by using the following equation:

$$CAR_{i(t1,t2)} = \sum_{t=t1}^{t2} AR_{i,t} \quad (4)$$

Where *t1* and *t2* define the start and end of the event window.

Subsequently, we compute the average abnormal return (AAR) for each day *t* within the event window across all *N* stocks in the sample, using the following equation:

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \quad (5)$$

Finally, we aggregate the average abnormal returns over the event window to calculate the cumulative average abnormal return (CAAR) using the following equation:

$$CAAR_{(t1,t2)} = \sum_{t=t1}^{t2} AAR_t \quad (6)$$

We implement the event study analysis across six event windows: [-10,-5], [-5,-3], [-3,+3], [+3,+5], [+5,+10], [+10,+15]. This method allows us to explore the effects of natural disasters on stock performance at various stages—before, during, and after the event—capturing both immediate and relatively longer-term market responses.

4.2. Cross-sectional Regression Analyses

To further investigate the factors influencing the stock market's reaction to natural disasters, we employ a multivariate Ordinary Least Squares (OLS) regression model. This model allows us to analyze the relationship between the cumulative abnormal returns (CARs) and various explanatory variables, including firm-specific characteristics, ownership structure, macroeconomic-specific factors, and disaster-specific factors. By incorporating multiple independent variables, the multivariate OLS regression provides a comprehensive understanding of the determinants of stock market performance in the context of natural disasters.

We express the regression model used in our study as follows:

$$CAR_{i,k} = \alpha + \beta_1(Leverage) + \beta_2(Liquidity) + \beta_3(ROA) + \beta_4(Firm\ Size) + \beta_5(Price\ to\ Book) + \beta_6(Tobin's\ Q) + \beta_7(Provincial\ GDP\ Index) + \beta_8(Provincial\ GDP\ per\ Capita) + \beta_9(SOE\ Dummy) + \beta_{10}(Adjusted\ Damage) + \varepsilon_i \quad (7)$$

Where $CAR_{i,k}$ represents the cumulative abnormal return of stock i during event window k. Leverage is defined as the ratio of total liabilities to total shareholders' equity. Liquidity is measured as cash and cash equivalents divided by total current liabilities. Return on Assets (ROA) is calculated as the ratio of net profit to total assets. Firm Size is the natural logarithm of total assets measured in Chinese Yuan (CNY). The Price-to-Book ratio is the market value of equity divided by total shareholders' equity, indicating how the market values the company relative to its book value. Tobin's Q is calculated as the sum of the market value of equity and the book value of liabilities, divided by the book value of assets. The Provincial GDP Index represents the annual percentage change in provincial GDP, expressed in decimal form and measured in Chinese Yuan (CNY). Provincial GDP per Capita is the natural logarithm of the GDP per capita of the affected province, measured annually in CNY. The SOE Dummy is a binary variable that takes a value of 1 if the enterprise is a state-owned enterprise and 0 otherwise. Lastly, Adjusted Damage refers to the natural logarithm of total economic damage caused by a given natural disaster in China, in US dollars, adjusted for inflation using China's Consumer Price Index (CPI) with 2015 as the base year (CPI = 100).

Given that tropical cyclones in China typically impact similar regions, particularly the southern and eastern coastal provinces, the companies affected by these disasters in our study may be common across different years. As a result, the same firms might experience multiple events, leading to repeated observations in our dataset. To address this, we employ a panel regression model, which allows us to account for the time-varying effects of natural disasters on the same companies across different years. This approach enables a more robust analysis of the cumulative and varying impacts of tropical cyclones over time while controlling for firm-specific characteristics.

5. Empirical Results

5.1. Event Study Results

Table 4 provides the event study results for our selected sample of natural disasters. Column 1 displays the total number of observations (abnormal returns) recorded for each event window. Column 2 reports the mean cumulative abnormal returns (CARs) of the affected stocks within each event window, accompanied by z-statistics and t-statistics in parentheses, offering an average measure of the market's reaction. Column 3 indicates the percentage of negative CARs in each event window, highlighting the proportion of stocks that experienced declines in response to the natural disaster.

The overall cumulative abnormal returns (CARs) across all six event windows are negative; however, only the event windows of [-5,-3], [-3,+3], [+3,+5], and [+5,+10] are statistically significant based on both the Patell-Z and cross-sectional t-statistic. The ex-ante period, during which the tropical cyclone is in its formation stage (typically as a tropical depression), is represented by the [-10,-5] event window. Although this window displays negative CAR, they are not statistically significant. This suggests that, during the formation period, the market remains uncertain about whether the developing tropical depression will eventually impact the market or not. While the market anticipates potential risks, these risks are not yet fully realized or confirmed. As a result, investors exhibit caution, leading to a negative CAR that lacks statistical significance. The [-5,-3] window captures the period following the formation of the tropical cyclone but preceding the issuance of a national typhoon alarm by the National Meteorological Center of CMA. During this phase, the tropical cyclone typically moves from the Pacific Ocean toward coastal countries, following a generally predictable path. However, the certainty of landfall in China remains unclear, although the risk of impact is elevated. This heightened uncertainty is likely the reason why the market exhibits a statistically significant negative CAR, at the 5% level using z-statistic and at the 1% level using t-statistic. The [-3,+3] window represents the period during which the affected provinces are directly experiencing the impact of the tropical cyclone. This timeframe begins after the National Meteorological Center of CMA issues the national typhoon alarm and continues until the cyclone dissipates following its landfall. The CAR during this period is significantly negative, at the 5% level using z-statistic and the 1% level using t-statistic. This finding indicates that tropical cyclones have a detrimental effect on the Chinese stock market. The significant negative CAR reflects heightened market uncertainty and potential disruptions to business operations, infrastructure, and investor sentiment, all of which contribute to the market's adverse reaction. The post-disaster periods, represented by the [+3,+5] and [+5,+10] windows, continue to exhibit significant negative CARs. This ongoing negative impact suggests that the market remains affected by the tropical cyclone even after its dissipation. One potential explanation is the aftermath of flooding caused by the heavy rainfall associated with the cyclone. Flooding can lead to extended disruptions in economic activities, damage to infrastructure, and increased recovery costs. Another reason for the continued negative CARs is the inherent volatility of the Chinese market, which often requires a longer time to recover from significant events. The combination of economic disruptions, infrastructure damage, and market volatility prolongs the negative impact, reflecting the market's difficulty in stabilizing and fully assessing the long-term effects of the tropical cyclone. The CAR for the [+10,+15] window is negative but not statistically significant when using z-statistic. However, it becomes significant at the 5% level when using t-statistic. This suggests that the market is gradually recovering, yet still experiencing high volatility, with some stocks beginning to rebound while others continue to struggle. This mixed performance explains the statistical discrepancy, where the t-statistic captures variations across individual stocks, whereas the z-statistic does not indicate an overall market-wide significance. Additionally, both the magnitude and the percentage of negative CARs show a decline during this period, further supporting the notion of a slow and uneven recovery in the market.

