



Article

How Does Climate Risk Affect the Cost of Debt in Chinese A-Share Listed Firms? Evidence from Financial and Non-Financial Transmission Channels

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Abstract

Drawing on a panel of Chinese A-share listed firms covering 2007 to 2024, we construct a firm-level measure of climate risk exposure based on textual analysis of annual reports. Employing a three-way fixed effects model combined with endogeneity corrections and a battery of robustness checks, we empirically identify the causal effect of climate risk on the cost of debt, as well as its underlying transmission mechanisms and heterogeneous boundary conditions. Our analysis yields three core findings. First, climate risk exerts a statistically significant and economically meaningful positive effect on the cost of debt, indicating that greater climate risk exposure amplifies firms' debt financing burdens. Second, the impact operates through two parallel transmission channels. On the one hand, climate risk erodes corporate financial fundamentals by disrupting production and operations and elevating default risk. On the other hand, it damages non-financial reputation by triggering downgrades in Environmental, Social, and Governance (ESG) ratings and weakening long-term financing credibility. Third, the relationship between climate risk and the cost of debt is significantly moderated by firm- and industry-level characteristics: high-quality information disclosure attenuates the adverse financing impact of climate risk, while affiliation with heavily polluting industries strengthens this positive association. These findings remain robust to alternative measures of climate risk and the cost of debt, alternative clustering specifications, high-dimensional interactive fixed effects, and sub-sample tests with restricted sample windows. To address endogeneity concerns stemming from reverse causality and omitted variable bias, we adopt two complementary identification strategies: using one-period lagged values of the core explanatory variable and conducting instrumental variable estimation via two-stage least squares (2SLS). Estimates from both approaches remain statistically and economically consistent with our baseline results. Further heterogeneity analyses show that the cost-increasing effect of climate risk is more pronounced for firms without ESG fund ownership, non-state-owned enterprises (non-SOEs), and firms located in non-eastern regions of China. Overall, this study provides novel firm-level evidence on the microeconomic consequences of climate risk in emerging economies, develops a dual transmission framework integrating financial fundamentals and non-financial reputation, and offers actionable implications for policymakers, financial institutions, and firms to improve climate risk governance and optimize the financing environment amid the low-carbon transition.



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1. Introduction

Driven by worsening global climatic conditions, climate risk has garnered increasing attention from scholars and policymakers alike and represents a pressing challenge for all economies. The physical risks stemming from climate change are intensifying and leading to significant economic losses. As documented in the *China Climate Change Blue Book (2025)* issued by the China Meteorological Administration (CMA) in June 2025, China stands as a region highly vulnerable to global climate change, with a warming pace that notably outpaces the global average for the corresponding period. Extreme weather events such as extreme heat, floods, droughts, and typhoons occur frequently. The global average surface temperature in 2024 reached a new high since 1850. To illustrate, the unprecedented rainstorm that hit Zhengzhou, Henan Province in 2021 caused direct economic losses of up to 133.7 billion yuan; the strong wind event in Nanchang in 2023 damaged the factory facilities of 14 local firms and disrupted their production lines, which impacted multiple downstream industries (China Meteorological Administration, 2025). For listed companies, the impact of physical risks is particularly profound: on the one hand, disasters directly reduce the value of corporate collateral assets, eroding the collateral value backing bank loans, forcing banks to tighten lending rates or contract credit lines; on the other hand, extreme weather triggers supply chain disruption risks along the industrial chain, pushing up the overall risk premium and amplifying firms' operational uncertainty. At the same time, creditors have increasingly factored climate vulnerability into their evaluation of firms' debt repayment capacity, and firms in high-risk areas often face more stringent credit conditions. Thus, climate risk not only directly disrupts corporate production and operations but also systematically raises the cost of debt through the financing channels.

Against the backdrop of global warming driven by anthropogenic carbon emissions, China unveiled its "dual carbon" objectives in 2020, namely attaining carbon peak by 2030 and carbon neutrality by 2060, marking a historic shift in China's economic growth model toward green and low-carbon development. The Report to the 20th National Congress of the Communist Party of China further emphasized "gradually shifting from energy consumption control to carbon emission control" and "actively participating in global climate governance". To achieve the "dual carbon" goals, China has rolled out a suite of supporting policies such as launching a national carbon emissions trading market, tightening environmental regulations, imposing stricter capacity constraints on high-carbon industries, and upgrading environmental information disclosure standards. These policies have significantly increased the transition risks faced by firms, especially high-carbon firms. To avoid negative consequences such as fines and mandatory production halts for rectification, firms must allocate substantial capital to low-carbon technology research and development, equipment renewal, and operational restructuring. These large-scale, long-cycle investments directly reshape firms' cash flows and capital structures and may further drive up the cost of debt. Accordingly, exploring how climate risk shapes the cost of debt and its underlying transmission mechanisms carries strong practical relevance amid the ongoing rollout of "dual carbon" policies.

In this context, this study systematically examines the impact of climate risk on the cost of debt and its underlying transmission mechanisms. By identifying the paths through which climate risk increases the cost of debt via the transmission channels of firm fundamentals (production and operation disruptions, rising default risks) and non-financial performance (decreased Environmental, Social and Governance (ESG) ratings), this paper attempts to reveal the moderating effects of factors such as information disclosure quality and industry pollution attributes, and provide a theoretical basis for formulating differentiated climate risk governance and green financing support policies. This study not only helps deepen the understanding of the microeconomic consequences of climate

risk but also provides empirical evidence and policy implications for firms to optimize financing decisions, financial institutions to improve risk pricing, and governments to advance the “dual carbon” goals.

Collectively, our study makes modest incremental contributions to the climate finance literature. From a theoretical perspective, we integrate the dual dimensions of financial fundamentals and non-financial reputation to systematically delineate the parallel transmission channels through which climate risk drives up the corporate cost of debt, offering a more cohesive analytical framework for unpacking how climate risk propagates to corporate financing outcomes. For heterogeneity analysis, we present novel empirical evidence from the lens of ESG institutional investors, complemented by moderating effect tests on information disclosure quality and industry pollution intensity, to deliver more granular empirical support for designing differentiated climate risk governance schemes and green financing policies. Our study also makes two methodological contributions. First, we develop a firm-level text-based climate risk indicator adapted to China’s institutional context and validate its effectiveness via multi-dimensional cross-validation against objective benchmarks, which provides a replicable measurement paradigm for future micro-level climate risk research. Second, we augment the standard two-way fixed effects specification by adding industry fixed effects to more thoroughly isolate the confounding effects of time-invariant industry attributes and cyclical industry trends. While these approaches leave room for further refinement, they offer a useful methodological reference for empirical research in climate finance.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and develops our research hypotheses. Section 3 outlines the research design. Section 4 reports the empirical findings and robustness tests. Section 5 investigates heterogeneity, while Section 6 explores the mechanisms via mediation and moderation analyses. Section 7 discusses the contributions, and Section 8 concludes with policy recommendations and avenues for future research.

2. Literature Review and Theoretical Hypotheses on Climate Risk and Cost of Debt

2.1. Related Literature

2.1.1. Conceptual Connotation and Measurement Approaches of Climate Risk

Climate risk refers to the potential impacts of climate-change-induced natural environmental alterations on corporate operations and financial conditions. It encompasses two core dimensions, namely physical risk and transition risk (Goodell et al., 2025). Physical risk stems from extreme weather events such as floods and droughts as well as long-term environmental degradation caused by climate change. By directly eroding corporate assets, supply chains, and operational capacity, physical risk induces balance sheet contraction and systemic financial risks, and ultimately undermines macroeconomic stability (Y. Sun et al., 2024). The adverse effects of physical risk are primarily manifested as financial risks arising from the failure to effectively address climate change, with more immediate short-term impacts on the financial system. For example, extreme events like floods significantly raise firms’ implied cost of equity, while drought exposure widens corporate bond credit spreads. Such risks drive up debt financing premiums by undermining cash flow stability and increasing the probability of financial distress (Dessaint & Matray, 2017).

By contrast, transition risk is associated with low-carbon economic policies such as carbon taxes, technological innovation, and shifts in market preferences. It may erode corporate value through stranded assets and rising compliance costs (Huang et al., 2018). This type of risk exerts indirect and potential long-term effects on the financial system.

Regarding the measurement of climate risk, existing studies have mainly developed three approaches. The first approach is based on textual analysis. This method relies on predefined dictionaries containing climate-related keywords and identifies firms' climate risk exposure by counting word frequencies in texts such as earnings conference call transcripts (Sautner et al., 2023; Hassan et al., 2019). The second approach measures climate risk indirectly from the perspective of firms' internal climate responses and policy adaptation, using indicators such as carbon emission intensity (Cheng et al., 2025), climate policy sensitivity, climate policy uncertainty, and carbon debt (Pelz et al., 2025). A third strand of the literature centers on exogenous extreme climate shocks and quantifies climate risk exposure based on the occurrence frequency of extreme weather events—including heatwaves, cold spells, and extreme precipitation—or firms' geographic exposure to climate hazards (Anghel et al., 2025).

2.1.2. Climate Risk and Corporate Behavior

In recent years, climate risk driven by worsening climatic conditions has drawn increasing academic and policy attention worldwide, emerging as a critical challenge for all economies. Climate risk exerts extensive impacts on corporate production and operations (Griffin et al., 2017). Existing literature indicates that climate risk not only has direct impacts on firms' production supply chains, operations, and cash flows (Hallegatte et al., 2011; Kousky & Cooke, 2012), but also produces indirect impacts, which operate primarily through three corporate response channels.

First, firms mitigate managerial myopia by strengthening internal awareness-building mechanisms and investor oversight systems (G. Liu et al., 2022), and develop robust climate risk governance frameworks to reinforce cash flow management (Busch et al., 2016; Z. Li et al., 2022). Second, firms improve the quality of climate risk information disclosure (Brooks & Oikonomou, 2018), guiding investors to assess relevant risks rationally and objectively so as to avoid drastic fluctuations in financial markets (W. Wang, 2025). Third, firms proactively adapt to the trend of policy- and market-driven transformation, increase investment in green and low-carbon transition, and enhance their resilience to climate-related risks (Busch et al., 2016). In addition, firms' responses to climate change are closely related to their social responsibility. Firms should actively address climate change to promote sustainable economic development (Orlitzky et al., 2011).

2.1.3. Climate Risk and the Cost of Debt

A growing body of empirical evidence confirms that elevated climate risk translates into a higher cost of debt for listed firms: the greater a firm's climate risk exposure, the higher its corporate cost of debt (Q. Li et al., 2024). Moreover, a high perception of climate risk incentivizes firms to diversify their debt structures, cut short-term borrowings, and extend long-term financing.

