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The Impact of Climate Risk on Investment Returns of Listed Companies: Evidence from China

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ABSTRACT

In recent years, as global climate change intensifies and ESG investment concepts gain prominence, climate risk has become a crucial factor for investors and financial markets. Investigating how climate risk is priced in the Chinese capital market is both theoretically and practically important for promoting the sustainable development of China's capital markets and advancing green finance. This study employs natural language processing (NLP) to quantify the proportion of climate risk-related content in the annual reports of listed companies, creating an indicator to assess their climate risk level. The study uses climate risk of listed companies as the explanatory variable and annual stock returns as the dependent variable, applying a fixed-effects model to empirically examine the impact of climate risk on investment returns. The study finds that: first, the climate risk of listed companies shows a clear trend of change over time; second, there is a significant positive correlation between the climate risk of listed companies and investment returns.

KEYWORDS

Climate Risk; Listed Companies; Return on Investment; Green Transition

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1. Introduction

Climate change is a major global challenge that has garnered widespread attention and concern from the international community. The intensification of global climate change has brought significant risks to both ecosystems and socio-economic systems (Diaz & Moore, 2017; Magnan et al., 2021; Matsumoto, 2019). With the rise in global temperatures, the impact of climate change on Earth's ecosystems has become increasingly evident. Climate change leads to global warming, rising sea levels, and more frequent natural disasters, all of which affect human socio-economic activities. The consequences of climate change have already threatened human survival. Countries and organizations are increasingly prioritizing the issue of climate change.

As the main entities in socio-economic activities, firms are inevitably affected by climate change. The impact of climate change on firms mainly manifests in two aspects: the effects of extreme weather events and natural disasters, and the impact of related policies. On the one hand, with the intensification of climate change, there is an increase in the frequency of extreme weather events and natural disasters (Robinson et al., 2021; Tabari, 2020; Wen et al., 2023). Extreme weather events include extreme high temperatures, extreme low temperatures, hurricanes, floods, droughts, wildfires, and so on. The occurrence of these extreme weather events and natural disasters not only causes damage to firms' physical facilities and fixed assets, but also potentially disrupts supply chains (Hennes et al., 2024; Yun & Ülkü, 2023). On the other hand, climate change policies impact firms through various channels, including higher operating costs, driving technological innovation, influencing market competitiveness, and altering the financing environment (Hennes et al., 2024; Ren et al., 2024).

Climate change has introduced climate risks for firms. Climate risk refers to the potential negative impacts on society, the environment, and economic activities caused by climate change and its associated effects. Climate change risks typically affect firms' business operations, asset values, investment returns, and other areas to varying degrees. Various methods exist to measure climate risks at the firm level. As climate change becomes more pressing, both researchers and financial markets have developed diverse approaches to assess these risks. Some studies construct climate risk indices using meteorological data such as rainfall, droughts, typhoons, high temperatures, and low-temperature freezes in a specific region to assess the climate risk of firms in that region (Javadi & Masum, 2021; Lee et al., 2022; Sun et al., 2020). Additionally, institutions such as the U.S. Securities and Exchange Commission (SEC) require publicly traded companies to disclose greenhouse gas emissions regularly. As a result, many studies use indicators like carbon emissions and emission productivity to measure corporate climate risk (Bolton & Kacperczyk, 2021; Chaudhry et al., 2020; Gu & Hale, 2023). With the advancement of big data and artificial intelligence technologies, an increasing number of companies and researchers have begun using natural language processing (NLP) techniques to conduct quantitative assessments of specific risks faced by firms (Baker et al., 2016; Engle et al., 2020; Hassan et al., 2019). Some researchers use NLP techniques to analyze textual information such as company annual reports, financial statements, and earnings call transcripts, extracting companies' disclosures on climate risks. This method can reveal a firm's attitude and actions toward climate risk management, thereby helping to assess the level of exposure to climate risks (Sautner et al., 2023).

In recent years, with the intensification of global climate change and the rise of Environmental, Social, and Governance (ESG) investing, climate risk has gradually become an important consideration for investors and financial markets. In developed markets such as Europe and the United States, climate risk is already considered an important factor in capital pricing (Eren et al., 2022; Faccini et al., 2023), with publicly listed companies and investors gradually recognizing the potential impact of climate risk on long-term financial performance. However, in China, an emerging market, although climate risk is receiving increasing attention, whether an effective pricing mechanism for climate risk has been established in the Chinese capital market remains an open question that warrants further research. As the world's second-largest economy and a major carbon emitter, China's climate risk pricing mechanism in its capital market may be influenced by multiple factors, including policy direction, market maturity, and investor awareness. Therefore, studying whether and how climate risk is priced in China's capital market is of significant theoretical and practical importance for advancing the sustainable development of China's capital market and promoting the deepening of green finance.

