

# **Climate Risk and Corporate Environmental Performance: Empirical Evidence from China**

Xiaohang Ren<sup>a</sup>, Yiyi Li<sup>a</sup>, Muhammad Shahbaz<sup>b,c</sup>, Kangyin Dong<sup>d,e,\*</sup>, Zudi Lu<sup>f</sup>

<sup>a</sup> *School of Business, Central South University, Changsha 410083, China*

<sup>b</sup> *School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China*

<sup>c</sup> *Department of Land Economy, University of Cambridge, Cambridge CB2 1TN, UK*

<sup>d</sup> *UIBE Belt & Road Energy Trade and Development Center, University of International Business and Economics, Beijing 100029, China*

<sup>e</sup> *School of International Trade and Economics, University of International Business and Economics, Beijing 100029, China*

<sup>f</sup> *Southampton Statistical Sciences Research Institute, University of Southampton, Southampton, SO17 1BJ, UK*

*E-mail addresses: [domrxh@outlook.com](mailto:domrxh@outlook.com) (X.H. Ren), [Yying.li@outlook.com](mailto:Yying.li@outlook.com) (Y.Y. Li), [muhdshahbaz77@gmail.com](mailto:muhdshahbaz77@gmail.com) (M. Shahbaz), [dongkangyin@uibe.edu.cn](mailto:dongkangyin@uibe.edu.cn) (K.Y. Dong), [Z.Lu@soton.ac.uk](mailto:Z.Lu@soton.ac.uk) (Z.D. Lu).*

*\*Corresponding author: [dongkangyin@uibe.edu.cn](mailto:dongkangyin@uibe.edu.cn) (K.Y. Dong).*

*Personal website: <https://scholar.google.com/citations?user=Ut15iYkAAAAJ&hl=en&oi=ao>*

OR

*[https://www.researchgate.net/profile/Kangyin\\_Dong](https://www.researchgate.net/profile/Kangyin_Dong).*

**Abstract:** This study creatively investigates the impact of extreme national climate risk on corporate environmental performance in the context of China. An innovative approach based on an assessment of the economic input-output life cycle is utilized to evaluate carbon footprint at the corporate level. We select the Chinese climate risk score calculated by Germanwatch to represent climate risk, and then test its effects on corporate carbon performance using the dynamic threshold model. The results indicate that an increase in national climate risk will promote corporate carbon emissions, which are more pronounced when the climate risk score is in the high-risk range. Furthermore, the effects of climate risk on corporate carbon performance differ across companies with different geographical locations and environmental restrictions. In addition, ownership and whether a company is listed on stock exchanges do not significantly affect the impact of climate risk on corporate carbon performance in China. Our findings reflect the subtle connections between Chinese companies and climate risk on the whole, and could help relevant business leaders, policymakers, and investors enhance related policies.

**Keywords:** Climate risk; Corporate carbon performance; Dynamic threshold model; Environment sensitivity

**JEL Classification:** C33; D51; G30

## List of symbols

Symbols	Definition	Unit
$A$	The direct consumption coefficients	1
$A_{m,k}$	Consumption of each energy in every sector	ton
$B$	The final carbon emission matrix for each sector	1
$C_e$	The carbon emission of direct energy burning	ton
$C_k$	The transformation coefficients of each energy	1
$C_m$	The direct carbon emissions of each sector	ton
$C_p$	The overall carbon emission of the process of industrial production	ton
$CO_{2industry}$	The amount of carbon dioxide emissions of each sector per year	ton
$CRI$	Climate risk index published by the Germanwatch	1
$E$	Carbon emissions of each company per year	ton
$K_{m,j}$	Carbon transformation coefficient of each product in the industrial production process of every sector	1
$OPCOST$	Operating cost of the central business	ten thousand yuan (RMB)
$P_{m,j}$	The output of each product in the industrial production process of every sector	ten thousand yuan (RMB)
$R$	The direct emission matrix of products and services of each industry	1
$R_m$	The carbon emissions directly emitted per unit of monetary output of each sector	ton
$V$	The threshold value	1
$x_m$	The output of each sector	ten thousand yuan (RMB)
$Z_{i,t}$	The control variables set	
$\varepsilon$	Error term	
$I(\cdot)$	The indicator function	
$\ln X$	The logarithmic value of each variable	
$\sigma_{fixed}$	The fixed effects	
$\Delta$	Difference	

## 1. Introduction

Climate risk brought on by extreme weather events has gradually become an unprecedented threat that could significantly harm humans' assets and threaten their safety and lives ([Dou et al., 2021](#)). The urgent need to mitigate climate risk has prompted various market participants, mainly in the corporate sector, to transition to low-carbon emissions. As the corporate sector is the leading producer of carbon emissions and the principal contributor to climate change, it needs to imminently rectify its practice of producing high-carbon emissions ([Sakhel, 2017](#); [Van and Rob, 2018](#); [Ren et al., 2021](#)). Moreover, the emergence of the corporate social responsibility (CSR) concept and the increasing attention stakeholders pay to environmental performance is making companies increasingly aware of the benefits of bringing ecological factors into their internal governance ([Dong et al., 2020](#); [Farah et al., 2021](#)).

The condition of the world's climate is already one of the most frequently discussed topics among executives; in fact, discussion on the subject has become more common than discussions on political and economic events ([S&P, 2018](#)). Clarifying companies' ability to respond to extreme climate risk and assessing their attitude toward climate risk will not only benefit economists and policymakers, but will also be crucial to business leaders and investors. However, it is often hard to quantify the specific connection between climate risk and individual corporates because of the lack of enterprise-level environmental information. This is particularly so in China, where quantification is incredibly difficult because there are

so many companies (Jensen and Traeger, 2021; Wei et al., 2021). To fill the gap, we use corporate carbon emissions as a proxy for environmental performance, and analyze the impacts of extreme climate risk on corporate environmental performance for the case of China.

Climate risk is generally classified as physical risk, transition risk, and regulatory risk, and its frequency and destructiveness can no longer be underestimated (Pinkse and Gasbarro, 2019). In the 20 years from 1999 to 2018, there have been more than 10,000 extreme climate events worldwide, resulting in more than 475,000 deaths and direct losses of approximately USD2.56 trillion (Eckstein et al., 2019; Ren et al., 2021). Climate events have had an enormous impact on the financial system, and created both physical and transition risks, harmfully affecting many companies (Clapp et al., 2017; Duan et al., 2021).