Climate risk imposes multifaceted pressures on listed firms' external financing: in addition to raising the cost of debt, it further restricts firms' access to capital and amplifies financing frictions. Related research further explores the impact of carbon risk on listed firms' investment and financing behavior and finds that carbon risk significantly shapes firms' financing preferences and capital structures (He & Zhang, 2024). Furthermore, Gregory (2024) reveals that climate risk increases firms' probability of debt default, which prompts financial institutions to tighten credit conditions and thus affects corporate financing constraints. The rising cost of debt can also trigger restrictive clauses in debt covenants, further constraining firms' financing flexibility (Dietz et al., 2016). In terms of debt maturity, climate risk exposure drives firms to shorten debt maturity to reduce liquidity risk (Huynh & Xia, 2021).

Accordingly, institutional investors pay increasing attention to climate risk in their investment decisions. This trend is of great significance for corporate sustainability and future development, as the investment decisions and preferences of institutional investors affect firms' financing costs and market value. Some scholars focus on policy uncertainty within transition risk. For example, stricter carbon regulation elevates investors' default risk expectations, leading to a higher cost of debt (P. Li et al., 2019).

2.1.4. Critical Review of the Literature

The accumulated body of established research delivers multifaceted theoretical and empirical support for ongoing inquiries into climate risk measurement, its microeconomic repercussions, and the determinants of corporate borrowing costs. Nonetheless, three critical research gaps persist: First, the validity of localized text-based climate risk metrics remains under-examined. Most existing lexicons are constructed in English-language contexts and fail to systematically control for confounding effects arising from heterogeneous disclosure styles. Second, the transmission mechanisms lack a unified analytical framework. Prior studies predominantly examine individual channels (e.g., default risk, ESG performance) in isolation, without differentiating the distinct logical mechanisms behind the financial fundamentals transmission pathway and the non-financial reputation transmission pathway. Third, the boundary conditions of heterogeneous effects are not fully explored. The moderating roles of internal and external governance factors—such as ESG institutional investors and information disclosure quality—have received limited scholarly attention.

To fill these gaps, this study makes three key extensions. First, we develop a firm-level textual climate risk indicator tailored to the Chinese institutional context and validate its effectiveness against objective benchmarks. Second, we propose a dual-channel framework integrating “financial fundamental transmission” and “non-financial reputation transmission” to disentangle the independent operational logics of the two pathways. Third, we conduct multi-dimensional heterogeneity and moderating effect analyses across ESG investor holdings, information disclosure quality, and industry pollution attributes, thereby delineating the boundary conditions of climate risk transmission.

2.2. Theoretical Analysis and Research Hypotheses

Extant literature has extensively examined the microeconomic impacts of climate risk, forming a broad consensus on climate risk measurement, transmission mechanisms, and financing implications. In terms of indicator construction, text mining-based firm-level risk measurement has become the mainstream paradigm. Sautner et al. (2023) constructed firm-level climate risk exposure and political risk indicators based on earnings conference call transcripts, respectively, laying a classic methodological foundation for micro-level risk identification. However, most existing lexicons are developed in English-language contexts, and localized indicators adapted to China's institutional setting still lack systematic multi-dimensional validity verification. In terms of economic consequences, existing research broadly confirms that climate risk significantly drives up the corporate cost of debt (Q. Li et al., 2024). Micro-geographic evidence based on flood risk (Bassetti et al., 2024) and bond market evidence based on climate news risk (Huynh & Xia, 2021) both provide multi-dimensional empirical support for this conclusion. Regarding transmission mechanisms, prior studies have examined channels such as default risk (G. Chen et al., 2023b) and ESG performance (H. Sun et al., 2022) in isolation, yet a cohesive integrated analytical framework is still lacking, and the distinct logics behind financial fundamentals and non-financial reputation transmission have not been clearly disentangled. Furthermore, existing research often conflates the concepts of debt financing cost and debt financing

capacity (financing constraints), which correspond to the “price dimension” and “quantity dimension” of debt financing, respectively, with markedly different operating mechanisms (Qiu et al., 2025).

Against this backdrop, this paper builds on classical risk premium theory, credit risk pricing theory, and signaling theory to construct a “dual-path parallel” analytical framework from two independent dimensions: financial fundamentals transmission and non-financial reputation transmission. This framework systematically clarifies the intrinsic mechanism by which climate risk affects the corporate cost of debt and fills research gaps such as the vague transmission mechanism framework and inadequate validation of localized measurement indicators. Research hypotheses are proposed accordingly.

2.2.1. The Impact of Climate Risk on the Cost of Debt

According to risk premium theory, the cost of debt essentially represents the pricing compensation charged by creditors for a firm’s risk exposure. The greater a firm’s operational uncertainty and default risk potential, the higher the risk premium demanded by creditors, which ultimately translates into a higher cost of debt. As an external shock characterized by both long-term persistence and abruptness, climate risk exerts a systemic impact on operational stability through physical risk and transition risk channels, serving as a critical factor driving up the cost of debt (Zhou et al., 2025).

Physical risk materializes through extreme weather events such as floods and heat-waves, which cause direct losses to firms’ tangible assets, disrupt production workflows, weaken cash flow stability, and raise the risk of financial distress, ultimately translating into higher debt financing premiums (Garbarino & Guin, 2021). Huynh and Xia (2021), using global bond market data, show that climate news risk significantly increases corporate bond yields by heightening investors’ risk perception, providing cross-market evidence for the debt cost effect of climate risk. From the transition risk perspective, amid the continuous advancement of low-carbon transition policies, institutional constraints such as carbon taxes and environmental regulations persistently raise firms’ compliance costs and asset impairment risks, exacerbating uncertainty in future earnings and cash flows (He & Zhang, 2024). Q. Li et al. (2024) point out that stricter carbon regulations raise investors’ expectations of firms’ default risk, ultimately driving up the cost of debt.

The two types of risks jointly elevate the overall risk level of firms. Rational creditors will incorporate climate risk into their credit risk assessment systems and raise lending rates to cover potential default losses. Climate risk exerts both direct effects on production factors (e.g., fixed assets and human capital) and indirect effects on future earnings and cash flows. These effects subject firms to higher risk premiums and, ultimately, more severe financing constraints (K. Guo et al., 2024). It should be clarified that this paper focuses on the price dimension of debt financing (i.e., the cost of debt), which differs from studies on “debt financing capacity/financing constraints” that emphasize financing availability and scale constraints (Qiu et al., 2025). We specifically examine creditors’ pricing adjustment behavior in response to climate risk, rather than the quantity contraction effect of credit scale. Based on the above theoretical analysis and literature support, this paper proposes Hypothesis 1:

H1. *Ceteris paribus, climate risk significantly drives up the corporate cost of debt.*

2.2.2. Financial Fundamental Transmission Path: Production Operations and Default Risk as Mediators

Credit risk pricing theory posits that firms’ production and operational performance and actual solvency are the core basis for creditors’ credit pricing. The degradation of corporate operational status directly elevates default risk exposure, and this heightened

default risk is ultimately priced into a higher cost of debt. As the core transmission path, the financial fundamentals channel underpins the primary effect of climate risk on corporate borrowing costs: climate risk disrupts normal production and operation activities, reduces profitability and cash flow quality, elevates debt default risk, and ultimately drives up the cost of debt.

Specifically, physical risk impacts production and operation through multiple pathways. On the one hand, extreme climate events directly destroy production factors such as fixed assets and inventories, leading to capital stock decline, lower labor productivity, and crowding-out of R&D resources, which ultimately reduce firms' total factor productivity and financial performance (Kousky & Cooke, 2012). Keen and Pakko (2011), based on a dynamic general equilibrium framework, also confirm that external shocks such as natural disasters exert persistent negative impacts on corporate production and operation through aggregate supply contraction and aggregate demand fluctuation channels. On the other hand, disaster shocks transmit along the industrial chain, triggering supply chain disruption risks that further amplify the negative impact on corporate operations (Ding et al., 2021). Driven by evolving regulatory restraints, transition risk imposes tangible constraints on firm operations. As China advances its dual-carbon targets, continuous policy tightening and stricter carbon reduction mandates raise corporate green transition overheads. Firms are required to invest heavily in equipment upgrading, technological innovation, and business restructuring, which collectively aggravate operational burdens and undermine operational stability (G. Chen et al., 2023a). The two types of risks jointly act on core production factors such as capital, labor, and total factor productivity, exerting a systematic negative shock on production and operation.

Persistent deterioration of production and operation will significantly increase firms' default risk. In the short term, extreme climate events reduce firms' production capacity and profitability while raising repair and response costs, directly weakening debt repayment capacity. In the long term, risks of asset stranding, declining investor confidence, and shifting market demand caused by climate-related policies, especially in high-carbon industries, exert sustained pressure on the stability of firms' capital chains and the likelihood of debt performance (G. Chen et al., 2023b). Most existing studies verify the mediating role of default risk separately; this paper further connects "hindered production and operation → rising default risk" into a complete chain transmission path, clearly depicting the full logical chain of climate risk penetrating into financial fundamentals. Based on stakeholder theory and the credit risk pricing mechanism, creditors will acutely identify operational difficulties and rising default risks caused by climate risk, and then demand higher risk premiums as compensation, specifically manifested as raising loan interest rates or tightening credit conditions (Zhang, 2022).

Based on the above analysis, this paper proposes Hypothesis 2:

H2. *Climate risk increases the cost of debt by impairing production and operations and elevating default risk. That is, there exists a financial fundamentals transmission path: climate risk → impaired production and operations → elevated default risk → higher cost of debt.*

2.2.3. Non-Financial Reputation Transmission Path: ESG Performance as a Mediator

Signaling theory and reputation theory indicate that in addition to financial fundamental information, firms' non-financial reputation is also an important reference dimension for creditors' risk assessment. Environmental, Social and Governance (ESG) performance, as a comprehensive reflection of firms' sustainable development capacity and social responsibility fulfillment, serves as the core carrier of corporate market reputation. Its quality affects creditors' risk perception and pricing decisions through signaling effects (Wu & Chen, 2024).

In debt pricing research, Cheng et al. (2025) further confirm based on signaling theory that ESG performance significantly affects corporate debt pricing through information transmission, and sound ESG performance can reduce creditors' risk perception and lower financing premiums (Shygun & Bezverkhyyi, 2026).

