Climate risk exposure and corporate financial distress

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ABSTRACT
This study investigates the relationship between firm-level climate risk and the occurrence of financial distress within a sample of Chinese listed companies spanning from 2007 to 2022. We find that climate risk significantly accelerates financial distress. Additionally, the empirical evidence suggests that climate risk exacerbates financial distress primarily through the mechanisms of heightened financial constraints and increased risk-taking.

KEYWORDS
Climate risk; Financial distress; Financial constraints; Risk-taking

JEL CLASSIFICATION
G32; Q54

1. Introduction

Since the introduction of accounting and market-based models by Altman (1968), the precise quantification of financial distress has become feasible. By the end of 2021, approximately one-sixth of publicly listed Chinese companies faced financial distress due to poor operational performance. Hence, the improvement in financial distress is favorable not only for sectors such as banking, investment, and manufacturing but also for national economic development. In this context, extensive research has explored the impact of internal governance mechanisms and external institutional factors on corporate financial distress (**?**).

However, research on climate risk's impact on firm outcomes remains relatively limited. Recently, regulatory authorities have sounded the alarm about the threat posed by climate change to the stability of the financial system. Global climate change not only leads to significant loss of life and wealth and impedes national development but also affects business operations (Kreft et al. 2013). Companies exposed to climate risk may face increased earnings volatility and operational disruptions, resulting in unfavorable bank loan terms and amplified risk-taking behavior within organizations (Huang et al. 2022; Xu et al. 2022). Investigating how climate risk affects corporate financial distress has more direct relevance and value for managers to addressing climate change, helps reduce the probability of financial hardship and also complements existing literature.

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Climate risk is associated with both uncertainty and potential adverse consequences for corporations. We aims to identify the potential channels through which climate risks affect financial distress and to provide targeted response strategies for business managers. Existing research and theory guide our exploration of how climate change affects financial distress through two main implications. First, climate risks may lead to heightened financial constraints for firms. Huang and Lin (2022) found that the presence of climate risks amplifies lenders' concerns, prompting them to impose more stringent loan terms, including higher interest rates, increased collateral quality, and additional covenant constraints. Greater climate risk leads firms to adopt a more cautious leverage strategy. Consequently, the detrimental impact of climate risk on business operations and intangible assets diminishes the borrowing capacity of affected firms following a catastrophic event. Additionally, as climate change risks are typically challenging to forecast, stakeholders, particularly investors and creditors, are likely to demand a higher risk premium (Javadi and Masum 2021). These factors potentially increase a company's financial constraints, leading to financial distress.

Second, climate risk can accelerate corporate financial distress by inducing greater risk-taking behavior. On one hand, the long-term nature of climate risk means that its impacts may not be immediately felt, leading to a perception of lower immediacy or urgency. This can cause some corporations to prioritize short-term financial gains over long-term sustainability (Xu et al. 2022). Managers may engage in riskier activities that yield quicker returns but expose them to greater long-term climate-related risks. On the other hand, according to loss aversion theory, corporate managers' risk-taking behavior becomes instinctive and less conscious when faced with significant losses (Schmidt and Zank 2005). They will tend to abandon excessive risk aversion and engage in risky projects with positive net present values to generate future profits for both the firm and themselves. Consequently, losses caused by climate risk compel risk-averse managers to embrace more risk, thereby increasing the likelihood of financial distress.

This paper contributes to the literature in several ways. First, we draw insights from emerging climate change research, expanding the study of financial distress risk determinants. While previous studies have emphasized the relationship between macroeconomic and internal corporate governance factors and financial distress (**?**Javadi and Masum 2021), quantitative analysis from the perspective of climate risk remains scarce. Second, we contribute to the literature on climate risk, including corporate social responsibility (Huang and Lin 2022), capital structure (**?**), and carbon emission reduction (Wang et al. 2024). This paper underscores that climate risk exposure can exacerbate financial distress by increasing financial constraints and risk-taking. Third, unlike the study by Alshahrani et al. (2023), who notes that climate risk disclosure mitigates financial distress for Australian firms, we highlight that climate risk exposure aggravates corporate financial distress in the Chinese market.

