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The Impact of Climate Risk Perception Bias on Corporate Investment Efficiency: Evidence from China

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Abstract:
As a long-term systematic risk factor that affects corporate earnings, climate risk profoundly impacts corporate behavior and decision-making. By making reasonable judgments about climate risk and adopting corresponding countermeasures, companies can mitigate inefficient investments resulting from biased perceptions of climate risk. This study analyzes the impact of climate-related perception bias on inefficient investment decisions among A-share listed companies in China from 2011 to 2023. The results demonstrate that biased perceptions of climate risk significantly increase business investment inefficiency; specifically, a greater degree of climate risk perception bias in a company correlates with a higher level of inefficient investment. The research fills the gap between climate risk perception and investment efficiency, providing valuable insights for policymakers and senior company management.

Keywords: Climate Risk, Climate Risk Perception, Cognitive Bias, Investment Efficiency

1 Introduction

At the beginning of the 21st century, extreme weather phenomena attributable to climate change have been occurring frequently and with increasing intensity, impacting the lives and economies of countries. In November 2023, S&P Global released a report titled "Lost GDP: Potential Impacts of Physical Climate Risks," which predicted a temperature rise of 2.1 degrees Celsius by 2025, with a potential annual loss of up to 4.4 percent of the world's GDP if no measures are taken. Given the ongoing climate concerns and their significant economic repercussions, topics relating to climate risk have garnered heightened interest. Currently, most studies concentrate on the economic effects of climate risk, including economic growth, financial stability, employment dynamics, and public health (Groen et al., 2020; Atsalakis et al., 2021; Battiston et al., 2021). Numerous studies have examined the effects of climate risk on enterprises. According to prior research, climate risk not only has direct impacts on production facilities and supply chains but also indirect impacts on businesses through policies, markets, and consumers (Hallegatte et al., 2011; Brouhle and Harrington, 2019). For indirect impacts, most studies indicate that climate risk is detrimental to firms' financial performance and earnings volatility (Huynh and Xia, 2021; Du et al., 2023). Based on this, this study uses A-share listed companies in China from 2011 to 2023 as the subject of investigation and empirically analyzes how companies' climate risk perception bias influences inefficient investment.

In comparison to current research, the contributions of this study are as follows: firstly, few studies have focused on the impacts of companies' own judgment bias regarding climate risk on their inefficient investment, which is a key factor related to companies' cash flow, value, and competitiveness (Li et al., 2024). This work enhances the understanding of climate risk and climate risk perception in the academic community. Second, this study broadens the investigation of the determinants that lead to companies' inefficient investment. Research on corporate investment efficiency primarily focuses on its determinants, such as information asymmetry, principal-agent problems, managerial characteristics, investment environment, etc. (Isabel and Emma, 2018; Bilyay et al., 2024). This study expands the research scope of corporate investment efficiency from the perspective of climate-related perception bias. Finally, the outcome of the heterogeneity analysis provides essential insights for authorities to develop policies and for companies to form top management teams.

2 Theoretical Analysis and Hypothesis Development

Climate risk can be classified as physical risk and transition risk, as delineated by the Task Force on Climate-related Financial Disclosures (TCFD). Among them, physical risk comes from large-scale natural disaster events caused by severe meteorological phenomena and prolonged alterations in climatic trends; transition risks refer to the risks in terms of policy costs and market operations with the transition of society to a zero-emission process (DU et al., 2023). Scholars currently focus on physical and transition risks (Chen et al., 2021), which interact with each other to impact companies and their investment activities.

Cognitive bias, a systematic pattern of deviation from norms or rationality in judgement, is not unique to a particular industry, as all humans can be irrational in their decision-making (Wattanacharoensil and La-ornual, 2019), so even the most prominent business executives can be unconsciously biased. The existing studies on climate risk perception bias mainly focus on micro-individuals, which are affected by personal experiences, social interactions, spatial dimensions, and psychological factors (Moussaïd et al., 2015; Kube et al., 2024). This study seeks to broaden research by examining the relationship between firms' judgmental bias on the climate risks they face and their investment efficiency. Climate risk perception bias refers to systematic errors in firms' perceptions and judgments of climate risk, which may stem from individual management's subjective risk biases, incomplete market information, or limitations of existing cognitive frameworks. Corporates facing climate risk without a scientific risk assessment methodology often find it challenging to find the optimal solution between different investment options. This may lead to overestimating or underestimating the extent of climate change risk. At the same time, corporate management also faces information asymmetry and principal-agent problems under the multidimensional impact of climate risk. The information asymmetry prevents shareholders from fully understanding management's decision-making process and weakens their trust in management's decision-making, exacerbating the corporation's agency problem. At the same time, the management may be more concerned with personal interests than shareholder interests; this misalignment of interests leads to the possibility that management may ignore long-term climate risk. Therefore, when management's assessment of climate risk is biased, either by overestimation or underestimation, it may lead to an inappropriate allocation of corporate resources. Based on the preceding analysis, the hypothesis is formulated as follows.