This study examines the impact of climate risk of publicly listed companies in the Shanghai and Shenzhen stock markets on investment returns, aiming to identify whether climate risk is effectively priced in China's capital markets. This study uses the climate risk of listed companies as the explanatory variable, and the annual stock return of the listed companies as the dependent variable. This study constructs a fixed-effects model using Ordinary Least Squares (OLS) regression and analyzes the main regression results. In addition, the study conducts robustness checks using methods such as substituting explanatory and dependent variables, and grouping regressions based on different types of ownership. Based on the research findings, policy recommendations are made to promote investment decisions based on the risks of listed companies and to fully leverage the role of capital markets in facilitating the green transformation of these companies.

The subsequent sections of this manuscript are structured as follows: Section 2 offers a comprehensive literature review. Section 3 outlines the research methodology and data sources. Section 4 presents the empirical findings along with robustness tests conducted. Section 5 summarizes this paper and offers policy recommendations.

2. Literature

2.1. Impact of climate risk on listed companies

The impact of climate change on the world is profound and complex, affecting multiple levels of the economy, society, and ecology. The essence of climate risk lies in the impact of natural disasters, extreme weather conditions, and the introduction of corresponding policies on publicly listed companies (Liang et al., 2024; Liu et al., 2024). As the global issue of climate change becomes more severe, the impact of climate risk on investment returns of listed companies has become an increasingly important topic for both academia and investors. Numerous empirical studies have explored how climate risk affects companies' financial performance, stock price volatility, and investment returns. Some studies suggest that companies with higher climate risks may face greater market volatility and long-term risks, but their investment returns may also be driven by the market's expectations of future climate policy changes (Naseer et al., 2024; Ren, Shi, et al., 2022; K. Wu et al., 2024).For example, some research points out that while climate-related risks may temporarily depress the stock prices of these companies, in the long run, good climate risk management will enhance their investment returns, as these companies will be better able to adapt to new environmental policies and market trends in the future (Görgen et al., 2020). With investors' growing attention to ESG factors, the disclosure of climate risks has become an important factor affecting companies' investment returns. Research shows that companies that proactively disclose climate risk information tend to enhance their brand image and credibility, attracting more investors, particularly those focused on social responsibility and sustainable development (N. Wu et al., 2022). The transparency of corporate climate risk information increases market trust in the company's future performance, thereby driving stock price increases (Lin & Wu, 2023; Yin et al., 2024). On the other hand, companies that do not disclose or have opaque information often face a crisis of investor trust, which may lead to a decline in their stock prices (Gan et al., 2024; Shao & Xue, 2024).

Although many studies have shown the performance of climate risk in Western capital markets, the impact of climate risk on investment returns in China, an emerging market, remains a relatively new research area. As one of the largest carbon emitters in the world, China has gradually strengthened its regulatory efforts on climate change in recent years, while investors' attention to climate risk has also been steadily increasing (Shu et al., 2023). However, due to the unique characteristics of China's capital market, such as policy uncertainty and the relative lag of the ESG investment framework, the performance of climate risk in the Chinese market may differ from that in mature markets. Therefore, whether climate risk can be effectively priced in China's capital market, and how Chinese companies will respond to this emerging risk, remains an important issue that warrants further exploration.

2.2. Measurement of Climate Risk for Listed Companies

Using climate risk indicators to measure corporate climate risk is a commonly used method (Fiedler et al., 2021; Ren et al., 2022; Yin et al., 2024). Climate risk indicators are typically quantitative metrics built from historical data, climate models, and company operational data, used to assess the short-term and long-term impacts of climate change on firms (Harrington et al., 2021; X. Li & Gallagher, 2022; Rising et al., 2022). In recent studies, climate risk indicators related to natural disasters and extreme weather are often used as proxy variables for physical risks (Javadi & Masum, 2021; Lee et al., 2022). Meteorological data such as temperature changes, precipitation variations, and wind speeds are commonly used to assess the impact of physical risks (e.g., extreme weather events) on business operations and supply chains (Bavandi et al., 2022; Shu & Fan, 2024; Sun et al., 2020; Sun et al., 2024). For companies affected by carbon reduction and carbon pricing policies, the direct cost of carbon emissions is an important indicator of transformation risk, as such policies impact operational costs and product prices (Shu et al., 2023; Wu & Wang, 2022). Indicators such as carbon emissions, emission productivity, and the increment of emission policies are often used as proxy variables for transformation risk (Chaudhry et al., 2020; Gu & Hale, 2023).