Physical risk usually refers to material damage to the environment directly caused by natural disasters (i.e., drought, forest fires, floods, hurricanes) (Caldecott et al., 2016). Extreme climate events can cause physical damage to various company assets, destroying their value and interrupting business activities. Such damage and disruptions negatively impact potential economic benefits (Huang et al., 2018). Transition and regulatory risks generally refer to the threat brought about by changes (i.e., transformation in policies, technologies, preferences) to improve the environment (Dunz et al., 2019). For example, formulating a series of international agreements, such as the Paris Agreement, and environmental policies, such as carbon taxes, to cope with environmental changes has brought enormous financial and

economic impacts (Monasterolo, 2020). In terms of corporates, the transition between different energy sources has led to decreased utilization of traditional fossil energy, and companies are facing the risk of stranded assets (Green and Newman, 2017). In addition to changes in policy and technology, changes in consumer and investor preferences can also create significant uncertainty in environmentally sensitive corporates (Pfeiffer et al., 2018).

However, studies have shown that a company's ability to manage climate risk is still inadequate, and the evidence of its sensitivity and countermeasures to extreme climate events is still scarce (Kouloukoui et al., 2019). The management of climate risk should become one of the essential aspects of corporate daily internal operations, thereby acting as a channel for dialogue with investors and other external parties (Weinhofer and Busch, 2013). It is deplorable that most enterprises do not have a scientific understanding and timely assessment of their exposure to climate risk. Sakhel (2017) has proved that companies face more regulatory pressure on climate risk than pressure from the market and physical damage. But a limitation is that his study does not conduct an empirical analysis of the relationship between those factors. Kouloukoui et al. (2019) investigate the top 100 companies in terms of emissions and find that even companies with the most severe pollution do not pay attention to climate risk or even to extreme climatic events. Nevertheless, their studies are not universally applicable since only 100 companies are targeted.

Therefore, we conduct an empirical analysis to test the impact of climate risk on companies' carbon performance in the Chinese market, one of the world's largest

carbon-emitting economies, to complement research in this field. Many scholars have studied corporate environmental performance, and expressed different opinions on the specific connotations of environmental performance, but it can be simplified as the impact of corporate behavior on the whole environment (Tyteca et al., 2002; Zopf and Guenther, 2015). The reason why carbon performance is used as a representative of corporate environmental performance is, on the one hand, that carbon dioxide is closely related to climate change and is also a major cause of climate change (Hoffmann and Busch, 2008; Zhou and Li, 2019). On the other hand, carbon emissions are one of the most commonly used indicators in corporate environmental performance research, which can also facilitate other related academic analyses as the research core (Doda et al., 2016; Wang et al., 2019; Luo and Tang, 2021). Due to the absence of a corporate carbon information database, we use the assessment path extended from the economic input-output life cycle assessment method to evaluate the carbon emissions of Chinese companies. This method comprehensively assesses the carbon footprint from direct energy consumption and indirect carbon redistribution from various industries' circulation of products and services. In addition, it has the characteristics of more effortless operation and universality (Ji et al., 2011; Wei and Shu, 2021).

We also select the Chinese climate risk index (CRI) calculated by Germanwatch to represent climate risk (i.e., exposure and vulnerability to extreme weather events). This index incorporates the impacts of several extreme weather events and can reflect the level of each country's relative climate risk (Eckstein et al., 2019). The

index has been widely used in corporate-level analyses. For instance, [Huang et al. \(2018\)](#) and [Ding et al. \(2021\)](#) have used this indicator to verify the correlation of climate risk with corporate financial performance and revenue management, respectively.

To better grasp the relationship between corporate carbon emissions and extreme climate risk, we further analyze potential corporate heterogeneities. We find that the carbon emissions of companies with more direct environmental constraints may be more susceptible to extreme climate events. Specifically, the companies that are not sensitive enough to environmental information may even exacerbate carbon emissions when climate risk rises.

To the best of our knowledge, this paper is the first to investigate the impact of extreme climate risk on corporate environmental performance in the Chinese market. In so doing so, we contribute to the literature in three ways. First, we explore whether extreme climate events, as external incentives, will affect corporate carbon performance, and the extent to which this effect is achieved. Second, although climate risk has attracted considerable attention from various stakeholders, it is difficult to quantify the company's environmental performance due to the lack of data at company level. Therefore, we empirically link Chinese corporate carbon performance with climate risk, adding new evidence to the measurement of corporate environmental performance and companies' responses to climate events. Third, our research has crucial implications for policymakers. China's "carbon neutrality" initiative has demonstrated the country's determination to transform its



economy into a low-carbon economy. Our research in the context of China has provided a solid basis for policymakers to formulate better policies on corporate climate risk-management issues, such as climate information disclosure and environmental restraint measures. Finally, and most importantly, our research demonstrates the need to establish a corporate environmental information database and forceful external supervision.

The remainder of this study is arranged as follows: Section 2 presents the related literature review and hypotheses. Section 3 introduces methodologies. Section 4 discusses the empirical results. The last section concludes and offers policy suggestions.

## **2. Literature review and research hypotheses**

### **2.1. Climate condition and company behaviors**

Extreme weather events, the failure of climate mitigation, and environmental losses will be the three most pressing risks globally in the future ([Forum, 2021](#)). Accordingly, reducing carbon emissions more scientifically to mitigate climate deterioration has been a hot topic in recent years. Climate risk has become a major issue of concern for companies pursuing sustainable development strategies ([Ikram et al., 2019](#)). Generally, companies have two ways of dealing with climate events and uncertainties.

The first is to ignore climate-related events, and do nothing to prevent or allay their effects - an attitude that reflects “insensitivity” toward climate change or a lack of understanding of the extreme risks of climate change. Instead of reducing carbon

emissions, such an attitude is likely to exacerbate the risks of climate change and its negative effects.

The literature supports such a contention. For example, a study by Kouloukoui et al. (2019) on 100 companies with the most severe carbon emissions found that even the world's largest polluters have low levels of disclosure of climate risk. In addition, some companies still do not believe in the severity of climate risk, and do not implement climate-related policies due to a lack of regulation. Quan et al. (2015) find a strong speculative atmosphere in China's current capital market, and that supervision of the system needs to be perfected. The awareness of enterprises engaged in the construction of substantive social responsibility is relatively weak, and corporate social responsibility tends to act as a self-interest tool employed by management in most situations.

Based on the above, many companies are not aware of the risks brought by climate events, and will not take active environmentally related measures to prevent the occurrence of these events. From this logic, we propose the first hypothesis:

**H1:** There is no significant impact of climate risk on corporate carbon performance.

However, as the topic of climate receives increasing attention, and many corporate operations will inevitably be exposed to the negative effects of climate change, these companies may also start giving more weight to climatic events and take corresponding actions to remedy these effects.