2. Research design

2.1. *Data sources*

This paper initiated the process by considering Chinese A-share stock market listed companies from 2007 to 2022. We excluded ST (Special Treatment) firms, those in financial industry, and firms in with missing key variables. Corporate financial and governance data were extracted from CSMAR, CNRDS and the Wind database. Ultimately, our sample comprises 29,819 firm-year observations originating from 3,401 distinct firms.

2.2. *Variable definition*

2.2.1. Measuring Financial distress

We employ the classic model developed by Altman (1968) to measure corporate financial distress risk, which is represented by the Z-score (Z). A lower Z suggests a higher probability of financial distress for a company, while the opposite indicates lower financial distress risk.

2.2.2. Measuring Climate risk

We basically followed the text analysis methods outlined by Wang et al. (2024), quantify the degree of climate risk (CR) by computing the ratio of the frequency of keywords associated with climate risk to the total word frequency found in the annual reports of the companies under consideration (Keywords see Appendix A). A higher value of this indicator signifies a greater climate risk faced by the enterprise.

$$CR = \frac{n_{i,t}}{N_{i,t}} \times 100 \tag{1}$$

Where $n_{i,t}$ represents the frequency of the keyword related to climate change appears in the annual report for year t, and $N_{i,t}$ represents the total number of words in the annual report for year t.

2.3. *Empirical model*

To assess the effect of climate-related risks on financial distress, we estimate the following model:

$$Z_{i,t} = \beta_0 + \beta_1 CR_{i,t} + \beta_2 Controls_{i,t} + \tau_t + \gamma_i + \varepsilon_{i,t} \tag{2}$$

This model is used as the baseline model. Where i denotes the firm, t denotes the year. $Controls_{i,t}$ is the set of control variables that may influence firm financial was conducted by García and Herrero (2021). τ_t and γ_i capture the time and individuals fixed effects, respectively. The specific definitions and descriptive statistics of the variables involved in this paper see the Appendix B.

3. Empirical results

3.1. *Baseline results*

Table 1 presents the regression results. In column (1), it is evident that climate risks are significantly and positively associated with corporate financial distress. In column (2), control variables are incorporated, and the results remain consistently positive and statistically significant at the 1% level.

Table 1. Baseline results.

	(1)	(2)
Variables	Z	Z
CR	-1.258***	-0.841***
	(0.333)	(0.303)
Size		-0.011***
		(0.001)
Lev		-0.128***
		(0.005)
Roa		0.099***
		(0.007)
Growth		-13.503**
		(6.455)
Dual		-0.001
		(0.001)
Indep		0.010
		(0.007)
TOP1		-0.006
		(0.005)
TMTPay1		0.002*
		(0.001)
Big4		-0.000
		(0.003)
SOE		0.001
		(0.002)
Age		0.019***
		(0.001)
_cons	0.050***	0.271***
	(0.001)	(0.022)
Year FE	YES	YES
Firm FE	YES	YES
N	29819	29819
adj. R^2	0.616	0.710

Notes: Robust standard errors clustered at the firm level are reported in parentheses, *,**, and *** indicate significance at 10%, 5%, and 1% significance levels, respectively. Year FE means time effect, and Firm FE means individuals effect (This also applies to the tables below).

3.2. *Potential channels*

To further understand the constraints channel, we used the financing constraint index (SA) developed by Hadlock and Pierce (2010), which is calculated based on company size and age. We compare the SA index of each enterprise with the industry average and categorized firms into high and low constraint groups accordingly. The interaction term $CR * SA$ exhibits a significant negative correlation -1.143 as shown in Table 2. This suggest that the effect of climate risk on financial distress is more pronounced for firms facing more severe financial constraints.

We also focus our analysis on how climate risk affects financial distress through risk-taking. Using the RT index calculated from enterprise ROA, as proposed by (Yu et al. 2023), to capture managerial risk-taking. RT are deemed high if the level of corporate risk-taking is greater than the industry average, and low otherwise. The interaction term $CR * RT$ is also significant, with a coefficient of -0.698 at the 5% statistical level, indicating that the effect of climate risk on financial distress is more pronounced for firms having more risk-taking.[1]

[1]For the specific definitions of channel variables, please refer to Table B2.