Climate risk impairs corporate ESG performance from multiple dimensions. In the environmental dimension, physical disasters such as floods and typhoons may cause secondary pollution problems, while carbon emission reduction gaps under transition pressure directly drag down firms' environmental performance scores. Meanwhile, climate-induced cash flow instability diminishes firms' incentives for low-carbon technology R&D, further weakening ESG performance (Cao et al., 2024). In the social dimension, issues such as supply chain disruption, employment fluctuation, and community impacts triggered by extreme climate increase firms' social risk exposure (Elliott et al., 2015). In the governance dimension, deficiencies in climate response strategies and imperfect risk control mechanisms expose shortcomings in internal governance. Moreover, transition risk-induced asset impairment losses adversely affect corporate financial statements, dragging down credit ratings and governance evaluations (Huynh & Xia, 2021; Bouri et al., 2022). In addition, when facing high external risks, firms tend to take a wait-and-see attitude toward ESG investment and postpone expenditures in environmental, social, and governance fields, further leading to declining ESG performance (J. Wang et al., 2023).

From the perspective of information transmission carriers, sustainability reports are the core medium for firms to disclose ESG information to external parties, and their disclosure quality and audit standardization directly determine the effectiveness of signal transmission (Meng & Zhang, 2022). The decline in ESG performance induced by climate risk shocks will directly weaken the positive signaling value of sustainability reports and exacerbate information asymmetry (Bezverkhyyi et al., 2025). Deteriorating ESG performance conveys a negative signal to creditors, indicating that the firm has limited long-term development resilience and fragile risk-bearing capacity, thereby prompting creditors to demand higher risk premiums to compensate for potential losses arising from reputational risks (Z. Li et al., 2022).

Different from the financial fundamental channel which focuses on changes in firms' actual solvency, the ESG channel emphasizes changes in creditors' risk perception and reputation evaluation. The two are parallel and independent transmission mechanisms, jointly constituting a complete logical framework for the impact of climate risk on the cost of debt.

Based on the above analysis, this paper proposes Hypothesis 3:

H3. *Climate risk increases the cost of debt by reducing ESG performance and undermining market reputation. That is, there exists a non-financial reputation transmission path: climate risk → impaired ESG performance → higher cost of debt.*

3. Empirical Strategy

3.1. Variable Definitions and Measurement

3.1.1. Measuring the Cost of Debt

The dependent variable is corporate debt financing cost, denoted as Cost. Following the standard empirical literature on Chinese listed firms, we measure Cost as the ratio of a firm's interest expense to its total liabilities at year-end, which captures the core interest burden of debt financing. Interest expense is extracted from the notes to the financial statements, representing the pure interest payments on debt obligations, excluding offsetting items such as interest income and exchange gains.

To ensure the robustness of the baseline findings, we adopt an alternative proxy Cost1 as a supplementary indicator. Calculated as the ratio of total financial expenses (including interest expenses, handling charges and other financing-related ancillary expenses) to total liabilities (Vig, 2013), Cost1 reflects the comprehensive actual burden of corporate debt financing.

3.1.2. Measuring Climate Risk

Climate risk (CR) indicator. Scientific measurement of firm-level climate risk is the key to the empirical study of this paper. Following the analytical framework of Sautner et al. (2023) and Q. Li et al. (2024), we develop a firm-level climate risk indicator adapted to China's institutional setting using text mining and Word2Vec word embedding techniques, based on listed firms' annual reports. Specifically, the measurement of the core explanatory variable climate risk (CR) includes three steps: initial word set selection of climate risk → expansion of similar words of climate risk → measurement and validity verification of climate risk indicators.

(1) Initial word set selection of climate risk. First, we use Youdao Translation and Google Translate to obtain the English–Chinese translations of the initial climate risk keywords identified in Sautner et al. and Li et al. Second, we exclude terms whose meanings clearly deviate from the concept of climate risk in the Chinese context. Third, we manually review more than 100 annual reports across various years and industries to resolve ambiguities in semantic meaning. Finally, we validate the initial word set with reference to the China Meteorological Disaster Yearbook. The resulting word set avoids the subjectivity of direct translation and aligns well with the Chinese context. Notably, this study performs textual analysis on the Chinese-language annual reports of Chinese A-share listed firms. The keyword set has been constructed in Chinese for word segmentation and frequency counting. Appendix A lists the English translations of these keywords, accompanied by an explanatory note that the original Chinese terms were used in the actual analysis.

(2) Expansion of similar words about climate risk. Since semantically equivalent terms may be phrased differently across annual reports, we further expand the initial keyword set to enhance its comprehensiveness and objectivity. We employ the Continuous Bag-of-Words (CBOW) model under the Word2Vec framework to conduct semantic expansion on the initial climate risk keyword set. The core hyperparameters are specified as follows: the dimensionality of word embeddings is set to 200, the context window size is 7, the minimum word frequency threshold is 5, the number of training epochs is 10, and the number of negative samples is 5. All other parameters are set to their default values as provided by the gensim library in Python 3.10. After model training, we rank candidate similar words corresponding to each initial keyword based on cosine similarity. Finally, we retain only those candidate terms that pass manual semantic verification and ambiguity resolution, incorporating them into the formal climate risk glossary.

(3) Measurement of climate risk indicators. Compared with using the raw frequency or its logarithm, the ratio of keyword frequency to total word count mitigates the confounding effect of document length on the validity of the measured indicator. Accordingly, using the predefined climate-related keyword dictionary, we compute the ratio of total keyword frequency to total text length, which serves as a proxy for firms' overall climate risk exposure. This indicator is positively associated with the firm's level of climate risk exposure.

Table 1 reports the descriptive statistics of climate risk across all dimensions. The aggregate climate risk index (CR) averages 0.037, meaning that climate-related terms account for 3.7% of the text in the average sample firm's annual report. This figure indicates that climate risk has become an important consideration in the operation and management

of Chinese firms. The CR index has a standard deviation of 0.041, a minimum of 0.000, a maximum of 0.118, and a median of 0.018. These figures reveal significant disparities in climate risk disclosure levels across firms, which provide a data foundation for subsequent heterogeneity analysis. In terms of sub-dimensional indices, the transition risk index has a mean of 0.002, while the physical risk index has a mean of 0.021, with the latter being approximately 10.5 times higher than the former. This indicates that physical risk dominates the climate risk disclosure of Chinese firms. This distribution pattern, in which physical risk predominates over transition risk, is consistent with the increasing frequency of extreme weather events and the associated substantial economic losses observed in China in recent years. The transition risk index exhibits a particularly low mean of 0.002, indicating that Chinese firms have devoted insufficient attention to long-term risks such as low-carbon policy adjustments and technological transformation. The corresponding disclosures are also limited, a pattern that may be explained by the still-incipient nature of the transition pressures currently facing these firms.

Table 1. Statistical Analysis of the Climate Risk Word Set.

	Mean	sd	Min	Max	P50
CR	0.037	0.041	0.000	0.118	0.018
Transition Risk Index	0.002	0.002	0.000	0.011	0.001
Physical Risk Index	0.021	0.028	0.000	0.115	0.012

Notes: All continuous variables are winsorized at the 1st and 99th percentiles. All three indicators are constructed under a unified measurement standard, calculated as the ratio of keyword frequency in the corresponding dimension to the total word count of the annual report. The sample consists of annual observations of Chinese A-share listed firms from 2007 to 2024.

Notably, the magnitude of CR reflects the intensity of climate risk disclosure in firms' annual reports, rather than a precise measure of the actual risk exposure faced by firms. Accordingly, a CR value of 0 does not mean that a firm faces zero actual climate risk; instead, it indicates that the firm does not disclose climate-risk-related information in its annual report for the current period. This represents a form of "silence" at the disclosure level, rather than the absence of risk itself. Several explanations may account for zero CR observations. First, some firms face inherently low climate risk, and management therefore does not consider it necessary to provide explicit attention or dedicated disclosure in annual reports. Second, some firms have not yet established formal risk identification and disclosure frameworks, even though they face some degree of climate risk. Third, some firms follow a conservative disclosure policy, confining themselves to regulatory minimums and refraining from voluntary disclosure. Fourth, some firms deliberately refrain from proactive disclosure after weighing the costs and benefits of revealing climate-related information. This interpretation aligns with the prevailing paradigm of constructing risk metrics based on corporate annual reports in text-based empirical research (Sautner et al., 2023; Q. Li et al., 2024).

To assess the validity of the CR indicator, we conduct correlation analyses between CR and two objective benchmarks: the number of extreme weather days at the firm's registered location and industry-level carbon emission intensity. The results show that CR is significantly and positively correlated with both objective benchmarks, confirming that, despite potential disclosure biases, the CR indicator still provides a reasonable proxy for firms' actual climate risk exposure overall.

(4) Validity Verification of the Climate Risk Indicator. To verify whether the text-based climate risk indicators can genuinely reflect firms' climate risk exposure rather than merely capture differences in disclosure styles, this paper conducts correlation tests with objective proxy variables from two dimensions: physical risk and transition risk.

To capture physical risk, we employ objective proxy variables, including the annual frequency of extreme weather days in the firm's province of registration and three specific subcategories: extreme cold, extreme heat, and gale-force wind days. The results show that the firm-level physical risk index is significantly and positively correlated with total extreme weather days and all three subcategories of extreme weather at the 1% statistical level. Specifically, the correlation coefficient with total extreme weather days is 0.070, and among the three subcategories, extreme high temperature days exhibit the strongest correlation, with a coefficient of 0.066. This indicates that the higher the frequency of extreme weather in the firm's location, the more physical risk-related content is disclosed in the annual report, confirming that the text-based physical risk index can effectively match the actual physical climate risk faced by firms.

For the transition risk dimension, we use a heavy-pollution industry dummy as the objective proxy variable, which captures the policy pressure of low-carbon transition and compliance costs faced by firms. The test results show that the transition risk index is significantly and positively correlated with the heavy-pollution industry dummy at the 1% statistical level, with a correlation coefficient of 0.178. This implies that firms in heavy-pollution industries have significantly higher transition risk indices, and the text indicator can effectively capture the low-carbon transition risk of firms.

Overall, the correlation test results for both dimensions are consistent with theoretical expectations, confirming that our climate risk indicators possess sound external validity and accurately reflect firms' actual climate risk exposure. This provides a solid empirical foundation for the subsequent regression analyses. This provides a solid empirical foundation for the subsequent regression analyses, as shown in Table 2.

Table 2. Validity Test of Climate Risk Indicators: Correlation Analysis.

Variables	Physical Risk Index	Total Extreme Weather Days	Extreme Low-Temperature Days	Extreme High-Temperature Days	Extreme Strong Wind Days	Transition Risk Index	Heavy-Pollution Industry Dummy
Physical Risk Index	1.000						
Total Extreme Weather Days	0.070 *** (0.000)	1.000					
Extreme Low-Temperature Days	0.030 *** (0.000)	0.508 *** (0.000)	1.000				
Extreme High-Temperature Days	0.066 *** (0.000)	0.507 *** (0.000)	−0.082 *** (0.000)	1.000			
Extreme Strong Wind Days	0.034 *** (0.000)	0.613 *** (0.000)	0.113 *** (0.000)	−0.023 *** (0.000)	1.000		
Transition Risk Index	—	—	—	—	—	1.000	
Heavy-Pollution Industry Dummy	—	—	—	—	—	0.178 *** (0.000)	1.000

Notes: *** denotes statistical significance at the 1% level. Values in parentheses are *p*-values of the corresponding coefficients. All coefficients and *p*-values are rounded to three decimal places. “—” indicates that the correlation coefficients of this group are not reported, as the two risk dimensions correspond to independent validity tests.

