

Article

Climate Risk and Real Estate Bond Pricing in China

Wenwen Zhang ^{1,2}, Ruixin Liang ^{3,*} and Xuepeng Qian ² 

¹ The Center for Studies of Hong Kong, Macao and Pearl River Delta, Sun Yat-sen University, Guangzhou 510275, China; zhangww85@mail.sysu.edu.cn

² Graduate School of Global Environmental Studies, Sophia University, Tokyo 102-8554, Japan; qianxp@sophia.ac.jp

³ Lingnan College, Sun Yat-sen University, Guangzhou 510275, China

* Correspondence: liangrx25@mail2.sysu.edu.cn

Highlights

What are the main findings?

- Empirical estimations indicate that climate transition risks (CTRI) and acute physical risks (AcuCPRI) expand corporate bond credit spreads within real estate sectors, whereas chronic physical risks (ChroCPRI) compress spreads, with these statistical patterns being more pronounced among state-owned enterprises.
- CTRI and AcuCPRI elevate spreads by tightening financing constraints and compressing operational cash flows; conversely, ChroCPRI decrease spreads, which suggests that policy frameworks provide liquidity support, implying that macroprudential policies must incorporate firm structural attributes to mitigate financial contagion.

What are the implications of the main findings?

- Fixed-income investors should convert climate transition and physical risks into quantified credit premium parameters and systematically integrate them into asset pricing models, rather than treating them merely as qualitative marginal metrics.
- Regulatory authorities need to construct a standardized disclosure framework for spatial asset exposures and introduce institutionalized climate stress testing within macroprudential policies, incorporating firm structural attributes to mitigate systemic financial contagion.

Abstract

Understanding the pricing of climate risks in bond markets is relevant to financial stability. The real estate sector, characterized by geographically fixed and long-duration assets, exhibits high exposure to environmental shocks; yet, empirical matching between specific climate channels and real estate bond pricing remains sparse. This analysis examines the impact of climate risks on corporate bond credit spreads within the real estate sector by constructing three thematic indicators: transition risk (CTRI), chronic physical risk (ChroCPRI), and acute physical risk (AcuCPRI). Initial feature selection via machine learning suggests all three risk categories as predictive covariates for bond pricing. Subsequent regression estimations indicate that climate transition risk and acute physical risk expand credit spreads, whereas chronic physical risk compresses them—with these statistical patterns being more pronounced among state-owned enterprises (SOEs). Mechanism analyses yield threefold insights: first, transition risk elevates spreads by tightening financing constraints and restricting corporate asset growth, a channel concentrated in short-term tranches and low-liquidity firms; second, the counterintuitive spread-compressing effect of chronic risk is localized among firms with lower credit ratings and lower profitability, consistent with institutional climate support frameworks and strategic green adaptations; third, acute



Academic Editor: Alberto
Pauca-Caceres

Received: 13 April 2026

Revised: 14 July 2026

Accepted: 19 July 2026

Published: 22 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

physical risk widens spreads by compressing operational cash flows and exacerbating financing friction, particularly for smaller enterprises. These channels align with the structural attributes of SOEs, which are characterized by larger asset scales, superior capital liquidity, and a higher propensity to secure state guarantees.

Keywords: climate risks; corporate bonds; real estate bonds; machine learning

1. Introduction

Amid accelerating global climate change, both physical and transition risks present structural risks to the stability of the financial system. International organizations such as the Bank for International Settlements (BIS) and the Financial Stability Board (FSB) have repeatedly emphasized that integrating climate-related risks into the macroprudential regulatory framework—and accurately assessing and pricing such risks—constitutes a core agenda for safeguarding global financial stability and sustainable development. Debt financing represents a critical funding channel for firms, while the bond market, highly sensitive to risk, stands at the forefront of incorporating climate risk into pricing. How climate risks are transmitted into bond valuations not only shapes the efficiency of resource allocation, but also directly determines the resilience of the financial system. Yet, research in this area remains nascent, with sector-specific analyses still conspicuously absent.

In China, the real estate sector, a substantial component of the national economy, contributed RMB 8.46 trillion in value added in 2024, or roughly 7.3% of GDP. Owing to its structural features, the sector exhibits distinctive exposures to climate risks. The immobility of real estate assets makes them particularly vulnerable to localized climate disasters, while their long-duration nature entails sustained exposure to climate shocks over decades. These characteristics imply dual vulnerabilities: potential devaluation and higher operational costs, on the one hand, and heightened uncertainty arising from regulatory pressures and shifting consumer preferences in the context of the green transition on the other hand. Nevertheless, the literature has yet to provide systematic evidence on how climate risks are reflected in the financing costs of real estate firms, especially through bond pricing. This gap constrains our understanding of the financial consequences of climate change and hampers both investors' ability to hedge risks and regulators' capacity to design effective responses.

Real estate corporate bonds are theoretically distinct from general corporate bonds due to two characteristics: spatial asset fixation and financial leverage. Unlike standard industrial firms with geographically mobile operations or dispersed supply chains, real estate developers hold capital-intensive assets—such as land reserves and housing projects—that are geographically fixed and illiquid. Consequently, physical climate risks reduce the value of the underlying collateral, which serves as security for bondholders. Moreover, climate transition policies impose green building mandates, generating capital expenditure shocks and regulatory frictions for leveraged developers. In this context, China offers an informative institutional setting. The dual-track credit market, characterized by the co-existence of state-owned enterprises (SOEs) with implicit guarantees and non-SOEs under market-clearing pressure, allows for the examination of how government interventions and ownership structures moderate climate risk shocks.

To analyze these dynamics, this study evaluates the credit pricing of three categories of climate risks: transition risk, chronic physical risk, and acute physical risk. Using a machine learning framework for feature selection followed by high-dimensional fixed-effects regressions, the empirical analysis provides evidence consistent with the asymmetric pricing of these risk factors. The results indicate that transition risks and acute physical

risks widen credit spreads, reflecting investor concerns over regulatory compliance costs and physical asset damage. In contrast, chronic physical risks relate to narrower spreads, a pattern consistent with the effects of local government climate subsidies and disaster resilience expenditures. Furthermore, ownership structures moderate these relationships: state-owned developers exhibit greater pricing sensitivity. This pattern is attributable to the dual institutional roles of state-owned enterprises: while these firms retain access to implicit government guarantees, they also encounter compressed liquidity and diminished profitability due to their mandate to bear higher social responsibilities.

The contributions of this paper are threefold. First, it provides empirical evidence on the asymmetric credit pricing of tripartite climate risks within a sector characterized by geographically fixed and long-duration assets. Second, the study analyzes how institutional features in emerging markets—specifically, implicit government guarantees—moderate climate risk shocks for state-owned enterprises (SOEs). Third, the empirical design employs a machine learning algorithm (RFECV) for objective feature selection to construct the control-variable set, mitigating variable-picking bias in the subsequent fixed-effects OLS regressions.

The remainder of the paper is organized as follows. Section 2 reviews the related literature; Section 3 applies machine learning models to identify the key determinants of real estate bond credit spreads; Section 4 incorporates climate risk indices into the analysis; Section 5 develops model to examine the effects of climate risk on bond credit spreads; Section 6 conducts robustness tests; Section 7 investigates the underlying mechanisms; and the final section concludes with implications and recommendations.

2. Literature Review and Hypothesis Development

2.1. Literature Review

Climate change is not only profoundly affecting social life but also reshaping the fundamental logic of economic activity. Nordhaus (1997) provided a pioneering framework for examining the interaction between climate risk and the real economy [1]. Subsequent research has extended in multiple directions, like the impact of rising temperatures on output and political stability as well as on economic growth and inequality [2,3].

Existing literature generally classifies climate risks into two categories: physical risk and transition risk. Physical risk refers to risks directly arising from climate change that affect economic activity. Drawing on Tankov and Tantet (2019), physical risk can be conceptualized in terms of hazard (the intensity and probability of climate events), exposure (the geographical distribution of affected entities), and vulnerability, such as productivity declines and asset impairments caused by rising sea levels [4]. Transition risk captures the broad range of effects firms may face in the process of green transition, like the effects of firms' operations and business model. Following Semieniuk et al. (2021), transition risk can be analyzed along with policy risk, technology risk, and preference change [5]. Examples include regulatory risks from carbon taxation for high-carbon-emission firms, risks arising from R&D investment and technological competition during green transitions, and risks from consumer preferences shifting toward low-carbon activities [6].

Numerous studies demonstrate that climate change reduces corporate profitability and that extreme weather and natural disasters adversely affect firms' operations and revenues [7]. For example, Pankratz et al. (2023) found that prolonged exposure to heat and flooding leads to declines in both revenue and operating profit [8]. These findings have heightened investors' attention to corporate climate risk. In recent years, significant progress has been made in studying its influence on asset prices, offering practical guidance for hedging strategies in financial markets. Most studies on climate risk and asset pricing focus on equity markets, although the conclusions remain mixed. Many argue that current

stock prices do not fully reflect climate risk. Bolton and Kacperczyk (2021), using U.S. equity market data, showed that a carbon premium persists after controlling for other return predictors like size and book-to-market ratio [9]. Choi et al. (2020) found climate risk premia in global equity markets, with similar evidence reported in the options market [10,11]. However, climate risk does not always exert negative effects. Chen et al. (2025) constructed indices for long-term physical risk, acute physical risk, and transition risk and conducted event studies on stock returns, finding heterogeneous impacts across industries with both positive and negative effects [12]. A smaller strand of research suggests partial pricing of climate risks in equity markets. Faccini et al. (2023), for instance, constructed climate risk indices based on natural disasters, global warming, international summits, and U.S. climate policy, showing that policy-related risks are already priced in, whereas the other three remain associated with premia [13].

More recently, the fixed income market has attracted increasing attention in the climate finance literature. Many studies rely on textual analysis to construct climate risk factors. These include indices derived from analyst reports, news, and corporate reports, which revealed significant effects of climate risk on bond issuance prices and subsequent yields [14–16]. Other work incorporated geographic and weather data, highlighting risk premia associated with physical climate risks. Painter (2020) showed that municipal bonds issued in areas expected to face substantial losses from sea-level rise carry significantly higher yields, and similar evidence has been found in corporate bonds [17,18]. Nevertheless, no study has yet systematically constructed climate risk factors to examine their impact on bond pricing, which represents an important gap in the literature that we want to bridge.

Chen et al. (2025) further highlighted heterogeneous effects of climate shocks across industries [12]. This motivates attention to sectors that are particularly vulnerable to climate risks, such as real estate. Once constructed, real estate assets are geographically immobile, making it impossible to evade regional climate risks through relocation. Therefore, it is especially fragile and complex in this context. On the one hand, assets are subject to short-term and long-term devaluation as well as additional operating costs. For example, Bernstein et al. (2019) showed that rising sea levels reduce property values [19]. On the other hand, regulatory pressures and consumer demand for green transformation introduce further uncertainty. Nguyen et al. (2022) found that lenders charge higher mortgage rates for properties facing greater exposure to sea-level rise, while Cho et al. (2024) documented that strict green building standards impose additional cost pressures on real estate firms [20,21]. On this basis, we believe that the real estate bond market will also be impacted by climate risks.

In summary, current research on climate risk focuses primarily on physical and transition risks and their economic and financial consequences. Studies on asset pricing are concentrated in equity markets, where evidence is mixed but relatively extensive. In contrast, fixed income markets have received less attention, and systematic construction of climate risk factors for bond pricing remains limited. Moreover, little work has examined industries with heightened vulnerability, such as real estate. Though some studies have discussed the effects of climate risks on real estate firms' physical assets and operations, no research has explicitly linked climate risks to the bond market of the real estate industry. This paper addresses this gap by incorporating climate risk factors into the pricing of real estate bonds and investigating the underlying mechanisms.

2.2. Hypothesis Development

Based on the literature review above, we propose hypotheses from three aspects: climate transition risk, chronic climate physical risk, and acute climate physical risk, to examine their impact on the credit spreads of real estate bonds.

An increase in climate transition risk often implies stricter environmental regulatory requirements and greater external investor focus on corporate environmental protection. This introduces pricing friction into corporate bond markets. Within the real estate sector, this transmission mechanism operates through two primary channels. First, transition regulations tend to increase capital expenditures and operating costs. To comply with evolving green building standards, real estate firms face energy efficiency mandates and retrofitting obligations. These expenditures reduce operating cash flows, lower profitability, and compress asset values, thereby potentially elevating default risks [22]. Second, transition uncertainty alters not only the present value of assets but also asset volatility, exacerbating corporate financing constraints. Regulatory uncertainty expands the variance of future asset values, which logically increases the option value of default and subsequently widens yield spreads [23]. Given that the real estate sector relies on long-term debt financing and fixed capital assets, exposure to carbon policies increases the probability of financial distress. Bondholders respond to such risk exposures by demanding wider credit spreads to hedge against potential rating downgrades and asset stranding risks. Based on this, we propose the following hypothesis:

H1: *Climate transition risk will increase the credit spreads of real estate corporate bonds.*

Conventional credit risk frameworks suggest that climate physical risks threaten corporate debt-servicing capacity by damaging physical assets or disrupting supply chains, thereby elevating credit spreads. However, this direct transmission mechanism from physical hazards to credit risks is conditioned by institutional dynamics within state-led market economies [24,25]. In regions characterized by elevated long-term physical climate risks, local governments face compliance pressures regarding environmental policy enforcement from higher-level authorities. Consequently, these local governments actively deploy targeted regulatory and fiscal interventions—what we term “climate support” policies.

On the one hand, subnational governments allocate green subsidies to mitigate these risks. For instance, under the Fourteenth Five-Year Plan for Building Energy Efficiency and Green Building Development issued by the Ministry of Housing and Urban–Rural Development, local authorities introduced R&D subsidies, tax incentives, and floor area ratio (FAR) bonuses to promote high-resilience green buildings. These measures assist real estate firms in enhancing innovation capabilities [26]. Also, facilitating explicit government endorsement assists in stabilizing investor confidence.

On the other hand, the authorities launched environmental projects, particularly in municipalities vulnerable to long-term climate impacts. Through initiatives such as the “Climate Investment and Financing Pilot” and the national “Sponge City” construction schemes jointly advanced by the Ministry of Ecology and Environment and other ministries, local governments direct investments into municipal adaptive public goods—including flood control networks, upgraded drainage systems, and public disaster-prevention infrastructure. These public investments stabilize real estate project valuations and support cash flows for property developers. Based on these insights, we propose the following hypotheses:

H2a: *Chronic climate physical risk will increase the credit spreads of real estate corporate bonds.*

H2b: *Chronic climate physical risk will decrease the credit spreads of real estate corporate bonds.*

Real estate firms depend on geographically fixed physical assets, rendering their operating cash flows and collateral values considerably sensitive to climate disaster shocks. Acute climate disasters, such as typhoons and floods, induce physical damage to the fixed assets of real estate firms. This destruction prompts asset impairments, on the one hand, and generates immediate reconstruction expenditures on the other hand [19,27], thereby weakening property operational capacities, compressing corporate cash flows, and elevating default risks.

