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# Effects of climate change on firm credit risk: evidence from China

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## ABSTRACT

Our study examines the impact of extreme weather on corporate credit risk, identifies the impact pathway, and explores the influences of different heterogeneity contexts. We propose a modified version of the climate risk measure, Modified Regional Wise Climate Risk Index for Company (MRW-CRIc), which considers not only the climate risk on financial loss but also company-specific factors. We find that climate risk significantly affects enterprise credit risk and that the impact of extreme weather varies across three industries. This research contributes to regulatory efforts by enhancing the measurement of climate risk and deepening understanding of its implications for market stability.

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## KEYWORDS

Climate change; extreme weather; credit risk; listed company; China

## 1. Introduction

Climate change is one of the greatest ongoing challenges that humanity has experienced. The escalation of global climate change, extreme precipitation, drought, temperature extremes, and other frequently occurring severe weather events pose an immense threat to the ecological environment on which human beings depend. According to the Intergovernmental Panel on Climate Change (IPCC) (2007), the global average temperature will rise by 2°C–5°C between 2030 and 2060 if climate change continues progressing. Furthermore, according to a National Oceanic and Atmospheric Administration (NOAA) report, 18 climate disasters cost the United States over USD 1 billion in 2022, and extreme weather caused USD 165 billion in damage. It includes Hurricane Ian, which devastated parts of Florida last September, costing USD 112.9 billion in damage and killing at least 150 people. Last year, economic losses caused by drought in the Midwest United States reached USD 22.2 billion.

Increasing evidence suggests that climate risk adversely affects social production and economic development. Located in the East Asian monsoon region, China has a vast territory with diverse climate change challenges and is significantly impacted by extreme weather conditions. According to China's National Climate Center, many regions have experienced persistently high temperatures since June 2022. Severe droughts have affected most of Hubei, Hunan, Jiangxi, Anhui, and Fujian provinces, as well as some areas in Zhejiang Province. In August, industrial energy restrictions were implemented in Sichuan and Chongqing, and energy-intensive enterprises in Anhui, Zhejiang, and Jiangsu suspended production. The negative impacts of extreme weather disasters on enterprise production have become increasingly apparent. According to the '2021 National Natural Disaster Basic Situation' Report published by the Ministry of Emergency Management of China, natural disasters in 2021 affected 107 million people. Furthermore, 867 people died or went missing, and 162,000 homes were destroyed, resulting in 334.02 billion yuan in direct economic losses.

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At prestigious institutions, climate risks have been recognized at the highest level and considered in investment decisions.<sup>1</sup> Furthermore, stress tests conducted by the Swiss Reinsurance Institute show that if no action is taken, the global economy will lose 18% of its gross domestic product (GDP) due to climate change by 2050, with Asian economies suffering the most severe effects and China losing 24% of its GDP due to climate change.

As Hong, Li, and Xu (2019) note, natural disasters caused by climate change significantly affect a company's production processes, which could negatively impact its revenue. According to Bouchet and Le Guenedal (2020), the energy, materials, and utility industries are the most affected. Thus, climate risk management should become integral to a company's operations (Weinhofer and Busch 2013). Sakhel (2017) demonstrates that companies face greater regulatory pressure concerning climate risk than pressure stemming from market dynamics and physical damages. Nevertheless, Kouloukoui et al. (2019) conclude that companies' sensitivity and responsiveness to extreme climate events are still limited, and their ability to cope with climate risk remains insufficient.

Credit is essential for the survival and development of companies. Credit risk is highly transmittable and can cause chain reactions. Since 2021, many large Chinese real estate companies have been exposed to credit risk, among which China's Evergrande is a representative company with total assets of 1.699 trillion yuan and liabilities of 1.898 trillion yuan. In such an external environment, it is important to study the impact of extreme weather on Chinese listed companies' credit risk to enhance their attention to climate risk and increase their enthusiasm for energy conservation and emissions reduction.

Porter (1998) indicates that industrial agglomeration could bring about technological advancement, technological diffusion, and competitive effects, which may further facilitate the development and realization of environmental protection technology, reduce environmental pollution, and optimize the efficiency of carbon emissions. Similarly, Geppert, Gornig, and Werwatz (2008) studied West Germany and found a positive relationship between industrial agglomeration and economic growth. Under the influence of the agglomeration economy, the significant concentration of industries in a particular region will create a larger market scale, thereby expanding the production scale of enterprises in the agglomeration area and generating economies of scale.

On the other hand, industrial agglomeration would attract more vendors and talents across the value chains to further cluster in the area for lower transaction costs, ample access to raw materials, high-quality intermediate products, and skilled labor. When extreme weather conditions are encountered, industrial agglomeration could also lead to firms in the same chain experiencing the same effects. Therefore, this study attempts to measure the impact of extreme weather on listed companies and their credit risk within the geographical scope of a province.

Based on the above, this study selects 22,505 Chinese A-share listed companies from 2005 to 2021 as the research sample to empirically test the relationship between extreme weather and corporate credit risk. The transmission channel of climate risk to corporate credit risk is analyzed, and the impact direction and degree of climate change on credit risk quantified, followed by a series of robustness tests. Based on the Global Climate Risk Index (CRI) published by Germanwatch, we have developed an updated Modified Regional Wise Climate Risk Index for Company (MRW-CRIc). In further analysis, we also find that a firm's climate risk level negatively correlates with its financial performance, suggesting that extreme weather affects credit risk through corporate operating performance. To assess endogeneity, we conduct a placebo test. In addition, a heterogeneity analysis shows that the impact of climate risk on firms is more significant in central-western China than in eastern China. Meanwhile, compared to private enterprises, the impact of climate risk on state-owned enterprises (SOEs) is more significant.

The main contributions of this study are as follows. First, it introduces a modified version of the climate risk measure MRW-CRIc, which considers the effect of climate risk on financial losses and company factors. Second, based on MRW-CRIc, it investigates the direct impact of extreme weather events on the credit risk of Chinese listed companies. Third, this study intends to deepen the

understanding of whether the impact of climate risk on corporate credit risk varies across ownership structures and geographical locations. Furthermore, our study assists regulators in measuring climate risk and comprehending its impact on financial market stability, thus promoting the development and rationalization of policy practices.

This study is structured as follows: [Section 2](#) examines the relevant literature and proposes the hypotheses. [Section 3](#) describes the main variables and methods. [Section 4](#) presents the empirical results and discusses their implications. [Sections 5](#) and [6](#) present the mechanism and the heterogeneity tests, respectively. A summary is presented in [Section 7](#).

## 2. Literature review and hypotheses

### 2.1. Early studies

Climate plays an important role in an economy. Professor Nordhaus pioneered the study of the topic in the field of climate economics, providing a theoretical foundation for studying the impact of climate change on the real economy. He emphasizes that there is a strong coupling between the economy and climate change response, rather than merely emphasizing their importance. Nordhaus (2006) finds that Africa's lower per-capita income compared to other regions of the world is mainly caused by climate. M. Burke, Hsiang, and Miguel (2015) propose a nonlinear relationship between temperature and economic production, indicating that productivity decreases as the annual average temperature exceeds 13°C.

According to the IPCC Sixth Assessment Report, the financial risks associated with climate change are primarily reflected in two aspects: physical and transition risks. Physical risk refers to the risk of direct damage to economic activities caused by extreme weather events such as floods, droughts, and typhoons. These events may result in significant financial losses. However, the transformation risk is caused by the government's adjustment to emission reduction policies, technology replacement, and upgrading. While the impact of transition risk demands higher-level attention in the long-term, in the short-term, credit risk arises from the frequent occurrence of extreme weather events due to climate change and the damage to company property, plant, and equipment caused by disasters such as floods, hurricanes, and typhoons. Therefore, this study focuses on credit risk, which is triggered by losses caused by physical risks to the production and operation of enterprises.

Climate risk manifests itself through direct property damage (e.g. buildings and equipment) used by companies for business operations and indirect damage to supply chains, products, and markets (European Bank for Reconstruction and Development 2018). According to the Intergovernmental Panel on Climate Change (2013), extreme weather and climate events have become more frequent and intense, causing significant first-order impacts on business activities. Climate change may also have secondary impacts beyond company boundaries, including limited natural resource availability; changes in energy supply and prices; and disruptions in transport, migration, and labor supply (European Bank for Reconstruction and Development 2018).

Credit risk, which is widely present in economic activities, refers to the possibility that creditors suffer losses due to the failure of the debtor to fulfill the contract or a change in credit quality. Thus, Klomp (2014) argues that the physical risk of climate change evolves into farm-related credit risk in two ways: (1) extreme weather events lead to the impairment of loan collateral for rural financial institutions, and (2) climate change shocks agricultural production, making loan programs less profitable than expected. In its 2014 annual report, the Nobel Corp. acknowledges that adverse weather conditions can result in less stable revenue and cash flows from oil and gas exploration and development. Reduced revenues and increased income uncertainty lead to increased credit risk, which is a major concern for creditors. In response to the adverse impacts of climate change on their operations and related business activities, many companies are taking strategic actions aimed at reducing or mitigating the potential risks arising from climate variability. Linnenluecke and

Griffiths (2010) demonstrate that firms rely on organizational resilience to systematically anticipate, absorb, adapt, and recover from the adverse effects of physical climate risks. These management practices have the potential to mitigate the effects of climate risk, which helps reduce firms' credit risk.