In summary, the event study results indicate that tropical cyclones have a significant negative impact on the Chinese stock market. The negative CARs observed across multiple event windows highlight the market's initial response to the forming and landfall stages of the cyclone, as well as the lingering effects in the post-disaster period. While the market begins to show signs of recovery in the [+10,+15] window, the continuing high volatility suggests an uneven recovery process, with some stocks rebounding while others remain affected. Overall, these findings indicate that the Chinese stock market is highly sensitive to large-scale tropical cyclones, particularly in the short term. The recovery process can be prolonged due to several factors, including market volatility and the extensive damage inflicted by these events, which can disrupt economic activities and investor confidence.

Insert Table 4 about here

5.2. Descriptive Statistics

Table 5 summarizes the descriptive statistics for the variables used in our regression model. The CARs for both the [-3,+3] and [+3,+8] windows have a mean of -0.3%, indicating that the affected companies experience a negative impact both during and after the tropical cyclone. The leverage ratio has a mean of 1.2986, indicating that, on average, the affected companies in the Chinese market rely more heavily on debt than on shareholders' equity for their financing. Additionally, the price-to-book ratio has a mean of 3.3418, suggesting that these companies are overvalued in the Chinese market, possibly reflecting investor expectations for strong future performance. Furthermore, the mean of Tobin's Q is 2.2873, highlighting that the market assigns a high valuation to the future growth prospects of these firms, which is typical for companies operating in an emerging market.

Insert Table 5 about here

5.3. Multicollinearity

To address the potential issue of multicollinearity in our study, we calculated the Variance Inflation Factor (VIF) for each independent variable, as presented in Table 6. All the independent variables exhibit a VIF of less than 10, indicating that multicollinearity is not a significant concern in our regression model. Additionally, we examined the correlation matrix shown in Tables 7 and Table 8, where we observed low to moderate correlations among most of the predictors. Notable exceptions include the correlation between the provincial GDP index and provincial GDP per capita, the correlation between the price-to-book ratio and Tobin's Q, and the correlation between adjusted damage and provincial GDP per capita, all of which range from moderate to strong. Since these variables act as provincial macroeconomic controls and firm valuation measures, such correlations are expected. Specifically, the correlation between adjusted damage and provincial GDP per capita arises because wealthier provinces tend to have more valuable assets and infrastructure at risk, leading to higher economic losses when disasters occur. By confirming that the VIF values remain within an acceptable range, we ensured that multicollinearity does not adversely affect the robustness of our analysis.

Insert Table 6 about here

Insert Table 7 about here

Insert Table 8 about here

5.4. Heteroskedasticity

Given that our regression model employs panel data, we further ensure the reliability and robustness of our results by testing for the presence of heteroskedasticity using the Breusch-Pagan test. The test results are statistically significant, indicating that the variance of the error terms is not constant across all observations. In response to this, following the recommendations of Petersen (2008) and Hayes & Cai (2007), we implement robust standard errors in our regression analysis. By applying robust standard errors, we are able to provide more reliable and robust results, mitigating the potential effects of heteroskedasticity in our model.

5.5. Regression Results

5.5.1. Regression Results of CARs during the Impact Period

Table 9 presents the OLS regression results for the cumulative abnormal returns (CARs) within the [-3,+3] window, which is defined as the tropical cyclone impact period. This window is selected because it captures the critical timeframe when the cyclone directly influences the affected companies, beginning from the initial warnings to the immediate aftermath of landfall, thus providing a comprehensive assessment of the market's reaction to the event. Model (1) presents the results with robust standard errors. Model (2) displays the results with year-fixed effects and clustered standard errors. Model (3) represents the results with industry-fixed effects and clustered standard errors. Model (4) shows the results considering both year and industry-fixed effects with clustered standard errors.

The results indicate that Return on Assets (ROA) is the only variable that is statistically significant at the 5% level with a negative coefficient across all four models. This finding suggests that highly profitable companies experience a more substantial decline in stock price during the impact period of the tropical cyclone. One possible explanation for this outcome is that companies with higher ROA possess more physical assets, which may be more vulnerable to damage caused by the cyclone. The destruction or impairment of these assets can lead to increased costs, disruption of operations, and reduced future earnings potential, ultimately exerting downward pressure on the firm's stock price. Additionally, investors may perceive that the impact on these profitable firms could be more severe due to their larger scale and asset intensity, further amplifying the negative market reaction. After controlling year-fixed effects, we find that the provincial GDP index, representing the annual percentage change in the province's GDP growth rate compared to the previous year, is statistically significant at the 5% level with a positive coefficient. This result suggests that companies headquartered in high-growth provinces tend to experience fewer losses during the tropical cyclone's impact period. One possible explanation is that provinces with high economic growth often have better infrastructure, resources, and disaster response systems, which make companies less vulnerable to disruptions and damage caused by disasters. Conversely, when both industry-fixed effects and year-fixed effects are included, the provincial GDP per capita becomes significant at the 5% level but with a negative coefficient. This indicates that firms located in wealthier provinces experience relatively larger losses. A possible reason for this is that wealthier provinces may have more valuable assets and infrastructure that are more expensive to repair or replace after a disaster, leading to larger financial losses and thereby increasing the overall negative impact on companies in these regions.