Table 2. Potential mechanism results.

	(1)	(2)
Variables	Z	Z
CR	-0.460	-0.528*
	(0.302)	(0.320)
SA	-0.007***	
	(0.001)	
CR*SA	-1.143***	
	(0.410)	
RT		0.002
		(0.001)
CR*RT		-0.698**
		(0.320)
Control	YES	YES
Year FE	YES	YES
Firm FE	YES	YES
N	29819	29819
adj. R^2	0.712	0.710

3.3. *Robustness checks*

3.3.1. Replacing core variable

We conducted two robust tests to further improve the reliability of the baseline regression. Firstly, following the approach of Boubaker et al. (2020), we introduced the O-score (O) to replace the Z for measuring the financial distress of the enterprise. A higher O indicates greater financial distress risk. The coefficient of CR in the first column of Table 3 confirms our previous findings.

Secondly, considering the potential lagged effect of climate risk disclosure on the financial distress of enterprises, we re-estimated the regression with a lagged one-period CR index. The results are reported in the second column of Table 3. It can be observed that the coefficient of $L.CR$ remains consistent with the main regression, remaining significantly negative.

3.3.2. Instrumental variable two-stage least squares model

It is possible that firms in financial distress inherently face higher levels of climate risk. To address the issue of reverse causality, the instrumental variable approach has been employed to replicate the baseline estimation.

Following Wang et al. (2024), we utilize the average climate risk exposure of other companies in the same year and industry as the company as the instrumental variable (iv_CR). The rationale behind this selection is that the degree of climate risk faced by enterprises may have peer effects within the same industry, but the average climate risk faced by other companies does not affect their financial distress. The results are presented in columns (3) and (4) of Table 3, indicate that iv_CR serves as an effective instrumental variable and again reaffirming the baseline results presented earlier.

4. Further analysis

Although we find a significant negative correlation between CR and Z, we may have overlooked factors that simultaneously affect both variables, potentially influencing

Table 3. Robustness checks results.

	Replacing variable		IV-2SLS	
	(1)	(2)	(3)	(4)
Variables	O	Z	Z	Z
CR	28.988**			-4.003***
	(12.592)			(0.262)
L.CR		-0.605*		
		(0.311)		
iv_CR			0.934***	
			(0.011)	
Kleibergen-Paap LM statistic				2547.697***
Kleibergen-Paap Wald F statistic				7325.995
Control	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
N	29819	26531	29819	29819
adj. R2	0.785	0.726		0.404

the robustness of our main findings. To further clarify the impact of climate change on CR, we follow **?**, who considers China's signing of the Paris Agreement in 2016 as an exogenous shock, and map the resulting changes in Z.

We use the Differences-in-Differences method (DID) and construct the following model to identify this path:

$$Z_{i,t} = \alpha_0 + \alpha_1 Treat_{i,t} + \alpha_2 Time_i + \alpha_3 Time_i * Treat_{i,t} + \alpha_4 Controls_{i,t} + \tau_t + \gamma_i + \varepsilon_{i,t} \quad (3)$$

Where $Treat_{i,t}$ is a dummy variable measuring climate change. Firms are ranked into high and low groups based on their Z. Firms with higher Z are used as the treatment group ($Treat_{i,t} = 1$), while the remaining firms are placed in the control group ($Treat_{i,t} = 0$). $Time_i$ is an event dummy variable, taking the value 1 for observations in 2016 and later, and 0 otherwise. The impact of CR on Z is mainly identified by the coefficient of the interaction term $Time_i * Treat_{i,t}$. The definitions of other factors are consistent with model (2).

Table 4 reports the regression results of model (3). The coefficient of $Time_i * Treat_{i,t}$ is significantly negative, indicating that after China's signed of the Paris Agreement, the impact of CR on Z in the treatment group is significantly greater than in the control group.

Table 4. The DID estimation.