## **2.2. Extreme weather and corporate credit risk**

The impact of extreme weather on enterprises' credit risk-taking is mainly reflected in the fact that such events can bring direct and indirect economic losses to enterprises. This in turn affects the probability of default. First, from the perspective of direct economic losses, climate risk can directly accelerate the depreciation of capital assets, for example, through extreme weather events such as floods or wildfires. If uninsured beforehand or if the risk is underestimated, losses from extreme weather are directly transferred to the firm, deteriorating its balance sheet and affecting the credit risk of the loan (Dietz et al. 2016). Second, in terms of indirect losses, extreme weather can cause crop damage, infrastructure and supply chain disruptions, higher transportation costs, disturbances in production, or higher production costs for firms (Pan, Liu, and Cheng 2022). The physical effects of climate change undermine firm performance and make firm prospects increasingly uncertain (Lenox and Duff 2021).

The deleterious effects of temperature on firm performance are more likely to be observed in developing countries, where production levels are relatively substandard and the costs of dealing with climatic adversities are higher. For instance, in Côte d'Ivoire, elevated temperatures tend to curtail the productivity of local firms and adversely affect business performance (Traore and Foltz 2018). Furthermore, the higher the risk of extreme climate change in a firm's location, the more volatile its business profitability (H. H. Huang, Kerstein, and Wang 2018). With impaired operating capacity, firms' ability and willingness to repay creditors decrease, transferring risk from the credit channel to banks. Schuwer, Lambert, and Noth (2019) find that Hurricane Katrina in 2005 caused US banks in the Gulf Coast region to face serious loan quality issues caused by increased business risks, the interruption of borrower cash flow, increased operating costs, and secondary damage caused by uninsured or underinsured businesses.

For listed companies, corporate credit risk positively correlates with the volatility of equity values. If the listed company's market value is higher than a certain multiple of the debt valuation (the default point) due to climate change, the company will pay the principal and interest. Conversely, if the company's value is lower than a certain multiple of the debt valuation, the company may choose to default on debt, resulting in a credit risk explosion (Yang et al. 2021). Some firms have taken measures to reduce losses from extreme weather disasters. For example, Dessaint and Matray (2017) show that managers increase corporate cash holdings out of concern for future hurricanes.

In response to the challenges posed by climate risk, companies have implemented various measures. Maintaining adequate levels of cash and other liquid assets can help mitigate a firm's default and credit risk. Ginglinger and Moreau (2019) highlight that companies are prone to reduce their debt and endorse more conservative leverage policies when they encounter higher climate risk levels. Similarly, Elnahas, Kim, and Kim (2018) find that US companies in regions more vulnerable to natural disasters exhibit lower leverage ratios than their counterparts elsewhere. Javadi et al. (2020) analyze a sample of companies across 41 countries and provide evidence that firms with greater exposure to climate risk augment their cash holdings. Moreover, the impacts of climate change can vary significantly across industries. The United Nations Environment Program (UNEP) (Unep 2006) has identified certain economic sectors as highly sensitive to climate change; these include coal, oil and gas, electricity, aluminum, cement, agriculture, paper and forestry, automobile manufacturing, real estate, and healthcare.

There is growing awareness among financial institutions regarding the urgent need to address climate crises and proactively manage credit risks associated with natural hazards (H. H. Huang

et al. 2022). Numerous banks have expressed concerns about the credit risks stemming from climate change. Ceres (2008) finds that most of the world's 40 largest banks have integrated climate change issues into their operations and implemented climate change risk assessment policies, including considering whether borrowing companies have strategies in place to mitigate or adapt to climate change.

The acceleration of climate change, updates to historical data, and the increasing extent of damage caused by extreme weather events are concerning trends. When physical assets destroyed by such events are pledged as collateral for loans to commercial banks, their value substantially diminishes. This weakens corporate solvency and increases the likelihood of default, leading to credit-risk crises. Despite overwhelming evidence of the gravity of climate risk, some companies continue to disregard the issue and fail to take measures to prevent or mitigate its impact. As Ren et al. (2022) highlight, this attitude indicates a lack of sensitivity and understanding of the severity of climate change. Some firms do not implement climate-related policies due to a lack of regulations. Based on this, this study proposes the following empirical hypothesis:

**Hypothesis 1:** Extreme weather will increase firms' credit risk.

### **2.3. The heterogeneous impact of extreme weather on corporate credit risk**

The impacts of climate change on different regions also vary. In general, a firm's environmental risks depend on various geographic and firm-specific factors (Ginglinger and Moreau 2019). To further identify the factors contributing to a firm's sensitivity to climatic events or uncertainties, we analyze companies based on their geographic location and other relevant characteristics. Given China's vast size and the varying developmental stages of its economic zones, the country can be divided into the eastern and midwestern regions.

Eastern China, with a high population density and robust economic development, is particularly susceptible to extreme precipitation events. For example, in 2012, the '7.21' rainstorm in Beijing caused 79 deaths 10,660 collapsed houses, and affected 1,602,000 people, in addition to causing billions of dollars in economic losses. Similarly, in May 2015, heavy rainfall in southeastern China triggered floods and landslides, resulting in many deaths (C. Burke et al. 2016). Regarding Midwest China, the western regions of China, with their plateau and monsoon climates, are more vulnerable to various weather changes and extreme climate events (Ren et al. 2022). In July 2021, Henan Province, located in the central region, experienced a rare rainstorm and severe flood disaster. This disaster affected a total of 14,786,000 people and resulted in the death or disappearance of 398 people. The direct economic losses caused by this catastrophic event amounted to 120.6 billion yuan. According to Gao et al. (2012), heat waves are projected to become more severe in much of the eastern United States by the late 2050s. Additionally, total annual severe precipitation in both the Northeast and Southeast is projected to increase by 35% or more, suggesting a heightened risk of flooding under future climate conditions.

In China, financial intermediaries tend to provide more credit to local SOEs, while private firms are more likely to face the dilemma of 'difficult to borrow' and 'expensive' loans (Yang et al. 2021). However, Cao, Ma, and Shen (2014) indicate that executives of SOEs may prioritize short-term gains by increasing investments. This orientation toward 'adventurism' can potentially result in losses and ultimately diminish long-term firm value. Qian (2009) discovers that SOEs are significantly more likely to experience financial risks and distress than non-SOEs. Therefore, normal production and operations are affected when extreme weather damages a company's fixed assets or equipment, resulting in greater uncertainty in its development. SOE managers tend to be more conservative and risk averse. With a high degree of uncertainty, managers may be more cautious in their decision making, tend to consult with superiors, and may even shirk their responsibilities.

Meyer and Pac (2013) compare the environmental performance of state-owned and private plants in Europe and find that state-owned plants emit more greenhouse gases, whereas privatization can reduce emissions by more than half. In China, SOEs have significantly lower pollution rates than non-SOEs and local governments prefer SOEs for environmental protection (Tang 2017). Although non-SOEs are at a disadvantage in terms of resource acquisition capacity, they are more flexible in operations and management, more cautious in various investment activities, and have better management monitoring mechanisms (Xianhuan H. H. Huang, Kerstein, and Wang 2018). Faced with climate risks, it is possible to provide quicker feedback and adjust the production process to minimize risk losses. Therefore, different ownership types can lead to differences in the operational efficiency of a company, which, in turn, affects its credit risk. Based on this, we propose the following hypotheses:

**Hypothesis 2:** Compared to the eastern region, climate risks have a more significant impact on corporate credit risk in the central and western regions.

**Hypothesis 3:** The impact of climate risk on the credit risk of state-owned companies is more significant than that of non-state-owned companies.

### 3. Data and main variables

#### 3.1. Data and sample

This study utilizes the data of Chinese A-share listed companies from 2005 to 2021 as the sample object and screens the original data according to the research demands by: (1) excluding the sample of companies in the financial industry to ensure the reliability of the conclusion because the accounting standards of the financial industry are different from those of other industries and are highly regulated; (2) excluding companies with ST markers; and (3) excluding the sample of listed companies with serious missing variables (companies with significant financial data missing). In total 22,505 firm-year observations are obtained. The study data are obtained from the CSMAR, WIND, and the *Yearbook of Meteorological Disasters* in China. To minimize the impact of extreme values on our research, we apply winsorized tailings at the 1–99% level to all continuous variables in the model. Additionally, we standardize the independent variable MRW-CR<sub>IC</sub> and the dependent variable Expected Default Frequency (EDF) to facilitate interpretation.

#### 3.2. Empirical model

To examine the impact of climate risk on corporate credit risk, we construct the following regression model:

$$edf_{i,t} = \alpha + \beta * mrwCRIC_{i,t} + \gamma * Controls_{i,t} + \theta * year + \kappa * industry + \varepsilon_{i,t} \quad (1)$$

$$edf_{i,t} = \alpha + \beta * mrwCRIC_{i,t} + \gamma * Controls_{i,t} + \theta * year + \kappa * ig + \varepsilon_{i,t} \quad (2)$$

$$edf_{i,t} = \alpha + \beta * mrwCRIC_{i,t} + \gamma * Controls_{i,t} + \theta * year + \kappa * ig + \delta * mrwCRIC_{i,t} * ig + \varepsilon_{i,t} \quad (3)$$

Where the subscripts *i* and *t* indicate individual samples and years, respectively. To better control for the industry effect on the correlation between climate change and corporate credit risk, we classify listed companies into 18 industries<sup>2</sup> according to the China Securities Regulatory Commission guidelines (see Table 1). Model 1 (equation 1) examines the impact of climate risk on credit risk, with dummy variables for years and industries controlled. To better investigate the effect of industries, we divide the 18 industries into more general