Insert Table 9 about here

5.5.2. Regression Results of CARs during the Post-disaster Period

Table 10 presents the OLS regression results for the cumulative abnormal returns (CARs) within the [+3,+8] window, representing the post-disaster period. This window is selected to capture the immediate market response following the impact of natural disasters, providing insights into the initial phase of the recovery process. Model (1) presents the results with robust standard errors. Model (2) displays the results with year-fixed effects and clustered standard errors. Model (3) represents the results with industry-fixed effects and clustered standard errors. Model (4) shows the results considering both year and industry-fixed effects with clustered standard errors.

The leverage variable is statistically significant at the 5% level across all four models, displaying a positive coefficient. This suggests that companies with higher leverage experience less negative cumulative abnormal returns (CARs) in the post-disaster period. One possible explanation is that firms with higher debt may have more stringent financial discipline and better risk management practices, enabling them to navigate the aftermath of natural disasters more effectively.

Return on Assets (ROA) is statistically significant at the 5% level across all four models, and consistently shows a negative coefficient. This indicates that more profitable companies suffer greater negative CARs in the post-disaster period. This aligns with the earlier findings that companies with higher ROA often possess more physical assets, which are more vulnerable to damage, leading to increased costs and a more pronounced market impact.

Firm size is significant at the 1% level with a negative coefficient, implying that larger companies experience a more substantial decline in stock prices following the disaster. Larger firms may have more extensive operations and assets, making them more susceptible to the widespread disruptions caused by natural disasters, and the market may perceive the potential financial impact on these firms as more significant.

Tobin's Q is statistically significant at the 5% level in models (2) and (4), where year-fixed effects are controlled. In models (1) and (3), it is significant at the 10% level. Across all models, Tobin's Q consistently exhibits a negative coefficient. This suggests that companies with higher market valuations relative to their asset replacement costs experience greater negative CARs in the post-disaster period. This could be because firms with high Tobin's Q are often expected to deliver strong future growth, and natural disasters introduce uncertainties that threaten these growth prospects, leading to a negative market reaction.

The provincial GDP index is statistically significant at the 10% level in model (3) (with industry-fixed effects controlled), displaying a negative coefficient. This finding suggests that companies headquartered in provinces with higher economic growth rates tend to experience more significant negative CARs in the post-disaster period. A possible explanation is that these high-growth provinces may have more valuable assets and economic activities at risk, resulting in greater market sensitivity to the damage caused by natural disasters. Similarly, adjusted damage is significant at the 1% level in both model (1) and model (3), also with a negative coefficient. This indicates that higher levels of economic damage from the natural disaster are associated with larger declines in stock prices for the affected companies. The negative coefficient aligns with the expectation that as the severity of the disaster increases, the market anticipates greater costs, disruptions, and recovery challenges, thereby exerting a more substantial negative impact on the stock returns of companies in the affected regions. When we include year-fixed effects, the provincial GDP index and adjusted damage lose their statistical significance. This suggests that the stock market reactions to natural disasters may be influenced more by broader annual economic conditions, policy changes, or market-wide sentiments, rather than by provincial growth rates or disaster-specific damage alone. Controlling for these year-specific factors reduces the isolated impact of provincial GDP and damage severity, indicating that the market's response is partially driven by the overall economic environment of each year.

Most importantly, the SOE dummy, the key variable in our study designed to compare the impact of natural disasters on state-owned enterprises (SOEs) versus privately-owned enterprises (POEs), is statistically significant at the 5% level across all four models. The positive coefficient of this variable suggests that SOE stocks perform better than POE stocks in the aftermath of natural disasters. This outcome could be attributed to several factors, such as government support and stronger political connections, which may provide SOEs with more robust financial resources and recovery mechanisms. Additionally, investors might perceive SOEs as less risky during crises due to their potential access to state-backed relief measures, thereby leading to a more favorable market response. This finding highlights the protective role that government ownership can play in mitigating the negative financial effects of natural disasters on the stock market.

Overall, our results indicate that companies with high leverage, low profitability, smaller size, and low market valuation, as well as state-owned enterprises (SOEs), tend to perform better in the post-disaster period. This suggests that despite their financial constraints, highly leveraged firms may have better risk management strategies, while smaller and lower-valued companies might be more agile in their recovery. Additionally, the superior performance of SOEs further underscores the potential advantages of government support and political connections during the recovery process after natural disasters.

Insert Table 10 about here

6. Robustness Tests and Further Analyses

6.1. Cumulative Abnormal Returns Based on the Capital Asset Pricing Model

As a robustness check, we conduct the event study using the Capital Asset Pricing Model (CAPM). The results of this analysis, presented in Table 11, are consistent with those we obtain using the one-factor market model. This consistency reinforces the reliability of our initial findings, suggesting that the observed market reactions to natural disasters are not sensitive to the choice of the underlying asset pricing model.

Insert Table 11 about here

6.2. Differences in Impact Across Industries

Building on previous literature, which suggests that different industries respond uniquely to natural disasters (Cao et al., 2020; Kousky, 2014; Malik et al., 2020), this section explores how the impact of natural disasters varies across industries. Given that each industry possesses distinct characteristics—such as asset structures, supply chain dependencies, and market dynamics—it is crucial to assess which sectors are more resilient and which are more vulnerable to these events. Understanding these differences will help identify industries that are likely to suffer significant negative effects and those that might, conversely, exhibit a positive effect.

To investigate the differences in the magnitude of natural disaster impacts among industries, we introduce binary variables for each industry into our regression model on the CARs within the [-3,+3] window. We use the mining industry as the baseline category, as it exhibits a mid-level impact relative to the 13 industries affected in our sample, as shown in Figure 1. The regression results, which are detailed in Table 12, provide insights into how various industries respond differently to natural disasters in terms of stock market performance.

The regression results reveal that the only industry showing statistical significance is the financial services sector, with a positive coefficient at the 10% level. This finding suggests that, during the [-3,+3] event window, companies in the financial services industry experience a positive stock market reaction to natural disasters. Several factors could explain this resilience. Firstly, financial institutions may benefit from an increase in demand for financial products, such as insurance claims, loans, and investment products, as businesses and individuals seek financial support for recovery. Additionally, government aid and disaster relief programs often flow through the financial sector, potentially boosting its revenues. Furthermore, investor sentiment might play a role, as the financial services industry is perceived to be more adaptable and less directly exposed to physical damages compared to other sectors, thereby contributing to its stronger performance in the aftermath of natural disasters. This result aligns with the CARs presented in Figure 1, where the financial services industry exhibits a positive cumulative abnormal return (CAR). This consistency further supports the notion that the financial sector not only withstands the immediate impacts of natural disasters more effectively but may also benefit from subsequent market dynamics and recovery efforts.