	(1)	(2)
Variables	Z	Z
$Time_i * Treat_{i,t}$	-0.609***	-0.070**
	(0.054)	(0.029)
Control	NO	YES
Year FE	YES	YES
Firm FE	YES	YES
N	30074	27543
adj. R^2	0.613	0.907

[Figure 1](#) show the parallel trend test. We designate the first year before the external shock as the base year, excluding this period to avoid complete covariance. Before the external shock, the estimated coefficients did not significantly differ from zero, whereas generally significantly negative and exhibited an expanding trend after external shock, confirming the validity of our DID results.

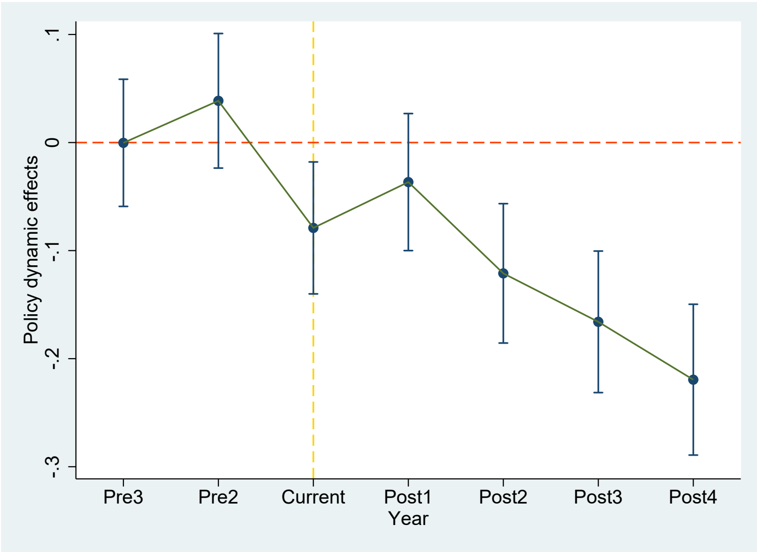

Figure 1. Parallel trend test result.

Note: Current is 2016, post1 is 2017, pre2 is 2015, and so on. Since period 1 before the policy point in time is used as the benchmark group, data for period are not available in the graph.

5. Conclusions

This paper provides Chinese evidence on the critical intersection between climate risk and financial distress. Our findings reveal that climate risk serves as a catalyst for financial distress by intensifying both financial constraints and risk-taking behavior within companies. A series of robustness checks confirm this conclusion, and the DID model estimation results, including policy shocks, provide strong support for our findings. This discovery not only extends the research scope of financial distress risk determinants but also enriches the literature on climate risk's impact on firms.

Based on these findings, we suggest that the government formulate relevant policies or provide subsidies, to alleviate financial pressure on firms and support them in addressing climate risk. Future research can further explore how firms can mitigate the financial pressure brought by climate risk through sustainable development strategies, providing more targeted recommendations for companies and policymakers.

Disclosure statement

The authors report there are no competing interests to declare.

Funding statement

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Appendix A.

Table A1. Climate risk keywords.

severe disaster, earthquake, typhoon, tsunami, drought, extreme weather conditions, severe weather, waterlogging, strong wind, sandstorm, hurricane, frost, flood, storm, mudslide, landslide, freezing, snow disaster, heavy rain, tornado, hailstorm, flood disaster, rain and snow, freezing weather, heavy snowfall, freeze damage, dryness, dry spell, heavy rainfall, floods, cold temperatures, wind and sand, climate, weather, water temperature, cooling, coldness climate, air temperature, rainfall, temperature, rainwater, rainy season, precipitation, cloudy and rainy, rainy, extremely cold, winter, flood season, high humidity, water condition, water level, sunlight, water shortage, high altitude, cold wave, subsidence, groundwater, flood situation, surface water, water storage, energy-saving, energy, clean, ecological, environment, transformation, solar energy, upgrade, circular, utilization rate, nuclear power, natural gas, efficiency improvement, fuel, efficiency, renewable, emission reduction, environmental protection, green, low-carbon, consumption reduction, water saving, photovoltaic, high efficiency, renovation, fuel consumption, power consumption, energy consumption, wind power, efficacy, intensive.