**Table 1.** Industry and general industry classification guidelines for listed companies.

| Industry                                                                        | Indices    | General Industry |
|---------------------------------------------------------------------------------|------------|------------------|
| Agriculture, Forestry, Animal Husbandry, and Fishery                            | industry1  | 1                |
| Mining Industry                                                                 | industry2  | 2                |
| Manufacturing Industry                                                          | industry3  | 2                |
| Electricity, Heat, Gas and Water Production and Supply Industry                 | industry4  | 2                |
| Construction Industry                                                           | industry5  | 2                |
| Wholesale and Retail Industry                                                   | industry6  | 3                |
| Transportation, Warehousing, and Postal Services industry                       | industry7  | 3                |
| Accommodation and Food Services industry                                        | industry8  | 3                |
| Information Transmission, Software and Information Technology Services Industry | industry9  | 3                |
| Real Estate Industry                                                            | industry10 | 3                |
| Leasing and Business Services                                                   | industry11 | 3                |
| Scientific Research and Technology Services                                     | industry12 | 3                |
| Water Conservancy, Environment and Public Facilities Management Industry        | industry13 | 3                |
| Residential Services, Repairs and Other Services                                | industry14 | 3                |
| Education Industry                                                              | industry15 | 3                |
| Health and Social Work                                                          | industry16 | 3                |
| Culture, Sports and Entertainment                                               | industry17 | 3                |
| Comprehensive Industry                                                          | industry18 | 3                |

classifications based on the ‘National Economic Classification of Industries’<sup>3</sup> (general industry, ig). Model 2 ( equation 2 ) has the same structure as Model 1, except that the 18 industry variables are replaced by three ig variables and used to test the baseline credit risk of the three general industries. Model 3 ( equation 3 ) introduces interaction terms between ig and climate risk ( $mrwCRIC_{i,t} \times ig, cig$ ) to investigate whether the impact of climate risk on corporate credit risk differs across industries. Continuous variables are standardized based on the maximum – minimum criterion. In addition, we focus on the MRW-CRIC variable. The significantly positive coefficient of MRW-CRIC indicates a positive correlation between climate risk and credit risk.

### 3.3. Explained variable: credit risk

Bharath and Shumway (2008) calculate the probability of EDF as a proxy variable for the annual enterprise credit risk level. The calculation process is as follows.

$$DD_{it} = \frac{\log\left(\frac{Equity_{it} + Debt_{it}}{Debt_{it}}\right) + \left(a_{it-1} - \frac{\delta_{vit}^2}{2}\right) \times T_{it}}{\delta_{vit} \times \sqrt{T_{it}}} \quad (4)$$

$DD_{it}$  measures the enterprise default distance.  $Equity_{it}$  represents the total market value of the company, expressed as the product of the stock price and the number of shares outstanding at the end of the year.  $Debt_{it}$  is identified as the face value of a company’s debt, expressed as the sum of current liabilities and 50% of non-current liabilities at the end of the year.  $r_{it-1}$  is the firm’s 1-year lagged annual return rate, obtained from the monthly return rate of the previous year.  $T_{it}$  is set to 1 year in the formula;  $\sigma_{vit}$  represents the firm’s asset volatility factor, which is calculated from  $\sigma_{Eit}$ .  $\sigma_{Eit}$  represents the volatility of stock returns obtained by taking the standard deviation of the firm’s monthly return data from the previous year. The equation used is as follows:

$$\delta_{vit} = \frac{Equity_{it}}{Equity_{it} + Debt_{it}} \times \delta_{Eit} + \frac{Debt_{it}}{Equity_{it} + Debt_{it}} \times (0.05 + 0.25 \times \delta_{Eit}) \quad (5)$$

Based on equations (4) and (5), we calculate the probability of default by converting the default risk distance into a cumulative standard normal distribution function.

$$EDF_{it} = Normal(-DD_{it}) \quad (6)$$

The EDF values follow a normal distribution and range from 0 to 1. The larger the EDF, the higher the default probability of listed companies' debts and the higher the credit risk of listed companies.

### 3.4. Explanatory variable: climate risk index

Germanwatch is an international non-governmental organization based in Bonn, Germany. The organization collaborates with other non-governmental organizations to collect a variety of economic and social data. The CRI is collected and published by Germanwatch and seeks to measure and analyze the impact of extreme weather events, including storms, floods, forest fires, and drought, on countries and regions. According to Eckstein, Künzel, and Schäfer (2021), the CRI is a national index that reflects the severity of a country's losses due to climate risk. The analysis includes both human impacts, measured by the number of deaths, and direct economic losses. In this study, we use the global CRI 2021 compiled and published by Germanwatch, which has been published annually since 2006; the 2021 edition is the sixteenth and latest edition.

The annual CRI scores are based on data from the two years before the edition year. For example, the 2021 edition contains annual scores based on 2019 data (Eckstein, Künzel, and Schäfer 2021). The scores are based on the following two absolute and two relative climate-related risk indicators: (1) number of deaths, (2) number of deaths per 100,000 inhabitants, (3) total losses in US dollars at purchasing power parity (PPP), and (4) losses per unit of GDP. Using the Germanwatch approach, each country's CRI is the sum of its scores in the first four indicator categories.

$$CRI_{GW} = \frac{1}{6} \times Death + \frac{1}{3} \times \frac{Death}{Population} + \frac{1}{6} \times Loss + \frac{1}{3} \times \frac{Loss}{GDP} \quad (7)$$

To calculate the CRI for each province in China, we rank the four indicators above. Germanwatch uses the rank between countries (e.g. Argentina ranked 37th with a total of 10 deaths in 2009; when calculating its CRI for 2011, the total number of deaths was 37 instead of 10). In this study, we use the ranking of the Chinese provinces. This normalization technique maintains all four indicators involved in the same interval, avoiding situations in which the CRI is dominated by a specific index.

Germanwatch's CRI is in descending order (CRI\_d); therefore, a higher index corresponds to a lower risk. That is, the higher the ranking, the lower the CRI score, implying a more severe impact of extreme weather conditions. H. H. Huang, Kerstein, and Wang (2018) multiply the CRI score by  $-1$  so that the higher score represents the higher level of climate risk. We select a different approach by directly using an ascending ranking (CRI\_i), where larger results represent higher risk. In addition to the calendar year indicator, there is a long-term indicator (CRI\_lt) calculated using the average rank of the four indicators over the calendar year. H. H. Huang, Kerstein, and Wang (2018) propose the CRIC indicator.

$$CRIC = \sum_{i=1}^n f_{i*} \frac{m_i}{M} \quad (8)$$

where  $i$  is the regional code (originally a state in the US),  $f_i$  is the number of meteorological risk occurrences in the region,  $m_i$  is the number of subsidiaries of the company in the region, and  $M$  is the total number of subsidiaries of the company in all regions.

This study proposes a new corporate climate risk index based on their work:

$$MRW\_CRIC = \sum_{i=1}^n CRI_{i \times \frac{m_i}{M} \times rr} \quad (9)$$

MRW-CRIC makes the following changes to CRIC:  $f_i$  is replaced with  $CRI_i$ ; and the relative rank (rr) weight is added. Specifically,  $CRI_i$  refers to the climate risk index of a region (based on the previous section). The CRIC calculation considers only the frequency of extreme weather events, which does not directly reflect the economic risk caused by such disasters. For rr, the rank of the total number of subsidiaries is calculated for each company in a given year in ascending order, and the result of the highest ranking of the number of subsidiaries for each company in the same year is divided.

The logic of rr weighting is as follows. For two firms, A and B, with the same distribution of subsidiaries across regions, if A has three subsidiaries in Region I and two subsidiaries in Region J, and B has six subsidiaries in Region I and four subsidiaries in Region J, although they share the same value of  $m_i/M$ , they cannot be considered as having the same risk. This is because firms with more subsidiaries are likely to suffer more severe losses. rr assigns the influence of the total number of subsidiaries on this indicator (MRW-CRIC). As its range falls between zero and one, it does not significantly change the range of the data and enhances the comparability of the metrics across different years. (The maximum rank across years is subject to variation.)

### 3.5. Control variable

Drawing on previous studies (Chen, Liu, and Dong 2013; H. H. Huang et al. 2022; S. H. Wang, Xu, and Liu 2022), as shown in Table 2, this study selects the following control variables, reflecting the characteristics of listed companies: roa (return on assets); roe (return on equity)<sup>4</sup>; ln\_ta (the natural

**Table 2.** Variable definition.

| Variable Type        | Variable Symbol | Variable Name                                         | Variable Description                                          |
|----------------------|-----------------|-------------------------------------------------------|---------------------------------------------------------------|
| Explained Variable   | EDF             | Probability of Debt Default                           | Calculated based on formula (4) - (6)                         |
| Explanatory Variable | MRW-CRIC        | Modified Regional Wise Climate Risk Index for Company | Calculated based on formula (7) - (9)                         |
| Control variables    | roa             | Return on Assets                                      | Net profit/Total assets                                       |
|                      | roe             | Return on Equity                                      | Net profit/Net assets                                         |
|                      | ln_ta           | Firm Size                                             | The natural logarithm of the firm size                        |
|                      | ln_age          | Firm Age                                              | The natural logarithm of firm age                             |
|                      | lev             | Leverage                                              | Total liabilities/Total assets                                |
|                      | cfoa            | Cash Flow Adequacy                                    | Net cash flows from operating activities/Total assets         |
|                      | growth          | Growth                                                | Operating income growth rate                                  |
|                      | ppe             | PPE                                                   | Equipment/Total assets                                        |
|                      | turnover        | Turnover of Total Assets                              | Sales revenue/Total assets                                    |
|                      | eps             | Earnings per share                                    | Earnings per share                                            |
|                      | top10           | Top10                                                 | Top 10 shareholders' shareholding ratio                       |
|                      | ln_board        | Board Size                                            | The natural logarithm of the total number of board members    |
|                      | outdir_rat      | Percentage of independent directors                   | Number of independent directors/Total number of board members |
|                      | soe             | Corporate Property                                    | Takes the value of 1 if the company is SOEs and 0 otherwise   |
|                      | currt           | Current Ratio                                         | Current assets/Current liabilities                            |
|                      | mana            | Operating Efficiency                                  | Operating income/Total assets                                 |
|                      | gdp_growth      | GDP Growth Rate                                       | GDP growth rate                                               |
|                      | qr              | Quick Ratio                                           | (Current assets - Net inventory)/Current liabilities          |
|                      | tagr            | Total Asset Growth Rate                               | Total asset growth rate                                       |
|                      | industry        | Industry                                              | Dummy variable                                                |
|                      | year            | Year                                                  | Dummy variable                                                |