Insert Figure 1 about here

Insert Table 12 about here

6.3. The Impact of Natural Disasters on the Profitability of Affected Firms

To further investigate whether the superior performance of SOEs is connected to their profitability and how natural disasters impact the profitability of affected firms, we conducted an OLS regression to analyze the influence of various factors on the change in Return on Assets (ΔROA). The dependent variable, ΔROA, is defined as the difference between the ROA of the quarter following the natural disaster (T+1) and the quarter preceding it (T-1). This change is regressed against a set of independent variables, including leverage, liquidity, firm size, price-to-book ratio, Tobin's Q, provincial GDP index, provincial GDP per capita, and an SOE dummy.

This test is conducted to identify which firm-specific and macroeconomic factors significantly affect the profitability of firms after a disaster. By examining these relationships, we aim to uncover whether certain characteristics, such as firm size or state ownership, play a role in a firm's resilience to natural disasters and its ability to recover in the short term.

Table 13 presents the regression results. In both model (1), which does not control for fixed effects, and model (3), which includes industry-fixed effects, the provincial GDP index and provincial GDP per capita are statistically significant at the 1% level. The positive coefficients for these variables suggest that firms located in provinces with higher GDP levels tend to experience a greater increase in profitability (ΔROA) following a natural disaster. This finding indicates that regions with stronger economic conditions may provide a more supportive environment for firms to recover and potentially enhance their performance in the aftermath of such events.

However, when we include year-fixed effects in the regression models (such as in model 2 and model 4), the significance of the provincial GDP index and provincial GDP per capita diminishes. This loss of significance may be due to the year-fixed effects capturing broader economic trends, macroeconomic shocks, or policy changes over time, which might also influence firm profitability. By accounting for these temporal variations, the unique contribution of provincial economic conditions to changes in ROA becomes less pronounced.

Moreover, other control variables, such as leverage, liquidity, firm size, price-to-book ratio, Tobin's Q, and the SOE dummy, do not show statistical significance across all models. This lack of significance could indicate that these firm-specific factors do not have a strong or consistent influence on the change in profitability following a natural disaster, possibly because the impact of such events on profitability is more heavily driven by external factors like provincial economic conditions rather than internal firm characteristics.

Overall, the better performance of SOEs compared to POEs is not driven by changes in profitability following a natural disaster. Instead, this outperformance could be attributed to government support, such as financial aid, subsidies, and preferential policies, which are often extended to state-owned enterprises in times of crisis. Additionally, SOEs may benefit from stronger political connections and access to resources that enable them to recover more quickly. These advantages can enhance investor confidence, leading to a more favorable market response, even if their fundamental profitability does not change significantly.

Insert Table 13 about here

7. Conclusions

Our study investigates the impact of natural disasters on the stock price performance of Chinese enterprises, with a focus on differentiating the effects on state-owned enterprises (SOEs) and privately owned enterprises (POEs). By employing an event study methodology, we examine the stock market reactions to large-scale tropical cyclones in China from 2000 to 2022. The results reveal that natural disasters have a significant negative effect on stock prices, particularly during the immediate impact period. Our findings further show that SOEs experience relatively smaller declines in stock prices compared to POEs during the post-disaster recovery period, suggesting that political connections and government support provide SOEs with a certain level of protection against market volatility.

Cross-sectional regression analysis provides additional insights into the factors that influence stock market performance in the wake of natural disasters. The results indicate that firms with high leverage, low profitability, smaller size, and low market valuation tend to recover more quickly in the post-disaster period. This suggests that despite their financial constraints, highly leveraged firms may have developed better risk management strategies. Additionally, the superior performance of SOEs underscores the potential benefits of government support and political connections in facilitating recovery. Interestingly, companies headquartered in provinces with higher GDP growth face smaller stock price declines, while those in wealthier provinces with higher GDP per capita exhibit less resilience, likely due to higher asset values and greater economic exposure to disaster disruptions.

Robustness checks using the Capital Asset Pricing Model (CAPM) reinforce the reliability of our results, indicating that the observed market reactions are consistent across different asset pricing models. Furthermore, an analysis of industry-specific impacts reveals that the financial services sector shows a unique positive response to natural disasters, possibly due to increased demand for financial products, government aid flowing through financial institutions, and favorable investor sentiment. Further test of change in ROA shows that provincial economic conditions, specifically the provincial GDP index and GDP per capita, have a significant positive influence on the change in a firm's profitability following a natural disaster; however, this significance diminishes when year-fixed effects are controlled, while other factors such as leverage, liquidity, firm size, and the SOE dummy remain statistically insignificant.

A limitation of our study is that we classify a company as affected if its headquarters are located in the impacted province. This method may overlook companies with significant infrastructure in the region but headquarters elsewhere. While this classification is not ideal, it reflects the best data available and may underestimate the broader impact on firms with assets beyond their headquarters.

Overall, this study contributes to the literature on environmental risks and stock market dynamics by highlighting the importance of political connections, firm characteristics, and regional factors in shaping market reactions to natural disasters. The findings offer practical implications for investors, policymakers, and corporate managers, emphasizing the need for effective risk management strategies and the potential advantages of government support in mitigating financial repercussions. By deepening our understanding of how natural disasters influence different types of enterprises, this research provides a foundation for future studies exploring the intersection of environmental risks, political connections, and financial markets in emerging economies.