Hypothesis: Climate risk perception bias has a significant positive effect on corporate inefficient investment.

3 Research Design

3.1 Sample Selection and Data Sources

This study selects A-share listed companies in China during 2011–2023 as the primary samples to examine the link between climate risk perception bias and investment efficiency. To guarantee the integrity of the data, the subsequent procedures are executed: (1) the samples of corporations in financial industries are omitted; (2) corporations labeled with ST, ST*, and PT are excluded; (3) samples with key variables omitted are excluded; (4) to mitigate the impact of severe outliers, all continuous variables are winsorized at the 1% and 99% deciles. Finally, 19,626 sample observations were obtained.

The climate risk index data comes from the China Climate Change Blue Book each year, and the climate risk perception index is collated from the China Stock Market & Accounting Research (CSMAR) database, the Chinese Research Data Services (CNRDS) platform, Germanwatch and the annual reports of listed companies.

3.2 Research Model

This study develops an empirical model to examine the association between climate risk perception bias ($Bias\_CRP$) and corporate investment efficiency (Inv_eff):

$$Inv\_eff_{i,t} = \alpha_0 + \alpha_1 Bias\_CRP_{i,t} + \sum_k \alpha_k Controls_{i,t} + Firm_i + Year_t + \epsilon_{i,t} \tag{1}$$

Where i denotes firm, t denotes time; $Inv\_eff_{i,t}$ is firm's inefficient investment; $Bias\_CRP_{i,t}$ is firm's climate risk perception bias; $Controls_{i,t}$ is a set of control variables; $Firm_i$ is an individual fixed effect; $Year_t$ is a year fixed effect; $\epsilon_{i,t}$ is the random error term.

If the hypothesis is valid, the regression coefficient α_1 of climate risk perception bias ($Bias\_CRP_{i,t}$) should be significantly positive.

3.3 Key Variables

3.3.1 Dependent variable

Corporate inefficient investment (Inv_eff). In this study, we chose Richardson (2006) residual measure model to calculate the company inefficient investment through the model residual, model (1) is expressed as follows:

$$Inv_{i,t} = \alpha_0 + \alpha_1 Growth_{i,t-1} + \alpha_2 Lev_{i,t-1} + \alpha_3 Cash_{i,t-1} + \alpha_4 Age_{i,t-1} + \alpha_5 Size_{i,t-1} + \alpha_6 Roa_{i,t-1} + \alpha_7 Inv_{i,t-1} + \sum Ind + \sum Year + \epsilon_{i,t} \tag{2}$$

Where i represents the corporate; t represents the time; $Inv_{i,t}$ denotes the actual new investment expenditures of corporate i in year t; $Growth_{i,t-1}$, $Lev_{i,t-1}$, $Cash_{i,t-1}$, $Age_{i,t-1}$, $Size_{i,t-1}$, $Roa_{i,t-1}$, $Inv_{i,t-1}$ denote the growth of corporation i in year $t-1$, gearing ratio, cash holding level, age of the corporation, size of the corporation, stock yield and new investment expenditure, respectively; $\sum Ind$, $\sum Year$ are the fixed effects, respectively; $\epsilon_{i,t}$ denotes residual value of regression of model (2). Residual value, the absolute value of which is the level of corporate inefficient investment, the larger the magnitude of the residual, indicating that the more inefficient the company's investment is. This study uses the absolute value of the residual $|\epsilon|$ to indicate the level of corporate inefficient investment.

3.3.2 Independent variable

Climate risk perception bias ($Bias\_CRP$). For the corporate climate risk perception level (CRP), this study refers to the research of Li et al. (2023) and Du et al. (2023b). It adopts the climate risk manager concern index to measure companies' climate risk perception level; the data is obtained from the MD&A sections in the annual filings of listed companies. The construction methodology involves initially developing a climate risk perception lexicon utilizing the Word2vec model. Subsequently, the word frequency pertaining to climate risk is obtained from the annual report using text analysis and machine learning. Furthermore, the aggregate word frequency associated with climate risk for each company is extracted from the annual report annually, employing the Jieba library for the word segmentation process, finally, dividing the frequency of climate-related terms by the overall word count in the text of the annual report and calculating the relative frequency of occurrence, and standardized them. For the climate risk index (CRI), this study takes the office location of each company as the target and refers to the construction method of Guo et al. (2024).