The aforementioned indicators are typically at the regional level, making it difficult to distinguish differences between companies in the same region. Recent studies choose to construct climate risk or other related indicators from the textual information of publicly listed companies, mainly because textual data can provide important insights into company behavior, strategies, risk exposure, governance structures, and other aspects (Li et al., 2024; Sautner et al., 2023). Constructing climate risk and related indicators from the textual information of listed companies can provide researchers with deep insights into how companies manage climate change and its associated risks. This is not only because textual data contains non-financial but critically important information (Gentzkow et al., 2019), but also because modern technology makes it possible to extract useful information from large volumes of unstructured data (King et al., 2017). With the continuous advancement of text analysis methods, this textual information will play an increasingly important role in climate risk assessment and decision support (Berkman et al., 2024; Dimmelmeier et al., 2024; Mbanyele & Muchenje, 2022).

3. Method and data

3.1. Model setup

To explore the relationship between climate risk and investment returns of listed companies, this study uses a Fixed Effects Model to model the relationship between them. The Fixed Effects Model is developed based on the Ordinary Least Squares method, primarily to address the endogeneity issue caused by omitted variables. In this study, the market environments faced by listed companies in different industries may vary, and these unobservable variables could impact the investment returns of listed companies. To mitigate the impact of omitted variables, this study incorporates fixed effects, and the regression model is constructed as follows:

$$Return_{it} = \propto_1 + \beta_1 Climate\ Risk_{it} + \beta_2 Controls_{it} + S_i + \varepsilon_{it} \tag{1}$$

Here, $Return_{it}$ represents the investment return of company i in year t; $Climate\ Risk_{it}$ represents the climate risk of company i in year t; $Controls_{it}$ represents the control variables of company i in year t. The control variables consist of two parts: one part includes company-specific characteristics, such as company size, ownership structure, institutional investor shareholding ratio, price-to-earnings ratio, etc., and the other part includes financial indicators of the company, such as financial leverage, profitability, and growth ability. S_i represents the inclusion of fixed effects in the model: industry-year fixed effects and year fixed effects. This study clusters standard errors at the company level.

3.2. Data sources

This study is based on the relationship between risk and return in classic investment theory, and selects the investment return of listed companies as the dependent variable. The investment return of a listed company specifically refers to the individual stock return of the company, that is, the ratio of the investment gain to the investment amount obtained by an investor who buys the company's stock on the last trading day of year t-1 and sells it on the last trading day of year t. The source of this part of the data is from the CSMAR database.

This study uses a climate risk index to measure the level of climate risk of listed companies. The main idea behind constructing the climate risk index is to use pre-trained language model techniques to identify climate risk-related content in the financial reports published by listed companies. This study first crawled the financial reports published by listed companies on the Shanghai Stock Exchange and the Shenzhen Stock Exchange from 2020 to 2022. The content in the "Management Discussion and Analysis" section of these reports was classified sentence by sentence, and the proportion of climate risk-related content was identified using the pre-trained language model ClimateBERT (Webersinke et al., 2021). This proportion serves as the indicator dataset to measure the climate risk of listed companies. This study uses the climate risk index constructed based on pre-trained language model technology as the independent variable for regression analysis. The annual report data for this part of the listed companies comes from the Cninfo website (www.cninfo.com.cn). The definition of climate risk for listed companies is as follows:

$$Climate\ Risk_{i,t} = \frac{Climate\ Related\ Sentences_{i,t}}{Total\ Sentences_{i,t}} \tag{2}$$

In the formula, $Climate\ Related\ Sentences_{i,t}$ represents the number of sentences related to climate risk in the "Management Discussion and Analysis" section of company i's annual report for year t. $Total\ Sentences_{i,t}$ represents the total number of sentences in the "Management Discussion and Analysis" section of company i's annual report for year t. $Climate\ Risk_{i,t}$ represents the climate risk index of company i for year t.