Appendix B.

Table B1. Descriptive statistics of main variables.

Variable	N	SD	Mean	Min	Median	Max
Z	29,819	5.652	4.840	-0.417	3.052	36.525
CR	29,819	0.170	0.143	0.012	0.128	0.781
Size	29,819	1.292	22.183	19.876	21.995	26.207
Lev	29,819	0.204	0.433	0.056	0.429	0.887
Roa	29,819	0.062	0.043	-0.208	0.040	0.224
Growth	29,819	0.000	0.000	-0.000	0.000	0.000
Dual	29,819	0.437	0.256	0.000	0.000	1.000
Indep	29,819	0.053	0.374	0.308	0.333	0.571
TOP1	29,819	0.149	0.348	0.091	0.328	0.743
TMTPay	29,819	0.745	14.456	12.612	14.441	16.500
Big4	29,819	0.245	0.064	0.000	0.000	1.000
SOE	29,819	0.488	0.391	0.000	0.000	1.000
Age	29,819	0.808	2.142	0.000	2.303	3.332

Table B2. Variable Definitions.

Variable	Definitions
Dependent variables	
Z-score	$Z = 1.2 * \frac{WC}{TA} + 1.4\frac{retEarnings}{TA} + 3.3 * \frac{EBIT}{TA} + 0.6 * \frac{MV}{TA} + 0.999 * \frac{SALE}{TA}$ Where WC is working Capital; TA is total assets; $retEarnings$ is retained earnings; $EBIT$ is earnings before interest and taxes; MV is market value of Equity; TL is total liabilities and $Sale$ is the sales.
O-score	$O = -1.32 - 0.407 * ln(TA) + 6.03 * \frac{TL}{TA} - 1.43 * \frac{WC}{TA} + 0.076 * \frac{CL}{CA} - 2.37 * \frac{NI}{TA} - 1.83 * \frac{ONC}{TL} + 2.085 * 5NLdummy - 1.72 * TLdummy - 0.521 * \frac{NI_t - NI_{t-1}}{\|NI_T\| + \|NI_{t-1}\|}$ Where TA is total assets; TL is total liabilities; WC is working capital; CL is current liabilities; CA is current assets; NI is net income, ONC is operating net cash flow. $NLdummy$ is means that marked as 1 if the net profit of the past two years has been negative and 0 otherwise. $TLdummy$ is means that marked as 1 if TL is greater than TA and zero otherwise.
Independent variables	
Climate risk	The ratio of the frequency the keyword related to climate change to the total word frequency in the annual reports.
Control variables	
Size	The natural logarithm of total assets.
Lev	Total liability divided by total asset.
Roa	Net income divided by average total asset.
Growth	Operating income for the year divided by operating income for the previous year – 1.
Dual	Chief Executive Officer and the Chairman are concurrently elected = 1, otherwise 0.
Indep	Independent director/board size.
TOP1	The proportion of shares owned by the largest shareholder.
TMTPay	The natural logarithm of the total compensation for the top three executives.
Big4	Enterprise audited by Big Four accounting firm assigned 1, otherwise 0.
SOE	State-owned enterprises dummy, SOE=1, 0 otherwise.
Age	The natural logarithm of the number of years since the company's incorporation.
Channel variables	
SA	Capture the model constructed by Hadlock and Pierce (2010) $SA = -0.737 * Size + 0.043 * Size^2 - 0.040 * Age$ Where $Size$ is total assets; Age is the number of years since the company's incorporation. This index is negatively correlated with the size of corporate financing constraints.
RT	$RT_{i,j,t} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{\infty}[(ROA_{i,j,t} - MeanROA_{j,t}) - \frac{1}{N}\sum_{i=1}^{\infty}(ROA_{i,j,t} - MeanROA_{j,t})]}$ Where N=3 and ROA is the net earnings to total assets, j represents firm i in year t corresponding industry classification. $MeanROA$ denotes the industry mean ROA. N=3 refers to the standard deviation of a rolling three-year period (Yu et al. 2023). This index is positive correlated with the size of corporate risk-taking.

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