3.1.3. Mediating Variable

Drawing on our dual-channel analytical framework, which distinguishes between financial fundamentals and non-financial reputation, we select a set of mediating variables to empirically examine the transmission mechanisms through which climate risk affects

the cost of debt. Specifically, our financial-level mediators are operational efficiency and default risk, while the non-financial mediator is corporate ESG performance.

Operational efficiency: To capture the impact of climate risk on firms' growth prospects, we employ the operating revenue growth rate (Growth), calculated as (current-year revenue – prior-year revenue)/prior-year revenue, to proxy for firm growth. This indicator directly captures the pace of scale expansion and shifts in competitive dynamics, serving as a key measure of how climate risk affects firms' operational performance (W. Wang, 2025).

Default risk: Following the established approach of Xu and Chen (2011) and Yang et al. (2020), we adopt the Z-score model (ZScore) to assess corporate default risk across five dimensions: profitability, liquidity, solvency, leverage structure, and operational capacity. The Z-score is an inverse indicator: a smaller Z-score implies weaker overall debt-servicing capacity and, consequently, a higher probability of default. The specific calculation formula of the Z-score model is as follows:

$$Z = 1.2 \times (\text{working capital}/\text{total assets}) + 1.4 \times (\text{retained earnings}/\text{total assets}) + 3.3 \times (\text{EBIT}/\text{total assets}) + 0.6 \times (\text{market value of equity}/\text{book value of total liabilities}) + 1.0 \times (\text{sales}/\text{total assets})$$

where working capital is defined as current assets minus current liabilities, EBIT is earnings before interest and taxes, and all variables are measured at the fiscal year-end.

ESG performance: This paper selects the China Securities ESG composite score as the mediating variable at the non-financial level. Considering that there is a time lag for firms' climate risk response strategies to be transformed into ESG practices and then captured by rating agencies and reflected in the scores, this paper uses the two-period lagged ESG composite score for the baseline mediation effect test. In addition, we conduct an extended analysis using the two-period lagged sub-dimension scores of environment (E), social (S), and governance (G) to identify the specific pathways through which the non-financial channel operates. The China Securities ESG rating system divides A-share listed companies into nine grades from C to AAA, with grade C being the lowest and grade AAA the highest. For empirical analysis, this paper assigns sequential values from 1 to 9 to the nine grades from C to AAA.

3.1.4. Moderating Variable

We examine the moderating effects along two dimensions: corporate information disclosure quality and industry pollution attributes. Theoretically, high-quality information disclosure mitigates information asymmetry between firms and creditors, thereby attenuating the positive cost-increasing effect of climate risk on the cost of debt. In contrast, firms in heavy-polluting industries face stricter environmental regulation constraints and higher low-carbon transition pressure, which will further amplify the financing cost effect of climate risk.

Information disclosure quality: We measure information disclosure quality using official ratings from the Shanghai and Shenzhen Stock Exchanges. The assessment results are classified into four grades: fail, pass, good and excellent, which are assigned values of 1, 2, 3 and 4, respectively. A larger indicator value indicates higher quality of corporate information disclosure (Bai et al., 2022; Lü & Zhang, 2022).

Industry pollution attribute: We employ a dummy variable that equals 1 if a firm belongs to a heavily polluting industry, and 0 otherwise.

3.1.5. Control Variables

Drawing on the extant literature (W. Wang, 2025; Bassetti et al., 2024), we control for a broad set of firm-level characteristics, including financial fundamentals, governance features, and regional macroeconomic conditions, to reduce omitted variable concerns and improve estimation precision.

For firm financial fundamentals, we include six core indicators. Firm size (Size) is the natural logarithm of total assets at fiscal year-end. Larger firms tend to have more stable operations, greater collateral capacity, and stronger market credibility, which lower creditors' risk expectations and are associated with a lower cost of debt. Profitability (ROE), computed as net profit divided by year-end net assets, reflects a firm's internal capital accumulation and debt-servicing capacity. Higher profitability signals lower default risk to creditors and reduces the financing premium. Operating cash flow (CashFlow), defined as net operating cash flow scaled by total assets, reflects short-term liquidity and debt-servicing capacity. Sustained cash inflows can reduce the risk premium demanded by creditors. Current ratio (Liquid), defined as current assets divided by current liabilities at fiscal year-end, captures a firm's short-term solvency and immediate liquidity buffer. A higher current ratio signals stronger near-term debt repayment capacity and lower liquidity risk, thereby lowering the risk premium demanded by creditors. Leverage (Lev), defined as total liabilities divided by total assets, captures a firm's financial leverage and long-term solvency. Higher leverage implies greater financial distress and default risk, which raises the risk premium demanded by creditors. Asset tangibility (Tangible) is defined as the share of total tangible assets in total assets, computed as total assets minus net intangible assets scaled by year-end total assets. This variable captures the overall collateral capacity of sample firms: tangible assets generally hold stable liquidation value and can be pledged as debt security, thus reducing creditors' expected loss given default. Stock liquidity is proxied by the market-adjusted turnover rate. Considering the substantial dispersion and extreme values observed in the preliminary descriptive statistics, we apply a natural logarithmic transformation to this variable (L_Var_Adj) for the empirical analysis. The transformation allows us to interpret the estimated coefficient as the elasticity of financing costs with respect to liquidity changes. The log-transformation is employed to mitigate the severe right-skewness and outlier influence of the raw series.

For corporate governance, we include four representative variables. Firm age (FirmAge), measured as the natural logarithm of (current year – year of incorporation + 1), reflects a firm's life-cycle stage, operational maturity, and market credibility. Board independence (Indep), measured as the share of independent directors on the board, can mitigate agency problems and enhance decision-making quality, which influences creditors' assessment of operational risk. The price-to-book ratio (PB), calculated as the ratio of share price to net asset value per share, reflects market valuation and growth expectations of the firm, and shapes creditors' risk appetite for debt issuance. In addition, ownership concentration (Top10), measured as the shareholding ratio of the top 10 largest shareholders, affects a firm's risk-taking preference and financing decision-making mode, and further influences the debt pricing of financial institutions.

For macroeconomic conditions, we include the provincial GDP growth rate (GDP_growth), defined as the annual real GDP growth rate of the province where the firm is headquartered. Regional economic prosperity shapes the local credit environment and systemic risk exposure, constituting an important contextual determinant of the cost of debt. Detailed definitions of all variables are reported in Table 3.

Table 3. Variable Definitions.

Variable Type	Variable Name	Symbol	Definition
Dependent Variable	Cost of debt	Cost	Interest expense divided by total liabilities at year-end
Core Independent	Climate risk	CR	Ratio of the frequency of climate-related keywords to the total word count of corporate annual reports
Mediating Variables	Revenue growth rate	Growth	(Current year revenue—Prior year revenue)/Prior year revenue, measuring the firm's growth capability
	Default risk	ZScore	Comprehensive corporate debt default risk measured by the Z-score model from profitability, liquidity and solvency dimensions; a smaller value indicates higher default risk
	ESG performance	ESG	Two-period lagged China Securities ESG composite rating. Nine grades from C to AAA are assigned values of 1 to 9 sequentially; a larger value indicates better ESG performance
Moderating Variables	Information disclosure quality	Qid	Based on the official assessment of information disclosure quality by the Shanghai and Shenzhen Stock Exchanges. Fail, pass, good and excellent are assigned values of 1, 2, 3 and 4, respectively
	Industry pollution attribute	Pt	Dummy variable, equals 1 if the firm belongs to a heavy-polluting industry, and 0 otherwise
Control Variables	Firm size	Size	Natural logarithm of total assets at year-end
	Profitability	ROE	Return on equity, calculated as net profit divided by net assets at year-end
	Operating cash flow	CashFlow	Net cash flow from operating activities divided by total assets at year-end
	Leverage	Lev	Total liabilities at year-end divided by total assets at year-end, measuring firms' financial leverage level
	Asset tangibility	Tangible	Total tangible assets scaled by year-end total assets (total assets minus net intangible assets), measuring firms' debt collateral capacity
	Current ratio	Liquid	Current assets divided by current liabilities at fiscal year-end, measuring a firm's short-term solvency and ability to meet near-term debt obligations
	Firm age	FirmAge	Natural logarithm of (current year—year of incorporation + 1)
	Board independence	Indep	Number of independent directors divided by the total number of directors on the board
	Price-to-book ratio	PB	Share price divided by net asset value per share
	Ownership concentration	Top10	Total shareholding ratio of the top 10 largest shareholders
	Stock liquidity	L_Var_Adj	Natural logarithm of the market-adjusted stock turnover rate, measuring the liquidity of firms' outstanding shares
	Provincial GDP growth	GDP_growth	Annual real GDP growth rate of the province where the firm is registered

Note: The empirical analyses in this study are based on data from CSMAR, Wind, and manually compiled textual information from firms' annual reports.

3.2. Data Sources and Sample Composition

Our analysis draws on an initial sample of all firms listed on China's A-share market spanning the period from 2007 to 2024. The year 2007 is selected as the starting point of our sample window for a well-supported rationale: the full implementation of the Accounting Standards for Business Enterprises (ASBE) in that year marked substantial convergence of Chinese accounting practices with international reporting standards. Setting 2007 as the time benchmark ensures uniform measurement of accounting indicators throughout the sample period and effectively rules out confounding effects driven by systematic adjustments to accounting rules.

Financial statement data and corporate governance variables are retrieved from two authoritative commercial databases: the China Stock Market & Accounting Research (CSMAR) database and the Wind database. The firm-level climate risk index is manually constructed via textual analysis of annual reports, which are publicly disclosed on the official CNINFO platform.

To ensure the validity and representativeness of the final sample, we apply a set of standard screening procedures in sequential order. First, we exclude firms in the financial industry, as their financial reporting frameworks, asset–liability structures, and operational patterns differ fundamentally from non-financial enterprises. Second, we remove firm-year observations under special treatment (ST), special treatment with delisting risk (*ST), or particular transfer (PT), since these firms face abnormal operational conditions and distorted financial performance that would introduce estimation bias. Third, we drop observations with missing values for the core dependent variable, key explanatory variable, and control variables.