Through the above steps of data crawling, text cleaning, and text analysis, a small number of non-compliant samples were removed, and the average and standard deviation of climate risk scores for listed companies in each year from 2020 to 2022 were summarized, as shown in the table 1. In 2020, the sample size of listed companies was 3,578, with an average climate risk score of 0.1686 and a standard deviation of 0.1483; In 2021, the sample size of listed companies was 4,103, with an average climate risk score of 0.2154 and a standard deviation of 0.1823. The climate risk score showed a significant increase compared to 2020, with greater volatility; In 2022, the sample size of listed companies was 4,206, with an average climate risk score of 0.2233 and a standard deviation of 0.1837. The climate risk score saw a slight increase compared to 2021. Overall, from 2020 to 2022, the climate risk of listed companies increased, especially with a significant rise in climate risk from 2020 to 2021.

Table 1. Descriptive statistics of climate risk for listed companies.

Year	Number of companies	Mean	Std. Dev.
2020	3578	0.1686	0.1483
2021	4103	0.2154	0.1823
2022	4206	0.2233	0.1837
Total	11887	0.2041	0.1749

To control for other factors that influence the asset returns of listed companies, this study includes control variables in the regression model. The control variables commonly used in existing similar studies can be divided into two categories: one category includes control variables related to financial indicators of the company, and the other category includes control variables related to the company's characteristics. When selecting control variables, the impact mechanism of each variable on the asset returns of listed companies must be considered, and this serves as the basis for determining whether to include the variable as a control variable. The control variables in this study include: financial leverage, profitability (measured by return on assets (ROA)), growth ability (measured by book-to-market ratio), company size (measured by market capitalization), ownership structure (1 for state-owned enterprises, 0 otherwise), institutional investor shareholding ratio, Tobin's Q, and price-to-earnings ratio. The data for the control variables comes from the CSMAR database.

4. Empirical result

4.1. Descriptive statistical analysis

Before conducting the regression analysis, this study precisely matched the data from each dataset using stock codes and years, ultimately obtaining 11,885 samples. The descriptive statistical analysis of all the variables used in this study is shown in the table 2. From the descriptive statistics table of the main variables, it can be seen that the minimum value of the annual stock return variable in this study is -0.78, indicating that the stock holdings of these listed companies result in a loss over one year. The maximum value is 14.28, suggesting that these companies' stocks can yield a large profit over one year. For the core explanatory variable, the average climate risk is 0.20, with a standard deviation of 0.17, a minimum value of 0, and a maximum value of 0.84. This suggests that climate risks are predominantly distributed at lower values among the listed companies. For the control variables in this study, the average financial leverage is 1.34, with a standard deviation of 3.51, a minimum value of -6.36, and a maximum value of 270.99. This indicates significant variation in financial leverage across the listed companies. In terms of profitability and growth ability, the average profitability is 0.043, with a standard deviation of 0.086, a minimum value of -1.23, and a maximum value of 1.28. The average growth ability is 0.63, with a standard deviation of 0.26, a minimum value of 0.034, and a maximum value of 1.60. This indicates significant differences in profitability among the listed companies, while growth ability shows relatively smaller variation. The average company size (billions of dollars) is 248, with a standard deviation of 874, a minimum value of 8.48, and a maximum value of 26,300, indicating significant variation in market capitalization across the listed companies. In terms of ownership structure, state-owned listed companies account for 28%, while non-state-owned listed companies make up the majority. The average institutional investor shareholding ratio is 42.14, with a standard deviation of 25.00, a minimum value of 0, and a maximum value of 100, indicating a large disparity in shareholding ratios among the listed companies. The average Tobin's Q and price-to-earnings (P/E) ratios are 2.07 and 112.30, with standard deviations of 1.62 and 3951.64, respectively. This indicates significant differences in Tobin's Q and P/E ratios among the listed companies in the regression sample.

Table 2. Descriptive statistics of the variables employed in this study.