In this study, a company's climate risk perception level (CRP) and the climate risk index (CRI) are standardized, and the absolute value of the difference between the two is calculated as a measure of the bias in the company's climate risk perception ($Bias\_CRP$).

3.3.3 Control variables

To minimize the error from omitted variables, this study primarily accounts for the financial and governance characteristics that may influence corporate investment efficiency. It selects the following control variables: factors directly affecting the investment efficiency of companies include firm size ($Size$), firm age (Age), corporate financial leverage (Lev), cash flow status ($Cash$), corporate growth opportunity ($Growth$), and net return on assets (Roa); company-level characteristic variables are selected as fixed assets ratio ($Fixed$); company governance level variables are selected as percentage of independent directors ($Inst$), management shareholding ratio ($Mshare$), and CEO duality ($Dual$) which is a dummy variable that equals one if the CEO is also the chairperson, and zero otherwise. The specific variable definitions are shown in Table 1.

Table 1 Variable definitions and descriptions

Variable Type	Variable Name	Variable Symbol
Dependent variable	Corporate inefficient investment	*Inv _ eff*
Independent variable	Climate risk perception bias	*Bias _ CRP*
	Firm size	*Size*
	Firm age	*Age*
	Corporate financial leverage	*Lev*
	Cash flow status	*Cash*
Control variables	Corporate growth opportunity	*Growth*
	Net return on assets	*Roa*
	Fixed assets ratio	*Fixed*
	Percentage of independent directors	*Inst*
	Management Shareholding Ratio	*Mshare*
	CEO duality	*Dual*

4 Analysis of Empirical Results

4.1 Descriptive Statistics

Table 2 demonstrates the results of descriptive statistical analysis of the main variables. As shown in Table 2, the mean value of inefficient investment (*Inv _ eff*) of China's A-share firms from 2011-2023 is 0.040, and the standard deviation is 0.049, indicating apparent differences in investment efficiency among firms. The mean value of corporate climate risk perception bias (*Bias _ CRP*) is 10.169, and their standard deviation is 10.568, indicating considerable fluctuations in climate risk perception bias across firms in the sample time interval. In addition, the descriptive statistics of each control variable are within reasonable limits.

Table 2 Descriptive statistics

Variable	Observations	Mean	Median	Standard deviation	Min	Max
Inv _ eff	19626	0.040	0.024	0.049	0	0.301
Bias _ eff	19626	10.169	6.587	10.568	0.148	52.645
Size	19626	22.415	22.231	1.305	20.044	26.153
FirmAge	19626	2.964	2.996	0.311	1.946	3.526
Lev	19626	0.442	0.436	0.205	0.065	0.889
Cash	19626	0.047	0.046	0.066	-0.144	0.224
Growth	19626	0.143	0.095	0.344	-0.504	1.795
Fixed	19626	2.964	2.996	0.311	1.946	3.526
Inst	19626	0.450	0.470	0.242	0.005	0.905
Mshare	19626	10.790	0.222	17.410	0	65.050
Dual	19626	0.251	0	0.433	0	1

4.2 Benchmark Regression

Column (1) of Table 3 presents the outcomes of the benchmark regression without control factors, accounting solely for individual and year fixed effects, whereas Column (2) displays the results of the regression after incorporating control variables. In columns (1) and (2), the corporate climate risk perception bias and its inefficient investment are highly positive at the one percent level, suggesting that the company's own climate risk perception bias will significantly reduce its investment efficiency. More climate risk perception bias correlates with increased inefficient investment, which preliminarily verifies the hypothesis of this study.

Table 3 Benchmark regression results

Variable	(1)	(2)
	Inv _ eff	*Inv _ eff*
Bias _ eff	0.0003***	0.0003***
	(0.000)	(0.000)
Size		-0.0030***
		(0.001)
Lev		0.0165***
		(0.004)
ROA		0.0696***
		(0.008)
Cash		-0.0296***
		(0.006)
Fixed		-0.0482***
		(0.005)
Growth		0.0151***
		(0.001)
FirmAge		-0.0172**
		(0.007)
Inst		0.0229***
		(0.004)
Mshare		0.0002***
		(0.000)
Dual		-0.0001
		(0.001)
_cons	0.0459***	0.1414***
	(0.002)	(0.027)
Firm\&Year	control	control
N	19626	19626
r^2_a	0.035	0.001

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Robustness Test

To validate the dependability of the benchmark regression results, further robustness tests will be conducted as follows.