With the frequent occurrence of extreme climate events and the increasing

importance of environmental factors, companies that hitherto paid little heed to climate change and the factors that produce it will realize the urgency of improving environmental performance and reducing carbon emissions. Extreme climate events directly affect companies' existing assets, such as fossil energy assets, causing massive impairment ([Green and Newman, 2017](#)). Climate uncertainties could also affect companies' asset structure, and decrease the financial leverage of enterprises with heavy carbon emissions, which would significantly impact enterprises with financial constraints ([Nguyen and Phan, 2020](#)). Moreover, the various uncertainties caused by the environmental changes will shock investors' moods and expectations, causing sharp fluctuations in asset prices ([Gros et al., 2016](#)). Furthermore, the pressure of transition and regulatory risks will impel a revolution of economic and social technology, policies and laws, which, in turn, will promote the innovation of green technology and green patents ([Flammer, 2021](#)).

Another possibility is that companies may disguise the pressure they face when climate events occur. [Huang et al. \(2018\)](#) found that climate risk negatively affects financial performance, especially the profit rate. Poor performance due to climate risk may increase the likelihood that companies will default on their debt covenants, and companies may be inclined to manipulate accounting practices and actual operations. The higher a company's exposure to climate risk, the greater the likelihood accounting skills will be used to cushion the adverse effects of extreme climate events on revenue ([Ding et al., 2021](#)).

Climate events and changes may cause direct or indirect losses to corporate

assets and promote technological reforms to reduce corporate carbon emissions. Companies are likely to improve their environmental behavior and strategies due to internal and external pressure. On the other hand, such pressure may also encourage companies to adopt more frequent production and operation activities before and after climate events to reassure investors and maintain stable stock prices, which could result in worse environmental performance. However, whatever the possibility, a company's environmental performance may have some relationship with the degree of climate risk.

Based on this analysis, we propose the second hypothesis:

**H2:** Climate risk has a significant impact on corporate carbon performance.

## **2.2. Geographical location and corporate environmental performance**

Generally, environmental risk at the enterprise level depends on geographical and enterprise-specific factors (Ginglinger and Moreau, 2019). To further identify the factors that cause a company to be sensitive to climate events or uncertainties, we analyze companies from the perspective of geographical location and other characteristics.

Geographical location is a crucial factor affecting a company's environmental performance. It may lead to differences in environmental technology and environmental awareness, and companies may also shape their social responsibility image based on the characteristics of geographical factors (Brammer et al., 2006).

Besides, larger and better-developed companies may also choose areas with less

stringent environmental regulations to run their business (Scaringelli, 2014; Kamal, 2018).

Due to China's vast land area and the influence of economic zones at different stages of development, the country is generally divided into eastern, central, and western regions. In western China, environmental technology and treatment efficiency are weaker and constrained by insufficient total input factors and low-scale efficiency (Lu, 2014). The differences in environmental governance in the east, central, and western parts are gradually expanding, deepening the disadvantages in the west and consolidating environmental inequality among regions (Yang and Xu, 2016). Zhu et al. (2020) measured and compared the ecological efficiency of each area in China from 2006 to 2015 by constructing a data envelopment analysis model (DEA). They found that environmental efficiency (output efficiency of the environmental economy measured by the DEA model) and conditions (i.e., carbon and sulphur dioxide emissions) in the western region are far worse than those in the eastern area.

Other studies show that the eastern, central, and western governments pay scant attention to ecological protection of the environment. The east and central areas have always borne much higher environmental costs than the western region (Wang and Dai, 2017). At the same time, the western region is more susceptible to changes in weather such as plateau climate and monsoon climate, which could result in its fragility to extreme climate events. Therefore, there is no conclusion on how sensitive each part is to climate risk. Based on this, we put forward a hypothesis as

follows and then test it:

**H3:** The impact of climate risk on companies in different geographical locations is not significantly different.

### **2.3. Corporate heterogeneities and environmental sensitivity**

Important factors in the domain of corporate environmental performance include the nature of the industry, the nature of ownership, and whether the company is listed or not. It is worth noting that listed companies generally face more stringent information-disclosure systems and environment-related punishment systems. The transparency of environmental information of unlisted companies is far less than that of listed companies, but if their ecological performance improves, they can obtain more financing benefits (Wellalage and Kumar, 2021). Many countries and regions have gradually raised their requirements for environmental information reporting of heavily polluting industries, which is somewhat mandatory (Clarkson et al., 2011; Zhang et al., 2021). Environmental policies will positively affect the environmental performance of enterprises, which is more evident in heavily polluting industries (Long et al., 2018; Lin and Chen, 2020).

Meyer and Pac (2013) compare the environmental performance of European state-owned and privatized factories. They find that state-owned factories emit more greenhouse gases, and privatization can reduce emissions by more than half. In China, many state-owned enterprises have advantages in environmental regulation and a record of poor environmental performance.

The pollution rates of state-owned enterprises (SOEs) are significantly lower

than those of non-state-owned (non-SOEs) enterprises, and the local government has given more concessions to SOEs in terms of environmental protection (Tang, 2017). Thus, different ownership will lead to a difference in operating efficiency and environmental constraints faced by a company, as well as enthusiasm for environmental performance, and non-SOEs generally have a sharper sense of information. External regulatory pressures related to the environment, such as incentives to improve corporate reputation, are more pronounced for non-state-owned enterprises (Zhu et al., 2019). The regression results of Jiang et al. (2021) show that the political relationship is negatively correlated with corporate proactivity of carbon emissions abatement (CPCEA). This result means that the weaker the political relationship among senior management personnel is, the more likely companies will be to promote positive carbon reduction.

Summing up these works, we can conclude that companies subject to stricter environmental regulation may be more sensitive to environment-related information, and their environmental behavior may be more proactive. Based on the above analysis, we propose the fourth hypothesis:

**H4:** Climate risk has a more significant impact on the carbon emissions of Chinese companies faced with stricter environmental policies.

### **3. Methodology and data description**

#### **3.1. The assessment of carbon performance**

This study evaluates corporate carbon emissions combining the economic input-output life cycle assessment for the industry level and the conversion formula

adopted by [Chapple et al. \(2013\)](#) for the corporate level. The specific steps are as follows:

$$E_i = CO_{2industry} * OPCOST_i / OPCOST_{industry} \quad (1)$$

where  $E_i$  is the carbon emissions of company  $i$ , while  $CO_{2industry}$  represents the total carbon emissions of the industry to which it belongs.  $OPCOST_i$  and  $OPCOST_{industry}$  are the operating costs of the central business of company  $i$  and the industry, respectively ([Shen and Huang, 2019](#)).

We consider two channels regarding industry carbon emissions ( $CO_{2industry}$ ); direct carbon emissions and indirect carbon emissions ([Wei et al., 2021](#)), considering the direct carbon footprint of the energy consumption of each sector, and the redistribution of carbon emissions across industries. The direct emissions from energy consumption are also divided into immediate energy consumption and industrial production activities.