Variable name	Shot form	Mean	Std. Dev.	min	max
annual stock return	return	0.10	0.53	-0.78	14.28
climate risk	climate_risk	0.20	0.17	0	0.84
financial leverage	FL	1.34	3.51	-6.36	270.99
profitability ability	ROA	0.043	0.086	-1.23	1.28
growth ability	MB	0.63	0.26	0.034	1.60
company size	size	248	874	8.48	26300

ownership structure	ownership	0.28	0.45	0	1
institutional investor shareholding ratio(%)	RIO	42.14	25.00	0	100
Tobin's Q	Tobin_Q	2.07	1.62	0.62	29.17
price-to-earnings ratios	PE	112.30	3951.64	0.0046	392617.1

4.2. Main regression results

The main regression results are shown in the table 3. The regression results consist of three columns, which include the results of the model regressions from no fixed effects to adding different fixed effects. Column (1) shows the regression results using OLS without adding fixed effects. From the results in column (1), it can be seen that there is a significant positive correlation between corporate climate risk and annual stock returns, with a regression coefficient of 0.400. Column (2) adds time fixed effects to the OLS regression, controlling only for year fixed effects. From the results in column (2), it can be seen that climate risk and annual stock returns are positively correlated at the 1% significance level, with a regression coefficient of 0.479. Column (3) shows the regression results controlling for both industry-year and year fixed effects. The results indicate that corporate climate risk and annual stock returns are positively correlated at the 1% significance level, with a regression coefficient of 0.482.

Table 3. Main regression results.

	(1) OLS	(2) FE1	(3) FE2
climate_risk	0.400***	0.479***	0.482***
	(0.03251)	(0.319)	(0.0470)
FL	0.00340	0.00203	0.00189
	(0.00279)	(0.00212)	(0.00182)
ROA	0.892**	0.989**	1.0374**
	(0.423)	(0.413)	(0.424)
MB	-0.320***	-0.275***	-0.358***
	(0.0407)	(0.0382)	(0.0405)
size	6.46e-14	4.29e-14	-9.11e-15
	(9.80e-14)	(8.78e-14)	(8.27e-14)
ownership	0.0792***	0.0571***	0.0500***
	(0.0128)	(0.0122)	(0.0122)
RIO	0.000240	0.000391*	0.000164
	(0.000244)	(0.000235)	(0.000233)
Tobin_Q	0.0662***	0.0596***	0.0563***
	.0(0.00987)	(0.00934)	(0.00910)
PE	2.33e-06***	2.98e-06***	3.49e-06***
	(3.16e-07)	(3.29e-07)	(3.95e-07)
Year	No	Yes	Yes
Industry - Year	No	No	Yes
sample size	8796	8796	8779
Adjusted R^2	0.146	0.243	0.295

*Note: Standard errors clustered to the company level are reported in parentheses, and ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.*

4.3. Robustness Tests

In empirical research analysis, to ensure that the results are not due to specific data or methods, robustness checks are necessary to validate the results and conclusions. This section mainly conducts robustness checks on the previous baseline regression results. The robustness checks conducted in this study mainly include three aspects: (1) categorizing corporate climate risk into levels and replacing the original explanatory variable with a categorical variable; (2) replacing the original dependent variable with return on equity (ROE); (3) conducting grouped regressions based on different ownership types of listed companies.

First, categorize corporate climate risk into levels and replace the original explanatory variable with a categorical variable for regression analysis. The explanatory variable used in the baseline regression results is the climate risk variable calculated using the NLP method. Currently, many third-party rating agencies classify risk levels into several categories, and a categorical variable can clearly show investors the climate risk level of listed companies. Therefore, in this study, the corporate climate risk variable calculated is ranked by value, with the top 20% classified as level 5, the 20%-40% range as level 4, the 40%-60% range as level 3, the 60%-80% range as level 2, and the lowest 20% classified as level 1.

Regression analysis is conducted based on the previous regression model, and the main regression results are shown in the table 4. Column (1) shows the traditional OLS regression results without fixed effects. From the results in Column (1), it can be seen that corporate climate risk is significantly positively correlated with annual stock returns, with a regression coefficient of 0.0506, significant at the 1% level. Column (2) shows the regression results with industry-year and year fixed effects controlled. From the results, it can be seen that corporate climate risk is significantly positively correlated with annual stock returns at the 1% significance level, with a regression coefficient of 0.0505.

Table 4. Regression results with climate risk level as explanatory variable.