After completing the above screening steps, we obtain an unbalanced panel dataset consisting of 32,718 firm-year observations for subsequent empirical analysis. To alleviate the potential distortion of extreme outliers on regression estimates, all firm-level continuous variables are winsorized at the 1st and 99th percentiles on an annual basis. For provincial macroeconomic indicators represented by the GDP growth rate, we retain their original officially released values without winsorization, so as to preserve authentic information about macroeconomic cyclical fluctuations and exogenous shocks.

3.3. Model Construction

To systematically control for time-invariant firm-specific characteristics, time-varying macroeconomic shocks, and inherent differences across industries, we construct a three-way fixed-effects model incorporating firm, year, and industry fixed effects. The baseline model is specified as follows:

$$Cost_{i,t} = \alpha_0 + \alpha_1 CR_{i,t} + \sum \alpha_2 Control_{i,t} + \delta_i + \mu_t + \eta_j + \varepsilon_{i,t}$$

where the dependent variable $Cost_{i,t}$ measures the cost of debt of firm i in year t ; the core independent variable $CR_{i,t}$ represents the climate risk exposure of firm i in year t ; $\sum Control_{i,t}$ denotes the set of control variables; δ_i is the firm fixed effect, which absorbs all time-invariant inherent characteristics of individual firms; μ_t is the year fixed effect, which captures common time-varying impacts such as macroeconomic fluctuations and policy shocks; η_j is the industry fixed effect, which accounts for inherent industry attributes and industry-level trends; $\varepsilon_{i,t}$ is the random disturbance term; α_0 is the constant term; and α_1 and α_2 are the regression coefficients of the core independent variable and control variables, respectively.

To uncover the internal mechanism, we place emphasis on improving the reliability of causal inference between the independent variable and the dependent variable (Baron &

Kenny, 1986; Wen & Ye, 2014), and adopt the following regression model for the mechanism test:

$$Med_{i,t} = \beta_0 + \beta_1 CR_{i,t} + \sum \beta_2 Control_{i,t} + \delta_i + \mu_t + \eta_j + \varepsilon_{i,t}$$

The moderating effect regression model is set out as follows:

$$Cost_{i,t} = \delta_0 + \delta_1 CR_{i,t} + \delta_2 Adj_{i,t} + \delta_3 Adj_{i,t} \times CR_{i,t} + \sum \delta_4 Control_{i,t} + \delta_i + \mu_t + \eta_j + \varepsilon_{i,t}$$

3.4. Descriptive Statistics of Variables

All data cleaning, sample screening, and statistical analysis are performed using Stata 17. After applying the sample selection criteria described above, we obtain an unbalanced panel of 32,718 firm-year observations for subsequent empirical analysis.

Table 4 reports descriptive statistics for the cost of debt, grouped by whether firms disclose climate risk-related content in their annual reports. The full sample has a mean cost of debt of 0.0174, with a standard deviation of 0.0137. Firms with no climate risk disclosure ($CR = 0$) exhibit a slightly higher average cost of debt (0.0175) than those with positive disclosure (0.0173). This preliminary univariate difference may be correlated with discrepancies in firm fundamentals such as size and profitability, and we will systematically control for these factors in the baseline regression analysis.

Table 4. Descriptive Statistics of Cost of Debt by Climate Risk Disclosure Status.

Group	Observations	Mean	Std. Dev.	Min	Max
CR > 0 group	16,459	0.0173	0.0142	0.0000	0.0823
CR = 0 group	16,259	0.0175	0.0130	0.0000	0.0823
Full sample total	32,718	0.0174	0.0137	0.0000	0.0823

Notes: This table reports descriptive statistics for the cost of debt, grouped by whether CR equals zero. In the univariate comparison, firms with no climate risk disclosure have a slightly higher average cost of debt, a pattern that may be associated with differences in firm fundamentals such as size and profitability. All firm-level continuous variables are annually winsorized at the 1st and 99th percentiles. The provincial GDP growth rate, as a macroeconomic indicator, is not winsorized.

For the core explanatory variable, the firm-level climate risk index (CR) has a mean of 0.0366 and a standard deviation of 0.0412, ranging from 0.0000 to 0.1179. The large standard deviation indicates substantial heterogeneity in climate risk exposure and disclosure practices across firms. In the full sample, 16,259 firm-year observations (approximately 49.70%) have a CR value of zero, meaning that nearly half of the listed firms do not explicitly disclose climate-risk-related content in their annual reports. This high proportion aligns with the reality that climate-related disclosure among Chinese listed firms is still in its early stage, with considerable variation in disclosure willingness and quality across firms. It should be clarified that a zero CR value represents silence at the disclosure level rather than zero actual climate risk exposure, as firms may face physical and transition risks even without relevant textual disclosure.

For the dependent variable, the cost of debt (Cost) ranges from 0.0000 to 0.0823 after winsorization. The minimum value appears as 0.0000 when rounded to four decimal places, and its actual value is a tiny positive number corresponding to firms with a high share of interest-free operating liabilities, rather than zero debt financing. The overall distribution falls within a reasonable range consistent with the real debt financing environment of Chinese A-share listed firms, and extreme outliers deviating from economic intuition have been effectively removed via standardized winsorization. The descriptive statistics for all control variables are reported in Table 5, and the distribution characteristics of each variable are generally consistent with existing studies on Chinese listed firms, confirming the reliability of the sample data.

Table 5. Descriptive Statistics.

Variable Symbol	Observations	Mean	Std. Dev.	Min	Max
CR	32,718	0.0366	0.0412	0.0000	0.1179
Cost	32,718	0.0174	0.0137	0.0000	0.0823
Size	32,718	22.2342	1.2712	20.0111	26.2181
ROE	32,718	0.0660	0.1024	−0.4994	0.3004
CashFlow	32,718	0.0498	0.0657	−0.1412	0.2381
Lev	32,718	0.4141	0.1901	0.0506	0.8449
Tangible	32,718	0.9309	0.0788	0.5714	1.0000
FirmAge	32,718	2.9104	0.3437	1.7918	3.6109
Indep	32,718	0.3746	0.0520	0.3333	0.5714
PB	32,718	3.3584	2.4962	0.5688	14.8897
Liquid	32,718	2.4693	2.4851	0.2438	34.6089
Top10	32,718	0.5879	0.1529	0.2083	0.9084
L_Var_Adj	32,718	0.2053	0.7630	−1.4694	3.4572
GDP_growth	32,718	7.2800	3.6543	−20.6300	25.8000

Notes: All firm-level continuous variables are annually winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. The provincial GDP growth rate retains its original official statistical value without winsorization. The empirical analyses in this study are based on data from CSMAR, Wind, and manually compiled textual information from firms' annual reports.

Among the control variables, we categorize them into three dimensions for systematic illustration: firm financial fundamentals, corporate governance characteristics, and macroeconomic conditions.

For financial fundamentals, firm size (Size) has a mean value of 22.2342 with a standard deviation of 1.2712, covering listed firms of different scales and conforming to the typical size distribution of China's A-share market. Return on equity (ROE) averages 0.0660 and ranges from −0.4994 to 0.3004, indicating that profitability still varies widely across sample firms even after extreme outliers are excluded. Operating cash flow (CashFlow) records a mean of 0.0498, reflecting that sample firms generally maintain positive net operating cash inflows on average. The leverage ratio (Lev) averages 0.4141, representing a moderate overall level of financial leverage. Asset tangibility (Tangible) averages 0.9309; calculated as total tangible assets (total assets minus net intangible assets) scaled by year-end total assets, this high value aligns with the typical asset structure of Chinese non-financial listed firms. The current ratio (Liquid) averages 2.4693 with a relatively large standard deviation, revealing pronounced heterogeneity in short-term solvency across enterprises. The price-to-book ratio (PB) has a mean of 3.3584, capturing the market valuation differentiation among sample firms.

In terms of corporate governance characteristics, firm age (FirmAge) averages 2.9104 in logarithmic form, corresponding to an average of approximately 18 years since incorporation. Board independence (Indep) has a mean of 0.3746, with a minimum value of 0.3333 that exactly meets the regulatory requirement of independent directors accounting for no less than one-third of the board, which further confirms the compliance and reliability of the sample data. Ownership concentration (Top10) averages 0.5879, presenting the typical feature of high shareholding concentration in China's A-share market. Stock liquidity (L_Var_Adj) has a mean of 0.2053 after logarithmic adjustment.

For the macroeconomic variable, the provincial GDP growth rate (GDP_growth) averages 7.2800, with a range from −20.6300 to 25.8000. The negative minimum corresponds to the severe economic downturn in individual provinces during the COVID-19 pandemic, while the maximum reflects the high-growth stage of some regional economies. Both are authentic macroeconomic fluctuations rather than statistical outliers, which justifies our choice of retaining the original values without winsorization.

Overall, the distribution of all control variables falls within reasonable economic ranges and is highly consistent with empirical findings in existing studies on Chinese listed firms, verifying the representativeness and reliability of the research sample.

4. Empirical Results

4.1. Baseline Regression Results

Table 6 reports the baseline regression results for the impact of climate risk on the cost of debt. All specifications are estimated using a three-way fixed effects framework that controls for firm, year, and industry fixed effects. Column (1) reports the estimation result without firm-level control variables, while Column (2) further incorporates the full set of control variables covering financial fundamentals, corporate governance, and macroeconomic conditions. The results in Table 6 show that the coefficient of climate risk is positive and statistically significant at the 1% level across both specifications. This finding supports Hypothesis 1, which posits that climate risk significantly raises the cost of debt. Quantitatively, the baseline coefficient of CR in column (2) equals 0.007. This indicates that, conditional on firm fundamentals, governance features and macroeconomic factors, a one-percentage-point rise in the climate risk share of annual reports corresponds to a 0.007-percentage-point increase in firms' cost of debt, an economically meaningful uplift in debt financing burdens.

Table 6. Benchmark Regression Results.

Variable	(1) Cost	(2) Cost
CR	0.008 *** (0.002)	0.007 *** (0.002)
Size		−0.001 * (0.000)
ROE		−0.015 *** (0.001)
CashFlow		0.014 *** (0.001)
Lev		0.018 *** (0.001)
Tangible		−0.006 *** (0.002)
Indep		0.004 ** (0.002)
PB		−0.001 (0.002)
Liquid		−0.000 *** (0.000)
Top10		0.000 ** (0.000)
L_Var_Adj		−0.005 *** (0.001)
GDP_growth		−0.000 (0.000)

Table 6. *Cont.*

Variable	(1) Cost	(2) Cost
Constant	0.017 *** (0.000)	0.021 ** (0.009)
Firm	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
N	32,670	32,670
R ²	0.612	0.641
adj. R ²	0.561	0.594

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2. Endogeneity

4.2.1. Lag Effect Test

Reverse causality represents a core endogeneity concern for our text-based climate risk indicator. Firms bearing higher debt financing costs may revise their climate-related disclosure practices when adjusting operational strategies, which in turn alters the measured value of the climate risk index. To alleviate estimation bias induced by such two-way causality, we re-estimate the baseline specification using the one-period lagged value of the core explanatory variable (denoted as ICR).