The final carbon emission matrix for each industry (defined as  $B$ ) is:

$$B = R(I - A)^{-1}Y \quad (2)$$

where  $R$  and  $Y$  are the direct emission matrix and final application amount diagonal matrix of products and services of each industry, respectively.  $(I - A)^{-1}$  represents the structure of input and output among industries, and the elements of  $A$  are the direct consumption coefficients, which are calculated from the national “*Input-output Table*.” The diagonal element ( $R_m$ ) of  $R$  is the carbon emissions directly emitted per unit of monetary output of sector  $m$ .



### 3.2. The dynamic threshold panel model

To better investigate the impact of extreme climate risk on corporate carbon emissions, we build a threshold model. To avoid interference caused by endogeneity in the static threshold model, we adopt a systematic generalized method of moments (GMM) to perform a dynamic threshold test following [Wu et al. \(2020\)](#). In terms of the Stata operation, we use the way [Diallo \(2020\)](#) proposed, which is extended from the traditional dynamic threshold model of [Kremer et al. \(2013\)](#). This method is more inclusive and applicable to both balanced and unbalanced panels. It can avoid the endogenous problem caused by static panels through first-order difference, and accurately measure the threshold value with a more straightforward operation. The equation of our model is as follows:

$$\begin{aligned} \ln E_{i,t} = & \alpha + \beta_1 \ln E_{i,t-1} + \beta_2 \ln CRI_{i,t} \cdot I_{\ln CRI_{i,t} \leq V} + \beta_3 \ln CRI_{i,t} \cdot I_{\ln CRI_{i,t} > V} + \\ & \sum_{k=1}^5 \beta_k Z_{i,t} + \sigma_{fixed} + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where  $\ln E_{i,t}$  is the logarithmic value of the carbon footprint of company  $i$  at time  $t$ , and  $\ln E_{i,t-1}$  is the lag term of it.  $\ln CRI_{i,t}$  represents the logarithmic value of the Chinese climate risk index published by Germanwatch, which captures the direct losses of extreme climate (i.e., storms, floods, and heatwaves). Apart from them,  $V$  represents the threshold value, and  $Z_{i,t}$  represents the series of control variables.  $\sigma_{fixed}$  is the fixed effects.  $\varepsilon_{i,t}$  represents the error term.  $I(\cdot)$  is the indicator function. The selection of control variables is divided into internal factors and macro background factors, referring to the practice of [Ilyas et al. \(2021\)](#) and [Wen et al. \(2021\)](#). The control variables at the corporate level are the liability on asset ratio

(LEV), the proportion of cash flows from operating activities to total assets (CASH), and the proportion of net profit to total assets (PROFIT). The macro background factors are the gross domestic product (GDP) and economic policy uncertainty (EPU) of China.

The climate risk index is a score calculated from four aspects: Total death toll in severe weather, deaths per 100,000 inhabitants, total loss on purchasing power parity (PPP), and per unit of GDP. The calculation of the score is based on the ranking of each country or region among 181 countries and areas in the world. In other words, the higher the ranking, the lower the CRI score, which means the more severe the impact of extreme weather. Therefore, for each threshold value  $V$  in the test results, when  $\ln CRI$  is lower than the threshold value, it represents a more severe climate risk (we call it the high-risk interval); on the contrary, when  $\ln CRI$  is higher than the threshold value, it means a relatively low climate risk (defined as the low-risk interval). When the impact coefficient  $\beta_2$  of  $\ln CRI_{i,t}$  is positive, it means that the occurrence of extreme climate events has a connection with less carbon emissions of companies. On the contrary, when  $\beta_2$  is negative, it means that an increase of extreme climate events leads to worse carbon performance by a company. The threshold value ( $V$ ) of the climate risk score ( $\ln CRI$ ) represents the critical point for a significant change in the company's environmental performance.

### **3.3. Data description**

Because our calculation is based on a company's financial position, we first exclude companies with missing financial data and then exclude all small and

medium-sized enterprises in this study. At the same time, companies established inside the sample period and companies belonging to the financial industry are excluded. However, we have ensured that all sectors of the national economy (except the financial industry) and provinces (including municipalities directly under the central government and autonomous regions) have two or more observed samples. Finally, based on the economic input-output life cycle approach, we calculated the carbon footprint of 1,089 companies. The original data, such as the physical quantities of energy consumption and direct consumption coefficients in the calculation process, are from various official documents issued by the National Bureau of Statistics of China. Financial information such as Chinese gross domestic product, net cash flow of each company, and other essential information are all from the WIND, IFIND databases and the official website of the Chinese National Bureau of Statistics.

We selected the economic policy uncertainty indices developed by Davis et al. (2019) based on two mainland Chinese newspapers, the Renmin Daily and the Guangming Daily, and chose their annual averages<sup>1</sup> to conduct our model. The research interval is from 2009 to 2018, and the descriptive statistics of the variables are shown in Table 1.

**Table 1. Descriptive statistic.**

Variables	Definition	Obs	Min	Mean	Max	Std.Dev
lnE	The logarithmic value of carbon emissions	10855	1.60	8.75	17.21	3.81
lnCRI	The logarithmic value of the Chinese climate risk index	10855	3.16	3.48	3.81	0.22
lnEPU	The logarithmic value of the Chinese	10855	3.79	4.67	6.24	0.72

<sup>1</sup> The raw information of EPU is from [http://www.policyuncertainty.com/china\\_monthly.html](http://www.policyuncertainty.com/china_monthly.html).

economic policy uncertainty						
lnGDP	The logarithmic value of the Chinese gross domestic product	10855	1.88	2.06	2.36	0.16
LEV	The liability on asset ratio	10855	0.11	0.56	0.89	0.17
CASH	Net cashflow from operating activities to total assets	10855	-0.19	0.02	0.23	0.07
PROFIT	Net profit to total assets	10855	-0.07	0.03	0.20	0.04

This table shows the descriptive statistic of variables used in this paper. Notably, lnE, lnCRI, lnGDP and lnEPU are the logarithmic forms of corporate carbon emissions, the Chinese climate risk index from the Germanwatch, Chinese gross domestic product, and the uncertainty of Chinese economic policies, respectively. Additionally, the unit of carbon emission is tons.

To reduce the differences between the data values, we deal with all variables except “proportions” (for example, the proportion of net operating cash to total assets) logarithmically. All the continuous variables are subjected to a 1% tail reduction, and the number of observation points obtained is 10,855. After this processing above, the numerical size difference between variables is slight, preventing the error caused by the significant difference among variables. The standard deviation of the variables is also stable, and the largest standard deviation is that of the company’s carbon emissions (3.81), which shows that the carbon emission gap between companies is quite obvious.