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Tables and Figures

Table 1. Sample of Tropical Cyclones from 2000 to 2022

Disaster Name	Date of Landfall	Affected Provinces	Total Damage (Billion USD)
Typhoon Utor	August 14th, 2013	Guangdong, Guangxi, Hainan	3.51
Typhoon Rananim	August 12th, 2004	Zhejiang, Jiangxi, Hunan	2.44
Typhoon Meranti	September 15th, 2016	Fujian, Guangdong, Jiangsu, Zhejiang, Jiangxi, Shanghai	4.76
Tropical Storm Durian	July 2nd, 2001	Guangdong, Hainan, Guangxi	0.449
Tropical Storm Bilis	July 14th, 2006	Fujian, Guangdong, Hunan, Jiangxi, Zhejiang, Guangxi	4.4
Typhoon Rammasun	July 18th, 2014	Hainan, Guangdong, Guangxi, Yunnan	7.14
Typhoon Fitow	October 7th, 2013	Fujian, Zhejiang	10.4
Typhoon Lekima	August 10th, 2019	Zhejiang, Fujian, Jiangsu, Shanghai, Anhui, Hebei, Shandong, Liaoning, Jilin	9.26

This table lists the eight most devastating tropical cyclone in China between 2000 and 2022, ranked by the size of the affected population. The data is sourced from the EM-DAT database, Wikipedia, and Baidu Baike. The table includes the name of each tropical cyclone, the date it hit mainland China, the provinces impacted, and the total reported damage in USD.

Table 2. Our Sample of Disaster-affected Chinese Publicly Traded Firms

Industry	CSRC Industry Code	Count
Agriculture, Forestry, Animal Husbandry, and Fishery	A	21
Mining	B	26
Manufacturing	C	913
Electricity, Heat, Gas, and Water Production and Supply	D	48
Construction	E	47
Wholesale and Retail Trade	F	63
Transportation, Warehousing, and Postal Services	G	212
Accommodation and Catering Services	H	97
Information Transmission, Software, and Information Technology Services	I	52
Financial Services	J	77
Real Estate	K	82
Leasing and Business Services	L	25
Scientific Research and Technical Services	M	15
Total		1,678

Table 3. Variable Definitions

Variable	Definition	Source
CAR	Cumulative abnormal return of a publicly traded enterprise's stock price during a specific event window.	CSMAR
Leverage	Total liabilities over total shareholders' equity.	CSMAR
ROA	Net profit over total assets.	CSMAR
Liquidity	Cash & cash equivalents over total current liabilities.	CSMAR
Firm Size	The natural logarithm of total assets (in CNY).	CSMAR
Price-to-Book	Market value of equity over total shareholders' equity.	CSMAR
Tobin's Q	The sum of the market value of equity and the book value of liabilities over the book value of assets.	CSMAR
SOE Dummy	Dummy variable that takes on a value of 1 if the enterprise is a state-owned enterprise, and 0 otherwise.	CSMAR
Provincial GDP Index	The annual percentage change in a province's GDP in decimals.	National Bureau of Statistics
Provincial GDP per Capita	The natural logarithm of the gross domestic product per capita of an affected province, measured quarterly.	National Bureau of Statistics
Adjusted Damage	The natural logarithm of total economic damage caused by a given natural disaster in China, in US dollars, adjusted for inflation using China's Consumer Price Index (CPI) (2015=100).	Wikipedia
Industry Dummies	Industry dummy variables that take on a value of 1 if the enterprise is in the corresponding industry, and 0 otherwise.	CSMAR

Table 4. Abnormal Stock Market Performance of Chinese Companies around Natural Disasters

Event Window	(1) N	(2) Mean CAR (%) (z-statistic) (t-statistic)	(3) Proportion of Negative CARs (%)
[-10,-5]	3,439	-0.138 (-0.27) (-1.59)	57.81
[-5,-3]	3,441	-0.23 (-2.51)** (-3.62)***	57.57
[-3,+3]	3,447	-0.356 (-1.97)** (-3.59)***	58.25
[+3,+5]	3,441	-0.198 (-2.07)** (-3.17)***	58.27
[+5,+10]	3,438	-0.4 (-2.81)*** (-4.58)***	58.55
[+10,+15]	3,450	-0.191 (-0.15) (-2.1)**	57.54

The table presents the cumulative abnormal returns (CARs) during multiple event windows before, amidst, and after natural disasters during the period 2000-2022. The results are based on the market model with an equally weighted market index. Column (1) shows the number of observations, Column (2) reports the mean CARs and the associated z-statistics and t-statistics in parentheses. Column (3) presents the percentage of negative CARs. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 5. Descriptive Statistics

Variables	N	Mean	Median	Min	Max	Standard Deviation
[-3,+3] CAR	3,487	-0.0033	-0.0069	-0.8181	0.5334	0.0584
[+3,+8] CAR	3,477	-0.0034	-0.0072	-0.6077	0.5560	0.0507
Leverage	3,487	1.2986	0.8014	0.0473	12.5157	1.7158
Liquidity	3,487	0.3836	0.3630	-17.7349	0.6414	0.3699
ROA	3,487	0.0202	0.0175	-0.9775	0.3246	0.0358
Firm Size	3,487	22.1167	21.9429	15.7596	29.9222	1.3995
Price to Book	3,487	3.3418	2.3429	0.4401	21.4254	3.2140
Tobin's Q	3,487	2.2873	1.7281	0.8036	10.0061	1.6475
Provincial GDP Index	3,487	0.0827	0.0760	0.0300	0.1480	0.0247
Provincial GDP per Capita	3,487	17.9460	18.0733	15.3562	18.8735	0.6943
Adjusted Damage	3,487	22.6084	22.8637	20.2791	22.8637	0.5540

The table displays the summary statistics for all dependent and independent variables used in our study.

Table 6. Variance Inflation Factors

Variable	(1) [-3,+3]	(2) [+3,+8]
Leverage	2.178	2.192
Liquidity	1.068	1.131
ROA	1.142	1.142
Firm Size	2.165	2.159
Price to Book	5.242	5.588
Tobin's Q	4.754	5.166
Provincial GDP Index	2.234	2.214
Provincial GDP per Capita	3.730	3.708
SOE Dummy	1.227	1.226
Adjusted Damage	2.156	2.159

This table reports the variance inflation factors (VIFs) for each independent variable in our regression model. Column (1) presents the VIFs calculated for the regression conducted over the event window [-3,+3], while Column (2) displays the VIFs for the regression over the event window [+3,+8].