4.3.1 Alternative the measure of dependent variable

Corporate inefficient investment (*Inveffi _ Bid*). Applying the method of Biddle et al. (2009) to develop the company investment efficiency measurement model, as shown in model (3). In this framework, the magnitude of the residual $|\epsilon|$ indicates the extent of investment inefficiency, with a higher value indicating lower investment efficiency. Inv denotes the corporate's new investment expenditure, and $SalesGrowth$ denotes the growth rate of sales revenue.

$$Inv_{i,t} = \alpha_0 + \alpha_1 SalesGrowth_{i,t-1} + \epsilon_{i,t} \tag{3}$$

The company investment efficiency measured by the above Biddle model is substituted into model (2) for regression, and column (1) in Table 4 indicates the regression results. The findings indicate that the climate risk perception bias ($Bias\_CRP$)coefficient is positive at 5% and passes the robustness test.

4.3.2 Alternative the measure of independent variable

Climate risk perception bias ($Bias\_CRP'$). Regarding the studies conducted by Du et al. (2023a), the terminology concerning climate change risk is derived from the analysis of corporate annual reports and the China Meteorological Disasters Yearbook to compile the lexicon. By dividing the cumulative frequency of climate-related risk terms by the total word count of the annual report, followed by logarithmic transformation, the climate risk index has been computed. Finally, the ratio of the climate risk index constructed by Kun et al. (2024) in the previous study to the logarithmic climate risk indicator is used as the level of perceived corporate climate risk bias. Column (2) of Table 4 shows that after replacing the explanatory variable, the regression coefficient of climate risk perceived bias ($Bias\_CRP'$) is significantly positive at the 1% level, suggesting that the result of the benchmark regression is robust.

4.3.3 Excluding effects of COVID-19

Considering the impact of COVID-19 on the global economy in 2020 and the increased risk faced by firms, this study excludes the sample data after 2019 to conduct the regression analysis again. The findings in Table 4, column (3), show that the regression coefficient for climate risk perception bias ($Bias\_CRP$) is significant at the 10 percent level and aligns with the sign of the baseline regression results, thereby passing the robustness test.

Table 4 Robustness test results

Variable	(1)	(2)	(3)
	$Inveffi\_Bid$	Inv_eff	Inv_eff
$Bias\_CRP$	0.0002** (0.000)		0.0002* (0.000)
$Bias\_CRP'$		0.0009*** (0.000)	
$\_cons$	0.0485* (0.025)	0.1391*** (0.027)	0.1522*** (0.042)
$Firm\backslash\&Year$	control	control	control
N	19626	19626	19626
R^2	0.144	0.133	0.130

\Standard errors in parentheses
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

4.4 Endogeneity Test

4.4.1 Propensity score matching

To mitigate the endogeneity issue arising from sample self-selection and acknowledge that enterprises' perceptions of climate risk may stem from both internal features and the external environment, this work draws upon Du et al. (2023b). It takes the median of the sample firm's climate risk perception bias ($Bias\_CRP$) as a criterion; samples larger than the median are considered the experimental group, while those smaller than the median form the control group. The control variables are treated as covariates, and the 1:1 nearest neighbor matching technique is applied. The matched experimental and control groups retained 19,600 observations; only 26 observations are lost, and after the balance test, the matching effect is good. Regression is performed based on the matched samples, and the regression findings indicate that the coefficient for climate risk perception bias ($Bias\_CRP$) is 0.0003 and is significant at the 1% level, aligning with the benchmark regression and confirming robustness.

4.4.2 Hysteresis effect analysis

Considering the lagged effect of sample firms' climate risk perception bias ($Bias\_CRP$) on investment decisions, this study lags the principal explanatory factors by one period. The regression results, column (2) of Table 5, demonstrate that the impact of climate risk perception bias on corporates' inefficient investment is considerably positive at the 1% level, aligning with the benchmark regression analysis findings and passing the robustness test.