Table 7 reports the lagged-effect test results. Column (1) controls for firm, year, and industry fixed effects only, while Column (2) further includes all control variables. In Column (2), the coefficient of ICR is 0.004 and statistically significant at the 5% level. The sign of the coefficient remains consistent with the baseline, while the magnitude declines slightly—consistent with the typical attenuation pattern for lagged explanatory variables. These results confirm that, after addressing potential reverse causality concerns, the positive effect of climate risk on the cost of debt remains statistically significant, reinforcing the robustness of our baseline findings.

Table 7. Regression Results with One-period Lagged Explanatory Variables.

Variable	(1) Cost	(2) Cost
ICR	0.006 *** (0.002)	0.004 ** (0.002)
Control	No	Yes
Constant	0.018 *** (0.000)	0.023 ** (0.010)
Firm	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
N	27,237	27,237
R ²	0.641	0.675

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, ** denote statistical significance at the 1% and 5% levels, respectively.

4.2.2. Instrumental Variable Method

To further address endogeneity concerns arising from omitted variables, reverse causality, and measurement error, we adopt the instrumental variable strategy of Cepni et al. (2024). Specifically, we instrument CR using the average climate risk of peer firms in the same city and industry (excluding the focal firm) and implement two-stage least squares (2SLS) estimation.

This IV meets both the relevance and exogeneity requirements. Firms in the same city face highly similar geographic and climatic conditions, including physical shocks from extreme weather, while firms in the same industry share comparable transition policy constraints and regulatory requirements. Consequently, peer firms in the same city and industry exhibit a natural alignment in climate risk exposure and disclosure behavior, which correlates with the focal firm's CR level and satisfies the relevance condition. The exogeneity condition holds because the average climate risk of peer firms is primarily shaped by regional climate endowments and industry-level factors. This instrument does not directly affect the debt pricing of any single firm, nor is it driven by the decisions of an individual firm.

Table 8 reports the diagnostic results of the IV estimation. In the first stage, the IV coefficient is 0.436 and significant at the 1% level, indicating a strong positive correlation between the instrument and the endogenous CR variable. The Cragg–Donald Wald F statistic of 90.393 far exceeds the Stock–Yogo 10% critical value of 16.38, decisively rejecting the null hypothesis of weak identification. Meanwhile, the Kleibergen–Paap rk LM statistic of 101.808 (p -value = 0.000) strongly rejects underidentification, confirming that the instrument is both relevant and valid. The second-stage results indicate that, after controlling for endogeneity, the CR coefficient remains positive and significant at the 5% level (coefficient = 0.078), which is broadly consistent with the baseline OLS estimates. These results confirm that climate risk exerts a significant positive effect on the cost of debt. This core finding remains robust to endogeneity concerns stemming from reverse causality, omitted variables, and measurement error.

Table 8. Results of Endogeneity Treatment using Instrumental Variable Method.

Variable	2SLS	
	First Stage	Second Stage
	CR	Cost
IV	0.436 *** (0.048)	
CR		0.078 ** (0.039)
Control	Yes	Yes
Constant	0.047 ** (0.024)	0.027 *** (0.009)
Firm	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
N	32,702	32,702
R ²	0.0598	0.3051
Cragg–Donald Wald F		90.393
Kleibergen–Paap rk LM statistic		101.808 ***

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, ** denote statistical significance at the 1% and 5% levels, respectively.

4.3. Robustness Test

4.3.1. Alternative Measure of the Independent Variable

To improve the distributional properties of the main independent variable and mitigate the influence of outliers, we apply a logarithmic transformation to the climate risk indicator and re-estimate the baseline model using $\ln(1 + CR)$ as an alternative proxy. This log transformation, with a plus-one term, not only retains zero-value observations ($CR = 0$) to avoid sample selection bias, but also improves the right-skewed distribution of the CR series. It is a standard robustness check paradigm for text-frequency-based risk indicators (Y. Guo et al., 2025).

The regression results show that after logarithmic transformation, the coefficient of climate risk remains significantly positive at the 1% significance level. Both the sign and economic implication of the coefficient are highly consistent with those of the baseline regression, which further verifies the robustness of the core conclusion to alternative variable measurement methods.

4.3.2. Alternative Measure of the Dependent Variable

This study uses “the proportion of corporate interest expenses plus commission expenses and other financial expenses in total liabilities at the end of the period” as a robust supplement to the alternative index of corporate cost of debt (Cost1). Specifically, other financial expenses mainly cover ancillary costs of debt financing incurred in the process of corporate debt financing, including exchange gains and losses, bond issuance expenses, financing guarantee fees, and consulting and handling fees related to bank credit. The regression results using this alternative measure are reported in Column (2) of Table 9, where the coefficient of CR remains positive and significant.

Table 9. Robustness Test: Alternative Variables, Error Clustering and Interactive Fixed Effects.

Variable	(1) Cost	(2) Cost1	(3) Cost	(4) Cost
Ln_CR	0.007 *** (0.002)			
CR		0.006 *** (0.002)	0.007 *** (0.001)	0.004 ** (0.002)
Control	Yes	Yes	Yes	Yes
Constant	0.024 *** (0.009)	0.021 *** (0.004)	0.024 *** (0.008)	0.020 ** (0.009)
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year $\times$ Industry	No	No	No	Yes
N	32,670	32,670	32,670	32,654
R ²	0.643	0.609	0.643	0.653

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, ** denote statistical significance at the 1% and 5% levels, respectively.

4.3.3. Time Clustering

Although the benchmark model has included macrocontrol variables with year fixed effects to maximize the control of the influence of time trends, the residual terms may still be correlated in the time dimension. To address this issue and ensure valid statistical inference, we follow Shen et al. (2020) and cluster standard errors at the time dimension.

The results are reported in Column (3) of Table 9, where the CR coefficient remains positive and significant.

4.3.4. Alternative Regression Specification

Following Z. Li et al. (2022), this section further controls for year $\times$ industry interactive fixed effects and performs a high-dimensional fixed effects regression on the sample. As reported in Column (4) of Table 9, after incorporating the year-industry interactive fixed effects, the regression coefficient of climate risk stands at 0.004 and remains significant at the 5% level, which further supports the core findings of this paper.

4.3.5. Shorten the Sample Period

To ensure the robustness of our findings and rule out potential confounding effects from major exogenous shocks, we perform a set of robustness tests by progressively restricting the sample window based on the baseline specification; the results are reported in Table 10. Specifically, we sequentially and cumulatively exclude observations from three representative shock years. First, we drop observations from 2008 to isolate the confounding impact of the global financial crisis, which reshaped market risk appetite and exerted long-term structural effects on firms' cost of debt. Second, we further exclude 2015 observations on the basis of the above restricted sample to eliminate interference from the sharp abnormal fluctuations in China's domestic capital market, which disrupted corporate financing environments and could have biased causal identification. Third, we additionally remove 2020 observations from the already restricted sample to disentangle the effects of the COVID-19 pandemic, which coincided with frequent extreme climate events and amplified overall market risk perception.

Table 10. Robustness Test: Restricted Sample Period Excluding Exogenous Shock Years.

Variable	(1) Cost	(2) Cost	(3) Cost
CR	0.007 *** (0.002)	0.006 *** (0.002)	0.006 *** (0.002)
Control	Yes	Yes	Yes
Constant	0.019 ** (0.009)	0.021 ** (0.009)	0.022 ** (0.009)
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	32,013	30,313	27,538
R ²	0.644	0.646	0.647

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, ** denote statistical significance at the 1% and 5% levels, respectively.

As reported in Table 10, the CR coefficient remains positive and significant at the 1% level across all specifications, with its sign and magnitude consistent with the baseline results. This confirms that major exogenous shocks do not significantly alter our core finding, reinforcing the robustness of our conclusion that climate risk increases the cost of debt.

5. Heterogeneity Test

5.1. ESG Investor Heterogeneity

ESG funds typically possess substantial market influence and informational advantages. Through their professional oversight, they can actively steer portfolio firms toward increased strategic investment in green innovation, environmental protection, and sustainable development (Hu et al., 2023). ESG-oriented investors, particularly ESG funds, play a significant role in influencing the cost of debt. On the one hand, their governance effect helps reduce agency costs. These investors possess strong motivation and professional analytical skills to scrutinize non-financial information, including corporate climate risk management and long-term sustainability strategies. Their active engagement can monitor managerial conduct and curb opportunism driven by managerial myopia that exacerbates climate risk, thereby enhancing corporate governance. Creditors interpret such active monitoring as a positive signal of sound operations and low agency risk, and thus offer debt financing at lower rates. On the other hand, ESG fund holdings signal firms' quality, thereby alleviating information asymmetry. When prominent ESG funds take long-term stakes in firms, this signals to the debt market that these firms have met stringent ESG standards and gained recognition from professional investors for their resilience and long-term risk management, including climate risk. This certification effect reduces information asymmetry between creditors and firms, as well as the uncertainty premium creditors demand when they cannot precisely assess firms' climate risk exposure. Consequently, it contributes to a lower cost of debt.

To examine the moderating role of ESG institutional investors, we partition our sample into two groups based on ESG fund shareholding. Table 11 presents the results in Columns (1) and (2). In the non-ESG fund subsample, climate risk has a stronger positive effect on the cost of debt. This suggests that ESG fund holdings may attenuate the financing premium associated with climate risk, though the moderating effect is only marginally significant.

Table 11. Heterogeneity Analysis Regression Results.

	ESG Investor Heterogeneity		Ownership Nature		Regional Heterogeneity	
	(1) With ESG Fund	(2) Without ESG Fund	(3) SOEs	(4) Non-SOEs	(5) Eastern Region	(6) Non-Eastern Region
CR	0.005 (0.003)	0.008 *** (0.003)	0.007 ** (0.003)	0.007 *** (0.002)	0.004 (0.002)	0.014 *** (0.004)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.007 (0.014)	0.028 ** (0.013)	0.058 *** (0.017)	0.002 (0.010)	0.014 (0.011)	0.034 * (0.018)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	8636	17,268	10,594	22,033	24,103	8557
R ²	0.732	0.672	0.678	0.639	0.635	0.661
Differences in coefficients between groups	0.003		0.000		0.010 **	

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2. Ownership Nature

To examine the heterogeneous effect of ownership structure on the climate risk–cost of debt relationship, we divide the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) and perform subsample regressions. The group-specific results are reported in Columns (3) and (4) of Table 11. The results show that the coefficient of climate risk is larger for non-SOEs than for SOEs, suggesting that the cost-increasing effect of climate risk is more pronounced in non-SOEs, although the group difference is not statistically significant. This may be because SOEs typically benefit from implicit government guarantees and policy support, as well as soft budget constraints, which help mitigate the adverse effect of climate risk on their credit ratings. In contrast, non-SOEs face more limited financing channels and rely more heavily on bank credit and other forms of debt financing. Without government credit endorsement, non-SOEs are more vulnerable to tighter credit rationing and deteriorating financing conditions, leading to a significant increase in their cost of debt.