	(1)	(2)
	OLS	FE
climate_risk	0.0506***	0.0505***
	(0.00384)	(0.00526)
FL	0.00354	0.00200
	(0.00285)	(0.00184)
ROA	0.923**	1.065**
	(0.420)	(0.422)
MB	-0.319***	-0.359***
	(0.0408)	(0.0409)
size	6.54e-14	-162e-15
	(9.86e-14)	(8.43e-14)
ownership	0.0805***	0.0492***
	(0.0128)	(0.0124)
RIO	0.000245	0.000157
	(0.000245)	(0.000236)
Tobin_Q	0.0669***	0.0565***
	(0.00997)	(0.00922)
PE	2.31e-06***	3.35e-06***
	(3.20e-07)	(4.07e-07)
Year	No	Yes
Industry - Year	No	Yes
sample size	8796	8779
Adjusted R^2	0.147	0.292

*Note: Standard errors clustered to the company level are reported in parentheses, and ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.*

The above results indicate that after categorizing corporate climate risk variables based on their values and performing regression, the impact on the annual stock returns of listed companies remains statistically significant. Replacing the explanatory variable does not affect the conclusion of the baseline regression results.

Second, replace the original dependent variable with ROE and perform regression analysis. ROE is an important indicator for evaluating a company's profitability and management efficiency, and due to its effectiveness, ease of understanding, and calculation, it is widely used in empirical research. By analyzing ROE, researchers can gain deep insights into a company's financial health and its performance in the market, thereby providing strong support for investment decisions. The definition of ROE is the ratio of net profit to shareholders' equity, and therefore, to some extent, it reflects the return on investment for shareholders of listed companies. This study uses ROE data from the CSMAR database, replacing the annual stock return of listed companies in the original regression model as the dependent variable, and the regression results are shown in the table 5. Column (1) shows the traditional OLS regression results without fixed effects. From the results in Column (1), it can be seen that corporate climate risk is significantly positively correlated with annual stock returns, with a regression coefficient of 0.00423, significant at the 1% level. Column (2) shows the regression results with industry-year and year fixed effects controlled. From the results, it can be seen that corporate climate risk is significantly positively correlated with annual stock returns at the 1% significance level, with a regression coefficient of 0.00425.

Table 5. Regression results for replacement of dependent variables.

	(1) OLS	(2) FE
climate_risk	0.00423***	0.00425***
	(0.000546)	(0.000592)
FL	0.0000305	0.0000214
	(0.0000877)	(0.0000662)
ROA	1.395***	1.404***
	(0.0405)	(0.0418)
MB	-0.00179	-0.0133**
	(0.00438)	(0.00527)
size	5.86e-14***	4.87e-14***
	(1.81e-14)	(1.79e-14)
ownership	0.00800***	0.00606**
	(0.00264)	(0.00282)
RIO	0.000110***	0.0000942**
	(0.0000387)	(0.0000367)
Tobin_Q	-0.00134*	-0.00222***
	(0.000757)	(0.000701)
PE	-6.92e-08**	-1.40e-07***
	(3.19e-08)	(5.24e-08)
Year	No	Yes
Industry - Year	No	Yes
sample size	9833	9814
Adjusted R^2	0.644	0.653

*Note: Standard errors clustered to the company level are reported in parentheses, and ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.*

The results above show that when replacing the original dependent variable (annual stock return) with ROE in the regression model, the impact of climate risk on a company's investment return remains statistically significant. Replacing the dependent variable does not change the conclusion of the baseline regression results.

Third, the ownership structure is categorized into four types: state-owned, private, foreign, and Sino-foreign joint ventures, and group regressions are performed for each type of ownership. Listed companies with different ownership structures usually show significant differences in their attention to climate risk. Foreign companies operate in multiple countries and regions, requiring adherence to relevant environmental regulations and international standards. Many countries have increasingly strict climate risk management requirements, and foreign companies must comply to avoid legal risks and penalties. On the other hand, foreign companies are often influenced by investors who emphasize ESG standards, and these investors tend to choose companies that perform well in climate risk management. Therefore, for foreign listed companies, the impact of climate risk on their annual stock return may be more pronounced. This study performs group regression analysis for listed companies with different ownership structures based on the regression model in section 4.2.

The group regression results for listed companies with different ownership structures are shown in the table 6. Column (1) shows the results for state-owned companies. From Column (1), it can be observed that the climate risk of state-owned listed companies is significantly positively correlated with their annual stock returns, with a regression coefficient of 0.361, which is significant at the 1% level. Column (2) presents the regression results for private companies. From Column (2), it can be seen that the climate risk of private listed companies is significantly positively correlated with their annual stock returns, with a regression coefficient of 0.505, which is significant at the 1% level. Column (3) shows the regression results for foreign companies. From Column (3), it can be observed that the climate risk of foreign listed companies is significantly positively correlated with their annual stock returns, with a regression coefficient of 0.731, which is significant at the 1% level. Column (4) presents the regression results for Sino-foreign joint venture companies. From Column (4), it can be seen that the climate risk of Sino-foreign joint venture listed companies is significantly positively correlated with their annual stock returns, with a regression coefficient of 0.763, which is significant at the 5% level.