logarithm of the firm size); Ln\_age (the natural logarithm of firm age); lev (leverage ratio); cfoa (cash flow adequacy); growth (operating income growth rate); ppe (equipment divided by total assets); turnover (turnover of total assets); eps (earnings per share); TOP10 (shareholdings of top 10 shareholders); ln\_board (natural logarithm of the total number of board members); Outdir\_Rat (percentage of independent directors); soe (dummy variable; takes the value of 1 if the company is an SOE and 0 otherwise); currt (current ratio); mana (operating efficiency); qr (quick ratio); and tagr (total assets growth rate). In addition, we control for the country-level macroeconomic factor gdp\_growth (annual growth of total GDP). Furthermore, because of the long sample period of this empirical study, the level of climate risk borne by listed enterprises may be affected by other factors, such as their regional economies and industries during the sample period, year effects, and industry effects, which are thus added to the control variables.

### 3.6. Descriptive statistics

Table 3 presents the descriptive statistics for the main variables. During the sample period, the mean and variance of EDF are 0.013 and 0.108, respectively. The median is 0, and the maximum value is 1, indicating that the default risk of Chinese listed companies is generally low, with over half of the enterprises having a default risk close to zero. The range of the climate risk index is 0–1, with a mean and median of 0.169 and 0.101, respectively. The standard deviation is 0.195, indicating that the level of climate risk varies greatly among companies in different regions. Overall, the data distribution is reasonable.

The Pearson correlation between MRW-CRlc and EDF is shown in Figure 1.

### 3.7. Correlation analysis

This study conducted a Pearson correlation analysis among the key variables, and the results are presented in Table 4. The table shows that there is a correlation coefficient of 0.104 between MRW-CRlc and EDF, indicating that an increase in climate risk will lead to a rise in corporate credit risk. The correlation coefficients among the main control variables are relatively small and fall within an acceptable range, suggesting that the regression results are not significantly affected by multicollinearity.

Table 3. Descriptive statistics.

| Variables  | N      | Mean   | SD     | Median | Min     | Max   |
|------------|--------|--------|--------|--------|---------|-------|
| edf        | 22,505 | 0.0130 | 0.108  | 0      | 0       | 1     |
| MRW-CRlc   | 22,505 | 0.169  | 0.195  | 0.101  | 0       | 1     |
| roa        | 22,505 | 0.0424 | 0.0526 | 0.0377 | −0.129  | 0.225 |
| roe        | 22,505 | 0.0756 | 0.0951 | 0.0735 | −0.269  | 0.351 |
| ln_ta      | 22,505 | 8.556  | 1.249  | 8.367  | 5.480   | 12.04 |
| ln_age     | 22,505 | 2.088  | 0.711  | 2.197  | 0       | 3.258 |
| lev        | 22,505 | 0.455  | 0.181  | 0.456  | 0.0564  | 0.852 |
| cfoa       | 22,505 | 0.0511 | 0.0669 | 0.0489 | −0.167  | 0.341 |
| growth     | 22,505 | 0.181  | 0.346  | 0.124  | −0.419  | 2.008 |
| ppe        | 22,505 | 0.230  | 0.163  | 0.199  | 0.00345 | 0.708 |
| turnover   | 22,505 | 0.699  | 0.490  | 0.581  | 0.101   | 2.985 |
| eps        | 22,505 | 0.421  | 0.601  | 0.292  | −1.057  | 3.232 |
| top10      | 22,505 | 0.569  | 0.147  | 0.573  | 0.248   | 1     |
| ln_board   | 22,505 | 2.154  | 0.201  | 2.197  | 1.099   | 2.708 |
| outdir_rat | 22,505 | 0.371  | 0.0528 | 0.333  | 0       | 0.571 |
| soe        | 22,505 | 0.449  | 0.497  | 0      | 0       | 1     |
| currt      | 22,505 | 1.899  | 1.542  | 1.483  | 0.346   | 15.79 |
| mana       | 22,505 | 0.655  | 0.449  | 0.547  | 0.0929  | 2.583 |
| gdp_growth | 22,505 | 0.0824 | 0.0302 | 0.0800 | 0.0170  | 0.153 |
| qr         | 22,505 | 1.445  | 1.394  | 1.061  | 0.226   | 14.44 |
| tagr       | 22,505 | 0.155  | 0.268  | 0.0977 | −0.224  | 2.273 |

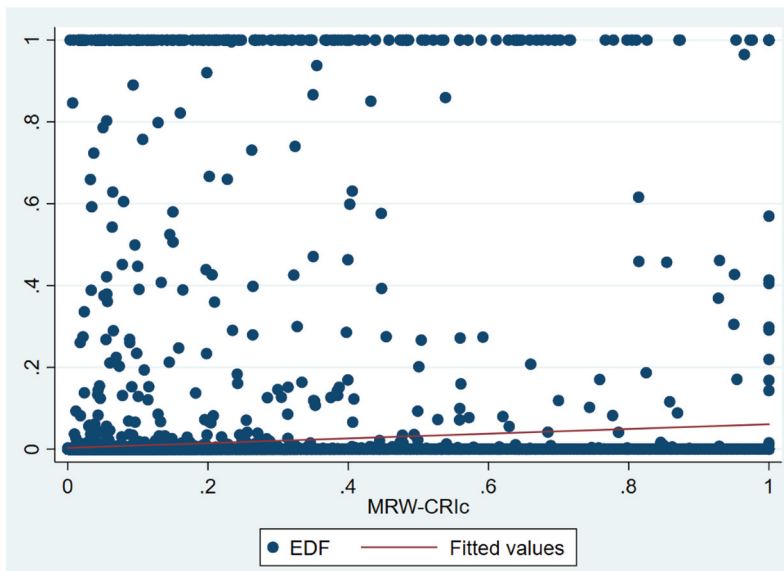


Figure 1. Correlation between MRW-CR1c and EDF.

#### 4. Main results

To assess the influence of climate risk on the credit risk of listed companies, this study performs a regression analysis with the EDF as the dependent variable, which is measured by the probability of default, and the MRW-CR1c as the independent variable in Model 1. The analysis reveals that there is a positive correlation between climate risk and firm credit risk ( $\beta = 0.018$ ,  $p < 0.01$ , see details in Table 5). This indicates that climate risk increases corporate credit risk and supports assumption 1. Based on the industry classification guidelines established by the China Securities Regulatory Commission (CSRC) for various types of enterprises, the 18 industries in Model 1 are further divided into three industries in Model 2, and the results indicate that the base EDFs between the industries did not differ significantly.

To investigate the necessity of Model 3, that is, whether the interaction terms improved the model significantly, an F test is performed to test the squared sum of residuals (RSS) in Model 3, which is significantly lower than that in Model 2. The results prove that introducing interaction terms significantly improves the model (see Table 6). Moreover, Model 3 indicates that the climate risk impact on credit risk in ig 2 is significantly higher than ig 1 ( $cig2 = 0.061$ ,  $p = 0.036$ ) and ig 3 ( $cig2 - cig3 = 0.025$ ,  $p = 0.001$ ), while no significant difference is observed between the climate risk impact on credit risk of ig 1 and ig 3 ( $cig3 = 0.036$ ,  $p = 0.217$ ). To control for the family wise error induced by multiple comparisons, Bonferroni correction is performed over the above p-values (see Table 7). The difference between the climate risk impact on credit risk of ig 2 and ig 3 survives the correction ( $p_{\text{bonferroni of cig2-cig3}} = 0.003$ ), suggesting that accepting this difference has a lower risk of type II error.