Investors likewise demand a higher risk premium for exposure to such climate hazards. Painter (2020) indicates that localized exposure to flood and wind risks increases bond yield spreads and underwriting costs, and it appears more pronounced in long-term securities facing greater cumulative risk exposure [17]. Based on these insights, we propose the following hypotheses:

H3: *Acute climate physical risk will increase the credit spreads of real estate corporate bonds.*

The above assumptions can be summarized as the following framework (Figure 1):

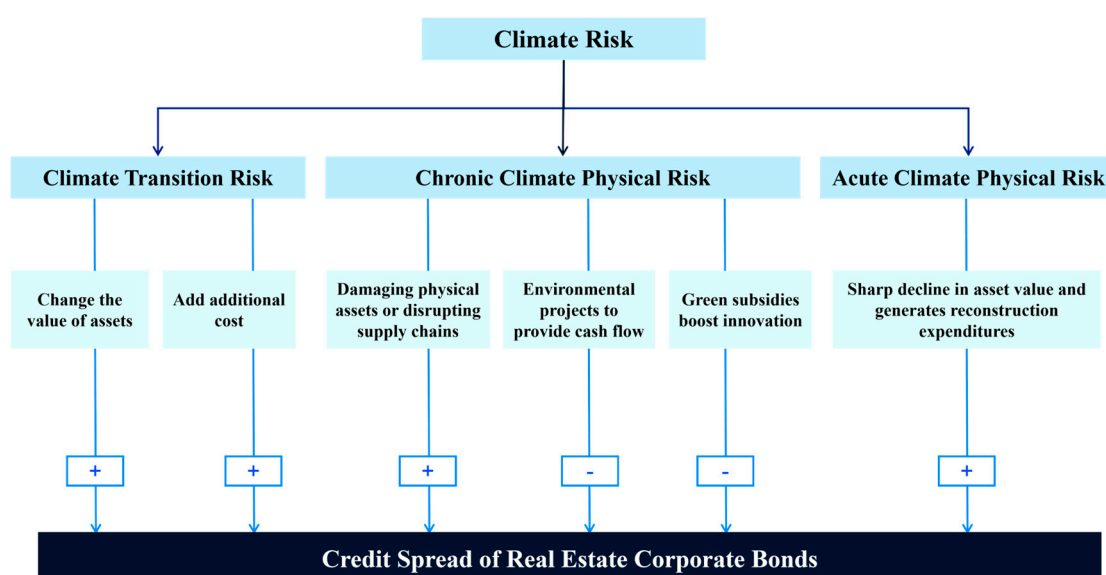


Figure 1. Logic diagram of climate risk and real estate bond credit spread assumptions.

Kornai pioneered the theory of implicit government guarantees, arguing that state-owned enterprises (SOEs) frequently receive state fiscal subsidies or bank credit bailouts during periods of financial loss due to political and economic objectives. This argument is consistent with Brandt and Li (2003), who demonstrated that banks preferentially allocate credit assets to SOEs owing to these implicit guarantees [28]. The mechanism remains valid within the Chinese context [29]. Furthermore, implicit guarantees lower the debt financing costs of firms, thereby narrowing bond credit spreads [30]. When facing external shocks, such as climate risks, SOEs tend to possess a comparative advantage in securing government assistance, suggesting that SOEs operate with greater resilience against climate-related disruptions. Under the Chinese institutional framework, the government typically steers climate governance, deploying targeted subsidies and tax incentives to stimulate corporate environmental initiatives. Because SOEs are often the primary recipients of these subsidies [29], their default risks are partially mitigated, ultimately leading to a compression of their bond credit spreads.

However, SOEs are characterized by a dual mission that encompasses both commercial profitability and the execution of social policies. In implementing climate transition policies,

SOEs regularly serve as the primary entities fulfilling environmental obligations. Within the real estate sector, state-owned developers typically act as exemplars in enforcing green building standards and reducing energy intensity. These decarbonization regulatory pressures introduce substantial compliance burdens, which escalate short-term capital expenditures and impair corporate profitability, thereby potentially widening bond credit spreads [23].

Similarly, during acute climate events, such as floods and typhoons, all real estate firms suffer losses from project disruptions and physical asset destruction. Nevertheless, SOEs and non-SOEs developers exhibit asymmetric financial burdens during post-disaster reconstruction [31]. Following natural disasters, SOEs must prioritize public welfare and social stability, leading disaster relief, funding local reconstruction, and maintaining employment levels. These administrative mandates divert substantial financial resources from commercial operations to emergency responses, exacerbating financial distress and cash flow volatility. Conversely, market-oriented non-SOEs remain unconstrained by such administrative obligations; these firms can dynamically scale back investments in disaster-affected regions or write off asset losses to preserve liquidity. Consequently, the burden of post-disaster social responsibility causes acute physical risks to exert a more pronounced upward pressure on the credit spreads of SOEs than on those of non-SOEs.

Based on the framework above, we propose the following hypotheses:

H4: *Climate transition risk and acute climate physical risk will increase the credit spreads of real estate corporate bonds, especially for SOEs.*

H5: *For SOEs, chronic climate physical risk will decrease the credit spreads of real estate corporate bonds.*

3. Feature Analysis for Credit Spreads of Real Estate Bond

3.1. Variable Selection

The dependent variable in this study is the credit spread at issuance, which effectively measures the risk compensation demanded by investors when a firm issues bonds. Following Fang et al. (2013), we defined the credit spread (CS) as the difference between a corporate bond's coupon rate and the yield on a government bond with an equivalent time to maturity [32]. Consistent with Zhou et al. (2012), we used interpolation to compute any missing yields for government bonds of a specific maturity [33].

Bond credit spreads are influenced by a multitude of factors. Key bond-specific characteristics, such as maturity, coupon rate, bond type, guarantee status, special provisions, bond credit rating, issuer credit rating, and so on, will directly influence issuance pricing and yield, which in turn affect the credit spread. For instance, longer maturities typically command higher risk premiums from investors, resulting in wider credit spreads. Provisions such as guarantees and put options tend to reduce a bond's risk exposure, whereas call options typically increase the credit spread. Corporate governance is another critical determinant. Extensive research demonstrates that strong corporate governance enhances operational performance and improves the quality of accounting information and so on [34,35]. Furthermore, Zhou et al. (2018) found that robust governance practices improve firm performance and reduce information asymmetry, consequently lowering bond credit spreads [36]. Accordingly, the inclusion of governance-related indicators is warranted.

Financial information provides a critical basis for assessing a firm's operational status and default risk [37,38], thereby exerting a substantial influence on its credit spreads. A firm's assets and asset structure reflect its overall strength; larger firms often mitigate investor concerns regarding creditworthiness, leading to lower credit spreads. Profitability

is a vital indicator of operational health. Stronger profitability in real estate firms typically alleviates market concerns about their solvency, resulting in narrower spreads. Solvency ratios directly reflect a firm's debt structure and default risk. Liquidity metrics indicate a firm's ability to meet short-term obligations. Currently, cash flow constraints from declining sales have intensified market anxiety over the credit standing of Chinese real estate firms. Indicators of operational efficiency reflect daily operational capabilities. Due to the unique nature of the pre-sale system adopted by real estate firms, the management of accounts receivable and inventory significantly impacts a firm's liquidity and further impacts credit spread. The structure of costs and expenses reveals insights into governance and strategic direction. A higher operating expense ratio may suggest greater agency costs, which would increase the credit spread, while a rising R&D expense ratio may signal innovation efforts, potentially bolstering investor confidence and reducing the spread. Finally, growth prospects reflect a firm's capacity for sustained operations. Consecutive declines in profit can erode investor confidence, thereby increasing the credit spread. In summary, the financial information of bond issuers influences their credit risk in multiple ways, thereby exerting multifaceted effects on bond credit spreads.

Based on the preceding theoretical framework and data availability, we initially selected 354 indicators across three dimensions for model training: bond characteristics, corporate governance, and corporate financials. The definitions and notations for these variables are provided in Appendix A, Table A1.

3.2. Data Source and Sample Screening

Our sample comprised all real estate bonds issued in China, subject to the following screening criteria: (1) we excluded floating-rate and convertible bonds; (2) we removed observations with missing values for key variables; and (3) we winsorized all continuous variables at the 1st and 99th percentiles. This process yielded a final sample of 4553 bond observations. Data on real estate bonds were sourced from the Choice and CSMAR databases, while related financial data were obtained from the CSMAR and CNRDS databases. We employed a stratified random sampling method to partition the data into training and testing sets at an 8:2 ratio. This approach preserves the temporal structure of the original data, ensuring a more reliable evaluation of the model's generalization performance. The sample of 4553 bonds was partitioned into a training set (3642 observations) and a testing set (911 observations) at an 8:2 ratio. The random forest regressor yielded an R^2 score of 0.7410 on the training set and 0.7098 on the testing set. The root mean squared error (RMSE) was 0.693 for the training set and 0.732 for the testing set. This small generalization gap between the training and testing datasets indicates the stability of the feature selection process.

3.3. Initial Feature Importance Ranking with Random Forest

First, we employed permutation importance to assess the predictive contribution of each feature. This technique mitigates the inherent bias in tree-based importance measures by quantifying the performance degradation caused by randomly permuting the values of a single feature [39]. Figure 2 displays the 20 most important predictors of real estate bond credit spreads, while Table A2 provides their corresponding permutation importance scores.

As shown in Figure 2, the five most influential features are the bond credit rating, state-owned enterprise (SOE) status, firm size, bond guarantee status, and the presence of separable special provisions. Corporate bond credit ratings serve as robust indicators of default risk; higher ratings signify lower default probabilities, compressing credit spreads. State-owned enterprises (SOEs) benefit from reputational advantages, and their debt is often perceived as carrying an implicit government guarantee [32], which lowers their

credit spreads. This effect is reinforced by SOEs typically receiving higher credit ratings and having access to government support, such as subsidies, favorable credit and direct financial assistance, which reduces their credit risk [40]. Firm size is a critical determinant of solvency. Alfaro et al. (2019) indicates that larger firm size significantly reduces financial vulnerability, which in turn lowers default risk and narrows the credit spread [41]. A third-party guarantee typically reduces a bond's credit risk, resulting in a lower credit spread. Separable provisions, which allow the bondholder to detach certain embedded rights, like warrants, and trade them as separate instruments, generally reduce the initial credit spread at issuance. These features ranked highest in the initial random forest analysis, indicating their significant contribution to explaining variations in real estate bond credit spreads. This initial ranking provides valuable guidance for the subsequent feature selection process.

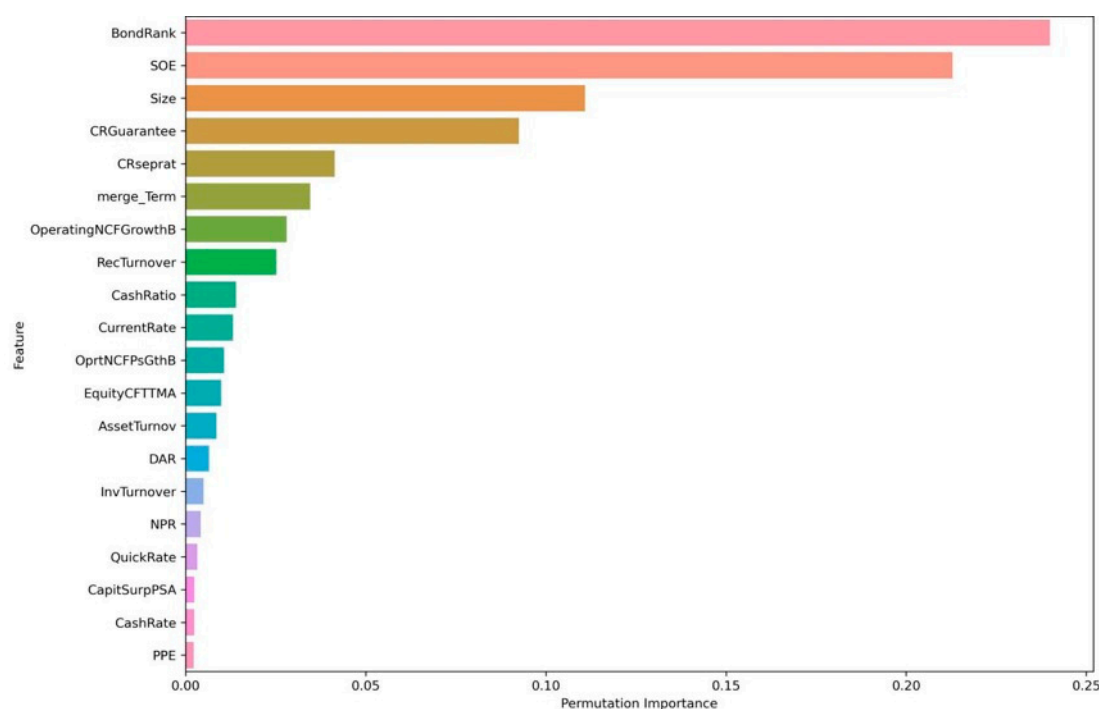


Figure 2. Top 20 permutation feature importance for predicting credit spread—initial model.

4. Climate Risk Factor Analysis

4.1. Definition of Climate Risk

Following Chen et al. (2025), we examined three categories of climate risk: transition risk, chronic physical risk, and acute physical risk [12]. Specifically, to measure climate transition risk, we adopted the approach of Peng et al. (2025) and Liu & Yuan (2025) [14,42]. We collected government work reports from 284 cities, including municipalities, and employ text analysis using Python 3.13.5. We then constructed the Climate Transition Risk Index (CTRI) as the keyword frequency.

For chronic climate physical risk, we adopted the methodology and data of Guo et al. (2024) [43]. We collected city-level data on the number of extreme climate events, which included extreme low temperatures, extreme high temperatures, extreme droughts, and extreme precipitation. After standardizing each of these four event-count indicators, we defined the Chronic Climate Physical Risk Index (ChroCPRI) as the average of the resulting standardized sub-indices.

For acute climate physical risk, consistent with Chen et al. (2025), we sourced provincial-level data from CNRDS on direct economic losses from natural disasters [12]. These disasters included droughts, floods, typhoons, landslides, mudslides, wind and

hailstorms, low temperature freezing, snowstorms, and pest plagues. We constructed the Acute Climate Physical Risk Index (AcuCPRI) by summing the total economic losses from all of these disasters and taking the natural logarithm of the total. For details on variable construction methods, please refer to Appendix B.