4.4.3 Instrumental variable (IV) approach

To address the errors associated with reverse causation, this study lags climate risk perception bias ($Bias\_CRP$) by one and two periods respectively, serving as an instrumental variable and uses two-stage least squares (2SLS) to deal with endogeneity. Since the formation of climate risk perception is usually a dynamic process influenced by historical experience, using lagged variables can better capture this time continuity and enhance the identification of causality. Table 5 displays the outcomes of the first-stage regression of instrumental variables concerning climate risk perception bias while accounting for individual and year-fixed effects. Column (3) of Table 5 presents regression results indicating that IV is significantly correlated with climate risk perception bias ($Bias\_CRP$) at the 1% level, and the findings show that the independent variable is significantly and positively correlated with the dependent variable. This aligns with the prior benchmark regression findings and further corroborates the robustness of the regression outcomes.

Table 5 Endogeneity test results

Variable	(1)	(2)	(3)	(4)
	Inv_eff	Inv_eff	Inv_eff first stage	Inv_eff second stage
$Bias\_CRP$	0.0003*** (0.000)	0.0003*** (0.000)		0.0007*** (0.000)
IV1			0.3687*** (0.010)	
IV2			0.0843*** (0.013)	
$\_cons$	0.0419 (0.044)	0.1318*** (0.033)	-7.5504* (3.902)	0.1259*** (0.042)
$Firm \backslash\& Year$	control	control	control	control
N	19600	19626	19626	19626
R^2	0.089	0.140	0.764	0.063

Standard errors in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

5 Heterogeneity Analysis

5.1 Environmental Background of Executives

Based on the upper echelons theory, many scholars have discovered that the professional experience of executives significantly impacts corporate innovation, risk-taking, financial performance, etc. (Benmelech and Frydman, 2015). Therefore, from the reasoning of the upper echelons theory, the environmental professional experience of executives will also contribute to corporate environmental decision-making (Wang et al., 2022). The study characterizes the employment of executives with environmental credentials; the item is a dummy variable. Assume the corporation possesses one or more leaders with environmental expertise on its executive team in the current year. In that case, the company is considered to possess executives with environmental expertise in the present year, and it takes the value of 1. Otherwise, it is 0. As for the measurement method of the environmental background indicator of the executives, following the study by Wang et al. (2022) and the personal biographical information published by the website of Sina Finance is collected. Personal resume information, such as personal resume contains ‘environment’, ‘environmental protection’, ‘new energy’, ‘clean energy’, ‘ecological’, ‘environmental protection’ and ‘clean energy’, ‘ecological’, ‘low-carbon’, ‘sustainable’, ‘energy-saving’, ‘green’, and other keyword samples will be recognized as having an environmental background.

Table 6 displays the findings of the analysis on how executives’ environmental background influences the effect of climate risk perception bias on companies’ inefficient investment. The results reveal that the significance level of climate risk perception bias ($Bias\_CRP$) affecting inefficient investment (Inv_eff) is much lower in firms whose executives have an environmental background than in companies whose executives do not. This study suggests that the reason for this may be that when executives have experience in environmental preservation and environmentally friendly growth, they have a deeper comprehension of ecological issues and climate-related risks, along with a heightened awareness regarding how climate change directly impacts business activities and associated market and policy dynamics, which makes them more objective and precise in assessing climate risks; this helps corporations use resources more efficiently and reduce ineffective inputs in environmental governance, thus mitigating the impact of climate risk perception bias on inefficient investments.

Table 6 Heterogeneity Analysis

Variable	(1)	(2)
	Environmental background of executives	
	Yes	No
$Bias\_CRP$	0.0002* (1.95)	0.0003*** (3.31)
Controlvariables	control	control
Firm\&Year	control	control
N	4557	15069
R^2	0.108	0.139

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

This study experimentally examines the influence of climate risk awareness bias on business investment efficiency, employing a two-way fixed effects approach with Chinese A-share listed businesses data spanning 2011 to 2023. The findings of this study are as follows: First, the lower the climate risk perception bias, the less inefficient the corporate investment tends to be. Following the endogeneity and robustness tests, this finding remains valid; secondly, the heterogeneity test indicates that in firms led by executives lacking an environmental background, the effect of climate risk perception bias is more significant. Considering the facts above, this article recommends the following policy recommendations: Government agencies should offer training to enhance companies’ understanding of climate risks, establish unified risk assessment standards, and encourage the integration of these into business strategies; companies should prioritize leaders with environmental expertise to reduce inefficient investments from climate risk biases. Incentivizing environmental performance can further promote green practices and social responsibility.

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