This is primarily attributable to the fact that the service sector is a crucial component of the tertiary industry, where services represent the primary function. Kuznets (1973) highlights that from the broadest grouping perspective, attention is only given to three key sectors: agriculture, industry, and services. He believes that they exhibit significant differences in terms of their use of natural resources, the production processes in which they are involved, and the final products they contribute. Yuan, Kellett, and Ren (2008) indicate that the primary industry relies on natural resources such as water and land, while the secondary industry primarily depends on the consumption of resources such as water, raw materials, and energy. The service products provided by the

Table 4. Correlation analysis of variables.

|            | edf     | cri      | roa        | roe     | ln_ta   | ln_age     | lev     | cfoa    | growth  | ppe     | turnover | eps     |
|------------|---------|----------|------------|---------|---------|------------|---------|---------|---------|---------|----------|---------|
| edf        | 1       |          |            |         |         |            |         |         |         |         |          |         |
| cri        | 0.104   | 1        |            |         |         |            |         |         |         |         |          |         |
| roa        | -0.0823 | 0.0061   | 1          |         |         |            |         |         |         |         |          |         |
| roe        | -0.0588 | 0.0913   | 0.923      | 1       |         |            |         |         |         |         |          |         |
| ln_ta      | 0.1675  | 0.4357   | 0.0367     | 0.1596  | 1       |            |         |         |         |         |          |         |
| ln_age     | 0.0617  | 0.1843   | -0.1173    | -0.0465 | 0.3994  | 1          |         |         |         |         |          |         |
| lev        | 0.1912  | 0.2952   | -0.3287    | -0.0828 | 0.4444  | 0.2414     | 1       |         |         |         |          |         |
| cfoa       | -0.0286 | 0.0015   | 0.3948     | 0.3426  | 0.0534  | 0.0134     | 0.0345  | 1       |         |         |          |         |
| growth     | -0.0152 | 0.0211   | 0.2641     | 0.2881  | 0.0266  | -0.1275    | 0.0303  | 0.0259  | 1       |         |          |         |
| ppe        | 0.0573  | -0.0766  | -0.0395    | -0.0446 | 0.0376  | 0.0426     | 0.144   | 0.1177  | -0.0548 | 1       |          |         |
| turnover   | -0.0169 | 0.1119   | 0.1708     | 0.2207  | 0.0086  | 0.034      | 0.0548  | 0.2657  | 0.15    | -0.0156 | 1        |         |
| eps        | -0.0333 | 0.1504   | 0.7361     | 0.778   | 0.3083  | -0.0066    | -0.0548 | 0.3035  | 0.2251  | -0.0794 | 0.1758   | 1       |
| top10      | 0.0161  | 0.0396   | 0.1917     | 0.1877  | 0.2069  | -0.3046    | -0.0214 | 0.1242  | 0.1019  | 0.0693  | 0.0507   | 0.2056  |
| ln_board   | 0.0661  | 0.1229   | 0.0386     | 0.0741  | 0.2163  | 0.1325     | 0.1361  | 0.0734  | -0.0038 | 0.1948  | 0.0293   | 0.0572  |
| outdir_rat | -0.0079 | -0.0064  | -0.0208    | -0.0245 | 0.0517  | -0.0212    | -0.0172 | -0.0329 | -0.007  | -0.084  | -0.0462  | 0.0128  |
| currt      | -0.0767 | -0.1737  | 0.2103     | 0.0542  | -0.267  | -0.192     | -0.6292 | 0.0014  | -0.0238 | -0.2648 | -0.1277  | 0.0572  |
| mana       | -0.016  | 0.1053   | 0.1272     | 0.1732  | -0.0061 | 0.0539     | 0.1394  | 0.1247  | 0.0779  | 0.0007  | 0.9873   | 0.1359  |
| gdp_growth | 0.0197  | 0.0737   | 0.064      | 0.1035  | -0.1738 | -0.0469    | 0.0999  | 0.0029  | 0.0936  | 0.1788  | 0.1196   | -0.0199 |
| qr         | -0.076  | -0.1771  | 0.2132     | 0.0502  | -0.2569 | -0.2051    | -0.6315 | 0.0453  | -0.0229 | -0.2219 | -0.1231  | 0.058   |
| tagr       | -0.0213 | 0.0292   | 0.2901     | 0.2974  | 0.0419  | -0.2007    | 0.0107  | -0.0591 | 0.4147  | -0.14   | 0.0384   | 0.2418  |
|            | top10   | ln_board | outdir_rat | currt   | mana    | gdp_growth | qr      | tagr    |         |         |          |         |
| top10      | 1       |          |            |         |         |            |         |         |         |         |          |         |
| ln_board   | 0.0432  | 1        |            |         |         |            |         |         |         |         |          |         |
| outdir_rat | 0.0229  | -0.4932  | 1          |         |         |            |         |         |         |         |          |         |
| currt      | 0.0283  | -0.1291  | 0.033      | 1       |         |            |         |         |         |         |          |         |
| mana       | 0.0311  | 0.0285   | -0.0464    | -0.1315 | 1       |            |         |         |         |         |          |         |
| gdp_growth | -0.0492 | 0.1897   | -0.1305    | -0.0849 | 0.115   | 1          |         |         |         |         |          |         |
| qr         | 0.0383  | -0.124   | 0.0309     | 0.965   | -0.1271 | -0.1025    | 1       |         |         |         |          |         |
| tagr       | 0.1077  | -0.0157  | 0.0025     | 0.0279  | -0.0575 | 0.054      | 0.0339  | 1       |         |         |          |         |

**Table 5.** Climate and credit risk.

| Variables   | Model 1               | Model 2               | Model 3               |
|-------------|-----------------------|-----------------------|-----------------------|
| MRW-CRlc    | 0.018***<br>(4.17)    | 0.019***<br>(4.64)    | −0.031<br>(−1.08)     |
| roa         | 0.499***<br>(10.59)   | 0.494***<br>(10.51)   | 0.490***<br>(10.42)   |
| roe         | −0.288***<br>(−11.39) | −0.282***<br>(−11.21) | −0.282***<br>(−11.19) |
| ln_ta       | 0.012***<br>(13.08)   | 0.011***<br>(12.49)   | 0.011***<br>(12.26)   |
| ln_age      | −0.004***<br>(−2.91)  | −0.004***<br>(−2.62)  | −0.004***<br>(−2.78)  |
| lev         | 0.135***<br>(19.78)   | 0.140***<br>(21.07)   | 0.141***<br>(21.18)   |
| cfoa        | −0.035***<br>(−2.78)  | −0.039***<br>(−3.17)  | −0.039***<br>(−3.12)  |
| growth      | 0.003<br>(1.34)       | 0.003<br>(1.13)       | 0.003<br>(1.13)       |
| ppe         | 0.042***<br>(7.61)    | 0.043***<br>(8.34)    | 0.043***<br>(8.32)    |
| turnover    | −0.000<br>(−0.02)     | −0.000<br>(−0.03)     | −0.000<br>(−0.00)     |
| eps         | −0.006***<br>(−2.99)  | −0.006***<br>(−3.14)  | −0.006***<br>(−2.93)  |
| top10       | −0.008<br>(−1.51)     | −0.009<br>(−1.62)     | −0.009*<br>(−1.71)    |
| ln_board    | 0.003<br>(0.67)       | 0.004<br>(0.92)       | 0.004<br>( 0.89 )     |
| outdir_rat  | −0.006<br>(−0.37)     | −0.004<br>(−0.26)     | −0.005<br>( −0.33 )   |
| soe         | 0.003<br>(1.55)       | 0.002<br>(1.09)       | 0.002<br>( 0.98 )     |
| currt       | 0.008***<br>(3.75)    | 0.006***<br>(3.42)    | 0.007***<br>( 3.69 )  |
| mana        | −0.007<br>(−0.52)     | −0.005<br>(−0.43)     | −0.006<br>( −0.44 )   |
| gdp_growth  | 0.015<br>(0.26)       | 0.005<br>(0.08)       | 0.008<br>( 0.14 )     |
| qr          | −0.001<br>(−0.63)     | 0.000<br>(0.18)       | −0.000<br>( −0.07 )   |
| tagr        | −0.006*<br>(−1.76)    | −0.006<br>(−1.63)     | −0.005<br>( −1.57 )   |
| industry_1  | 0.015*<br>(1.82)      |                       |                       |
| industry_3  | 0.025***<br>(5.30)    |                       |                       |
| industry_4  | 0.040***<br>(6.90)    |                       |                       |
| industry_5  | 0.033***<br>(5.30)    |                       |                       |
| industry_6  | 0.029***<br>(5.19)    |                       |                       |
| industry_7  | 0.015***<br>(2.69)    |                       |                       |
| industry_8  | 0.015<br>(1.22)       |                       |                       |
| industry_9  | 0.028***<br>(5.24)    |                       |                       |
| industry_10 | 0.017***<br>(2.77)    |                       |                       |
| industry_11 | 0.036***<br>(4.91)    |                       |                       |
| industry_12 | 0.026***<br>(2.83)    |                       |                       |
| industry_13 | 0.022***              |                       |                       |

(Continued)

**Table 5.** (Continued).

| Variables    | Model 1   | Model 2   | Model 3   |
|--------------|-----------|-----------|-----------|
|              | (3.01)    |           |           |
| industry_14  | 0.066     |           |           |
|              | (0.90)    |           |           |
| industry_15  | 0.012     |           |           |
|              | (0.81)    |           |           |
| industry_16  | 0.023     |           |           |
|              | (1.51)    |           |           |
| industry_17  | 0.018**   |           |           |
|              | (2.27)    |           |           |
| industry_18  | 0.029***  |           |           |
|              | (2.64)    |           |           |
| lg2          |           | 0.010     | −0.004    |
|              |           | (1.44)    | (−0.43)   |
| lg3          |           | 0.009     | −0.001    |
|              |           | (1.27)    | (−0.06)   |
| cig2         |           |           | 0.061**   |
|              |           |           | (2.09)    |
| cig3         |           |           | 0.036     |
|              |           |           | (1.24)    |
| Constant     | −0.172*** | −0.155*** | −0.142*** |
|              | (−10.17)  | (−9.01)   | (−7.54)   |
| Observations | 22,505    | 22505     | 22505     |
| R-squared    | 0.082     | 0.079     | 0.08      |
| Year FE      | YES       | YES       | YES       |

This table presents regression results for the impact of climate risk on credit risk. The regressions include year- and industry-fixed effects. t-statistics in parentheses: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table 6.** Analysis of variance table.

|         | Res.Df | RSS    | Df | D     | F     | Pr(>F)   |
|---------|--------|--------|----|-------|-------|----------|
| Model 2 | 22466  | 241.51 |    |       |       |          |
| Model 3 | 22466  | 241.36 | 2  | 0.150 | 6.963 | 0.001*** |

Res.Df: degrees of freedom of residuals; RSS: squared sum of residuals; Df: degrees of freedom of difference between RSS in Models 2 and 3; D: difference between RSS in Models 2 and 3; F: F value =  $(D/Df)/(RSS/Res. Df)$  in Model 3).

tertiary industry have unique characteristics, generally lacking material entities and manifesting as labor activities (Yu 1994). Therefore, compared with primary and secondary industries, it is less susceptible to the impact of extreme weather. In addition, the tertiary sector is knowledge and labor intensive. S. H. Wang, Xu, and Liu (2022) argue that the modern service industry is significantly dependent on knowledge-intensive human capital. Therefore, firms pay more attention to the prevention of various risks (including climate change) during operations and management.