4.2. Feature Importance Ranking Including Climate Risk Factors

In this section, we still employ permutation importance to evaluate the predictive contribution of each feature. Figure 3 presents the top 20 most important predictors of real estate bond credit spreads after including the climate risk factors, and Appendix A, Table A3 reports their corresponding permutation importance scores.

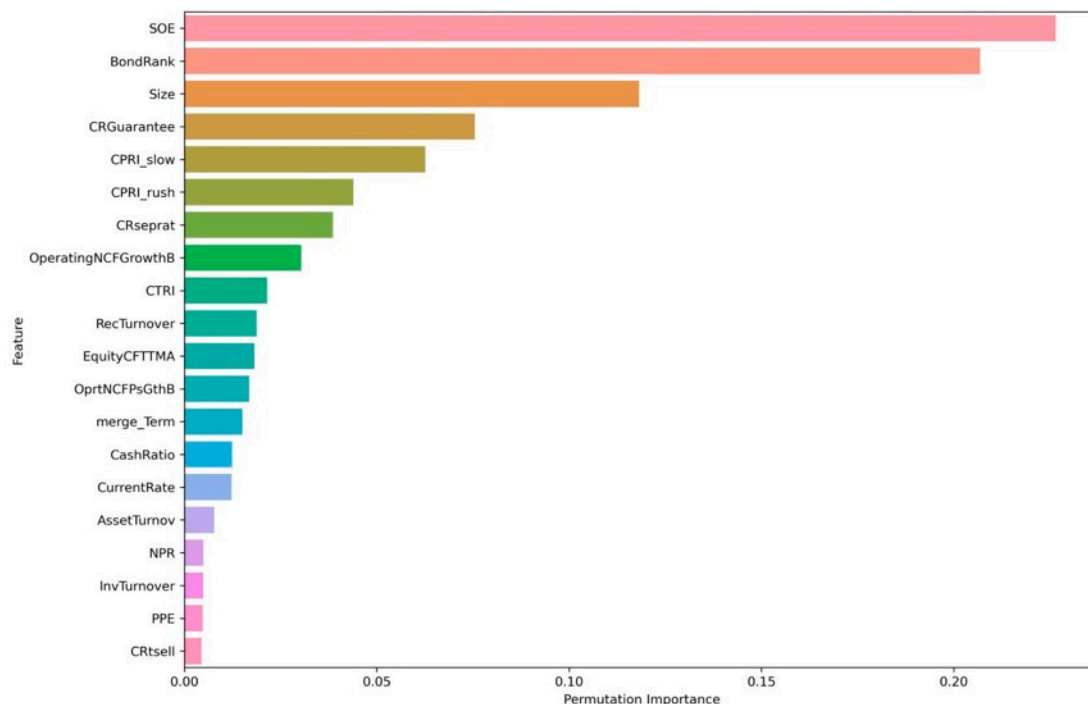


Figure 3. Top 20 permutation feature importance for predicting credit spread—adding climate risk.

Figure 3 reveals that climate risk factors are significant predictors of credit spreads. The chronic physical risk, acute physical risk, and transition risk factors ranked fifth, sixth, and ninth in importance, respectively. This finding suggests that amid growing global climate concerns, climate risk exerts a subtle yet significant influence on the real estate bond market. A comparison of Figures 2 and 3 shows that state-owned enterprise (SOE) status, bond credit rating, firm size, and bond guarantee status remained the four most dominant predictors. This phenomenon draws our attention, prompting a further investigation into the mechanisms through which these key factors affect real estate bond CS.

4.3. Selecting the Optimal Feature Subset Using Rfecn

Control variables were selected via a machine learning framework. The primary specification employs a random forest (RF) regressor, a bagging ensemble method less susceptible to overfitting in corporate finance datasets with high-dimensional, multicollinear features. For robustness, we compared the prediction performance of random forest with XGBoost and LightGBM using 5-fold cross-validation on an 80% training set (see Appendix A Table A4). The results show that random forest (with 191 trees, Test $R^2 = 0.7115$; and with 38 trees, Test $R^2 = 0.6985$) performed competitively with XGBoost (Test $R^2 = 0.7125$) and outperformed LightGBM (Test $R^2 = 0.6995$), providing evidence consistent with the stability of the primary baseline estimator.

After incorporating the three climate risk factors into our feature set, we employed recursive feature elimination with cross-validation (RFECV) to select an optimal subset of predictive indicators. The RFECV procedure was implemented using a random forest model. We first determined that the optimal number of trees (estimators) for the random forest was 38¹, as this value achieved the highest mean cross-validation score on the training set (Figure 5). Using this optimized model, feature importance was evaluated based on the mean decrease in Gini impurity. The RFECV process then iteratively removes the least important features, with the optimal number of features selected by using 5-fold stratified cross-validation to maximize the R-squared (R^2) score. This method is adept at selecting the most predictive subset of variables from a large feature set. It also effectively mitigates overfitting, avoids the subjectivity of manual thresholding, preserves information from feature interactions, and enhances model interpretability. The entire process was implemented using the scikit-learn library in Python.

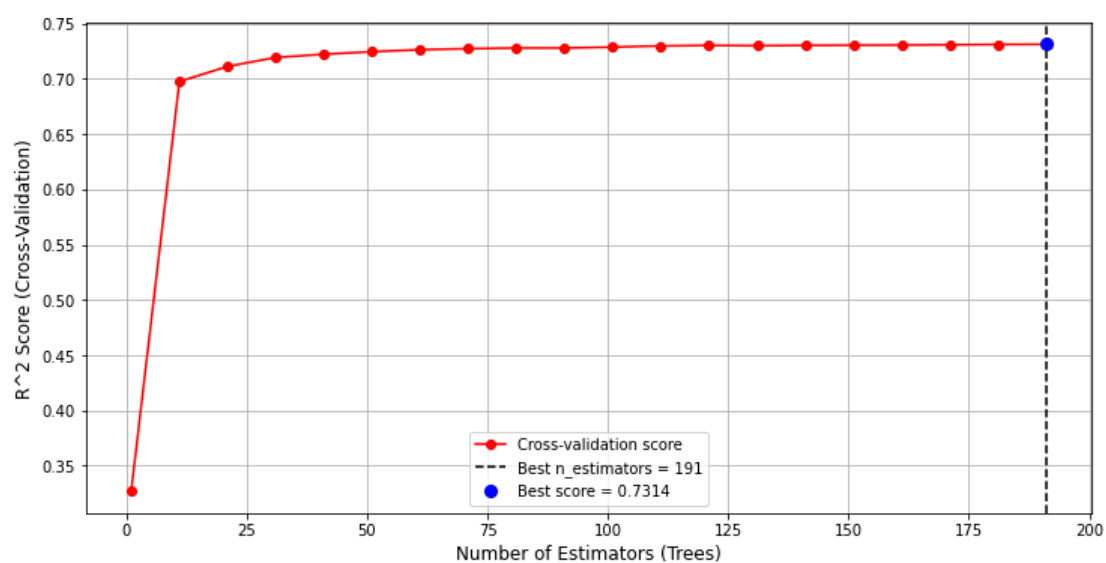


Figure 4. Learning curve for the random forest regressor (0–200 estimators).

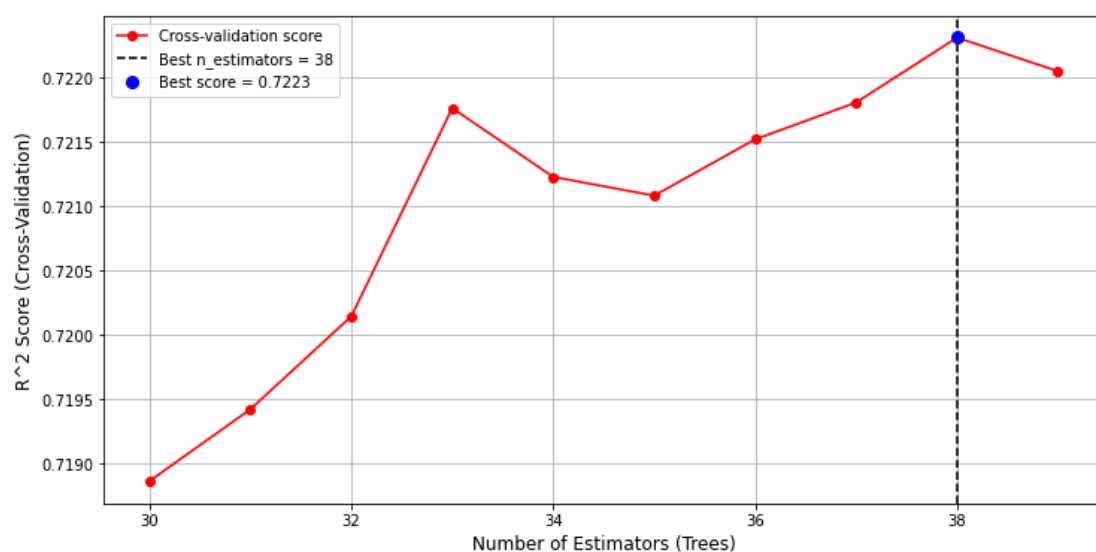


Figure 5. Learning curve for the random forest regressor (30–40 estimators).

As illustrated by the cross-validation scoring curve in Figure 6, the model achieved its highest R^2 score with a subset of 44 features. Consequently, the RFECV process reduced the initial feature set from 357 to this optimal subset of 44.

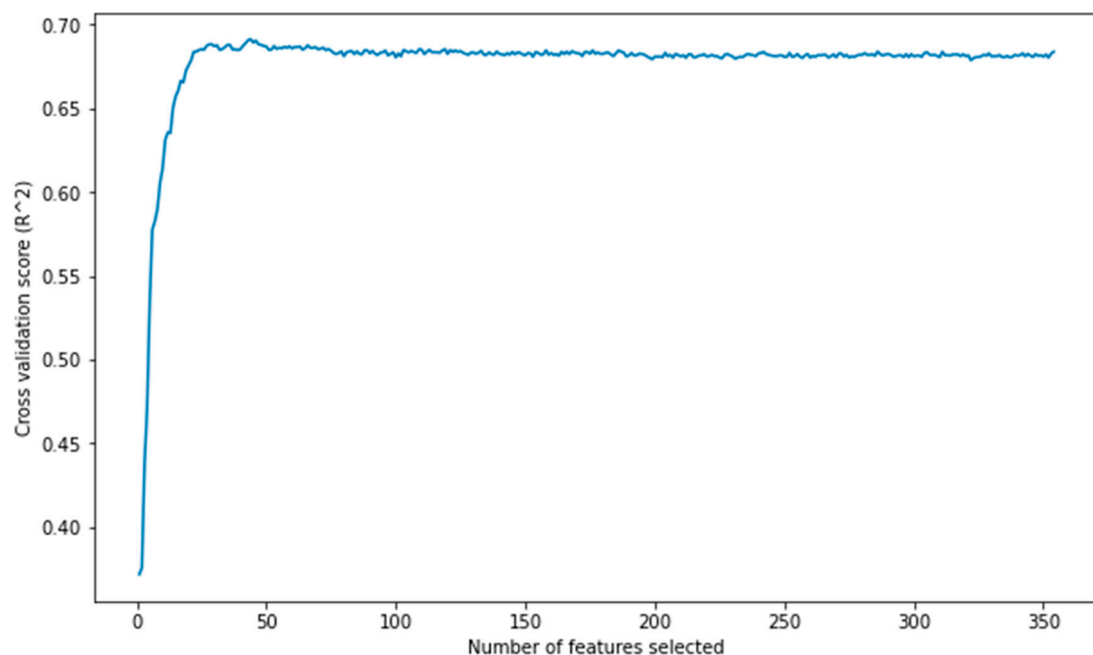


Figure 6. Recursive feature elimination with cross-validation.

Appendix A, Figures A1–A3 and Table 1 display the feature importance rankings of the top 20 most important predictors derived from models incorporating each of the different climate risk factors (the specific importance values for all 44 selected features are detailed in Appendix A, Table A5). The results indicate that the climate transition risk, chronic physical risk, and acute physical risk factors all made a significant contribution to predicting real estate bond CS, ranking as high as fourth in feature importance. Also, the inclusion of these factors individually led to a significant enhancement in the model's predictive power. The final R^2 scores for models including transition risk, chronic physical risk, and acute physical risk were 0.6929, 0.7098, and 0.6952, respectively, with the model incorporating chronic physical risk achieving the highest performance.

Table 1. Top 20 best feature importance for predicting credit spread in the final model—adding climate risk.

Panel A: CTRI		Panel B: ChroCPRI		Panel C: AcuCPRI	
Final model R^2 score	0.6929	Final model R^2 score	0.7098	Final model R^2 score	0.6952
Feature	Importance	Feature	Importance	Feature	Importance
SOE	0.1139	SOE	0.1138	SOE	0.1139
BondRank	0.1037	BondRank	0.1035	BondRank	0.1039
Size	0.1004	Size	0.0984	Size	0.0998
CTRI	0.0525	ChroCPRI	0.0634	AcuCPRI	0.0598
Maturity Term	0.0398	EquityCFTTM	0.0395	EquityCFTTM	0.0394
EquityCFTTM	0.0394	Maturity Term	0.0363	Maturity Term	0.0384
Guarantee	0.0357	Guarantee	0.0361	Guarantee	0.0343
RecTurnover	0.0305	CashRatio	0.0296	RecTurnover	0.0297

Table 1. Cont.

Panel A: CTRI		Panel B: ChroCPRI		Panel C: AcuCPRI	
CashRatio	0.0296	RecTurnover	0.0290	CashRatio	0.0294
Separability	0.0235	Separability	0.0231	Separability	0.0244
InvTurnover	0.0234	InvTurnover	0.0227	InvTurnover	0.0229
CurrentRate	0.0228	NPR	0.0224	OperatingNCFGrowth	0.0207
OperatingNCFGrowth	0.0205	CurrentRate	0.0215	CurrentRate	0.0206
PPE	0.0202	OperatingNCFGrowth	0.0213	PPE	0.0201
NPR	0.0200	PPE	0.0205	NPR	0.0200
AssetTurnover	0.0196	AssetTurnover	0.0193	AssetTurnover	0.0195
CapitSurpPSA	0.0173	QuickRate	0.0180	QuickRate	0.0171
QuickRate	0.0173	CapitSurpPSA	0.0169	CapitSurpPSA	0.0170
Cash	0.0159	Cash	0.0153	Cash	0.0161
OpntNCFPsGrowth	0.0158	CashRate	0.0152	DAR	0.0148

Notably, state-owned enterprise (SOE) status, bond credit rating, and firm size remained among the top four most important features influencing CS. This underscores the need for our further investigation into their operational mechanisms. Furthermore, by comparing Tables A2 and A3, we found that the feature importance of SOE status, bond credit rating, firm size, and bond guarantee status decreased significantly after model optimization with climate risks variables. This finding suggests that climate risk has a material impact on the bond market, likely sharing explanatory power with these traditional indicators.