Table 6. Sub-sample regression results for listed companies with different ownership.

	(1) state-owned	(2) private	(3) foreign	(4) Sino-foreign
climate_risk	0.361***	0.505***	0.731***	0.763**
	(0.0719)	(0.0644)	(0.277)	(0.368)
FL	0.0000240	0.00908	0.0479	-0.0592
	(0.000525)	(0.00562)	(0.0533)	(0.0475)
ROA	0.382	1.263**	0.909	0.0452
	(0.275)	(0.549)	(0.643)	(0.770)
MB	-0.204***	-0.441***	-0.554**	-0.611**
	(0.0553)	(0.0666)	(0.211)	(0.293)
size	-8.17e-14	2.42e-13	-4.96e-13	-1.04e-13
	(7.21e-14)	(2.33e-13)	(4.81e-13)	(1.08e-12)
ownership	/	/	/	/
	/	/	/	/
RIO	0.000429	0.000239	-0.000252	0.00104
	(0.000486)	(0.000297)	(0.00104)	(0.00149)
Tobin_Q	0.0597***	0.0575***	0.0140	0.0433
	(0.0150)	(0.0138)	(0.0249)	(0.0335)
PE	0.000200**	3.11e-06***	-0.000347	-0.000237
	(0.0000815)	(2.07e-07)	(0.000247)	(0.000519)
Year	Yes	Yes	Yes	Yes
Industry - Year	Yes	Yes	Yes	Yes
sample size	2662	5116	298	180
Adjusted R^2	0.326	0.296	0.300	0.418

*Note: Standard errors clustered to the company level are reported in parentheses, and ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.*

The above results indicate that the impact of climate risk on annual stock returns is consistently positive across different ownership types of listed companies, which is consistent with the baseline regression results. Specifically, the regression coefficients for foreign and Sino-foreign joint venture listed companies are larger, indicating that their annual stock returns are more sensitive to climate risk.

Fourth, group the sample of listed companies by different stock exchanges for regression analysis. The sample in this study consists of companies listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), and there may be differences in the impact of climate risk on annual stock returns based on listing location. Different stock exchanges may have varying sensitivities of their listed companies to climate risk due to differences in regulatory environments, investor structures, and industry distributions. The grouped regression results for companies from different industries are shown in the table 7. Column (1) displays the regression results for the full sample, showing a significant positive correlation between climate risk and annual stock returns, with a coefficient value of 0.482, significant at the 1% level. Column (2) shows the regression results for SSE-listed companies, indicating a significant positive correlation between climate risk and annual stock returns, with a coefficient value of 0.460, significant at the 1% level. Column (3) presents the regression results for SZSE-listed companies, demonstrating a significant positive correlation between climate risk and annual stock returns, with a coefficient value of 0.528, significant at the 1% level.

Table 7. Sub-sample regression results for different stock exchanges.

	(1) All sample	(2) SSE	(3) SZSE
climate_risk	0.482***	0.460***	0.528***
	(0.0470)	(0.0649)	(0.0646)
FL	0.00189	0.00505	0.000631
	(0.00182)	(0.00449)	(0.000903)
ROA	1.0374**	1.255***	1.036
	(0.424)	(0.249)	(0.679)
MB	-0.358***	-0.317***	-0.392***
	(0.0405)	(0.0511)	(0.0662)
size	-9.11e-15	-6.33e-14	7.67e-14
	(8.27e-14)	(9.97e-14)	(1.07e-13)
ownership	0.0500***	0.0583***	0.0412**
	(0.0122)	(0.0144)	(0.0181)
RIO	0.000164	0.000556*	-0.000247
	(0.000233)	(0.000307)	(0.000337)
Tobin_Q	0.0563***	0.0469***	0.0624***
	(0.00910)	(0.0105)	(0.0146)
PE	3.49e-06***	0.000146*	3.17e-06***
	(3.95e-07)	(0.0000808)	2.39e-07
Year	Yes	Yes	Yes
Industry - Year	Yes	Yes	Yes
sample size	8779	3959	4820
Adjusted R^2	0.295	0.318	0.286