The primary industries include agriculture, forestry, animal husbandry, and fisheries. Climate change can significantly alter the production environment of primary industries, such as precipitation, temperature, and air humidity, which can further affect production efficiency. Therefore, according to the characteristics of the industry, listed companies in the primary industry tend to

**Table 7.** Multiple comparison of climate risk impact on credit risk between industries.

|                     | Estimate | Std. Error | T-value | Pr(> t ) |
|---------------------|----------|------------|---------|----------|
| lg2-ig1 (cig2)      | 0.061    | 0.029      | 2.092   | 0.036**  |
| lg3-ig1 (cig3)      | 0.036    | 0.03       | 1.235   | 0.217    |
| lg2-ig3 (cig2-cig3) | 0.025    | 0.008      | 3.286   | 0.001*** |

P-values corrected by Bonferroni: 0.109; 0.650; 0.003.

estimate and lock in the risk of possible meteorological disasters in advance by hedging or purchasing insurance products. As a result, compared with the secondary industry, the primary industry is relatively less affected by extreme weather.

## 5. Addressing endogeneity

This study focuses on the impact of climate risk on a firm's credit risk; however, different degrees of corporate credit risk rarely lead to extreme weather (i.e. reverse causality). Endogeneity tests were conducted to improve the reliability of the study.

### 5.1. Lag of core explanatory variables

Due to a potential time lag in the impact of climate risk on corporate default risk, the climate risk index is regressed using a one-stage lag (L.DT). Column 2 of Table 8 lists the test results. The regression coefficient of climate risk lagged one period on the probability of EDF is 0.016, which is significant at the 1% level. This empirical finding confirms the earlier results, underscoring the reliability of previous empirical conclusions.

### 5.2. Placebo analysis

In this study, we draw on the approaches of Li, Lu, and Wang (2016) and Cantoni et al. (2017) to construct placebo tests. These tests aim to determine whether the observed relationship between weather events and the credit risk of listed firms is driven by random factors. We randomly generate the treatment group and repeat the regressions 1,000 times to construct the empirical distribution of the t-value of the climate risk regression coefficient and compare it with the t-values of climate risk in the main regression. From the kernel density map in Figure 2, we can deduce that only a few regression t-values exceed the t-values of the regression coefficients in the main regression, indicating that climate risk is relatively robust to the credit risk of listed companies.

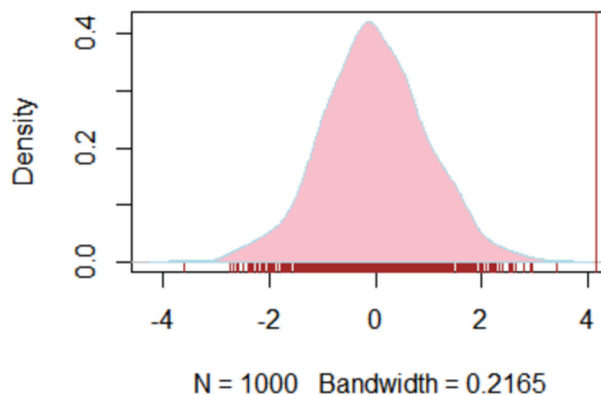


Figure 2. Kernel density of T-value.

## 6. Mechanism analysis

Corporate credit risk is an inherent feature of the prevailing economic framework and, therefore, cannot be entirely eradicated. A company's ability to repay debt is directly influenced by profitability. When a company exhibits strong profitability (return on assets [ROA] and revenue [growth] can reflect a firm's

Table 8. Endogeneity analysis.

|                          | MRW-CR1            |                    | roa      | roe                  | ln_ta               | ln_age               | lev                 | cfoa                 | growth          | ppe                | turnover        | eps                  | top10             |
|--------------------------|--------------------|--------------------|----------|----------------------|---------------------|----------------------|---------------------|----------------------|-----------------|--------------------|-----------------|----------------------|-------------------|
| Explanatory Variable Lag | 0.016***<br>(3.46) | 0.496***<br>(9.14) |          | -0.280***<br>(-9.84) | 0.013***<br>(12.45) | -0.006***<br>(-3.16) | 0.140***<br>(17.90) | -0.037***<br>(-2.58) | 0.003<br>(1.11) | 0.046***<br>(7.29) | 0.004<br>(0.32) | -0.006***<br>(-2.82) | -0.009<br>(-1.38) |
| ln_board                 |                    | soe                |          | currt                | mana                | gdp_growth           | qr                  | tagr                 | Constant        | Observations       | R-squared       | industry FE          | Year FE           |
| 0.004                    | -0.015             | 0.003              | 0.009*** | -0.013               | -0.013              | 0.006                | -0.002              | -0.007*              | -0.186***       | 18,983             | 0.086           | YES                  | YES               |
| (0.75)                   | (-0.87)            | (1.39)             | (3.90)   | (-0.88)              | (-0.88)             | (0.09)               | (-0.81)             | (-1.77)              | (-9.71)         |                    |                 |                      |                   |

t-statistics in parentheses \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

profitability), it generates significant free cash flow, leading to a reduction in its credit risk (Xu 2017). Excessive investment by a company can result in declining profitability, a shortage of operating cash flow, and increased financial leverage, thus increasing the company's credit risk (Aggarwal and Samwick 2006). Thus, operating performance influences changes in a company's credit risk.

Because a corporation's operating performance affects its credit risk, to further examine the mechanism by which climate risk affects corporate credit risk, we adopt McGuire's, Sundgren, and Schneeweis (1988) approach by regressing the indicators of ROA and Growth as dependent variables, which represent corporate operating performance. The estimation results in Column 1 of Table 9 indicate that climate risk has a significant impact on a firm's ROA. In other words, for every 1% increase in climate risk, a firm's ROA decreases by 0.004. The estimation results in Column 2 of Table 9 show that climate risk has a negative effect on the Growth indicator, which is significant at the 5% level. This implies that climate risk has a significant negative impact on business performance. Growth in corporate credit risk is likely to be more pronounced as climate risk worsens corporate operating results.

**Table 9.** Climate risk and firm operating performance.

|              | Roa                   | Growth                |
|--------------|-----------------------|-----------------------|
| MRW-CRlc     | -0.004***<br>(-3.37)  | -0.028**<br>(-2.39)   |
| ln_ta        | -0.002***<br>(-8.02)  | -0.014***<br>(-5.60)  |
| ln_age       | 0.002***<br>(5.32)    | -0.017***<br>(-4.34)  |
| lev          | -0.079***<br>(-46.61) | 0.069***<br>(4.05)    |
| cfoa         | 0.136***<br>(40.30)   | 0.150***<br>(4.45)    |
| ppe          | -0.012***<br>(-7.90)  | 0.018<br>(1.15)       |
| turnover     | 0.046***<br>(14.34)   | 1.384***<br>(43.60)   |
| eps          | 0.055***<br>(138.29)  | 0.052***<br>(12.91)   |
| top10        | 0.012***<br>(7.74)    | 0.044***<br>(2.80)    |
| ln_board     | 0.005***<br>(3.97)    | -0.005<br>(-0.38)     |
| outdir_rat   | -0.003<br>(-0.79)     | -0.027<br>(-0.63)     |
| soe          | -0.003***<br>(-6.52)  | -0.021***<br>(-4.07)  |
| currt        | 0.001**<br>(2.27)     | -0.002<br>(-0.29)     |
| mana         | -0.041***<br>(-11.85) | -1.420***<br>(-40.96) |
| gdp_growth   | 0.035**<br>(2.25)     | 0.231<br>(1.47)       |
| qr           | -0.002***<br>(-2.62)  | -0.007<br>(-1.15)     |
| tagr         | 0.020***<br>(21.19)   | 0.255***<br>(27.02)   |
| Constant     | 0.036***<br>(7.66)    | 0.250***<br>(5.26)    |
| Observations | 22,505                | 22,505                |
| R-squared    | 0.694                 | 0.293                 |
| industry FE  | YES                   | YES                   |
| Year FE      | YES                   | YES                   |

This table presents the regression results for the impact of climate risk on firms' operating performance. The regressions include year- and industry-fixed effects. t-statistics in parentheses \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## 7. Heterogeneity analysis

Using a benchmark regression, this study examines the impact of climate risk on a firm's credit risk. At the micro level, the impact of extreme weather on default risk may exhibit heterogeneity across firm types. Therefore, this study conducts further group regression according to firms' property rights and locations to gain a more comprehensive understanding of the impact of climate risk.

### 7.1. Regional heterogeneity

The impacts of climate change on different regions of China vary. Compared with the eastern region, the western region is more vulnerable to climate change, such as highland and monsoon climates, and is susceptible to extreme weather events. The eastern region is particularly affected by extreme precipitation events and has dense populations. However, compared to the eastern region, the central and western regions have a lower level of economic development, relatively slow development of capital markets, poor external financing and operating environments, and poor operating conditions and solvency (Mao and Jin 2021). Therefore, our study hypothesizes that the impact of extreme weather on corporate credit risk is more significant in the central-western regions of China. To test our hypothesis, we split our sample into two groups based on their geographical locations: the eastern and central-western regions, and we test the model in the groups.