4.4. The Role of State Ownership in Determining Real Estate Bond Credit Spreads

The preceding analysis consistently suggests that firm ownership is a determinant of real estate bond CS, both with and without the inclusion of climate risk factors. This section explores the underlying mechanisms that drive the significance of state ownership. In Figures 2 and 3 below, SOE = 1 denotes a state-owned enterprise, while SOE = 0 denotes a non-state-owned enterprise.

Figure 7a shows that state-owned real estate firms are more likely to secure guarantees for their bonds. This enhancement strengthens their debt-servicing capacity and bolsters investor confidence. As shown in Figure 7b, a larger proportion of bonds issued by SOEs received high credit ratings. However, the rating distribution for SOEs also displayed greater variance. Notably, the share of SOE bonds with a zero-credit rating² was 33.2%, which was higher than the 24.7% observed for non-SOE bonds. This finding supports the concept of an “implicit guarantee” for SOEs. This implicit guarantee enhances investor confidence, enabling SOE bonds to maintain market access and viability even when they possess low formal credit ratings.

Figure 8a reveals that non-SOE real estate firms exhibited greater variance in firm size, with a tail of smaller enterprises. In contrast, SOEs were generally larger, which typically endows them with stronger operational capacities and a greater ability to manage risk. Liquidity is another critical factor in determining bond default probability. As Figure 8b illustrates, SOEs tend to have better and more evenly distributed liquidity profiles, which contributes to a lower default probability for their bonds. Finally, Figure 8c indicates that non-SOE firms showed greater variance in their return on assets (ROA), with a higher incidence of losses. The ROA for SOEs, however, was more tightly clustered, suggesting more stable profitability. This stability further contributes to the lower default risk associated with their bonds.

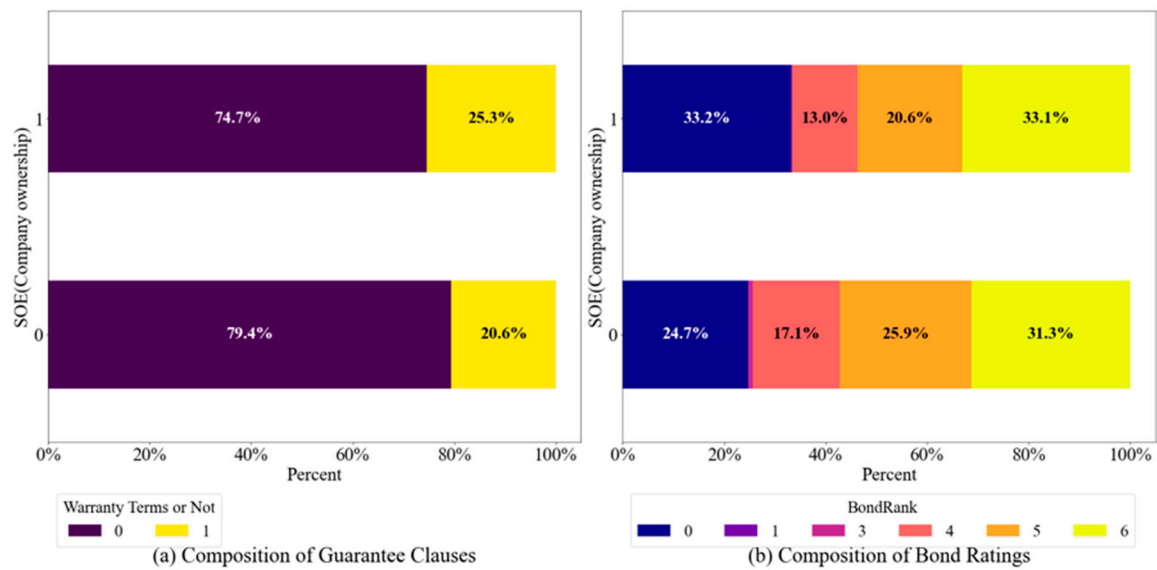


Figure 7. Comparison of bond features between SOEs and non-SOEs: (a) Composition of guarantee clauses of SOEs and non-SOEs; (b) Composition of bond rating of SOEs and non-SOEs.

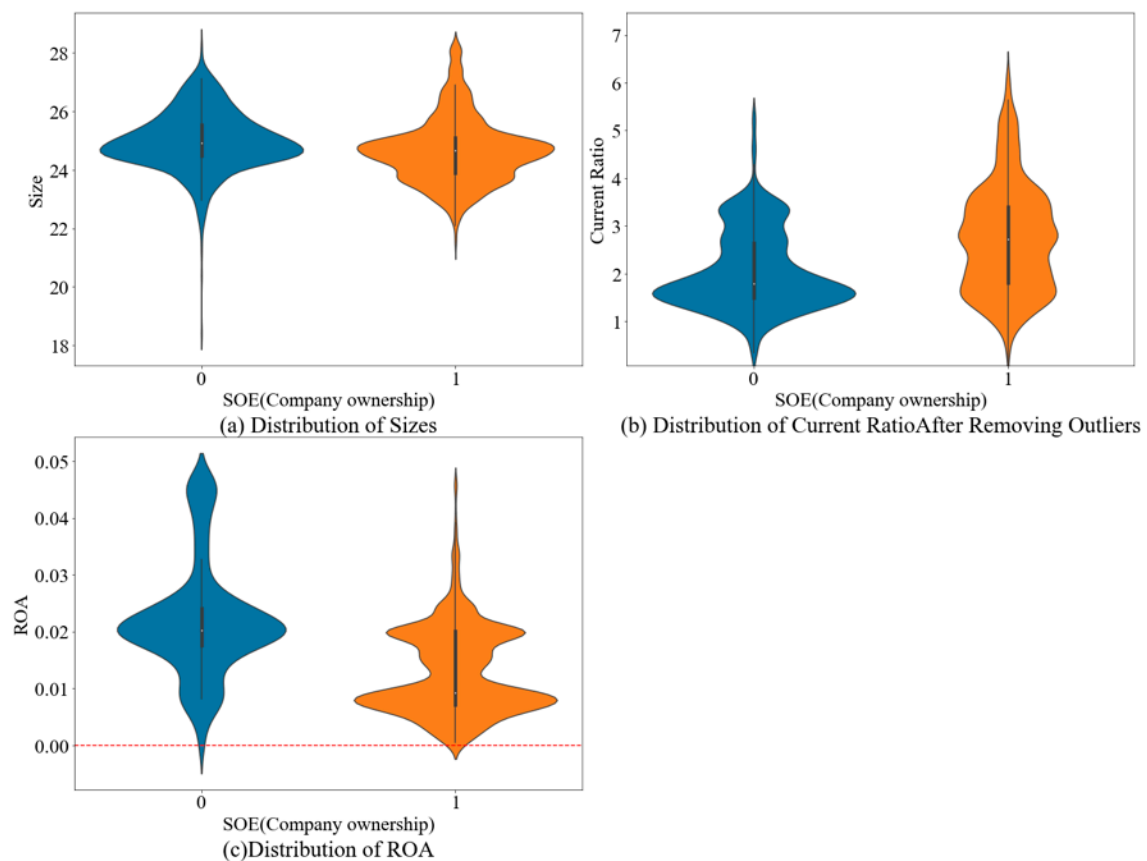


Figure 8. Comparison of financial features between SOE and non-SOE: (a) Distribution of size for SOEs and non-SOEs; (b) Distribution of current ratio (after removing outliers) for SOEs and non-SOEs; (c) Distribution of ROA for SOEs and non-SOEs.

5. Regression Model

5.1. Model Construction

To investigate the impact of climate risk on the credit spreads of Chinese real estate bonds, we constructed the following fixed-effects regression model:

$$CS_{i,t} = \alpha + \beta_1 ClimateRisk_{it} + \sum \beta_j Control_{it} + \tau_t + \varepsilon_{it} \quad (1)$$

where $CS_{i,t}$ is the credit spread for bond i at time t . $ClimateRisk_{it}$ represents one of the three climate risk factors: climate transition risk (CTRI), chronic climate physical risk (ChroCPRI), or acute climate physical risk (AcuCPRI). $Control_{it}$ is a vector of control variables. Guided by the feature importance results from our RFECV analysis in Section 4 and the variable selections in previous studies [16,44], this vector includes a corporate governance variable (SOE status), bond-specific characteristics (Guarantee, Bond Rank, Term), and firm-level financial indicators (Size, ROE, DAR, NPR, RecTurnover, Cash Ratio). τ_t denotes year fixed effects, and ε_{it} is the error term. Our primary coefficient of interest is β_1 , which captures the effect of climate risk.

5.2. Descriptive Statistics

Table 2 presents the descriptive statistics for the main variables used in our analysis. The mean credit spread for real estate bonds in our sample was 2.317, with a standard deviation of 1.36. For the climate risk factors, the Climate Transition Risk Index had a mean of 0.177 and a standard deviation of 0.079. The Chronic Climate Physical Risk Index had a mean of 27.57 and a relatively large standard deviation of 5.86. The Acute Climate Physical Risk Index had a mean of 3.731 and a standard deviation of 1.48. The descriptive statistics for the other control variables are comparable to those reported in He et al. (2025) and Cang & Li. (2024) [16,44].

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
CS	4553	2.317	1.36	0.307	5.612
CTRI	4553	0.177	0.079	0.047	0.417
ChroCPRI	4553	27.57	5.86	15.879	41.301
AcuCPRI	4553	3.731	1.48	0.182	6.378
SOE	4553	0.853	0.355	0	1
Guarantee	4553	0.246	0.431	0	1
BondRank	4553	3.589	2.545	0	6
Term	4553	4.455	2.026	0.5	20
Size	4553	24.717	1.108	18.421	28.293
ROE	4553	0.047	0.033	0.001	0.164
DAR	4553	0.65	0.114	0.298	0.868
OperatingNCFGrowth	4553	−0.783	1.875	−5.328	2.184
InvTurnover	4553	0.43	0.179	0.002	0.798
CashRatio	4553	0.412	0.336	0.027	2.275
PPE	4553	0.032	0.046	0	0.342

5.3. Baseline Regression

Table 3 reports the regression results for model (1). Columns (1) and (2) show the results for climate transition risk. After including year fixed effects, the coefficient on transition risk was positive and statistically significant. This suggests that the bond market prices in investor concerns are about the transition challenges that firms face from climate-related policies. Higher transition risk leads to investors demanding greater risk compensation, which in turn widens CS. The coefficient on climate transition risk (CTRI) exhibits a sign

reversal between Column (1) and Column (2). Without controlling for temporal variation in Column (1), the coefficient was negative and statistically insignificant. With year fixed effects in Column (2), the estimate was positive and statistically significant at the 1% level. This variation suggests an omitted variable bias in the temporal dimension. In China, environmental regulations and low-carbon policies targeting the housing sector are clustered chronologically. Excluding year fixed effects conflates macroeconomic credit cycles with local regulatory shocks. The inclusion of year fixed effects isolates the cross-sectional variation in transition risk across cities, indicating that investors demand risk premiums on corporate bonds from firms operating in jurisdictions with stricter policy enforcement. To assess the economic significance of these findings, we benchmarked the coefficient of CTRI in Column (2) against the impact of state ownership (SOE), which is traditionally recognized as one of the most powerful institutional determinants of credit spreads in the Chinese corporate bond market. As shown in Column (2), the coefficient on SOE was -1.316 , indicating that state-owned developers enjoy a spread discount of approximately 1.316 percentage points (or 131.6 basis points). Strikingly, a one-unit increase in CTRI increased the credit spreads by 1.159 percentage points (115.9 basis points), which is highly comparable in absolute magnitude to the institutional advantage of state ownership.

Columns (5) and (6) indicate that acute climate physical risk is significantly and positively associated with real estate bond CS. This relationship remains robust after the inclusion of year fixed effects. This indicates that the bond market is sensitive to the impact of natural disasters. When massive natural disasters occur, the economic losses are transmitted to the bond market, raising investor concerns about firms' solvency and leading to demands for wider CS. Also, Column (6) reveals that a one-unit increase in AcuCPRI is associated with a 0.070 percentage point (7.0 basis points) increase in bond credit spreads. Although this effect is smaller than that of CTRI, it remains economically meaningful when compared to standard financial covariates. For instance, this impact is larger than the spread reduction associated with a standard increase in operating cash flow growth (OperatingNCFGrowth, coefficient of -0.056), and represents approximately 27% of the impact of a unit change in firm size (Size, coefficient of -0.262). This suggests that physical climate shocks exert a non-trivial, independent pricing pressure on property bonds.

The results in Columns (3) and (4) show that chronic climate physical risk had a significant negative relationship with credit spreads and was robust to the inclusion of year fixed effects. While this result may seem counterintuitive, it aligns with the findings of Chen et al. (2025), whose research on the U.S. stock market suggests that chronic climate physical risk can have a more positive impact on the real estate sector [12]. Several potential explanations exist for this finding. On the one hand, chronic climate physical risks typically manifest as long-term threats rather than immediate economic losses, which may lead to a lag in market recognition. Furthermore, in regions prone to extreme weather, governments often implement policies to improve local disaster resilience through fiscal subsidies, tax incentives, and targeted infrastructure investments, and so on. In the short-term, investors may be more sensitive to the benefits of these government support policies than to the long-term climate threats, resulting in a reduction in CS. On the other hand, this finding may indicate that real estate firms in high-risk areas are proactively turning long-term climate challenges into market opportunities. They may enhance their competitiveness through business model transformation and technological upgrades, which could boost investor confidence in their solvency and consequently lower their bond CS. The mitigating effect of ChroCPRI is statistically significant but relatively modest in magnitude. As shown in Column (4), a one-unit increase in ChroCPRI reduces credit spreads by only 0.006 percentage points (0.6 basis points). This small economic footprint suggests that while adaptation policies, subsidies, and corporate proactive upgrades successfully counteract

the negative externalities of chronic climate risks, their net downward impact on credit spreads is marginal compared to the substantial upward pricing pressures exerted by transition policies (1.159) and acute disasters (0.070). In summary, we can accept H1, H2b, and H3 within a 95% confidence interval.

Table 3. Basic regression: Climate risk and credit spread.