5.3. Regional Heterogeneity

To investigate the heterogeneous impact of climate risk on the cost of debt, we further divide the sample into eastern and non-eastern regions based on geographic location. There are systematic differences in factor endowments and economic development modes between the eastern and non-eastern regions of China. The eastern region usually has higher levels of urbanization, economic development, per capita income, and better infrastructure. In contrast, the non-eastern regions concentrate most of the country's mineral resources, and their natural resource endowment has a profound impact on the local industrial structure, resulting in a high proportion of traditional heavy industries with strong resource dependence and high energy consumption, thus forming an industrial development path significantly different from that of the eastern region.

Columns (5) and (6) of Table 11 report the grouped test results of climate risk shocks faced by firms in different regions. The estimation results suggest that the cost-increasing effect of climate risk is significantly stronger in non-eastern regions. This is likely because the economic structure of non-eastern regions relies more heavily on resource-based and high-carbon industries, and their firms have limited transformation capacity, exposing them to higher transition and physical risks. When climate risk intensifies, creditors expect such firms to bear higher compliance costs and asset impairment risks, thereby demanding higher risk premiums. In contrast, firms in the eastern region generally occupy the middle-to-high end of the industrial chain, possess more advanced climate adaptation technologies and diversified financing channels, and are more resilient to climate risk, thus buffering the impact on financing costs.

6. Further Analysis

6.1. Mediation Effect Regression Analysis

6.1.1. Deterioration of Corporate Production and Operation

As established in the preceding theoretical analysis, climate risk significantly affects corporate debt financing by disrupting production and operations. To capture firms' operational performance and profitability, we employ the operating revenue growth rate (Growth) as the proxy to examine the disruptive impact of physical climate shocks on firm operations (Y. Liu et al., 2024). The regression results are presented in Table 12. In Column (2), where Growth is the dependent variable, the coefficient of CR is negative and statistically significant. This implies that heightened climate risk suppresses corporate operating revenue, thereby driving up the cost of debt.

Table 12. Regression Results of Mediation Effect Test.

	Firm Operations		Corporate Default Risk			Corporate ESG Performance			
	(1) Cost	(2) Growth	(3) Cost	(4) Zscore	(5) Cost	(6) ESG(t + 2)	(7) E(t + 2)	(8) S(t + 2)	(9) G(t + 2)
CR	0.007 *** (0.002)	−0.159 ** (0.065)	0.007 *** (0.002)	−0.915 * (0.472)	0.007 *** (0.002)	−2.802 *** (0.873)	−2.129 * (1.237)	−4.576 *** (1.553)	−2.266 * (1.181)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.021 ** (0.009)	−0.565 *** (0.172)	0.021 ** (0.009)	−5.093 ** (1.995)	0.018 * (0.009)	58.262 *** (3.820)	49.865 *** (4.986)	32.804 *** (7.117)	78.870 *** (4.859)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	32,670	30,270	32,638	32,505	30,725	23,379	23,379	23,379	23,379
R ²	0.641	0.168	0.642	0.801	0.655	0.535	0.597	0.598	0.495

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.1.2. Increase in Corporate Default Risk

As outlined in the preceding theoretical analysis, climate risk increases the cost of debt by elevating default risk. We employ the Z-score model (ZScore) to comprehensively capture corporate default risk across five dimensions: profitability, liquidity, solvency, leverage, and operational efficiency. Table 12 reports the regression results. Column (4), which takes the Z-score as the proxy for default risk, returns a significantly negative coefficient. This indicates that climate risk raises default risk by weakening production and operational capacity, which ultimately increases the cost of debt. Overall, these empirical results provide support for Hypothesis 2.

6.1.3. Reduction in Corporate ESG Performance

Our earlier theoretical analysis establishes the mechanism through which climate risk raises the cost of debt by weakening corporate ESG performance. To test this mediating channel, we first adopt the two-period lagged composite ESG score from China Securities as the primary mediator. We then use the two-period lagged E, S, and G sub-dimension scores as alternative mediators for further analysis.

Column (5) of Table 12 presents the baseline regression results for the full sample. The CR coefficient is 0.007 and statistically significant at the 1% level, indicating that higher climate risk is associated with a higher cost of debt. Column (6) reports the transmission mechanism regression results with the two-period lagged composite ESG score as the mechanism variable. The results show that climate risk exerts a significantly negative effect on the two-period lagged composite ESG score; that is, rising climate risk impairs firms' overall ESG performance. Columns (7), (8) and (9) display the transmission mechanism results for the two-period lagged E, S and G sub-dimension scores, respectively. To explain the heterogeneous mediation effects across ESG sub-dimensions at the two-period lag, we ground our analysis in information economics and signaling theory, focusing on creditors' information demand. The environmental (E) dimension exhibits an insignificant mediating effect, as the economic consequences of environmental performance—such as regulatory penalties, climate-related asset impairment, and green investment—are largely capitalized in contemporaneous financial statements and have already been captured by core financial controls (e.g., profitability and leverage) in our model. After a two-period lag, the information content of lagged environmental performance adds little explanatory power for debt pricing beyond conventional accounting measures. In contrast, the social

and governance dimensions convey soft non-financial signals that are not fully quantifiable in financial statements. Their influence on firms' long-term risk resilience unfolds gradually and requires time to be perceived by the market. Against the backdrop of heightened information asymmetry induced by climate risk, lagged S and G performance conveys critical information to creditors regarding firms' management quality, reputational capital, and long-term viability, thereby exhibiting significant mediating effects at the two-period lag. Notably, this heterogeneity does not negate the overall mediating role of ESG performance but rather refines the transmission mechanism: the non-financial pathway via which climate risk raises the cost of debt is mainly driven by the soft information value embedded in the S and G dimensions, rather than by hard environmental performance. Collectively, the empirical evidence confirms that corporate ESG performance functions as a transmission channel through which climate risk affects the cost of debt, lending support to Hypothesis 3.

6.2. Moderation Effect Test

6.2.1. Corporate Information Disclosure Quality

We adopt information disclosure quality (Qid) as a moderating variable to examine its role in the pathway through which climate risk affects the cost of debt. To this end, we incorporate the interaction term of information disclosure quality and climate risk ($Qid \times CR$) into the regression model, with the results reported in Column (1) of Table 13.

Table 13. Moderation Effect Test Regression Results.

Variables	(1) Corporate Information Disclosure Quality	(2) Industrial Emission Attributes
	Cost	Cost
$CR \times Adj$	−0.010 * (0.008)	0.020 *** (0.004)
CR	0.047 * (0.024)	0.003 * (0.002)
Adj	−0.001 *** (0.000)	0.003 *** (0.000)
Control	Yes	Yes
Constant	0.036 * (0.021)	0.028 *** (0.004)
Firm	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
N	23,261	32,718
R ²	0.640	0.635

Notes: Robust standard errors clustered at the firm level are reported in parentheses. ***, * denote statistical significance at the 1% and 10% levels, respectively.

The coefficient of the interaction term ($Qid \times CR$) is negative and significant at the 10% level, indicating that information disclosure quality attenuates the positive effect of climate risk on the cost of debt. Specifically, when facing the same level of climate risk, firms with higher disclosure quality experience a smaller increase in the cost of debt.

This moderating effect operates through an information-based channel. High-quality disclosure alleviates information asymmetry by providing creditors with fuller details on firms' climate risk management, response measures, and exposure, which in turn reduces

the likelihood of excessively pessimistic default risk evaluations. Consequently, the risk premium demanded by creditors decreases, ultimately attenuating the positive effect of climate risk on the cost of debt.

6.2.2. Industrial Emission Attributes

We capture industry pollution attribute (Pt) using a dummy variable that takes the value of 1 for heavily polluting firms and 0 otherwise. We include Pt and its interaction with CR ($Pt \times CR$) in the regression model. The results in Column (2) of Table 13 show that the coefficients of both Pt and the interaction term ($Pt \times CR$) are positive and significant at the 1% level, indicating that the industry pollution attribute positively moderates the effect of climate risk on the cost of debt.

This result suggests that operating in heavily polluting industries strengthens the positive impact of climate risk on the cost of debt. A plausible explanation is that heavily polluting industries inherently face stricter environmental regulations and more intense transition pressure, creating a notable superimposed and amplified relationship between their operational activities and climate risk. As climate risk escalates, creditors need to assess not only firms' physical damage losses and transition costs, but also the higher risk that their high-carbon assets will become stranded assets amid the low-carbon transition, as well as uncertainties stemming from more stringent environmental policies and litigation risks. These factors collectively amplify the expected losses from climate risk and prompt creditors to require a higher risk premium in compensation, thereby reinforcing the positive effect of climate risk on the cost of debt.

7. Discussion

Our findings provide robust empirical evidence that climate risk significantly increases the cost of debt in the Chinese A-share market. Our study contributes to the climate finance literature by offering new evidence on the microeconomic consequences of climate risk and its transmission mechanisms to corporate financing.

Theoretical Contributions and Mechanism Insights. Our results demonstrate that climate risk operates through two parallel channels: the financial fundamental pathway (deteriorating production operations and elevating default risk) and the non-financial reputation pathway (reducing ESG performance). This dual-channel framework advances the existing literature by reconciling previously fragmented findings. While earlier studies examined either default risk (G. Chen et al., 2023b; W. Wang, 2025) or ESG performance in isolation, our integrated approach reveals that both channels operate simultaneously and independently, suggesting that creditors price climate risk through both financial solvency assessments and non-financial reputation evaluations. The finding that ESG performance mediates this relationship is particularly noteworthy, as it implies that climate risk erodes the reputational capital firms have built through sustainability practices, and this in turn triggers higher financing premiums. This aligns with stakeholder theory (Orlitzky et al., 2011) and extends it by quantifying the specific mechanism through which climate-related reputation damage translates into higher borrowing costs. Moreover, our mediation results show that the social (S) and governance (G) sub-dimensions of ESG are the primary drivers of this transmission, while the environmental (E) dimension exhibits a weaker effect, suggesting that creditors place greater weight on firms' social responsibility and governance quality than on environmental performance per se when pricing climate risk—a finding that adds nuance to the existing ESG–debt cost literature (Cheng et al., 2025).