Beniston et al. (2007) suggest that heavy winter precipitation is projected to increase in central and northern Europe while decreasing in the south by the end of the twenty-first century. Additionally, heavy summer precipitation is anticipated to rise in northeastern Europe and decline in the southern regions. To estimate the effects of climate change and trends in extreme 100-year events of temperature and rainfall amounts in the United States, Shenoy et al. (2022) also estimated these factors after dividing the continental geographic area into west, south, and east partitions.

The regression results in Columns 1 and 2 of Table 10 show that the coefficient of the MRW-CR<sub>it</sub> in the eastern region is 0.009, which is significant at the 10% level. The coefficient of MRW-CR<sub>it</sub> in the central-western regions is 0.032, which is significant at the 1% level. Additionally, the significance of the difference in the MRW-CR<sub>it</sub> coefficient (East – Midwest) is determined through a permutation test (simulation times = 1000, Table 10, 3rd column). The results indicate that the effect of climate risk on corporate credit risk is significantly greater in the central-western regions than in the eastern region, thus verifying the hypothesis 2.

### 7.2. Heterogeneity of property rights

First, compared with non-SOEs, SOEs bear the responsibility of maintaining social stability and dominating the state-owned economy. The State-owned Assets Supervision and Administration Commission (SASAC) of China took social responsibility as an important performance assessment indicator for SOEs in 2009. This may have indirectly increased the motivation for enterprises to invest in social responsibility in the pursuit of performance, leading to decision-making detached from the actual demands of enterprises and waste of corporate resources, thus increasing the risks of enterprises (Lin 2021). Second, SOEs have close relationships with local governments, and financial intermediaries tend to provide more bank credit to local SOEs. Therefore, SOEs have lower financing and bankruptcy risk (Yang et al. 2021). Despite SOEs having stronger financing advantages, they tend to have a large amount of idle capital, resulting in low efficiency in capital use and inadequate risk

**Table 10.** Heterogeneity analysis.

|              | ( 1 )                 | ( 2 )                | ( 3 )                      | ( 4 )                | ( 5 )                | ( 6 )             |
|--------------|-----------------------|----------------------|----------------------------|----------------------|----------------------|-------------------|
|              | Eastern Region        | Midwest Region       | Eastern-<br>Midwest Region | SOEs                 | Non-SOEs             | SOEs-<br>Non-SOEs |
| MRW-CRlc     | 0.009*<br>(1.94)      | 0.032***<br>(3.75)   | -0.023**                   | 0.029***<br>(4.00)   | 0.003<br>(0.62)      | 0.027 ***         |
| roa          | 0.420***<br>(7.81)    | 0.647***<br>(6.76)   |                            | 0.822***<br>(8.69)   | 0.222***<br>(5.40)   |                   |
| roe          | -0.226***<br>(-7.78)  | -0.414***<br>(-8.29) |                            | -0.476***<br>(-9.96) | -0.127***<br>(-5.68) |                   |
| ln_ta        | 0.014***<br>(13.13)   | 0.009***<br>(4.71)   |                            | 0.015***<br>(8.96)   | 0.008***<br>(9.09)   |                   |
| ln_age       | -0.005***<br>(-3.41)  | -0.000<br>(-0.11)    |                            | -0.003<br>(-1.18)    | -0.001<br>(-0.63)    |                   |
| lev          | 0.115***<br>(14.70)   | 0.170***<br>(12.20)  |                            | 0.220***<br>(16.13)  | 0.062***<br>(10.56)  |                   |
| cfoa         | -0.028**<br>(-2.02)   | -0.046*<br>(-1.69)   |                            | -0.055**<br>(-2.31)  | -0.007<br>(-0.64)    |                   |
| growth       | 0.001<br>(0.26)       | 0.008*<br>(1.67)     |                            | 0.005<br>(1.08)      | -0.001<br>(-0.54)    |                   |
| ppe          | 0.027***<br>(4.04)    | 0.069***<br>(6.43)   |                            | 0.067***<br>(6.82)   | 0.007<br>(1.25)      |                   |
| turnover     | -0.005<br>(-0.39)     | 0.003<br>(0.13)      |                            | -0.005<br>(-0.26)    | 0.004<br>(0.41)      |                   |
| eps          | -0.011***<br>(-4.79)  | 0.004<br>(0.87)      |                            | -0.004<br>(-1.03)    | -0.005***<br>(-2.97) |                   |
| top10        | -0.001<br>(-0.18)     | -0.021*<br>(-1.79)   |                            | -0.032***<br>(-2.99) | 0.004<br>(0.85)      |                   |
| ln_board     | 0.010**<br>(2.08)     | -0.006<br>(-0.74)    |                            | -0.005<br>(-0.70)    | 0.015***<br>(3.63)   |                   |
| outdir_rat   | 0.026<br>(1.45)       | -0.055*<br>(-1.80)   |                            | -0.066**<br>(-2.36)  | 0.051***<br>(3.55)   |                   |
| soe          | 0.002<br>(1.06)       | 0.002<br>(0.46)      |                            |                      |                      |                   |
| currt        | 0.007***<br>(3.39)    | 0.007<br>(1.58)      |                            | 0.011***<br>(2.63)   | 0.004**<br>(2.46)    |                   |
| mana         | 0.002<br>(0.14)       | -0.016<br>(-0.62)    |                            | -0.004<br>(-0.19)    | -0.007<br>(-0.56)    |                   |
| gdp_growth   | 0.086<br>(1.08)       | -0.104<br>(-0.96)    |                            | -0.066<br>(-0.70)    | 0.120**<br>(2.09)    |                   |
| qr           | -0.002<br>(-0.93)     | 0.001<br>(0.20)      |                            | -0.001<br>(-0.13)    | -0.002<br>(-0.83)    |                   |
| tagr         | -0.005<br>(-1.37)     | -0.007<br>(-0.98)    |                            | -0.014*<br>(-1.76)   | -0.003<br>(-1.26)    |                   |
| Constant     | -0.215***<br>(-10.10) | -0.116***<br>(-3.66) |                            | -0.180***<br>(-6.12) | -0.161***<br>(-8.95) |                   |
| Observations | 15,843                | 6,662                |                            | 10,102               | 12,403               |                   |
| R-squared    | 0.076                 | 0.104                |                            | 0.108                | 0.048                |                   |
| industry FE  | YES                   | YES                  |                            | YES                  | YES                  |                   |
| Year FE      | YES                   | YES                  |                            | YES                  | YES                  |                   |

This table presents the regression results of the impact of climate risk on firm credit risk. Meanwhile, it divides the sample into different groups: state-owned enterprises and non-state-owned enterprises; and eastern region and central-western region. t-statistics in parentheses: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

management. This in turn exacerbates operating risks. Finally, compared with non-SOE managers, SOE managers are shortsighted in accomplishing assessment targets and invest funds in high-risk and high-return real estate and finance industries, which is more damaging to future core business performance (Du, Zhang, and Chen 2017).

By contrast, non-SOEs may be at a disadvantage in terms of resource acquisition, but demonstrate greater flexibility in their operational management, are more cautious in various

investment activities, and have better management supervisory mechanisms (Xianhuan H. H. Huang, Kerstein, and Wang 2018). Therefore, the impact of climate risk on the risk of default is expected to be more significant for SOEs than for non-SOEs. To test this hypothesis, we divide the sample into two groups according to the ownership nature of the enterprise: state-owned and non-state-owned. The regression results in Columns 4 and 5 of Table 10 show that the regression coefficient of MRW-CR1c is significantly positive at the 1% level in the sample of SOEs but not in the sample of non-SOEs, assumption 3 has been confirmed. Moreover, the significance of the difference in the MRW-CR1c coefficient (SOEs – non-SOEs) is determined by permutation test (simulation times = 1000, Table 10, 6rd column). The results indicate that the impact of climate risk on the credit risk of SOEs is significantly higher than that on non-SOEs.

## 8. Robustness tests

### 8.1. Replacing the dependent variable

Drawing on Altman (1968) and Favara et al. (2017), this study utilizes the Z-score model to re-measure corporate default risk for robustness tests. The calculation formula is as follows:

$$Z - score = 1.2 \times \frac{Working\ Capital}{Total\ Assets} + 1.4 \times \frac{Retained\ Earnings}{Total\ Assets} + 3.3 \times \frac{EBIT}{Total\ Assets} + 0.6 \times \frac{Market\ value\ of\ equity}{Book\ value\ of\ total\ liabilities} + 0.999 \times \frac{Operating\ Income}{Total\ Assets} \quad (10)$$

Greater Z-scores represent a lower likelihood of default risk for the firm and, correspondingly, lower credit risk. As shown in Column 1 of Table 11, the MRW-CR1c coefficient is 0.004, which is significant at the 1% level. In conclusion, the regression analysis results support the initial hypothesis after modifying the measurements of the main variables.

### 8.2. Tobit model regression

As the value of default risk ranges from 0 to 1, the Tobit model is used to further test the influence of climate risk on corporate default risk. As shown in Column 2 of Table 11, the regression coefficient is 0.028, which is significant at the 5% level.

### 8.3. Change in sample period

With the outbreak of the subprime mortgage crisis in 2008, firms faced huge default risks, and the impact of climate risk on firms was easily diluted by the outbreak. Thus, the study period is adjusted to 2011–2021 for robustness testing, and the empirical results are presented in Column 3 of Table 11. The results demonstrate that the regression coefficient of MRW-CR1c to EDF is 0.02 after excluding noisy year data, and is significant at the 1% level, which is consistent with the main test conclusion, further verifying the robustness of the empirical conclusion.