## 4. Results and discussion

### 4.1. Main empirical results

The main results of the dynamic threshold panel regression are shown in Table 2. The coefficient of the lag term of corporate carbon emissions ( $L.lnE$ ) is significantly negative at the 1% significance level, indicating that the previous condition will affect the company's carbon performance. The threshold value of  $lnCRI$  is 3.6376, and its coefficients are negative at the 1% significance level, whether in the high-risk or low-risk intervals. The results reject our hypothesis  $H1$ , while hypothesis  $H2$  is confirmed (i.e., climate risk has a significant impact on corporate carbon performance). The increase in extreme climate events or damage may be linked with a rise in corporate carbon footprint, and this connection is more pronounced when the climate risk score ( $lnCRI$ ) falls behind the threshold value. It is the opposite of Hypothesis  $H1$ , suggesting that extreme weather events will prompt a company to pay more attention to climate information, and thus take corresponding action.

Explaining these empirical results from another angle, that is to say, an increase in the impacts or losses from extreme weather events, has not been associated with Chinese companies' improved carbon performance. On the contrary, it has significantly boosted corporate emissions. This effect of climate risk on corporate carbon emissions is more significant (-0.349) when the climate risk index is lower than 3.6376 (the threshold value). Compared with the case of the low-risk range (higher than the threshold value), the climate risk score of the high-risk range (lower

than the threshold value) suggests a more significant positive impact on the company's emissions.

From a realistic perspective, when extreme climate damage is at a higher level, it may be accompanied by a more pronounced increase in company carbon emissions, leading to more severe environmental degradation. As mentioned in Section 2, when an enterprise faces extreme climate events, it may improve its environmental performance to cater for climate change or adopt more frequent economic activities and accounting techniques to make up currency losses. When the risk of extreme climate increases, enterprises may carry out more business activities to avoid or “save” assets from being damaged by extreme events, resulting in more emissions. Judging from our results, the possibility of adopting more frequent economic activities and accounting skills may be much greater than changing environmental strategies. Our assessment of carbon emissions by the economic input-output life cycle approach is based on a company's revenue (Shen and Huang, 2019), which enhances the credibility of this possibility. Still, we cannot conclude whether this is due to a lack of specific governance and environmental data details.

**Table 2. Main results.**

Variables	Coefficients	P-value	Std. err	Confidence interval	
L.lnE	-0.0554***	0.003	0.0183	-0.0913	-0.0195
lnCRI (lnCRI≤3.6376)	-0.349***	0.000	0.0459	-0.4393	-0.2592
lnCRI (lnCRI>3.6376)	-0.159***	0.000	0.0335	-0.2250	-0.0939
LEV	-6.037***	0.000	1.2409	-8.4691	-3.6049
lnEPU	-0.0318	0.238	0.0269	-0.0846	0.0210
CASH	-1.428	0.207	1.1312	-3.6451	0.7890
PROFIT	-2.823***	0.000	4.1419	-3.6346	-2.0110
lnGDP	1.171***	0.000	0.2266	0.7269	1.6151

constant	12.43***	0.000	1.0282	10.4103	14.4409
Obs	9763	9763	9763	9763	9763

This table shows the main results of the impact of climate risk on corporate carbon emissions. Our sample period is 2009-2018, and “lnCRI” (climate risk score) is the core explanatory variable, and the lower its value is, the more serious the actual climate risk will be. Corporate carbon emissions “lnE” is the interpreted variable and “L.lnE” is its lag term with one year lag. We control the year and the company fixed effects to reduce the bias of the empirical models. At last, significance levels are represented by “\*\*\*” (1%), “\*\*”(5%) and “\*” (10%).

## 4.2. Robustness tests

To confirm the robustness of our main results, we use the classical ordinary least squares (OLS) regression and the GMM to test robustness following [Uddin et al. \(2017\)](#). We choose the two-step system GMM method to avoid the bias caused by the lag terms and first-order difference processing ([Arellano and Bover, 1995](#); [Wu et al., 2020](#)). The OLS and GMM regression models are shown in Equations (4), (5), and (6), respectively.

$$\ln E_{i,t} = \alpha_1 + \varphi_1 \ln CRI_{i,t} + \varphi_k Z_{i,t} + \delta_{fixed} + \varepsilon_1 \quad (4)$$

$$\ln E_{i,t} = \alpha_2 + \mu_1 \ln E_{i,t-1} + \mu_2 \ln CRI_{i,t} + \mu_k Z_{i,t} + \delta_{fixed} + \varepsilon_2 \quad (5)$$

$$\Delta \ln E_{i,t} = \alpha_2 + \mu_1 \Delta \ln E_{i,t-1} + \mu_2 \Delta \ln CRI_{i,t} + \mu_k \Delta Z_{i,t} + \Delta \delta_{fixed} + \Delta \varepsilon_2 \quad (6)$$

where  $\alpha_1$  and  $\alpha_2$  are the constant terms, while  $\varepsilon_1$  and  $\varepsilon_2$  are the error terms.  $Z_{i,t}$  stands for the control variables set.  $\delta_{fixed}$  represents the fixed effects. Equation 4.3 is the first-order difference form of Equation 4.2. The results of these two approaches are displayed in Table 3. We control the individual effect of the company to make

these two regression models more scientific. At the same time, we do some necessary tests on the dynamic GMM model. The model has passed the Arellano-Bond (AR) tests, and the value of P indicates that the serial correlation in the error term is not second order (Arellano and Bover, 1995). The number of instruments is far less than that of companies, and their effectiveness is confirmed by the P-value obtained by the Hansen J test. Therefore, we can ensure that the GMM model is efficient (Uddin et al., 2017).

The coefficients of *lnCRI* of the OLS and GMM models are -0.4703 and -0.1387, respectively. The results of the two robustness tests for the impact of climate risk on corporate carbon performance are consistent with the dynamic threshold model we used in the main empirical process, and have a significance level of 1%. These results confirm our *H2* once again; extreme climate risk is positively linked to a company's emissions. This shows that even in different empirical models, the impacts of climate risk on corporate carbon performance are consistent, proving our main conclusions' robustness.