Dependent Variables = CS VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	CTRI		ChroCPRI		AcuCPRI	
	Year FE = No	Year FE = Yes	Year FE = No	Year FE = Yes	Year FE = No	Year FE = Yes
CTRI	−0.024 (−0.105)	1.159 *** (5.278)				
ChroCPRI			−0.010 *** (−3.464)	−0.006 ** (−1.989)		
AcuCPRI					0.089 *** (7.739)	0.070 *** (6.356)
SOE	−1.349 *** (−22.762)	−1.316 *** (−23.288)	−1.356 *** (−22.950)	−1.344 *** (−23.860)	−1.307 *** (−22.181)	−1.310 *** (−23.267)
Guarantee	0.457 *** (9.777)	0.540 *** (12.217)	0.469 *** (10.055)	0.557 *** (12.549)	0.433 *** (9.282)	0.527 *** (11.862)
BondRank	−0.096 *** (−12.525)	−0.109 *** (−14.941)	−0.096 *** (−12.568)	−0.110 *** (−15.055)	−0.097 *** (−12.750)	−0.111 *** (−15.211)
Maturity Term	0.002 (0.170)	−0.016 * (−1.851)	0.001 (0.153)	−0.016 * (−1.891)	−0.007 (−0.765)	−0.022 ** (−2.562)
Size	−0.340 *** (−19.321)	−0.253 *** (−13.698)	−0.334 *** (−18.994)	−0.249 *** (−13.538)	−0.350 *** (−19.774)	−0.262 *** (−14.115)
ROE	1.682 *** (2.856)	−5.424 *** (−8.092)	1.540 *** (2.613)	−5.504 *** (−8.158)	1.879 *** (3.256)	−5.094 *** (−7.626)
DAR	−0.122 (−0.633)	0.012 (0.066)	−0.092 (−0.480)	−0.030 (−0.164)	0.019 (0.099)	0.077 (0.417)
OperatingNCFGrowth	−0.102 *** (−10.968)	−0.062 (−1.427)	−0.096 *** (−10.184)	−0.067 (−1.507)	−0.102 *** (−10.970)	−0.056 (−1.295)
InvTurnover	0.590 *** (5.620)	0.643 *** (6.371)	0.578 *** (5.520)	0.621 *** (6.168)	0.525 *** (5.024)	0.582 *** (5.796)
CashRatio	−0.231 *** (−4.483)	−0.546 *** (−9.072)	−0.231 *** (−4.480)	−0.552 *** (−9.072)	−0.242 *** (−4.836)	−0.561 *** (−9.421)
PPE	0.342 (0.903)	0.358 (1.019)	0.340 (0.897)	0.283 (0.802)	0.339 (0.896)	0.278 (0.789)
Constant	11.860 *** (30.354)	9.950 *** (24.492)	11.984 *** (30.610)	10.303 *** (25.134)	11.697 *** (29.975)	10.136 *** (25.088)
Observations	4553	4552	4553	4552	4553	4552
Adjusted R-squared	0.297	0.390	0.299	0.387	0.306	0.392
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F	213.4	171.5	213.5	168.9	218.2	171.5

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The explanatory power (R^2) differs between the fixed-effects OLS models (≈ 0.39) and the machine learning model (≈ 0.70). This difference reflects their distinct objectives: the OLS specifications aim at causal inference and unbiased parameter estimation by controlling for confounding factors, whereas the random forest algorithm is optimized for predictive capacity, incorporating high-order non-linear interactions across 44 variables. The inclusion of Year FE increases the adjusted R^2 by approximately 9 percentage points, indicating that macroeconomic cycles constitute a systematic component of bond spread variation.

5.4. The Particularities of State-Owned Enterprises

Table 4 presents the results from subgroup regressions, separating the sample into bonds issued by state-owned enterprises (SOEs) and non-SOEs. Columns (1) and (2) showed that the widening effect of climate transition risk on CS was statistically significant only for SOEs, suggesting that SOEs are more exposed to the impacts of climate transition policies. In Columns (3) and (4), the mitigating effect of chronic climate physical risk on CS was also found to be significant only for SOEs. This finding aligns with our baseline discussion. The long-term threats of chronic climate physical risk are difficult for investors to perceive directly, and governments often implement “climate-tolerant” policies such as fiscal subsidies, tax incentives, and targeted infrastructure investments in regions prone to extreme weather events, so SOEs are better positioned to benefit from these policies and are more likely to be compelled by policy directives to undertake strategic transitions. Consequently, the spread-narrowing effect is stronger for them. In contrast, non-SOEs appeared to be negatively affected by chronic physical risk, though this effect was not statistically significant.

Table 4. Basic regression: Difference of SOE in climate risk and credit spread.

Dependent Variables = CS VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	CTRI		ChroCPRI		AcuCPRI	
	SOE = 0	SOE = 1	SOE = 0	SOE = 1	SOE = 0	SOE = 1
CTRI	0.004 (0.007)	1.115 *** (4.730)				
ChroCPRI			0.004 (0.534)	−0.009 *** (−2.710)		
AcuCPRI					0.048 * (1.698)	0.069 *** (5.758)
Guarantee	0.336 *** (2.751)	0.578 *** (12.189)	0.327 *** (2.655)	0.598 *** (12.590)	0.312 ** (2.522)	0.571 *** (12.016)
BondRank	−0.128 *** (−6.373)	−0.104 *** (−13.365)	−0.127 *** (−6.445)	−0.106 *** (−13.432)	−0.128 *** (−6.485)	−0.106 *** (−13.590)
Maturity Term	−0.109 *** (−2.821)	−0.018 ** (−2.012)	−0.108 *** (−2.815)	−0.018 ** (−2.024)	−0.107 *** (−2.789)	−0.024 *** (−2.713)
Size	−0.506 *** (−7.181)	−0.228 *** (−12.414)	−0.509 *** (−7.283)	−0.224 *** (−12.301)	−0.511 *** (−7.348)	−0.239 *** (−12.948)
ROE	−4.838 *** (−3.339)	−4.523 *** (−6.290)	−4.807 *** (−3.308)	−4.519 *** (−6.228)	−4.807 *** (−3.329)	−4.124 *** (−5.757)
DAR	5.025 *** (7.576)	−0.713 *** (−3.821)	5.020 *** (7.587)	−0.774 *** (−4.201)	4.971 *** (7.553)	−0.649 *** (−3.480)
OperatingNCFGrowth	−0.159 ** (−2.548)	0.037 (0.677)	−0.153 ** (−2.448)	0.036 (0.664)	−0.142 ** (−2.259)	0.038 (0.712)
InvTurnover	1.286 *** (3.520)	0.392 *** (3.737)	1.282 *** (3.516)	0.353 *** (3.388)	1.275 *** (3.521)	0.321 *** (3.092)
CashRatio	−0.804 *** (−2.981)	−0.528 *** (−8.573)	−0.801 *** (−2.971)	−0.536 *** (−8.611)	−0.784 *** (−2.898)	−0.549 *** (−9.005)
PPE	3.548 * (1.860)	−0.115 (−0.342)	3.579 * (1.874)	−0.186 (−0.547)	3.637 * (1.850)	−0.180 (−0.532)
Constant	13.132 *** (8.561)	8.571 *** (21.433)	13.082 *** (8.506)	8.995 *** (22.255)	13.125 *** (8.621)	8.805 *** (22.199)
Observations	669	3882	669	3882	669	3882
Adjusted R-squared	0.377	0.334	0.378	0.331	0.380	0.336
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F	40.56	126.2	41.02	124.4	40.86	128.9

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results in Columns (5) and (6) show that acute climate physical risk had a significant negative impact on both SOEs and non-SOEs. However, a comparison of the coefficients reveals that the magnitude of this effect was significantly larger for SOEs. Reasons might be that SOEs shoulder special social responsibilities, including furthering national strategic goals and ensuring social stability. As a result, they are often expected to take a leading role in disaster relief efforts, which exposes them to greater financial and operational burdens and thus a more pronounced adverse impact from acute climate physical risks.

Additionally, the OLS regression exhibited a higher adjusted R^2 for the non-SOE subgroup (0.38) than for the SOE subgroup (0.33). This variation suggests that non-SOE bond pricing aligns more closely with observable financial covariates. For SOEs, bond yields contain pricing variations related to bailout expectations and implicit government guarantees that are difficult to quantify, reducing the explanatory power of the baseline financial controls.

An examination of our regression sample revealed a 5.8 to 1 ratio of SOE to non-SOE bond observations, a composition which corroborates our earlier discussions. The mechanisms underlying these patterns are structured as follows. Historically, Chinese capital markets maintained a sector-level implicit guarantee for real estate developers. Market participants operated under the assumption that regulatory authorities would not permit material defaults by systemic property firms, given the foundational role of the real estate sector in macroeconomic stability. This implicit protection was dismantled following the implementation of the “Three Red Lines” regulatory framework in 2020. Subsequent defaults among private developers redirected these implicit safety nets toward SOEs. During the ensuing market consolidation, SOEs maintained operational viability due to structural advantages in scale, liquidity access, and retained state backing. Consequently, SOEs are expected to exhibit greater debt issuance volumes and face more comprehensive market pricing.

6. Robustness Tests

6.1. Controlling the Fluctuations for City-Level Macroeconomic and Real Estate Cycles

To examine whether the baseline findings are driven by omitted macroeconomic fluctuations or real estate sector cycles, we introduced a series of city-level macro control variables into our baseline model. Specifically, we controlled for the city GDP growth rate, which captures local macroeconomic vitality; the log of city fixed asset investment, which captures regional investment intensity; and the log of the commodity housing price index, which captures the local housing market cycle. Table 5 presents the regression results.

As shown in Table 5, the coefficients on CTRI, ChroCPRI and AcuCPRI were all statistically significant and carried the expected signs. This indicates that after considering macroeconomic fluctuations and industry cycle fluctuations, the main effect remained significant.

The coefficients on the macroeconomic control variables carried the expected signs: local GDP growth was negatively associated with spreads, suggesting that a stronger regional economic environment reduces corporate default risks; commodity housing price growth was also negatively associated with spreads, suggesting that a rising local housing market improves property developers' liquidity and reduces bond yields. In sum, these results show that the pricing of climate risks is not confounded by regional macroeconomic cycles or real estate industry cycles.

Table 5. Robust regression: Controlling the fluctuations for city-level macroeconomic and real estate cycles.

Dependent Variables = CS VARIABLES	(1) CTRI CS	(2) ChroCPRI CS	(3) AcuCPRI CS
CTRI	1.316 *** (6.073)		
ChroCPRI		−0.010 *** (−3.375)	
AcuCPRI			0.039 *** (3.392)
SOE	−1.343 *** (−23.773)	−1.378 *** (−24.455)	−1.350 *** (−23.941)
Guarantee	0.513 *** (11.710)	0.536 *** (12.169)	0.516 *** (11.678)
BondRank	−0.110 *** (−15.354)	−0.112 *** (−15.500)	−0.112 *** (−15.515)
Maturity Term	−0.019 ** (−2.298)	−0.020 ** (−2.347)	−0.023 *** (−2.650)
Size	−0.242 *** (−13.243)	−0.236 *** (−12.986)	−0.247 *** (−13.401)
ROEA	−5.237 *** (−7.896)	−5.315 *** (−7.961)	−5.111 *** (−7.685)
DAR	0.129 (0.708)	0.084 (0.464)	0.111 (0.612)
OperatingNCFGrowth	−0.042 (−1.043)	−0.050 (−1.211)	−0.042 (−1.024)
InvTurnover	0.612 *** (6.179)	0.583 *** (5.905)	0.575 *** (5.815)
CashRatio	−0.609 *** (−10.567)	−0.614 *** (−10.589)	−0.611 *** (−10.532)
PPE	0.236 (0.645)	0.145 (0.393)	0.184 (0.501)
LocalGDPGrowth	−1.220 ** (−2.473)	−1.231 ** (−2.507)	−1.237 ** (−2.503)
FixAssetInvestment	−0.246 *** (−9.408)	−0.250 *** (−9.499)	−0.210 *** (−7.724)
CommodityHouseIDX	−0.960 *** (−2.585)	−0.772 ** (−2.080)	−0.696 * (−1.857)
Constant	18.682 *** (10.333)	18.335 *** (10.126)	17.082 *** (9.268)
Observations	4552	4552	4552
Adjusted R-squared	0.405	0.401	0.401
Year FE	Yes	Yes	Yes
F	146.9	145.0	144.2

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2. Alternative Fixed Effects and Clustered Standard Errors

To further verify the robustness of our results, we subjected our model to alternative fixed effects and clustered standard error specifications. First, to control for unobserved, time-invariant regional institutional environments, financial development, and local support policies, we added province fixed effects to our model. Columns (1) to (3) in Table 6 present these results. The coefficients on CTRI and ChroCPRI remained statistically significant with their expected signs. However, the coefficient on AcuCPRI became -0.027 and was statistically insignificant. This outcome is consistent with the geographical nature

of extreme weather events. Acute climate physical risk, such as floods and typhoons, are highly localized and spatially fixed. The introduction of province fixed effects absorbs a substantial portion of the cross-sectional geographic variation in acute physical climate risk. Given that within-province temporal variation in extreme weather events is limited and year dummies control for annual nationwide shocks, the remaining variation is insufficient to identify a statistically significant coefficient.

Table 6. Robust regression: Alternative fixed effects and clustered standard errors.