### 8.4. Sensitivity analysis

Drawing on the research by Cinelli, Ferwerda, and Hazlett (2020), we conducted sensitivity analysis to address potential concerns regarding omitted variables and ensure the robustness

**Table 11.** Robustness tests.

|              | (1)<br>Z-score        | (2)<br>Tobit          | (3)<br>Excluding Noisy Year |
|--------------|-----------------------|-----------------------|-----------------------------|
| MRW-CRlc     | 0.004***<br>(5.38)    | 0.028**<br>(2.07)     | 0.020***<br>(4.27)          |
| roa          | 0.168***<br>(20.65)   | 0.281<br>(1.39)       | 0.489***<br>(9.51)          |
| roe          | -0.051***<br>(-11.34) | -0.398***<br>(-4.25)  | -0.285***<br>(-10.28)       |
| ln_ta        | -0.003***<br>(-15.55) | 0.049***<br>(15.23)   | 0.011***<br>(11.54)         |
| ln_age       | 0.004***<br>(21.12)   | -0.019***<br>(-3.71)  | -0.004***<br>(-2.63)        |
| lev          | -0.001<br>(-0.57)     | 0.878***<br>(30.86)   | 0.127***<br>(17.37)         |
| cfoa         | 0.011***<br>(5.18)    | -0.373***<br>(-8.12)  | -0.027*<br>(-1.91)          |
| growth       | 0.001**<br>(1.98)     | 0.006<br>(0.66)       | 0.004<br>(1.52)             |
| ppe          | 0.008***<br>(8.43)    | 0.199***<br>(9.93)    | 0.043***<br>(6.97)          |
| turnover     | 0.007***<br>(3.35)    | 0.008<br>(0.18)       | 0.003<br>(0.22)             |
| eps          | -0.001*<br>(-1.67)    | -0.027***<br>(-3.42)  | -0.006***<br>(-2.93)        |
| top10        | -0.001<br>(-0.58)     | -0.124***<br>(-6.11)  | -0.010*<br>(-1.71)          |
| ln_board     | -0.002**<br>(-2.15)   | -0.014<br>(-0.88)     | 0.003<br>(0.62)             |
| outdir_rat   | -0.000<br>(-0.05)     | -0.088<br>(-1.59)     | 0.005<br>(0.30)             |
| soe          | -0.000<br>(-0.02)     | -0.002<br>(-0.23)     | 0.003<br>(1.46)             |
| currt        | 0.006***<br>(18.34)   | 0.008<br>(0.83)       | 0.009***<br>(4.35)          |
| mana         | -0.004*<br>(-1.71)    | -0.041<br>(-0.91)     | -0.009<br>(-0.65)           |
| gdp_growth   | -0.011<br>(-1.10)     | -0.130<br>(-0.67)     | -0.058<br>(-0.91)           |
| qr           | 0.001***<br>(2.75)    | -0.024**<br>(-2.31)   | -0.004<br>(-1.53)           |
| tagr         | -0.001<br>(-1.33)     | -0.038***<br>(-2.83)  | -0.005<br>(-1.24)           |
| Constant     | 0.033***<br>(10.75)   | -0.757***<br>(-12.35) | -0.166***<br>(-9.04)        |
| Observations | 27,199                | 22,505                | 18,522                      |
| R-squared    | 0.446                 |                       | 0.078                       |
| Pseudo R2    |                       | 0.5262                |                             |
| industry FE  | YES                   | YES                   | YES                         |
| Year FE      | YES                   | YES                   | YES                         |

Note: In column (1), the dependent variable use the Z-score model to re-measure corporate default risk. In column (2), report results from Tobit regression. In column (3), the study period was adjusted to 2011–2021. t-statistics in parentheses \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

of our findings. In [Figure 3](#), the contour lines represent t-statistics, while the red line denotes the critical value of 1.96 (corresponding to a 95% confidence interval). The four numerical points represent scenarios where omitted variables of varying strengths (0–3 times the effect of ROA) are included. Notably, all four values fall to the left of the red line, indicating that even with the inclusion of an omitted variable with a threefold intensity of ROA, the estimated coefficients remain significant. This further reinforces the reliability of our empirical findings.

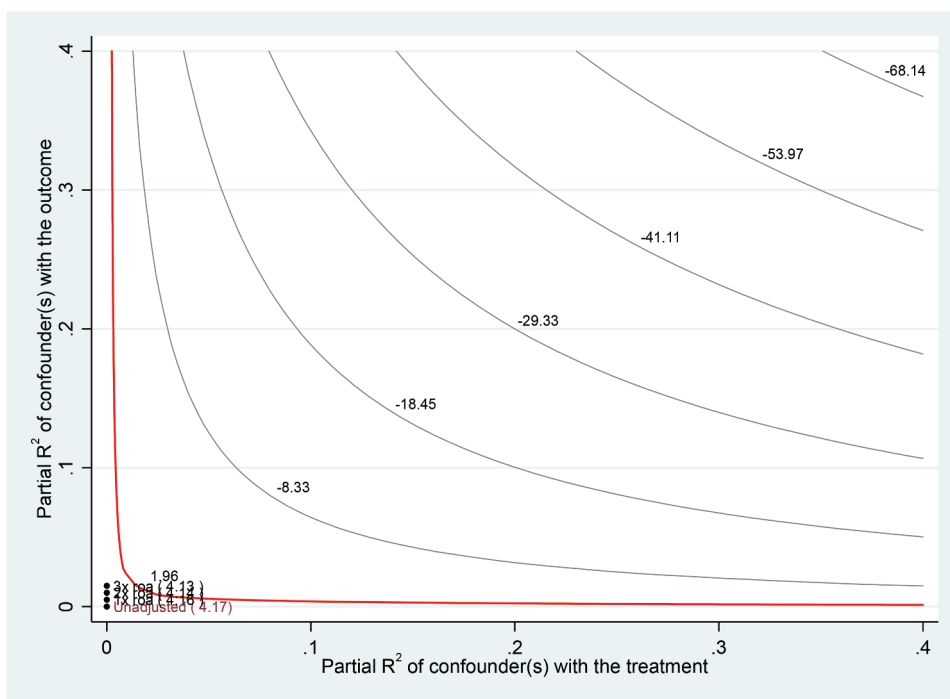


Figure 3. Sensitivity analysis.

## 9. Conclusion

This study examines the impact of extreme weather on corporate credit risk in China by analyzing a sample of A-share listed companies. The collected data covers the period 2005–2021. Furthermore, we investigate the impact path of extreme weather on corporate credit risk and identify the contextual factors that may contribute to heterogeneity. Besides, according to the Task Force on Climate-Related Financial Disclosures (TCFD) definition (Retrieved from <https://www.fsb-tcfd.org/recommendations/>), climate risks broadly encompass uncertainties related to climate factors, such as extreme weather events, natural disasters, global warming, and societal transformation towards sustainability, including both physical and transitional risks, for financial and economic activities. However, with limited space and in light of the broader background of global warming, this paper concentrates on credit risk stemming from losses incurred by corporate production and operations due to physical risks. The main findings of this study are as follows.

First, climate risk increases corporations' credit risk, a valid finding even after a series of robustness tests. Second, climate risk increases the credit risk of both SOEs and non-SOEs. However, compared to non-SOEs, the impact of climate risk on SOEs is more significant. For every 1-unit increase in climate risk, a firm's credit risk increases by 0.029%. Third, weather events have a discernible impact on the credit risk of eastern and central – western Chinese enterprises. Notably, such events have a more pronounced effect on credit risk for companies located in the central-western region of China. Fourth, channel test studies indicate climate risk is associated with lower firm performance. Corporate credit risk increases due to deteriorating operating performance derived from climate risks.

To cope with corporate credit risk arising from climate risk, the improved results of this study have several policy implications. First, to raise awareness among listed companies on extreme weather risks, especially those that may result in losses to both fixed assets and operations, measures are needed to augment the capital management abilities of enterprises.

Crucially, companies must allocate sufficient cash flows to minimize the adversities caused by extreme weather. Second, enterprises should prepare contingency plans for extreme weather disasters (e.g. drought, heavy rainfall, flooding, low-temperature freezing, and typhoons) based on the characteristics of their own industries and production methods. Losses can be minimized at the first moment of a meteorological disaster through early warning and safeguarding measures within the enterprise. Finally, financial institutions should innovate climate risk management tools, such as credit disaster insurance and meteorological disaster insurance, to enhance enterprises' ability to recover and reestablish operations after experiencing the effects of extreme weather events and strive to alleviate credit risks stemming from climate disasters.

## Notes

1. [https://globescan.wpenginepowered.com/wp-content/uploads/2022/04/GlobeScan\\_Analysis\\_Larry\\_Fink\\_Annual\\_Letters\\_to\\_CEOs\\_Jan2020.pdf](https://globescan.wpenginepowered.com/wp-content/uploads/2022/04/GlobeScan_Analysis_Larry_Fink_Annual_Letters_to_CEOs_Jan2020.pdf).
2. <http://www.csrc.gov.cn/csrc/c101864/c1024632/content.shtml>.
3. [http://www.stats.gov.cn/zsk/snapshoot?reference=33e2b9cdb6391521c53328be6244e40b\\_635F9BD4DE71F957D711CD972E0F8918&siteCode=tjzsk](http://www.stats.gov.cn/zsk/snapshoot?reference=33e2b9cdb6391521c53328be6244e40b_635F9BD4DE71F957D711CD972E0F8918&siteCode=tjzsk).
4. We have verified that including either ROA or ROE individually as control variables does not impact the validity of the regression results. Detailed figures can be obtained from the authors upon request.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Data availability statement

The data are available from the authors upon request.

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