**Table 3. Robust tests results.**

Variables	OLS	GMM
L.lnE		-0.2606***(0.0414)
lnCRI	-0.4703***(0.0507)	-0.1387***(0.0318)
LEV	0.7833*** (0.1454)	0.8813***(0.2963)
lnEPU	0.2073***(0.0142)	0.1607***(0.0183)
CASH	-0.1931(0.1938)	-0.6157***(0.2308)
PROFIT	2.9329*** (0.4097)	2.9797***(0.6483)
lnGDP	-0.7079***(0.0675)	-0.2660***(0.1273)
constant	12.4335***(0.5318)	10.9762***(0.4769)
Obs	10855	8,673
R-Square	0.7941	
Fixed effects	Yes	Yes
Number of instruments		36
Arellano-Bond: AR(1)		0.005
Arellano-Bond: AR(2)		0.069



Sargan test (p-val)	0.000
Hansen test (p-val)	0.034

This table shows the results of robust tests based on the ordinary least squares (OLS) method and the generalized two-step method of moments (GMM). Our sample period is 2009-2018, and “lnCRI” (climate risk score) is the core explanatory variable, and the lower its value is, the more serious the actual climate risk will be. Corporate carbon emissions “lnE” is the interpreted variable and “L.lnE” is its lag term with one year lag. We control the year and the company fixed effects to reduce the bias of the empirical models. At last, significance levels are represented by “\*\*\*\*” (1%), “\*\*\*”(5%) and “\*\*” (10%).

### 4.3. Results of corporate characteristics

This section tests our hypotheses *H3* and *H4*, whether the geographical location and other characteristics may cause companies to perform differently according to information they receive on the effects of extreme climate. Will these factors change the extent or form of the impact of climate risk on corporate carbon performance? To resolve these doubts, we subsequently conducted several sub-sample operations.

#### 4.3.1 Results of geographical position

The responses to extreme climate risk from the carbon emissions of companies located in different geographical locations are shown in Table 4. The threshold value of *lnCRI* for the western and central regions is 3.2320, and that for the eastern region is 3.6376. It should be noted again that, in the global climate risk report of Germanwatch, a smaller number represents a greater climate risk. Therefore, the lower the threshold, the more serious the climate risk will be. Combined with this premise, we can see that when the risk level of extreme climate events continues to deteriorate, the western and central regions’ response to such risk will be slower,

while the eastern region will be earlier. Most of the influential coefficients of climate risk on corporate carbon emissions are at a significance level of 1%, and the coefficients of the western part are positive at 0.9946 and 0.8350, in contrast to the central (-1.2153 and -0.7856) and eastern (-0.3073 and -0.1430) areas. This indicates that our hypothesis *H3* has been refuted and that geographical location can lead to different results of the impact of extreme climate events on corporate carbon performance. More specifically, for companies in the western region, climate risk, which is produced by climatic events, negatively correlates with the corporate carbon footprint. In addition, this phenomenon is more evident when climate risk is in a high-risk interval (corresponding to the situation in which the climate risk score is lower than the threshold value). For companies in the central and eastern regions, climate risk is positively connected with their carbon emissions, and the degree of this connection in the central region is even more severe.

Although the western region has unexpectedly performed better than expected in terms of carbon performance, there are some important points to consider. From the logic of environmental protection, Guo et al. (2017), through interviews and questionnaires, find that environmental awareness in the western region has increased significantly in recent years, and the people in this area have gradually accepted environmental protection concepts such as the circular economy. In addition, the western region may have experienced relatively low ecological efficiency and poor primary ecological conditions in the past. Therefore, the

potential for improved carbon performance is more powerful than that in the eastern and central regions. Lin and Xu's (2018) study, through empirical analysis of China's carbon emission efficiency, confirm this possibility by concluding that the potential reduction of carbon emissions in the western part is above 70%, and that this potential is much greater than in the eastern region. Miao et al. (2019) find that the environmental regulation on an individual area does not have much effect, and requires cross-regional cooperative governance to achieve low-carbon development. From this point of view, the advantages of environmental efficiency and environmental policies in the central and eastern regions have been significantly weakened.

According to the logic of economic development, companies in the central and eastern regions face fierce competition, are more savvy in terms of efficient business management, and are generally very well funded (Deng et al., 2019). On account of these factors, even if all the regions are equally vulnerable to extreme climate risk, the central and eastern areas are more likely to engage in frequent economic activities to achieve financial benefits. In addition, economic development in the central and eastern regions depends mainly on the secondary and tertiary sectors, which are less restricted by the natural environment. Therefore, an increase in extreme climatic events will not affect the major business operations of companies. The two channels of logic above may lead to a positive impact of climate risk on corporate carbon emissions in the central and eastern parts, and a negative impact in

the western region.

**Table 4. Sub-sample results for geographical location.**

Variables	WEST	CENTRAL	EAST
L.lnE	0.1357**(0.0596)	0.1343***(0.0395)	0.0687***(0.0238)
lnCRI (lnCRI≤3.2320)	0.9946**(0.2665)		
lnCRI (lnCRI>3.2320)	0.8350***(0.2348)		
lnCRI (lnCRI≤3.2320)		-1.2153***(0.1901)	
lnCRI (lnCRI>3.2320)		-0.7856***(0.1678)	
lnCRI (lnCRI≤3.6376)			-0.3073***(0.0641)
lnCRI (lnCRI>3.6376)			-0.1430***(0.0459)
LEV	-2.9317(2.0143)	1.6535*(0.8711)	2.5736(2.0439)
lnEPU	-0.1576**(0.0632)	-0.0823**(0.0409)	-0.0601*(0.0349)
CASH	-0.0095***(1.7737)	-6.3830***(1.3532)	4.0990***(1.2391)
PROFIT	-31.5286***(7.4011)	11.6145**(4.7629)	-16.0157***(4.8464)
lnGDP	-2.3847***(0.5011)	-0.9534***(0.3343)	1.4360***(0.2703)
constant	10.6058***(2.1912)	5.2764***(1.2931)	5.7693***(1.6267)
Obs	1413	2071	6279

This table shows the sub-sample results for the geographical location of companies: western part (WEST), central part (CENTRAL) and eastern part (EAST) of China. Our sample period is 2009-2018, and “lnCRI” (climate risk score) is the core explanatory variable, and the lower its value is, the more serious the actual climate risk will be. Corporate carbon emissions “lnE” is the interpreted variable and “L.lnE” is its lag term with one year lag. We control the year and the company fixed effects to reduce the bias of the empirical models. At last, significance levels are represented by “\*\*\*” (1%), “\*\*”(5%) and “\*” (10%).

### 4.3.2 Results of corporate heterogeneities

Hypothesis *H4* assumes that environmental regulation interferes with the climate sensitivity of companies, and thus affects the response of carbon emissions to extreme climate events. We test this through empirical analysis of three factors (industry, ownership, and whether listed on stock exchanges) that have the most noticeable influence on environmental performance ([Braam et al., 2016](#); [Eaton and Kostka, 2017](#); [Ikram et al., 2019](#); [Zhang et al., 2021](#)).