Table 7. Correlation Matrix for Variables Based on CAR [-3,+3]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) CAR	1.000										
(2) Leverage	0.025*	1.000									
(3) Liquidity	-0.028**	-0.160***	1.000								
(4) ROA	-0.083***	-0.206***	0.152***	1.000							
(5) Firm Size	-0.003	0.388***	-0.029**	0.081***	1.000						
(6) Price to Book	-0.052***	0.172***	0.001	0.019	-0.382***	1.000					
(7) Tobin's Q	-0.047***	-0.184***	0.108***	0.056***	-0.458***	0.821***	1.000				
(8) Provincial GDP Index	0.035**	0.033**	-0.067***	-0.080***	-0.305***	-0.013	-0.040*	1.000			
(9) Provincial GDP per Capita	-0.038**	-0.031**	0.082***	0.096***	0.305***	-0.064***	-0.012	-0.708***	1.000		
(10) SOE Dummy	0.015	0.137***	-0.044***	-0.068***	0.273***	-0.171***	-0.222***	0.134***	-0.219***	1.000	
(11) Adjusted Damage	-0.012	-0.031**	0.021	0.065***	0.244***	-0.167***	-0.113***	-0.387***	0.705***	-0.143***	1.000

Table 8. Correlation Matrix for Variables Based on CAR [+3,+8]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) CAR	1.000										
(2) Leverage	0.047***	1.000									
(3) Liquidity	-0.012	-0.004	1.000								
(4) ROA	-0.079***	-0.205***	0.125***	1.000							
(5) Firm Size	-0.013	0.379***	0.079***	0.079***	1.000						
(6) Price to Book	-0.052***	0.181***	0.003	0.013	-0.389***	1.000					
(7) Tobin's Q	-0.077***	-0.170***	0.140***	0.048***	-0.463***	0.824***	1.000				
(8) Provincial GDP Index	0.005	0.029**	-0.058***	-0.076***	-0.301***	-0.012	-0.037**	1.000			
(9) Provincial GDP per Capita	-0.021	-0.032**	0.070***	0.093***	0.301***	-0.065***	-0.013	-0.706***	1.000		
(10) SOE Dummy	0.047***	0.134***	-0.009	-0.069***	0.274***	-0.172***	-0.222***	0.134***	-0.219***	1.000	
(11) Adjusted Damage	-0.045***	-0.031**	0.010	0.063***	0.242***	-0.164***	-0.109*	-0.389***	0.707***	-0.143***	1.000

Table 9. Regression Results for CAR [-3,+3]

Variables	(1) Robust Standard Errors	(2) Clustered Standard Errors	(3) Clustered Standard Errors	(4) Clustered Standard Errors
SOE Dummy	0.000	0.000	0.000	0.000
	(-0.198)	(-0.143)	(-0.210)	(-0.161)
Adjusted Damage	0.002	0.006	0.003	0.007
	(0.560)	(0.847)	(0.995)	(0.993)
Leverage	0.001	0.002	0.001	0.001
	(1.495)	(1.512)	(0.898)	(0.900)
Liquidity	-0.002	-0.002	-0.001	-0.001
	(-0.506)	(-0.455)	(-0.633)	(-0.536)
ROA	-0.110**	-0.109**	-0.112**	-0.112**
	(-2.314)	(-2.254)	(-2.330)	(-2.261)
Firm Size	-0.001	-0.001	-0.001	-0.002
	(-0.928)	(-1.020)	(-1.050)	(-1.118)
Price to Book	-0.002	-0.002	-0.002	-0.002
	(-1.400)	(-1.429)	(-1.277)	(-1.282)
Tobin's Q	0.001	0.001	0.001	0.001
	(0.581)	(0.547)	(0.583)	(0.536)
Provincial GDP Index	-0.006	0.292**	-0.023	0.295**
	(0.067)	(2.156)	(-0.343)	(2.160)
Provincial GDP per Capita	-0.003	-0.005	-0.004	-0.007**
	(-1.063)	(-1.608)	(-1.363)	(-2.004)
Constant	0.051	-0.025	0.047	-0.014
	(0.999)	(0.144)	(0.860)	(-0.081)
Observations	3,487	3,487	3,487	3,487
Year Fixed Effects	No	Yes	No	Yes
Industry Fixed Effects	No	No	Yes	Yes
Adjusted R^2	0.009	0.009	0.014	0.015

The table presents OLS regression results for a regression of affected companies' CARs on various explanatory factors. The dependent variable is the cumulative abnormal return (CAR) over the event window [-3,+3]. **Leverage** is measured as total liabilities over total shareholders' equity. **Liquidity** is defined as Cash & cash equivalents over total current liabilities. **ROA** is calculated as the ratio of net profit to total assets. **Firm Size** is the natural logarithm of total assets (in CNY). **Price to Book** is defined as the market value of equity over total shareholders' equity. **Tobin's Q** is the sum of the market value of equity and the book value of liabilities over the book value of assets. **Provincial GDP Index** is the annual percentage change in provincial GDP in decimals. **Provincial GDP per Capita** is the natural logarithm of the gross domestic product per capita of an affected province, measured annually in CNY. **SOE Dummy** is a dummy variable that takes on a value of 1 if the enterprise is a state-owned enterprise, and 0 otherwise. **Adjusted Damage** is the natural logarithm of total economic damage caused by a given natural disaster in China, in US dollars, adjusted for inflation using China's Consumer Price Index (CPI) (2015=100). Model (1) presents the results with robust standard errors. Model (2) displays the results with year-fixed effects and clustered standard errors. Model (3) represents the results with industry-fixed effects and clustered standard errors. Model (4) shows the results considering both year and industry-fixed effects with clustered standard errors. T-statistics are shown in parentheses. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 10. Regression Results for CAR [+3,+8]