Moderating Effects and Boundary Conditions. The moderating analysis reveals two important boundary conditions. First, high-quality information disclosure weakens the positive effect of climate risk on the cost of debt. This finding corroborates the information

asymmetry perspective (Bai et al., 2022; Lü & Zhang, 2022) and suggests that transparent disclosure acts as a “credibility-enhancing” mechanism that reduces creditors’ uncertainty about firms’ climate risk exposure. When firms voluntarily disclose comprehensive climate-related information, creditors can more accurately assess the firm’s risk profile, thereby reducing the ambiguity premium demanded. Second, heavy-polluting industry attributes amplify this effect, consistent with the transition risk literature. Firms in these industries face dual pressures from physical climate shocks and stringent environmental regulations, creating a compounding effect that magnifies creditor concerns about asset stranding and compliance costs. This finding underscores the heterogeneous vulnerability of different industries to climate risk and has important implications for sectoral climate policy design.

Heterogeneity Insights and Institutional Context. The heterogeneity analysis reveals that the main effect is more pronounced in non-ESG fund holding enterprises, non-state-owned enterprises (non-SOEs), and firms in non-eastern regions. The moderating role of ESG institutional investors is particularly instructive: their presence attenuates the financing cost effect, suggesting that these investors serve as effective external monitors who discipline corporate climate risk management and signal firm quality to creditors (X. Wang et al., 2024). The stronger effect in non-SOEs reflects China’s unique institutional environment, in which state-owned enterprises benefit from implicit government guarantees and soft budget constraints, insulating them from the full financial consequences of climate risk. Similarly, the regional heterogeneity highlights the importance of economic development patterns and industrial structures in shaping climate risk vulnerability, with resource-dependent non-eastern regions facing greater financing challenges. These findings collectively suggest that the financing cost effect of climate risk is not uniform but is systematically moderated by institutional and structural factors.

Methodologically, our study makes two valuable contributions to the climate finance literature. First, our multi-dimensionally validated textual analysis approach fills a critical measurement gap in existing research. We develop a localized firm-level climate risk indicator tailored to China’s institutional context and verify its external validity through correlation tests against two objective benchmarks: regional extreme weather data and industry-level carbon emission intensity. Our evidence demonstrates that when appropriately adapted to local institutional settings, text-based firm-level risk measures can effectively capture firms’ actual climate risk exposure. This provides a replicable measurement paradigm for similar studies in emerging markets where granular climate data remain relatively scarce.

In addition, we strengthen causal identification through a more rigorous fixed-effects specification. Most existing studies examining the impact of climate risk on corporate financing rely on the conventional two-way fixed effects framework that controls only for firm and year fixed effects. This standard specification cannot fully isolate confounding effects from time-invariant industry heterogeneity and industry-specific cyclical trends—factors that may be jointly correlated with firms’ climate risk exposure and creditors’ pricing decisions. To address this limitation, we employ a three-way fixed effects model that simultaneously incorporates firm, year, and industry fixed effects. This augmented specification absorbs inherent industry attributes and industry-level systematic shocks, thereby more precisely isolating the independent impact of firm-specific climate risk on the cost of debt and enhancing the reliability of causal inference.

Comparison with Prior Literature. Our findings are broadly consistent with Bassetti et al. (2024) and Huynh and Xia (2021) in confirming the positive climate risk–debt cost relationship, but we extend their work by disentangling the distinct transmission channels through which this effect operates. We diverge from studies that treat ESG performance merely as a direct determinant of the cost of debt (S. Chen et al., 2024) by demonstrating

that ESG serves as a mediating channel through which climate risk exerts its influence. This distinction is crucial because it implies that improving ESG performance is not only a value-enhancing strategy but also a risk-mitigation tool that can buffer the adverse financing effects of climate shocks.

8. Conclusions and Policy Implications

8.1. Conclusions

Using a comprehensive panel of Chinese A-share listed firms covering the 2007–2024 period, this paper empirically examines how climate risk shapes the corporate cost of debt. Through textual analysis and machine learning algorithms, we construct a firm-level climate risk indicator tailored to the Chinese context and employ a three-way fixed effects model to identify the causal relationship. Our empirical findings reveal three key conclusions.

First, climate risk significantly increases the cost of debt. This effect remains robust across a series of endogeneity tests, including lagged explanatory variables and instrumental variable estimation, and various robustness checks, such as alternative variable measurement, sample truncation, and high-dimensional fixed effects. In economic terms, the baseline estimate indicates that a one-unit increase in the climate risk index raises the cost of debt by approximately 0.007 units.

Second, the transmission mechanism operates through two distinct and independent channels: the financial fundamental channel (where climate risk impairs production operations and elevates default risk) and the non-financial reputation channel (where climate risk deteriorates ESG performance, particularly the social and governance dimensions). These dual pathways collectively illustrate how climate risk permeates corporate systems and ultimately affects the cost of debt.

Third, the relationship is subject to important moderating and heterogeneous effects. High-quality information disclosure significantly weakens the positive effect, while heavy-polluting industry attributes strengthen it. The main effect is more pronounced in non-ESG fund holding enterprises, non-SOEs, and firms in non-eastern regions, revealing the critical roles of external governance mechanisms, institutional support structures, and regional development patterns in shaping climate risk vulnerability.

8.2. Policy Implications

For Regulators and Policymakers. First, the significant effect of climate risk on the cost of debt suggests that climate-related financial risks have already permeated China's real economy and financial system. Policymakers should move swiftly to establish uniform, mandatory climate risk disclosure requirements that oblige firms to report their climate risk exposure, response strategies, and transition roadmaps. Such standards would reduce information asymmetry, enable more accurate risk pricing, and facilitate the efficient allocation of credit resources. Second, differentiated regulatory approaches are warranted given the heterogeneous effects across industries and regions. Heavily polluting industries in non-eastern regions face disproportionately larger financing challenges and may require targeted transition support, such as green transformation subsidies, low-interest transition loans, or technical assistance for carbon abatement technologies. Third, the moderating role of ESG institutional investors highlights the importance of cultivating a mature, responsible institutional investment ecosystem. Policymakers should incentivize ESG integration in asset management through tax benefits, preferential treatment in public procurement, or inclusion in pension fund investment mandates.

For Financial Institutions. Banks and other creditors should integrate climate risk assessment into their credit evaluation frameworks, moving beyond traditional financial metrics to incorporate physical risk exposure, transition vulnerability, and ESG performance.

Our findings suggest that such integration would improve risk pricing accuracy and loan portfolio resilience. Financial institutions should also develop specialized green financial products that offer preferential terms to firms with robust climate risk management systems, thereby incentivizing proactive climate adaptation and mitigation efforts.

For Corporate Managers. Our results underscore that climate risk management is not merely a compliance exercise but a strategic imperative that directly affects financing costs. Firms should invest in comprehensive climate risk identification and response systems, improve the quality and timeliness of climate-related disclosures, and strengthen ESG performance across all dimensions. The finding that production and operational efficiency and default risk mediate the climate–cost of debt relationship suggests that operational resilience measures, such as supply chain diversification, business continuity planning, and low-carbon technology adoption, can generate tangible financial benefits through lower borrowing costs. Moreover, firms in heavy-polluting industries should prioritize decarbonization roadmaps to mitigate the amplified cost of debt effects identified in this study.

8.3. Limitations and Future Research

This study has several limitations that suggest avenues for future research. First, the firm-level climate risk indicator constructed via textual analysis inherently captures the intensity of climate-related information disclosure in annual reports, rather than a direct and objective measure of actual risk exposure. Despite the validity tests against two objective benchmarks, the measured value remains inevitably influenced by heterogeneous reporting practices, managerial awareness of climate risks, and strategic disclosure incentives across firms. Firms with equivalent actual risk exposure may differ in disclosure length and detail due to divergent information strategies, management cognition, and regulatory pressure, which introduces a certain degree of measurement bias. Future research could combine satellite-derived geographic risk data, field-level physical risk exposure statistics, and granular enterprise carbon emission data to construct more objective and fine-grained climate risk indicators, so as to further mitigate the bias caused by disclosure heterogeneity.

Second, while our mediation analysis verifies the dual transmission channels of financial fundamentals and non-financial reputation, it cannot fully establish strict causality along the mediation paths. Unobserved factors such as managerial capability may jointly affect climate risk disclosure, mediating variables, and the cost of debt. Future studies could exploit quasi-natural experiments such as extreme climate shocks and staggered low-carbon policies to strengthen causal inference of transmission mechanisms.

Third, our findings are based on Chinese A-share listed firms and embedded in China's unique institutional context, so their generalizability to other emerging markets requires further investigation. Future cross-country comparative research can explore how institutional heterogeneity shapes the climate risk–debt cost nexus.

Finally, this study provides a relatively static assessment. As China's "dual carbon" policies continue to evolve, the dynamic interaction between policy shocks, corporate adaptive strategies, and the cost of debt warrants further exploration over a longer horizon.

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Appendix A

Table A1. Glossary of Climate Risks.

Risk Type	Word Set
Physical Risk	disaster, earthquake, typhoon, tsunami, drought and flood, extreme, severe weather, waterlogging, gale, dust storm, hurricane, frost, flood, storm, debris flow, landslide, icy freezing, snow disaster, drought, flood, rainstorm, tornado, hail, flood, rain and snow, freezing, blizzard, freezing injury, drought, drought condition, heavy rainfall, flood, severe cold, wind and sand, climate, weather, humidity, water temperature, temperature drop, cold, air temperature, precipitation, temperature, rainfall, precipitation condition, precipitation, overcast rain, rainy, extreme cold, winter, flood season, high temperature, water regime, water level, sunlight, water shortage, high-cold, cold wave, subsidence, groundwater, flood situation, surface, water storage (63 terms)
Transition Risk	energy saving, energy, clean, ecology, environment, transition, solar, upgrade, recycling, utilisation rate, nuclear power, wind power, natural gas, efficiency enhancement, fuel oil, efficiency, regeneration, emission reduction, environmental protection, green, low-carbon, consumption reduction, fuel, water conservation, photovoltaic, high-efficiency, renovation, fuel consumption, electricity consumption, energy consumption, performance, intensive (32 terms)

Notes: This table provides the English translations of the original Chinese keyword set that was actually used for the textual analysis of Chinese-language annual reports. The word segmentation and frequency counting were performed on the Chinese texts using the corresponding Chinese terms. The translations are supplied solely for the convenience of international readers and do not replace the original Chinese keywords employed in the computational procedure. The numbers in parentheses indicate the total count of keywords in each category.

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