According to the official list of crucial environmental performance management industries published in 2008, categories of heavily polluting industries are set as environmental constraint enterprises (CONs), and the rest are non-constraint enterprises (non-CONs). Environmentally constrained enterprises face more detailed environmental regulations and penalties. In terms of companies' ownership and listing, they are divided into state-owned (SOEs) and non-state-owned companies (non-SOEs) and listed (LISTs) and non-listed (non-LISTs) companies. The SOEs include wholly state-owned enterprises and state-owned capital holding companies managed by the central and local governments. The LISTs are companies listed on the Shanghai and Shenzhen Stock Exchanges. The results are shown in Tables 5, 6, and 7.

### **(1) Sub-sample results of the industry nature**

The influence coefficients of climate risk on the carbon emissions of CONs are positive at 0.2608 and 0.2882, but those of non-CONS are negative at -1.2153 and -0.7856, and all are valid at the 1% significance level. For companies in environmentally constrained industries, climate risk negatively affects carbon emissions, while for those in non-environmentally constrained sectors, it may have some strengthening effect (Table 5). Our “environmentally constrained industries” are dominated by heavily polluting industries, which are the core of low-carbon transformation ([Wei and Shu, 2021](#)). Many of these industries are engaged in natural resource exploitation, and when extreme climatic events occur, these climate

changes may have a massive impact on their related businesses (Green and Newman, 2017). At the same time, they are often subject to more environmental regulations and face increasing pressure from various stakeholders (Liu et al., 2021a) than other sectors. Therefore, it is reasonable for companies' carbon emissions in environmentally constrained industries to respond to extreme climate risks by reducing emissions.

There is little difference between the two kinds of companies regarding the threshold value of the climate risk score (*lnCRI*). More specifically, the threshold value of *lnCRI* of companies with strict environmental constraints (*CONs*) is slightly bigger than others (3.7455 is bigger than 3.6376), and the *CONs* have significant carbon-emission reductions when the climate condition is still in the low-risk interval (when the climate risk score is above the threshold value). As climate losses gradually rise, the risk level for these companies to change their environmental strategies is also earlier, indicating they are indeed quicker in dealing with climate information than companies with loose environmental constraints. This result also confirms that these companies with more strict environmental regulations will be more sensitive to environmental information. However, from this sub-sample analysis, Hypothesis *H4* does not seem to be tenable. From the significance level, the impact of carbon performance on the two types of companies and climate risk are significant. Additionally, the environmentally constrained companies may be more inclined to reduce carbon emissions when climate events occur.

**Table 5. Sub-sample results for environmental constraints.**

Variables	CONs	Non-CONs
L.lnE	0.0218(0.0480)	-0.1916***(0.0321)
lnCRI (lnCRI $\leq$ 3.7455)	0.2608***(0.0358)	
lnCRI (lnCRI $>$ 3.7455)	0.2882***(0.0372)	
lnCRI (lnCRI $\leq$ 3.6376)		-1.2153***(0.0951)
lnCRI (lnCRI $>$ 3.6376)		-0.7856***(0.0703)
LEV	0.6783(0.8045)	-12.3872***(2.1606)
lnEPU	0.0485**(0.0212)	-0.3829***(0.0499)
CASH	4.4052***(1.3811)	6.7466***(2.0004)
PROFIT	-1.0273(1.5002)	2.2121(7.6201)
lnGDP	-0.3327(0.1522)	-0.5437(0.3588)
constant	10.3289**(0.9666)	22.2506***(1.8353)
Obs	2275	7488

This table shows the sub-sample results for the companies which belong to environmentally constraint industries (CONs) and companies with looser environmental constraints (Non-CONs). Our sample period is 2009-2018, and “lnCRI” (climate risk score) is the core explanatory variable, and the lower its value is, the more serious the actual climate risk will be. Corporate carbon emissions “lnE” is the interpreted variable and “L.lnE” is its lag term with one year lag. We control the year and the company fixed effects to reduce the bias of the empirical models. At last, significance levels are represented by “\*\*\*” (1%), “\*\*”(5%) and “\*” (10%).

## (2) Sub-sample results of ownership

Concerning ownership, we initially assumed that non-SOEs face more stringent environmental control and more intense competition than SOEs do (Tang, 2017). This would lead them to change their strategies to cater to an environmentally friendly development trend when extreme climatic events occur. However, to our surprise, from the results in Table 6, we find that all of the influence coefficients of climate risk scores are negative, except for the scenario in which the climate risk score (lnCRI) for non-SOEs exceeds the threshold value (low-risk interval). The threshold value of the climate risk item of SOEs is 3.1709, which is much lower than



that of non-SOEs (3.6376), which have a higher significance level of coefficients. This shows that state-owned enterprises may react to climate events and change their environmental strategies only when the climate risk reaches a severe level. This verifies that state-owned enterprises are not sensitive to climate change.

To sum up, we find that although climate risk has a greater impact on the carbon emissions of SOEs, non-SOEs have not adopted more beneficial carbon emission-reduction strategies in the presence of extreme climate risk, as we expected. Although a negative correlation occurs when the climate risk score is above the threshold value for non-SOEs, it is not statistically significant. The above results indicate that although ownership will cause SOEs to be more prone to adverse outcomes in environmental performance than non-SOEs, the latter are not very keen to grasp the changes in the environment and efficiently improve their carbon performance. Judging from the results of this sub-sample, non-state-owned enterprises are generally subject to stricter environmental regulations, but their sensitivity to the climatic environment is not sufficient to enable them to improve their environmental performance. In this subsection, the results also overthrow our Hypothesis *H4* since environmentally sensitive companies' carbon performance is not more significantly affected by climate risks. Not all companies that are more sensitive to environmental information necessarily respond to climate risks by improving carbon performance.

**Table 6. Sub-sample results for ownership.**

Variables	SOEs	Non-SOEs
L.lnE	-0.0575*(0.0349)	0.2016***(0.0460)
lnCRI (lnCRI $\leq$ 3.1709)	-0.6397***(0.1501)	
lnCRI (lnCRI $>$ 3.1709)	-0.5680***(0.1333)	
lnCRI (lnCRI $\leq$ 3.6376)		-0.1315*(0.0781)
lnCRI (lnCRI $>$ 3.6376)		0.0338(0.0552)
LEV	-0.5838(1.7761)	-3.1545*(1.6544)
lnEPU	0.2830***(0.0641)	-0.1533***(0.0473)
CASH	-4.6251*(2.5953)	4.0263***(1.3263)
PROFIT	-6.750(13.1308)	0.1319(2.6969)
lnGDP	0.7950(0.5967)	-0.4601*(0.2407)
constant	9.1086***(2.0411)	10.6610***(1.2478)
Obs	6924	2839

This table shows the sub-sample results for the state-owned companies (SOEs) and companies non-state-owned (Non-SOEs). Our sample period is 2009-2018, and “lnCRI” (climate risk score) is the core explanatory variable, and the lower its value is, the more serious the actual climate risk will be. Corporate carbon emissions “lnE” is the interpreted variable and “L.lnE” is its lag term with one year lag. We control the year and the company fixed effects to reduce the bias of the empirical models. At last, significance levels are represented by “\*\*\*” (1%), “\*\*” (5%) and “\*” (10%).