Dependent Variables = CS VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
	Add Province Fix Effect			Cluster at Issuer		
	CTRI	ChroCPRI	AcuCPRI	CTRI	ChroCPRI	AcuCPRI
CTRI	0.910 *** (4.206)			1.277 *** (2.999)		
ChroCPRI		−0.006 * (−1.853)			−0.011 * (−1.818)	
AcuCPRI			−0.027 (−1.471)			0.044 * (1.786)
SOE	−1.474 *** (−25.987)	−1.486 *** (−26.264)	−1.487 *** (−26.299)	−1.338 *** (−8.402)	−1.372 *** (−8.621)	−1.342 *** (−8.512)
Guarantee	0.379 *** (9.450)	0.381 *** (9.446)	0.378 *** (9.391)	0.543 *** (6.126)	0.565 *** (6.426)	0.543 *** (6.059)
BondRank	−0.079 *** (−12.440)	−0.080 *** (−12.475)	−0.079 *** (−12.358)	−0.111 *** (−8.481)	−0.113 *** (−8.622)	−0.113 *** (−8.641)
Maturity Term	−0.032 *** (−4.187)	−0.033 *** (−4.314)	−0.033 *** (−4.270)	−0.015 (−1.069)	−0.016 (−1.104)	−0.019 (−1.326)
Size	−0.210 *** (−10.907)	−0.209 *** (−10.858)	−0.209 *** (−10.850)	−0.240 *** (−6.108)	−0.234 *** (−6.021)	−0.247 *** (−6.144)
ROEA	−3.129 *** (−4.812)	−3.113 *** (−4.776)	−3.168 *** (−4.870)	−5.288 *** (−4.369)	−5.359 *** (−4.402)	−5.131 *** (−4.272)
DAR	0.803 *** (4.563)	0.797 *** (4.521)	0.784 *** (4.469)	0.323 (0.802)	0.272 (0.685)	0.301 (0.752)
CashRatio	−0.531 *** (−10.713)	−0.530 *** (−10.663)	−0.530 *** (−10.639)	−0.623 *** (−6.516)	−0.627 *** (−6.420)	−0.624 *** (−6.511)
OperatingNCFGrowth	−0.099 *** (−2.580)	−0.102 *** (−2.633)	−0.100 *** (−2.587)	−0.454 (−0.669)	−0.513 (−0.754)	−0.460 (−0.679)
PPE	−1.145 *** (−3.621)	−1.167 *** (−3.671)	−1.174 *** (−3.707)	−0.049 (−1.100)	−0.057 (−1.266)	−0.048 (−1.074)
LocalGDPGrowth	0.076 (0.164)	0.085 (0.184)	0.033 (0.071)	−1.112 (−1.309)	−1.127 (−1.329)	−1.134 (−1.321)
FixAssetInvestment	−0.466 *** (−13.673)	−0.446 *** (−13.223)	−0.450 *** (−13.339)	−0.253 *** (−3.741)	−0.258 *** (−3.812)	−0.214 *** (−3.112)
CommodityHouseIDX	1.258 *** (3.607)	1.424 *** (4.082)	1.386 *** (3.971)	−0.956 (−1.635)	−0.771 (−1.319)	−0.685 (−1.157)
Constant	11.205 *** (6.286)	10.387 *** (5.826)	10.595 *** (5.913)	18.883 *** (6.520)	18.558 *** (6.403)	17.178 *** (5.805)
Observations	4552	4552	4552	4552	4552	4552
Adjusted R-squared	0.524	0.522	0.522	0.399	0.397	0.397
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	No	No	No
F	131.0	130.1	130.1	40.53	40.42	39.49

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Second, to address the potential correlation of standard errors across multiple bonds issued by the same firm, we clustered standard errors at the issuer level. Columns (4) to (6) in Table 6 present the results. The coefficients on CTRI, ChroCPRI and AcuCPRI were

all statistically significant and carried the expected signs. These results suggest that our baseline findings remain robust when accounting for potential within-firm autocorrelation and heteroskedasticity.

6.3. Lagged Explanatory and Control Variables

To address potential concerns regarding reverse causality and contemporaneous endogeneity, we re-estimated our baseline model using one-period lagged explanatory and control variables. L_CTRI, L_ChroCPRI, and L_AcuCPRI denote the one-period lagged measures of transition risk, chronic physical risk, and acute physical risk, respectively. Table 7 presents the regression results.

Table 7. Robust regression: Lagged explanatory and control variables.

Dependent Variables = CS VARIABLES	(1) L_CTRI CS	(2) L_ChroCPRI CS	(3) L_AcuCPRI CS
L_CTRI	2.450 *** (6.092)		
L_ChroCPRI		−0.016 *** (−2.984)	
L_AcuCPRI			0.040 * (1.895)
L_SOE	−1.437 *** (−16.853)	−1.541 *** (−18.840)	−1.505 *** (−17.961)
L_Guarantee	0.495 *** (5.232)	0.550 *** (5.566)	0.484 *** (4.945)
L_BondRank	−0.123 *** (−8.536)	−0.125 *** (−8.592)	−0.127 *** (−8.756)
L_Maturity Term	0.005 (0.228)	−0.003 (−0.163)	−0.010 (−0.466)
L_Size	−0.290 *** (−9.917)	−0.244 *** (−8.529)	−0.266 *** (−9.149)
L_ROEA	−7.990 *** (−5.574)	−8.111 *** (−5.808)	−8.395 *** (−5.893)
L_DAR	2.233 *** (6.685)	1.777 *** (5.379)	1.909 *** (5.734)
L_OperatingNCFGrowth	−0.335 *** (−3.161)	−0.333 *** (−3.084)	−0.293 *** (−2.660)
L_InvTurnover	0.393 ** (2.409)	0.441 *** (2.676)	0.490 *** (2.941)
L_CashRatio	−0.609 *** (−3.951)	−0.549 *** (−3.575)	−0.588 *** (−3.800)
L_PPE	1.406 ** (1.999)	1.005 (1.508)	1.363 ** (2.012)
l_LocalGDPGrowth	−2.675 (−1.566)	−1.760 (−1.054)	−2.240 (−1.293)
l_FixAssetInvestment	0.000 (1.495)	0.000 (0.551)	0.000 ** (1.982)
l_CommodityHouseIDX	−0.009 (−1.455)	−0.003 (−0.460)	−0.004 (−0.719)
Constant	10.160 *** (10.669)	9.545 *** (10.067)	9.646 *** (10.141)
Observations	1419	1419	1419
Adjusted R-squared	0.477	0.466	0.464
Year FE	Yes	Yes	Yes
F	75.67	68.80	67.57

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As shown in Table 7, the coefficients on CTRI, ChroCPRI and AcuCPRI were all statistically significant and carried the expected signs. These results suggest that historical climate risk exposure continues to explain future credit spreads. The temporal separation between the independent variables and the dependent variable mitigates contemporaneous feedback effects and suggests that climate risk exposure is a leading indicator of real estate bond spreads rather than a reflection of contemporaneous credit market shocks.

7. Mechanism Analysis

To investigate the mechanisms through which different climate risks operate, we employed both mediation and moderation analysis.

The mediation model is specified in a two-step framework:

$$Mediator_{i,t} = \alpha + \beta_1 ClimateRisk_{it} + \sum \beta_j Control_{it} + \tau_t + \varepsilon_{it} \quad (2)$$

$$CS_{i,t} = \alpha + \beta_1 ClimateRisk_{it} + \beta_2 Mediator_{i,t} + \sum \beta_j Control_{it} + \tau_t + \varepsilon_{it} \quad (3)$$

However, as Jiang (2022) notes, obtaining a consistent estimator for β_1 and β_2 in Equation (3) is only possible if the mediator is an exogenous random intervention [45]. This is a condition rarely met in practice. Therefore, the most reliable approach is to focus on the significance of the coefficient in the first stage of the mediation model (Equation (2)). Accordingly, our analysis focuses on estimating β_1 , the coefficient of $ClimateRisk_{it}$ in the first stage, and we draw upon existing literature to support the link between the mediator and the dependent variable.

In addition, we constructed a moderation model specified as follows:

$$CS_{i,t} = \alpha + \beta_1 ClimateRisk_{it} + \beta_2 Moderator_{i,t} + \beta_3 ClimateRisk_{it} \times Moderator_{i,t} + \sum \beta_j Control_{it} + \tau_t + \varepsilon_{it} \quad (4)$$

Here, $Moderator_{i,t}$ is the moderating variable, and our coefficient of interest is β_3 on the interaction term $ClimateRisk_{it} \times Moderator_{i,t}$.

7.1. Mechanism of Climate Transition Risk

Table 8 presents the results for the mechanism analysis of climate transition risk. Column (1) shows a significant negative coefficient on the interaction term between CTRI and bond maturity, indicating that the spread-widening effect of CTRI is stronger for bonds with shorter maturities. Column (2) reveals a significant negative interaction term with the cash ratio, implying that strong liquidity can mitigate the adverse impact of CTRI. The interaction term with ROE in Column (3) was significantly positive, suggesting that the negative impact of CTRI is more pronounced for firms with higher profitability. Notably, the main effect of CTRI became insignificant after including this interaction term, which implies that CTRI primarily affects CS by threatening firm profitability. This conclusion is further supported by the further analysis in Column (4). Due to the distinctiveness of the real estate industry, its core business expansion primarily involves developing real estate projects, establishing industrial parks and commercial centers, and providing property management services. Therefore, an increase in fixed asset investment can, to some extent, reflect the expansion of real estate operations. We found that higher CTRI significantly reduces a firm's fixed asset ratio. This provides evidence that CTRI impacts firms' growth prospects, and consequently, their future profitability. This is consistent with Bernstein et al. (2019), which found that climate risks have a significant negative impact on real estate prices [19].

Table 8. Mechanisms of climate transition risks.

VARIABLES	(1) CS	(2) CS	(3) CS	(4) PPE	(5) SA
CTRI	2.921 *** (5.604)	1.659 *** (4.540)	0.490 (1.256)	−0.018 ** (−2.300)	0.523 *** (10.527)
Term_CTRI	−0.404 *** (−4.210)				
CashRatio_CTRI		−1.290 * (−1.923)			
ROE_CTRI			14.297 ** (2.256)		
SOE	−1.309 *** (−23.058)	−1.314 *** (−23.230)	−1.310 *** (−23.119)	0.001 (0.668)	−0.086 *** (−6.832)
Guarantee	0.543 *** (12.320)	0.538 *** (12.181)	0.543 *** (12.286)	−0.001 (−1.026)	0.049 *** (5.481)
BondRank	−0.108 *** (−14.744)	−0.109 *** (−14.877)	−0.109 *** (−14.909)	0.000 (0.137)	−0.008 *** (−4.186)
Term	0.055 *** (2.955)	−0.016 * (−1.880)	−0.017 ** (−1.973)	0.002 ** (2.333)	0.004 * (1.879)
Size	−0.253 *** (−13.734)	−0.253 *** (−13.668)	−0.254 *** (−13.789)	0.001 (1.606)	0.051 *** (9.145)
ROE	−5.322 *** (−7.926)	−5.424 *** (−8.091)	−7.714 *** (−6.348)	−0.081 *** (−3.424)	−0.182 (−0.948)
DAR	−0.001 (−0.008)	0.019 (0.101)	0.008 (0.042)	−0.028 *** (−3.603)	−0.309 *** (−7.762)
OperatingNCFGrowth	−0.061 (−1.385)	−0.060 (−1.367)	−0.060 (−1.387)	−0.002 (−1.233)	−0.016 (−1.396)
InvTurnover	0.652 *** (6.481)	0.643 *** (6.368)	0.634 *** (6.288)	−0.074 *** (−13.617)	0.004 (0.187)
CashRatio	−0.549 *** (−9.120)	−0.335 *** (−2.683)	−0.551 *** (−9.117)	0.002 (0.697)	−0.003 (−0.236)
PPE	0.363 (1.025)	0.369 (1.049)	0.364 (1.039)		−0.490 *** (−5.258)
Constant	9.640 *** (23.260)	9.853 *** (24.022)	10.089 *** (24.728)	0.043 ** (2.035)	−4.837 *** (−35.730)
Observations	4552	4552	4552	4552	4458
Adjusted R-squared	0.392	0.390	0.391	0.159	0.126
Year FE	Yes	Yes	Yes	Yes	Yes
F	157.3	158.6	162.6	24.83	27.95

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Another potential mechanism involves financial constraints. Within the literature on the cost of debt financing, financial constraints frequently operate as a critical underlying mechanism. Heightened financial constraints tend to elevate a firm's default risk, thereby potentially driving up its debt financing costs [46]. Column (5) examines the channel of financing constraints and shows that higher CTRI significantly tightens these constraints, thereby increasing CS. This is consistent with Nguyen et al. (2022), who suggested that real estate enterprises facing risks of sea-level rise are often charged higher loan interest rates [20]. On the one hand, increased CTRI may lead to new regulatory requirements for banks, therefore increasing the financing constrain of real estate firms. On the other hand, the increased government attention to climate risks has, to some extent, heightened public awareness of climate change. Consequently, the public requires lower prices for properties that face higher risks of climate transition [19]. This reduces the value of collateral for real estate enterprises when obtaining mortgages, thereby increasing their financing constraints.

In summary, the spread-widening effect of climate transition risk is more pronounced for short-term bonds and for firms with weaker liquidity. CTRI operates primarily by tightening firms' financing constraints and impeding business expansion, which in turn adversely affects profitability. This corroborates our earlier findings in Section 4. SOEs are better able to withstand transition risk shocks because they tend to maintain better liquidity and more stable profitability, and receive preferential treatment in credit markets, allowing their bonds to remain viable rather than delist due to default.

7.2. Mechanism of Chronic Climate Physical Risk

Table 9 presents the mechanism analysis for chronic climate physical risk. Column (1) shows a significant positive interaction term between ChroCPRI and bond credit rating, indicating that the spread-narrowing effect of ChroCPRI is more pronounced for lower-rated bonds. Similarly, the interaction term with ROE in Column (2) was significantly positive, meaning the effect is stronger for less profitable firms. These findings suggest that firms with lower bond credit rating or weaker initial financial standing are more likely to be the focus of government "climate support" policies in high-risk areas, highlighting the importance of government backstops. Column (3) provides further evidence, showing that ChroCPRI is associated with an increase in firms' equity cash flow, likely reflecting direct government support. However, this support appears short-lived. Column (4) shows the impact of ChroCPRI on the growth rate of operating cash flow. This indicates that climate risk can slow down the acquisition of operating cash flow by real estate enterprises. However, this argument does not necessarily imply a deterministic reduction in operating cash flows. This argument is consistent with institutional settings in China. Under the Fourteenth Five-Year Plan for Building Energy Efficiency and Green Building Development issued by the Ministry of Housing and Urban-Rural Development, local authorities introduced R&D subsidies, tax incentives, and floor area ratio bonuses to promote high-resilience green buildings. Furthermore, the "Climate Investment and Financing Pilot" and the national "Sponge City" construction schemes, jointly advanced by ministries including the Ministry of Ecology and Environment, prioritized investments in flood control networks and upgraded drainage systems and public disaster-prevention infrastructure. These initiatives supply the cash flows of real estate enterprises.

In climate change research, green innovations serve as a transmission channel. The "pollution halo" hypothesis suggests that external regulations enhance firm-level innovation rates. As chronic physical climate risks escalate, heightened environmental awareness among external investors impels firms to expand their green innovation capacities. Such advancements in green innovation subsequently lower corporate debt financing costs: enhanced green innovation capacities mitigate the volatility of future corporate cash flows, thereby reducing default probabilities [47]; concurrently, the acquisition of green patents alleviates market information asymmetry and signals environmental compliance—this attracts investors with green preferences [48,49], generates asset premiums, and ultimately compresses credit spreads. Column (5) evaluates the impact on technological shifting, yielding a significant positive coefficient on utility patent applications. This finding suggests that ChroCPRI promotes green innovation, which subsequently suppresses credit spreads. This evidence is consistent with the hypothesis in Section 5—real estate firms facing prolonged ChroCPRI may capture strategic opportunities for structural transformation, thereby sustaining competitive advantages.