*Note: Standard errors clustered to the company level are reported in parentheses, and ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.*

The above results indicate that after grouping listed companies by different stock exchanges for regression, the results of both sub-samples remain consistent with the baseline results, showing a significant positive correlation between climate risk and annual stock returns. Specifically, the regression coefficient for climate risk is larger for SZSE-listed companies, indicating that the annual stock returns of SZSE-listed companies are more sensitive to climate risk. This may be because SZSE-listed companies attract more individual investors, who are more responsive to market information and may have a more direct perception and reaction to changes in climate risk. This makes the stock prices of SZSE-listed companies more volatile when responding to climate risks, resulting in a larger regression coefficient.

5. Conclusion

This study uses cutting-edge artificial intelligence technology to extract information from listed companies' annual reports and construct climate risk assessment indicators for these companies. It quantitatively analyzes the climate risk levels of listed companies in China and, based on this, examines the impact of climate risk on investment returns. The main conclusions are:

First, the climate risk of listed companies shows a clear trend of change over time. From 2020 to 2022, the climate risk of listed companies in China has generally increased, which may be related to the introduction of the "dual carbon" goals of carbon peak and carbon neutrality. The attention to climate risk from market regulators, investors, and even the companies themselves has steadily increased.

Second, there is a significant positive correlation between the climate risk of listed companies and investment returns. Specifically, for each unit increase in a listed company's climate risk, investment returns increase by 0.482. This indicates that the climate risk of listed companies is effectively priced in China's capital market. When investors take on more climate risk, they receive higher investment returns, and this result has passed robustness tests. In addition, the regression coefficients of climate risk and investment returns vary across companies of different ownership types. In terms of ownership structure, foreign and Sino-foreign joint venture listed companies show greater sensitivity of investment returns to climate risk.

Based on the above conclusions, the following policy recommendations are proposed: First, improve the climate risk evaluation system for listed companies and promote the application of artificial intelligence technology. To more comprehensively and scientifically assess the climate risks of listed companies, it is recommended that regulatory bodies and industry associations promote the establishment of a robust climate risk evaluation system. Currently, some companies perform poorly in climate risk management and urgently need clearer standards and guidelines to improve their management capabilities. At the same time, encourage the use of cutting-edge artificial intelligence technology to efficiently analyze climate-related information disclosed by listed companies, extracting valuable information from unstructured data such as text, images, audio, and video to construct dynamic and precise climate risk indicators. This will not only help optimize listed companies' assessment and management of their risks but also provide investors with more valuable decision-support tools.

Second, allocate regulatory resources reasonably, with a focus on listed companies with higher climate risks. Since listed companies in different industries, with different ownership structures, and in different listing locations exhibit significant differences in climate risk levels and sensitivity to investment returns, it is recommended that regulatory bodies allocate resources based on these heterogeneous characteristics. For industries with high carbon emissions and greater climate risks (e.g., power, construction, etc.), it is necessary to strengthen policy supervision and technical support to help these sectors accelerate their green transformation. For foreign-invested or Sino-foreign joint venture enterprises with good climate risk management, regulatory pressure can be appropriately reduced, and they should be encouraged to share their experiences and best practices. In addition, attention should be paid to the increasing climate risk trend among companies listed on the Shenzhen Stock Exchange and Shanghai Stock Exchange, and targeted policies should be formulated to urge relevant companies to improve their management while assessing the potential impact on investors and the capital market.

This study also has certain limitations. In constructing the climate risk indicators for listed companies, this study employed a pre-trained language model to classify the text of annual reports, primarily to determine whether the content was related to climate risk. However, this method remains relatively coarse in classification accuracy and fails to distinguish specific types of climate risks, such as physical risks and transition risks. Future research could refine the classification criteria further and conduct a more nuanced analysis of text content to reveal the different categories of risks faced by companies. Additionally, sentiment analysis techniques could be introduced to identify the emotional tone of statements about climate risk in the text, such as positive or negative sentiments, enabling a more comprehensive and accurate assessment of climate risk levels for listed companies. This would provide more practically relevant references for related fields.

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Conflict of interest

The authors affirm that they do not have any identifiable competing financial interests or personal relationships that could be perceived as influencing the work presented in this paper.

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