### (3) Sub-sample results of the listing

The sub-sample results of whether a company is listed are shown in Table 7. The coefficients of *lnCRI* on the carbon emissions of listed and unlisted corporates are negative in all cases, and only for the “LISTs” is the coefficient at a prominent significance level while climate risk is below the threshold value (3.6375), indicating that the carbon emissions of listed companies are vulnerable to the losses or uncertainties caused by climatic events. This result may be affected by two factors. On the one hand, listed companies tend to be larger, both in assets and human

resources (Darko et al., 2016). Therefore, when climatic events arise, listed companies are unlikely to be hit hard, and can deal with possible losses more quickly by developing more business. On the other hand, the financial performance of listed companies is much more noticeable than that of non-listed companies, and even the slightest disturbance will cause a massive chain reaction (Liu et al., 2021b). To avoid causing panic among investors, listed companies are also more likely to strive to achieve better economic benefits, which may lead to an increase in carbon emissions.

Judging from the threshold value of climate risk score, the threshold value of listed companies is much higher than that of unlisted companies, indicating that listed companies are still more sensitive to climate risk. This aligns with the realistic logic that listed companies have more potent information collection and processing capabilities. The results of this sub-sample again prove that hypothesis *H4* is tenable in some cases.

From the analysis of three heterogeneous companies, we find that companies in heavily polluting industries are highly sensitive to climatic conditions. They tend to improve their carbon performance to counter climate changes, which indicates that environmental regulations for these industries may have played an outstanding role.

**Table 7. Sub-sample results for listed and unlisted corporates.**

Variables	LISTs	Non-LISTs
L.lnE	0.2196***(0.0546)	0.0058(0.0512)
lnCRI (lnCRI $\leq$ 3.6375)	-0.2312**(0.0971)	
lnCRI (lnCRI $>$ 3.6375)	-0.0062(0.0741)	
lnCRI (lnCRI $\leq$ 3.1709)		-0.1936(0.2688)
lnCRI (lnCRI $>$ 3.1709)		-0.1736(0.2401)
LEV	-3.6860(2.5045)	-2.0837(2.2477)
lnEPU	-0.2120*** (0.0547)	0.3205*** (0.0905)
CASH	10.1839*** (1.7186)	-22.7417*** (4.7866)
PROFIT	-5.0081(5.0730)	-17.1659(20.9004)
lnGDP	0.3189(0.3014)	1.3163(0.8611)
constant	10.3289*** (1.6647)	6.6126* (2.8593)
Obs	4225	5538

This table shows the sub-sample results for the companies listed on Shenzhen and Shanghai stock exchanges (LISTs) and companies unlisted (Non-LISTs). Our sample period is 2009-2018, and “lnCRI” (climate risk score) is the core explanatory variable, and the lower its value is, the more serious the actual climate risk will be. Corporate carbon emissions “lnE” is the interpreted variable and “L.lnE” is its lag term with one year lag. We control the year and the company fixed effects to reduce the bias of the empirical models. At last, significance levels are represented by “\*\*\*” (1%), “\*\*”(5%) and “\*” (10%).

## 5. Conclusions and policy suggestions

This study examines whether climate risks affect companies’ environmental performance. Chinese companies are considered in this study since China is one of the world’s largest carbon-emitting regions and promotes low-carbon transformation through the “carbon peak, carbon neutralization” plan. We consider the climate risk index published by Germanwatch to represent climate risk, and innovatively assess corporate carbon emissions as representative of environmental performance using the economic input-output life cycle approach. We test whether the climate risk

index will significantly impact the carbon performance of enterprises. We find that climate risk affects carbon emissions for the Chinese companies in the sample since climate events will increase their emissions.

To investigate the impact of climate risk on corporate carbon performance more comprehensively, we further analyze the company's geographical location and three other characteristics to explore the factors that affect the company's responses to climate risk. We find that different from what we expected, geographical location does lead to a different performance of the climate risk's effects on a company's carbon performance. Along with the increase in climate events, companies' carbon emissions in the western region will decrease accordingly. Still, companies in the central and eastern areas will increase carbon emissions, especially in the central area. In addition, heavily polluting industries, which are subject to stricter environment-related regulations in China, will achieve significant carbon emission reductions while confronting climatic events.

For companies with different ownership, the effects of climate risk on state-owned enterprises' carbon performance contrast with those of non-state-owned companies. Furthermore, the listed companies are not as sensitive to climate risk as expected. Combined with the empirical results of the three kinds of heterogeneity of companies, this shows that heavily polluting industries respond more quickly to climate information since they perform better in reducing carbon emissions when climatic events increase. This may be because heavily polluting industries have

performed poorly in countering carbon emissions, and accordingly have a greater potential to reduce carbon emissions. From another perspective, heavily polluting industries are the key industries to be rectified in China's economic low-carbon transformation, and are aware of the need for more environmental efforts. However, other companies, both state-owned and listed, have not improved their environmental performance when facing more severe climate risk, and even have demonstrated worse carbon performance.

Our results show that, in addition to the environmental regulations that target heavy polluting industries directly, other environmental rules, including the policies for listed companies, do not result in improved environmental effects. Our research also has certain limitations. The climate risk index calculated by Germanwatch focuses mainly on extreme climatic events, such as floods, and does not include slow climate risk events, such as rising sea levels. Our research analyzes historical data, and cannot be used as a basis for future predictions. The economic input-output life cycle method can only estimate a company's carbon footprint as accurately as possible, and inevitably, there may be some errors.

However, to a certain extent, our findings support the conclusion that currently, companies are not paying enough attention to climate risks and environmental improvement. For Chinese companies, extreme climatic events are not associated with reducing corporate carbon emissions. We cannot determine how exposed these companies are to environmental risk or whether they will use misleading measures to

cover up losses from climate events. This has led to numerous obstacles to research the specific impact and influence channels between climate risks and company environmental behaviors.

Therefore, it is necessary to have an environmental information disclosure system and regulatory system for all companies that standardize relevant reward and punishment measures. Our research reflects the importance and need to raise public attention to climate information, demonstrate the urgency of establishing an ecological information database, and inspire other researchers. Besides, the Chinese government should establish an authoritative environmental database and promote environmental awareness among market participants.

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## **Data Availability Statement**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## **Disclosure statement**

No potential conflict of interest was reported by the authors.



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