Table 9. Mechanisms of chronic climate physical risks.

VARIABLES	(1) CS	(2) CS	(3) EquityCF	(4) OperatingNCFGrowth	(5) UtilityPatentsAquire
ChroCPRI	−0.022 *** (−3.701)	−0.032 *** (−6.204)	1.033 ** (2.513)	−0.003 *** (−3.296)	0.095 *** (5.122)
BondRank_ChroCPRI	0.004 *** (3.548)				
ROE_ChroCPRI		0.501 *** (6.279)			
SOE	−1.348 *** (−23.893)	−1.354 *** (−24.198)	−17.172 ** (−2.110)	0.009 (0.373)	−0.160 (−0.614)
Guarantee	0.551 *** (12.337)	0.539 *** (12.095)	7.515 ** (1.977)	0.009 (0.744)	0.253 (0.701)
BondRank	−0.225 *** (−6.741)	−0.110 *** (−15.034)	−1.875 (−1.579)	−0.004 ** (−2.089)	−0.036 (−0.649)
Maturity Term	−0.016 * (−1.808)	−0.016 * (−1.820)	−0.629 (−0.353)	−0.004 (−1.375)	0.008 (0.088)
Size	−0.251 *** (−13.682)	−0.258 *** (−13.954)	−84.817 *** (−13.572)	0.007 (1.302)	0.501 *** (4.399)
ROE	−5.481 *** (−8.184)	−18.859 *** (−8.724)	−63.796 (−0.336)	0.362 (1.180)	12.625 * (1.823)
DAR	−0.044 (−0.241)	−0.042 (−0.227)	466.431 *** (11.406)	−0.045 (−0.600)	−0.620 (−0.560)
OperatingNCFGrowth	−0.063 (−1.413)	−0.062 (−1.443)	−15.890 * (−1.950)		1.102 *** (3.016)
InvTurnover	0.617 *** (6.137)	0.616 *** (6.133)	−38.667 *** (−3.033)	−0.059 * (−1.764)	−0.837 (−0.777)
CashRatio	−0.549 *** (−8.980)	−0.544 *** (−8.894)	31.745 *** (2.981)	−0.124** (−2.446)	1.457 ** (2.218)
PPE	0.285 (0.812)	0.347 (0.983)	−149.477 (−1.644)	−0.171 (−1.225)	−9.767 *** (−2.944)
Constant	10.783 *** (24.812)	11.233 *** (25.381)	1617.981 *** (11.753)	−0.751 *** (−6.625)	−13.203 *** (−4.452)
Observations	4552	4552	4552	4552	619
Adjusted R-squared	0.388	0.391	0.317	0.967	0.228
Year FE	Yes	Yes	Yes	Yes	Yes
F	156.9	159.1	20.19	3.029	13.71

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In summary, the spread-narrowing effect of ChroCPRI is more pronounced for firms with lower bond credit ratings and profitability, pointing to the positive impact of “climate support” policies. Concurrently, some firms will respond by pursuing green transformation. At the same time, some enterprises will seize market opportunities to pursue green transformation while operating in environments characterized by ChroCPRI. This supports our hypothesis and earlier discussion in Section 4, as SOEs are often better positioned to benefit from such policies and have the resources to capitalize on these opportunities. We further found that these policies primarily manifest as increased cash flow, but this effect is not long-term. In the long run, real estate bonds must remain vigilant against the impact of ChroCPRI.

7.3. Mechanism of Acute Climate Physical Risk

Table 10 presents the mechanism analysis for acute climate physical risk. Column (1) reveals a significant negative interaction term between firm size and AcuCPRI, indicating

that the spread-widening effect is more pronounced for smaller firms, which are more financially fragile [50].

Table 10. Mechanisms of acute climate physical risks.

VARIABLES	(1) CS	(2) EquityCF	(3) OperatingNCFGrowth	(4) SA
AcuCPRI	0.773 *** (3.496)	−4.510 *** (−2.724)	−0.005 * (−1.672)	0.054 *** (19.640)
Size_AcuCPRI	−0.028 *** (−3.201)			
SOE	−1.310 *** (−23.245)	−19.916 ** (−2.373)	0.009 (0.410)	−0.075 *** (−6.354)
Guarantee	0.529 *** (11.904)	10.089 *** (2.716)	0.007 (0.584)	0.035 *** (4.020)
BondRank	−0.111 *** (−15.281)	−1.858 (−1.563)	−0.004 ** (−2.075)	−0.009 *** (−4.749)
Maturity Term	−0.023 *** (−2.616)	−0.258 (−0.144)	−0.004 (−1.212)	−0.000 (−0.083)
Size	−0.148 *** (−3.674)	−83.779 *** (−13.654)	0.007 (1.245)	0.043 *** (8.060)
ROE	−5.113 *** (−7.660)	−88.923 (−0.461)	0.328 (1.070)	0.110 (0.603)
DAR	0.081 (0.440)	461.126 *** (11.177)	−0.061 (−0.813)	−0.246 *** (−6.367)
OperatingNCFGrowth	−0.055 (−1.253)	−17.048 ** (−2.091)		−0.012 (−1.046)
InvTurnover	0.564 *** (5.598)	−36.752 *** (−2.865)	−0.053 (−1.578)	−0.039 * (−1.833)
CashRatio	−0.565 *** (−9.533)	32.428 *** (3.054)	−0.124 ** (−2.440)	−0.013 (−0.947)
PPE	0.279 (0.789)	−150.448 * (−1.661)	−0.163 (−1.173)	−0.542 *** (−5.805)
Constant	7.331 *** (7.500)	1640.299 *** (11.721)	−0.807 *** (−7.076)	−4.761 *** (−37.059)
Observations	4552	4552	4552	4458
Adjusted R-squared	0.392	0.317	0.967	0.179
Year FE	Yes	Yes	Yes	Yes
F	159.2	19.93	2.448	49.19

Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Cash flow frequently serves as an essential indicator for evaluating a firm's debt-servicing capacity. Existing literature indicates that cash flows can transmit positive signals to creditors [51], thereby potentially enhancing corporate debt capacity [52,53]. This will narrow the credit spread [54]. Consequently, this study further investigates cash flow as a potential underlying mechanism. Columns (2) and (3) present the corresponding empirical results. Column (2) shows that AcuCPRI significantly reduces firms' equity cash flow. This suggests that AcuCPRI primarily impact investors' confidence in the debt-servicing capacity of real estate enterprises by reducing their equity cash flows. Column (3) shows a significant negative impact on the growth of operating cash flow, indicating that natural disasters impact real estate companies' cash flows not only in the short-term but also in the long-term. This, in turn, reduces investors' confidence in the long-term debt-repayment capabilities of real estate enterprises. Consistent with Section 7.1, financing constraints are also an important variable affecting the cost of debt due to climate disasters. Column (4) shows that AcuCPRI significantly tightens firms' financing constraints, thereby increasing

CS. This is consistent with the findings of Zhai et al. (2022) [46] as well as with Nguyen et al. (2022), and may be driven by the reduction in property collateral values in disaster-prone areas [19,20].

In summary, AcuCPRI primarily operates by compressing firms' short-term and long-term cash flows and by tightening financing constraints. This exacerbates investor concerns about default and further leads to higher CS. It is more pronounced for smaller firms. This conclusion supports our hypothesis and earlier discussion in Section 4. In the face of natural disaster shocks, SOEs have taken on more post disaster reconstruction responsibilities, which will affect their cash flow. However, by combining the advantages of large-scale and implicit guarantees, they still survive in the market.

8. Conclusions

Climate risk is profoundly impacting our lives and economic activities, representing one of the most severe global challenges of the 21st century. As a vital component of capital markets, the bond market's ability to price climate risk is critical for maintaining the long-term stability and development of the financial system. The real estate sector, with its geographically fixed and long-duration assets, is particularly sensitive to climate risk. However, the existing literature has yet to establish a direct link between climate risk and real estate bonds. This study addresses this gap by investigating the impact of climate risk on the pricing of corporate bonds in the real estate industry. We constructed and analyzed three distinct measures of climate risk: transition risk, chronic physical risk, and acute physical risk. First, using a machine learning approach, the analysis identified the determinants of real estate bond pricing and suggests that all three categories of climate risk are important predictive features. We also found that state ownership (SOE status) is the single most important predictor of credit spreads. This is an interesting finding. To understand the significance of firm ownership, we compared SOEs and non-SOEs from both bond characteristics and financial characteristics and found that SOEs possess significant advantages in terms of firm size, liquidity, and profitability, and are more likely to secure guarantees and receive higher credit ratings for their bonds.

Building on these findings, we used regression models to conduct an in-depth analysis of the direction, magnitude, and underlying mechanisms of the impact of different climate risks on credit spreads. Our research found that climate transition risk and acute climate physical risk significantly widen real estate bond credit spreads, whereas chronic climate physical risk significantly narrows them. These effects are more pronounced for SOEs, which we attribute to a market "reshuffling" process where SOEs are more resilient to climate, economic, and political shocks, leading to their increased prevalence in the market. Our mechanism analysis reveals the following. (1) The spread-widening effect of CTRI is more pronounced for short-term bonds and firms with weaker liquidity, operating by tightening financing constraints and impeding business expansion. (2) The spread-narrowing effect of ChroCPRI is stronger for firms with lower bond ratings and profitability, which points to the existence of "climate support" policies that manifest as short-term increases in firm cash flow. Concurrently, some firms respond to this risk by pursuing green transformations. (3) AcuCPRI compresses firms' short-term and long-term cash flows and tightens financing constraints, thereby increasing credit spreads. This effect is more significant for smaller firms. These mechanisms align with the unique characteristics of SOEs, whose larger scale, superior liquidity, profitability, and access to an "implicit guarantee" allow their bonds to remain viable amid climate risk shocks.

Based on the empirical findings, this study outlines policy and practical implications for three stakeholders. First, for bond investors, the results suggest that climate risk exposures should be integrated into fixed-income valuation and credit rating models.

Rather than treating climate risk as a qualitative ESG metric, investment institutions should quantify a climate risk premium in their credit assessments. Specifically, based on the empirical estimates, a one-standard-deviation increase in transition and acute physical risks corresponds to a spread widening of approximately 9 to 10 basis points. Investors should therefore incorporate these parameters into their required yield to maturity. Furthermore, given the impact of climate shocks on corporate financing constraints, credit analysts should rigorously evaluate the liquidity buffers and cash ratios of high-exposure issuers. Second, for financial regulators, the findings suggest the need to transition from voluntary, qualitative reporting to a standardized, mandatory disclosure framework. Regulatory bodies (such as central banks and securities commissions) should mandate the disclosure of spatial asset climate exposures. Bond-issuing real estate firms should be required to report the geographic distribution of their land banks and construction projects rather than corporate-level aggregate statements. Additionally, macroprudential supervisors should incorporate climate-related stress tests into the regulatory framework, particularly for leveraged industries, to monitor systemic credit risks arising from climate shocks. Third, for real estate developers, the results provide a guide for risk management and sustainable financing decisions. Given that climate risks widen spreads primarily by tightening financing constraints and compressing cash flows, firms are advised to maintain robust liquidity buffers and cash ratios to absorb regulatory and physical shocks. Concurrently, because physical risks are spatially concentrated, developers should geographically diversify their land reserves and project portfolios to reduce localized physical exposures. Finally, since green innovation is shown to mitigate the credit pricing impact of chronic physical risks, developers should allocate resources toward utility patent acquisitions and green R&D to signal adaptive capacity to the bond market.

Although this study provides empirical evidence on climate risk pricing, several limitations remain for future research to address. First, due to data limitations, this study relied on headquarters-based climate risk metrics in the baseline regressions. Although we attempted to construct spatially-weighted risk indices using project-level land reserves from the CSMAR database, unlisted issuers do not systematically disclose geographical asset distributions. Merging these spatial indices reduces the sample size from 4553 to approximately 200 observations, introducing selection bias and rendering high-dimensional joint fixed effects unfeasible. Future research could manually extract project portfolios for unlisted issuers from bond prospectuses and local land registries to construct asset-level databases.

Second, the sample sizes in the subgroup analysis were unbalanced: state-owned enterprises (SOEs, $N = 3882$) outnumbered non-state-owned enterprises (non-SOEs, $N = 669$), representing a ratio of 5.8:1. This asymmetry limits statistical power within the non-SOE subsample and potentially biases coefficient estimates. Future studies could employ matching estimators or extend the sample period to balance the comparative analysis.

Third, the mechanism analysis employed a two-step framework rather than a simultaneous structural system to mitigate the endogeneity of the mediating variables. Therefore, the identified transmission channels suggest potential pathways rather than definitive causal chains. Future designs could utilize exogenous policy shocks or targeted instrumental variables for the mediators to examine these pathways.

Author Contributions: Conceptualization, W.Z.; methodology, W.Z.; software, R.L.; validation, R.L.; formal analysis, R.L.; investigation, R.L.; data curation, R.L.; writing—original draft preparation, R.L.; writing—review and editing, W.Z. and X.Q.; visualization, R.L.; supervision, W.Z. and X.Q. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: This article does not contain any studies with ethical issues performed by any of the authors.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Description of the main control variables.

Variable Types	Dimension	Variable Names	Definition
Basic Feature of Bonds	Maturity Term	Maturity Term	The time from bond issuance to maturity, measured in years
	Special Provisions	Redeemability	1 indicates redeemable, 0 indicates non-redeemable
		Resellability	1 indicates that it can be resold, 0 indicates that it cannot be resold.
		Prepayable	1 means can be repaid in advance, 0 means cannot be repaid in advance
		Separability	1 means separable, 0 means inseparable
		Guarantee	1 means guaranteed, 0 means not guaranteed
	Bond Type	Cross-Market	1 means cross-market, 0 means non-cross-market
	Bond Rank	Bond Rank	If the bond rating is AAA, take 6; AA+ take 5; AA take 4; AA- take 3; A+ take 2; A take 1; all others take 0.
Corporate Governance	Nature of Property Rights	State-Owned Enterprise (SOE)	A dummy variable: take 1 if the property right is state-owned, otherwise take 0
	Issuer Rating	Issuer Ranking	If the bond issuer rating is AAA, take 6; AA+ take 5; AA take 4; AA- take 3; A+ take 2; A take 1; otherwise, take 0.
	Listing Status	Listing Status	=1 if it is a listed company, otherwise 0
Assets and Asset Structure		Size	Take the logarithm of the company’s total assets plus 1
		DA	“Depreciation” + “Amortization of Intangible Assets” + “Amortization of Long-term Deferred Expenses” from Cash Flow Statement
		Free Cash Flow to Firm	EBIT\times (1 – Tax Rate) + Depreciation & Amortization – Increase in Working Capital – Capital Expenditures
		Free Cash Flow to Equity (FCFE)	Net Income + Depreciation & Amortization – Increase in Working Capital – Capital Expenditures + Net Debt Issued
		Receivables to Income	(Ending) Accounts Receivable/(Current) Total Operating Revenue

Table A1. Cont.