Variables	(1) Robust Standard Errors	(2) Clustered Standard Errors	(3) Clustered Standard Errors	(4) Clustered Standard Errors
SOE Dummy	0.005**	0.004**	0.004**	0.004**
	(2.470)	(2.416)	(2.255)	(2.226)
Adjusted Damage	-0.006***	-0.006	-0.006***	-0.006
	(-3.012)	(-0.936)	(-2.899)	(-0.910)
Leverage	0.002**	0.002**	0.002**	0.002**
	(2.090)	(2.313)	(1.978)	(2.237)
Liquidity	0.000	0.001	0.001	0.001
	(0.593)	(0.734)	(0.574)	(0.655)
ROA	-0.077**	-0.070**	-0.074**	-0.067**
	(-2.476)	(-2.103)	(-2.362)	(-1.970)
Firm Size	-0.004***	-0.005***	-0.004***	-0.005***
	(-3.787)	(-4.031)	(-3.687)	(-3.961)
Price to Book	-0.001	-0.001	-0.001	-0.001
	(-0.676)	(-0.924)	(-0.717)	(-0.984)
Tobin's Q	-0.002*	-0.003**	-0.003*	-0.003**
	(-1.788)	(-2.174)	(-1.829)	(-2.222)
Provincial GDP Index	-0.070	-0.154	-0.082*	-0.160
	(-1.407)	(-1.376)	(-1.659)	(-1.424)
Provincial GDP per Capita	0.004	0.004	0.003	0.004
	(1.568)	(1.521)	(1.353)	(1.330)
Constant	0.174***	0.178	0.177***	0.183
	(4.162)	(1.156)	(4.140)	(1.187)
Observations	3,477	3,477	3,477	3,477
Year Fixed Effects	No	Yes	No	Yes
Industry Fixed Effects	No	No	Yes	Yes
Adjusted R^2	0.018	0.021	0.017	0.020

The table presents OLS regression results for a regression of affected companies' CARs on various explanatory factors. The dependent variable is the cumulative abnormal return (CAR) over the event window [+3,+8]. **Leverage** is measured as total liabilities over total shareholders' equity. **Liquidity** is defined as Cash & cash equivalents over total current liabilities. **ROA** is calculated as the ratio of net profit to total assets. **Firm Size** is the natural logarithm of total assets (in CNY). **Price to Book** is defined as the market value of equity over total shareholders' equity. **Tobin's Q** is the sum of the market value of equity and the book value of liabilities over the book value of assets. **Provincial GDP Index** is the annual percentage change in provincial GDP in decimals. **Provincial GDP per Capita** is the natural logarithm of the gross domestic product per capita of an affected province, measured annually in CNY. **SOE Dummy** is a dummy variable that takes on a value of 1 if the enterprise is a state-owned enterprise, and 0 otherwise. **Adjusted Damage** is the natural logarithm of total economic damage caused by a given natural disaster in China, in US dollars, adjusted for inflation using China's Consumer Price Index (CPI) (2015=100). Model (1) presents the results with robust standard errors. Model (2) displays the results with year-fixed effects and clustered standard errors. Model (3) represents the results with industry-fixed effects and clustered standard errors. Model (4) shows the results considering both year and industry-fixed effects with clustered standard errors. T-statistics are shown in parentheses. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 11. Abnormal Stock Market Performance Based on the CAPM Model

Event Window	(1) N	(2) Mean CAR (%) (z-statistic) (t-statistic)	(3) Proportion of Negative CARs (%)
[-10,-5]	3,439	-0.143 (-0.30) (-1.65)*	57.81
[-5,-3]	3,441	-0.233 (-2.53)** (-3.67)***	57.57
[-3,+3]	3,447	-0.361 (-1.99)** (-3.64)***	58.25
[+3,+5]	3,441	-0.201 (-2.09)** (-3.22)***	58.27
[+5,+10]	3,438	-0.404 (-2.83)*** (-4.63)***	58.55
[+10,+15]	3,450	-0.195 (-0.18) (-2.15)**	57.54

The table presents the cumulative abnormal returns (CARs) during multiple event windows before, amidst, and after natural disasters during the period 2000-2022. The results are based on the capital asset pricing model with an equally weighted market index. Column (1) shows the number of observations, Column (2) reports the mean CARs and the associated z-statistics and t-statistics in parentheses. Column (3) presents the percentage of negative CARs. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 12. Regression Results for CAR [-3,+3] with Industry Dummies

Variables	Coefficient (t-statistic)
SOE Dummy	0.000
	(-0.208)
Adjusted Damage	0.003
	(0.940)
Leverage	0.001
	(1.136)
Liquidity	-0.001
	(-0.683)
ROA	-0.112**
	(-2.335)
Firm Size	-0.001
	(-0.736)
Price to Book	-0.002
	(-1.385)
Tobin's Q	0.001
	(0.759)
Provincial GDP Index	-0.019
	(-0.279)
Provincial GDP per Capita	-0.004
	(-1.331)
Agriculture, Forestry, Animal Husbandry, and Fishery Industry Dummy	-0.012
	(-1.090)
Manufacturing Industry Dummy	0.002
	(0.251)
Electricity, Heat, Gas, and Water Production and Supply Industry Dummy	0.001
	(0.095)
Construction Industry Dummy	0.002
	(0.156)
Wholesale and Retail Trade Industry Dummy	-0.001
	(-0.152)
Transportation, Warehousing, and Postal Services Industry Dummy	-0.002
	(-0.250)
Accommodation and Catering Services Industry Dummy	0.004
	(0.392)
Information Transmission, Software, and Information Technology Services Industry Dummy	-0.010
	(-0.946)
Financial Services Industry Dummy	0.019*
	(1.927)
Real Estate Industry Dummy	0.005
	(0.476)
Leasing and Business Services Industry Dummy	-0.012
	(-0.565)
Scientific Research and Technical Services Industry Dummy	0.005
	(0.455)
Constant	0.037
	(0.691)
Observations	3,487
Adjusted R^2	0.014

The table presents OLS regression results for a regression of affected companies' CARs on various explanatory factors with robust standard errors. The dependent variable is the cumulative abnormal return (CAR) over the event window [-3,+3]. **Leverage** is measured as total liabilities over total shareholders' equity. **Liquidity** is defined as Cash & cash equivalents over total current liabilities. **ROA** is calculated as the ratio of net profit to total assets. **Firm Size** is the natural logarithm of total assets (in CNY). **Price to Book** is defined as the market value of equity over total shareholders' equity. **Tobin's Q** is the sum of the market value of equity and the book value of liabilities over the book value of assets. **Provincial GDP Index** is the annual percentage change in provincial GDP in decimals. **Provincial GDP per Capita** is the natural logarithm of the gross domestic product per capita of an affected province, measured annually in CNY. **SOE Dummy** is a dummy variable that takes on a value of 1 if the enterprise is a state-owned enterprise, and 0 otherwise. **Adjusted Damage** is the natural logarithm of total economic damage caused by a given natural disaster in China, in US dollars, adjusted for inflation using China's Consumer Price Index (CPI) (2015=100). **Industry Dummies** are industry dummy variables that take on a value of 1 if the enterprise is in the corresponding industry, and 0 otherwise. T-statistics are shown in parentheses. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

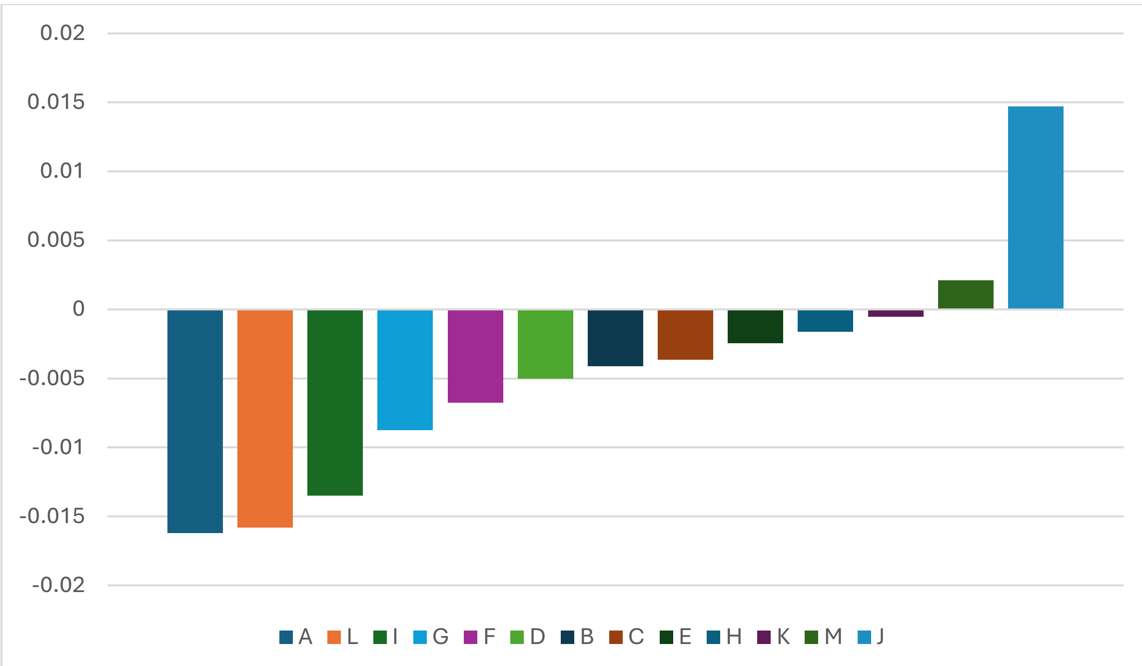
Table 13. Regression Results on ROA Changes

Variables	(1) Robust Standard Errors	(2) Clustered Standard Errors	(3) Clustered Standard Errors	(4) Clustered Standard Errors
SOE Dummy	0.437	0.487	0.433	0.417
	(1.023)	(1.143)	(1.054)	(1.026)
Leverage	-0.792	-0.776	-0.761	-0.788
	(-1.544)	(-1.534)	(-1.357)	(-1.406)
Liquidity	0.358	0.363	0.348	0.348
	(1.454)	(1.472)	(1.275)	(1.268)
Firm Size	0.210	0.235	0.215	0.213
	(0.647)	(0.677)	(0.698)	(0.653)
Price to Book	0.061	0.121	0.046	0.122
	(0.086)	(0.172)	(0.064)	(0.171)
Tobin's Q	-0.745	-0.588	-0.753	-0.627
	(-0.586)	(-0.480)	(-0.589)	(-0.508)
Provincial GDP Index	54.704***	45.478	54.899***	46.197
	(2.679)	(1.251)	(2.765)	(1.263)
Provincial GDP per Capita	3.096***	-0.050	3.096***	-0.102
	(3.036)	(-0.091)	(3.029)	(-0.198)
Constant	-62.664***	-6.386	-61.914***	-4.874
	(-2.734)	(-0.441)	(-2.770)	(-0.390)
Observations	3,474	3,474	3,474	3,474
Year Fixed Effects	No	Yes	No	Yes
Industry Fixed Effects	No	No	Yes	Yes
Adjusted R^2	0.025	0.039	0.023	0.037

The table presents OLS regression results for a regression of changes of ROA on various explanatory factors. The dependent variable is **ΔROA** which is calculated as the difference between ROA of the quarter after the natural disaster (T+1) and the quarter preceding the natural disaster (T-1). ROA is calculated as the ratio of net profit to total assets. **Leverage** is measured as total liabilities over total shareholders' equity. **Liquidity** is defined as Cash & cash equivalents over total current liabilities. **Firm Size** is the natural logarithm of total assets (in CNY). **Price to Book** is defined as the market value of equity over total shareholders' equity. **Tobin's Q** is the sum of the market value of equity and the book value of liabilities over the book value of assets. **Provincial GDP Index** is the annual percentage change in provincial GDP in decimals. **Provincial GDP per Capita** is the natural logarithm of the gross domestic product per capita of an affected province, measured annually in CNY. **SOE Dummy** is a dummy variable that takes on a value of 1 if the enterprise is a state-owned enterprise, and 0 otherwise. Model (1) presents the results with robust standard errors. Model (2) displays the results with year-fixed effects and clustered standard errors. Model (3) represents the results with industry-fixed effects and clustered standard errors. Model (4) shows the results considering both year and industry-fixed effects with clustered standard errors. T-statistics are shown in parentheses. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Figures

Figure 1. Cumulative Abnormal Returns of each Industry during the Event Window [-3,+3]



A	Agriculture, Forestry, Animal Husbandry, and Fishery
B	Mining
C	Manufacturing
D	Electricity, Heat, Gas, and Water Production and Supply
E	Construction
F	Wholesale and Retail Trade
G	Transportation, Warehousing, and Postal Services
H	Accommodation and Catering Services
I	Information Transmission, Software, and Information Technology Services
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