Variable Types	Dimension	Variable Names	Definition
Assets and Asset Structure		Inventory to Income	Inventory/Income
		Current Asset to Income	(Ending) Total Current Assets/(Current) Total Operating Revenue
		Fixed Asset Ratio	(Ending) Net Fixed Assets/(Ending) Total Assets
		Intangible Asset Ratio	(Ending) Net Intangible Assets/(Ending) Total Assets
		Equity Ratio	(Ending) Total Equity/(Ending) Total Assets
		Fixed Asset to Income	(Ending) Net Fixed Assets/(Current) Total Operating Revenue
		Capital Intensity	(Ending) Total Assets/(Current) Total Operating Revenue
Long-Term Solvency		Asset Liability Ratio	(Ending) Total Liabilities/(Ending) Total Assets
		Equity Multiplier	(Ending) Total Assets/(Ending) Total Equity
		Long-term Asset Liability Ratio	(Ending) Total Long-term Liabilities/(Ending) (Total Long-term Liabilities + Total Equity)
Liquidity		Current Ratio	(Ending) Total Current Assets/(Ending) Total Current Liabilities
		Quick Ratio	(Ending) (Total Current Assets – Inventory)/(Ending) Total Current Liabilities
		Cash Ratio	(Ending) (Cash & Cash Equivalents + Marketable Securities)/(Ending) Total Current Liabilities
		Interest Coverage Ratio	(Current) EBIT (Earnings Before Interest and Taxes)/(Current) Interest Expense
		NCF to Net Profit	(Current) Net Cash Flow from Operating Activities/(Current) Net Income
		Sales Cash Content	(Current) Net Cash Flow from Operating Activities/(Current) Total Operating Revenue
		Cash to Operating Income Ratio	(Current) Net Cash Flow from Operating Activities/(Current) Total Operating Revenue
		NCF to Operating Profit	(Current) Net Cash Flow from Operating Activities/(Current) Operating Profit
		Debt Holder Financing NCF	(Current) (Cash received from borrowings – Cash paid for debt repayment)
		Shareholder Financing NCF	(Current) (Cash from equity issued – Cash paid for dividends/interest – Cash paid for share repurchases)

Table A1. Cont.

Variable Types	Dimension	Variable Names	Definition
Profitability		ROA	$\text{Net Income} / [(\text{Beginning Total Assets} + \text{Ending Total Assets}) / 2]$
		ROE	$\text{Net Income} / [(\text{Beginning Total Equity} + \text{Ending Total Equity}) / 2]$
		Net Profit to Current Asset	$\text{Net Income} / [(\text{Beginning Current Assets} + \text{Ending Current Assets}) / 2]$
		Net Profit to Fixed Asset	$\text{Net Income} / [(\text{Beginning Net Fixed Assets} + \text{Ending Net Fixed Assets}) / 2]$
		EBIT	$\text{Net Income} + \text{Income Tax Expense} + \text{Interest Expense (or: Operating Profit} + \text{Interest Expense)}$
		EBTAT	$\text{EBIT} \times (1 - \text{Effective Tax Rate})$
		EBITDA	$\text{EBIT} + \text{Depreciation Expense} + \text{Amortization Expense}$
		Operating Margin Ratio	$(\text{Operating Revenue} - \text{Operating Cost}) / \text{Operating Revenue}$
		Operating Profit to Revenue	$\text{Operating Profit} / \text{Total Operating Revenue}$
		ROIC	$\text{EBIAT} / [(\text{Beginning Invested Capital} + \text{Ending Invested Capital}) / 2]$
		Return On Invested Capital	$\text{EBIAT} / [(\text{Beginning Invested Capital} + \text{Ending Invested Capital}) / 2]$
		EBIT to Revenue	$\text{EBIT} / \text{Total Operating Revenue}$
		Profit to Cost	$\text{Total Profit} / (\text{Cost of Goods Sold} + \text{Total Operating Expenses})$
Cost Management		Sales Expense Rate	$(\text{Current}) \text{ Selling Expenses} / (\text{Current}) \text{ Total Operating Revenue}$
		Management Expense Rate	$(\text{Current}) \text{ Administrative Expenses} / (\text{Current}) \text{ Total Operating Revenue}$
		Financial Expense Rate	$(\text{Current}) \text{ Financial Expenses} / (\text{Current}) \text{ Total Operating Revenue}$
		R&D Expense Rate	$(\text{Current}) \text{ R\&D Expenses} / (\text{Current}) \text{ Total Operating Revenue}$
		Total Revenue Growth	$(\text{Current Total Operating Cost} - \text{Prior Total Operating Cost}) / \text{Prior Total Operating Cost}$
		Sales Expense Growth	$(\text{Current}) \text{ Selling Expenses} - (\text{Prior}) \text{ Selling Expenses} / (\text{Prior}) \text{ Selling Expenses}$
		Management Expense Growth	$(\text{Current}) \text{ Administrative Expenses} - (\text{Prior}) \text{ Administrative Expenses} / (\text{Prior}) \text{ Administrative Expenses}$

Table A1. Cont.

Variable Types	Dimension	Variable Names	Definition
Market Value		Earnings Per Share (EPS)	(Current) Net Income/(Current) Total Outstanding Shares (or Weighted Average Shares)
		Net Asset Value Per Share	(Ending) Total Equity/(Ending) Total Outstanding Shares
		Liabilities Per Share	(Ending) Total Liabilities/(Ending) Total Outstanding Shares
		Current Assets Per Share	(Ending) Total Current Assets/(Ending) Total Outstanding Shares
		Operating Profit Per Share	(Current) Operating Profit/(Current) Total Outstanding Shares (or Weighted Average Shares)
		Retained Earnings Per Share	(Ending) Total Retained Earnings/(Ending) Total Outstanding Shares
		Free Cash Flow to Firm (FCFF) Per Share	(Current)FCFF/(Current) Total Outstanding Shares
		Operating NCF Per Share	(Current) Net Cash Flow from Operating Activities/(Current) Total Outstanding Shares
		Financing NCF Per Share	(Current) Net Cash Flow from Financing Activities/(Current) Total Outstanding Shares
		Investing NCF Per Share	(Current) Net Cash Flow from Investing Activities/(Current) Total Outstanding Shares
		Cash Increase Per Share	(Current) Net Increase in Cash and Cash Equivalents/(Current) Total Outstanding Shares
Growth Potential		Assets Growth	(Ending Total Assets – Prior Ending Total Assets)/Prior Ending Total Assets
		ROE Growth	Current ROE – Prior ROE
		EPS Growth	Current EPS – Prior EPS
		Diluted EPS Growth	Current Diluted EPS – Prior Diluted EPS
		Net Profit Growth	(Current Net Income – Prior Net Income)/Prior Net Income
		Total Profit Growth	(Current Total Profit – Prior Total Profit)/Prior Total Profit
		Operating Profit Growth	(Current Operating Profit – Prior Operating Profit)/Prior Operating Profit
		Parent Profit Growth	(Current Net Income Attributable to Parent – Prior)/Prior Net Income Attributable to Parent
		Comprehensive Growth	(Current Total Comprehensive Income – Prior)/Prior Total Comprehensive Income

Table A1. Cont.

Variable Types	Dimension	Variable Names	Definition
Growth Potential		Parent Comprehensive Growth	(Current Comprehensive Income Attributable to Parent – Prior)/Prior Comprehensive Income Attributable to Parent
		Operating Revenue Growth	(Current Operating Revenue – Prior Operating Revenue)/Prior Operating Revenue
		Total Revenue Growth	(Current Total Operating Revenue – Prior Total Operating Revenue)/Prior Total Operating Revenue
		NAV Growth	(Ending NAV per Share – Prior Ending NAV per Share)/Prior Ending NAV per Share
		Fixed Assets Growth	(Ending Net Fixed Assets – Prior Ending Net Fixed Assets)/Prior Ending Net Fixed Assets
Operational Capability		Receivable Turnover	(Current) Total Operating Revenue/[(Beginning A/R + Ending A/R)/2]
		Receivable Turnover Days	365/Receivable Turnover
		Inventory Turnover	(Current) Cost of Goods Sold/[((Beginning Inventory + Ending Inventory)/2)]
		Inventory Turnover Days	365/Inventory Turnover
		Operating Cycle	Inventory Turnover Days + Receivable Turnover Days
		Working Capital Turnover	(Current) Total Operating Revenue/[(Beginning Working Capital + Ending Working Capital)/2]
		Cash Equivalents Turnover	(Current) Total Operating Revenue/[(Beginning Cash Equiv. + Ending Cash Equiv.)/2]
		Current Asset Turnover	(Current) Total Operating Revenue/[(Beginning Current Assets + Ending Current Assets)/2]
		Fixed Asset Turnover	(Current) Total Operating Revenue/[(Beginning Net Fixed Assets + Ending Net Fixed Assets)/2]
		Noncurrent Asset Turnover	(Current) Total Operating Revenue/[(Beginning Non-current Assets + Ending Non-current Assets)/2]
		Asset Turnover	(Current) Total Operating Revenue/[(Beginning Total Assets + Ending Total Assets)/2]
		Equity Turnover	(Current) Total Operating Revenue/[(Beginning Total Equity + Ending Total Equity)/2]

Note: Some indicators have multiple calculation adjustment methods, which are not detailed here.

Table A2. Top 20 permutation feature importance for predicting credit spread—initial model.

Feature	Permutation Importance
BondRank	0.2399
SOE	0.2129
Size	0.1109
Guarantee	0.0926
Separability	0.0414
Maturity Term	0.0346
OperatingNCFGrowth	0.0280
RecTurnover	0.0252
CashRatio	0.0140
CurrentRate	0.0132
OpNCFPsGrowth	0.0107
EquityCFTTM	0.0099
AssetTurnover	0.0086
DAR	0.0065
InvTurnover	0.0050
NPR	0.0042
QuickRate	0.0032
CapitSurpPSA	0.0025
CashRate	0.0024
PPE	0.0022

Table A3. Top 20 permutation feature importance for predicting credit spread—adding climate risk.

Feature	Permutation Importance
SOE	0.2266
BondRank	0.2068
Size	0.1182
Guarantee	0.0755
ChroCPRI	0.0626
AcuCPRI	0.0439
Separability	0.0386
OperatingNCFGrowth	0.0304
CTRI	0.0215
RecTurnover	0.0188
EquityCFTTM	0.0182
OpNCFPsGrowth	0.0169
Maturity Term	0.0151
CashRatio	0.0124
CurrentRate	0.0122
AssetTurnover	0.0077
NPR	0.0050
InvTurnover	0.0048
PPE	0.0048
Resellability	0.0045

Table A4. Machine learning algorithm performance comparison.

Model	Train CV R ²	Test R ²	Test MSE	Test RMSE	Test MAE
Random Forest (n = 38)	0.6987	0.6985	0.5380	0.7335	0.5324
Random Forest (n = 100)	0.7041	0.7082	0.5208	0.7217	0.5267
Random Forest (n = 191)	0.7113	0.7115	0.5149	0.7176	0.5243
XGBoost	0.7177	0.7125	0.5132	0.7164	0.5278
LightGBM	0.6975	0.6995	0.5364	0.7324	0.5472

Table A5. Best feature importance for predicting credit spread in the final model—adding climate risk.

Metric	Value	Metric	Value	Metric	Value
Final model R ² score	0.6929	Final model R ² score	0.7098	Final model R ² score	0.6952
Feature	Importance	Feature	Importance	Feature	Importance
SOE	0.1139	SOE	0.1138	SOE	0.1139
BondRank	0.1037	BondRank	0.1035	BondRank	0.1039
Size	0.1004	Size	0.0984	Size	0.0998
CTRI	0.0525	ChroCPRI	0.0634	AcuCPRI	0.0598
Maturity Term	0.0398	EquityCFTTM	0.0395	EquityCFTTM	0.0394
EquityCFTTM	0.0394	Maturity Term	0.0363	Maturity Term	0.0384
Guarantee	0.0357	Guarantee	0.0361	Guarantee	0.0343
RecTurnover	0.0305	CashRatio	0.0296	RecTurnover	0.0297
CashRatio	0.0296	RecTurnover	0.0290	CashRatio	0.0294
Separability	0.0235	Separability	0.0231	Separability	0.0244
InvTurnover	0.0234	InvTurnover	0.0227	InvTurnover	0.0229
CurrentRate	0.0228	NPR	0.0224	OperatingNCFGrowth	0.0207
OperatingNCFGrowth	0.0205	CurrentRate	0.0215	CurrentRate	0.0206
PPE	0.0202	OperatingNCFGrowth	0.0213	PPE	0.0201
NPR	0.0200	PPE	0.0205	NPR	0.0200
AssetTurnover	0.0196	AssetTurnover	0.0193	AssetTurnover	0.0195
CapitSurpPSA	0.0173	QuickRate	0.0180	QuickRate	0.0171
QuickRate	0.0173	CapitSurpPSA	0.0169	CapitSurpPSA	0.0170
Cash	0.0159	Cash	0.0153	Cash	0.0161
OprtNCFPsGrowth	0.0158	CashRate	0.0152	DAR	0.0148
DAR	0.0157	OprtNCFPsGrowth	0.0149	CashRate	0.0148
CashRate	0.0147	DAR	0.0149	OprtNCFPsGrowth	0.0147
EquityCF	0.0138	EquityCF	0.0138	EquityCF	0.0138
ReceivableRatio	0.0109	ReceivableRatio	0.0109	MaturingLiabilityCoverage	0.0112
MaturingLiabilityCoverage	0.0107	TangibleAssetRatio	0.0108	ReceivableRatio	0.0108
TangibleAssetRatio	0.0105	FinancialLiabilityRatio	0.0103	TangibleAssetRatio	0.0106
FinancialLiabilityRatio	0.0099	EM	0.0098	FinancialLiabilityRatio	0.0106
CashEquivalentTurnover	0.0099	MaturingLiabilityCoverage	0.0097	EquityCF	0.0099
EquityCF	0.0096	EquityTurnover	0.0096	EquityTurnover	0.0098
EM	0.0095	DER	0.0096	DER	0.0098
DER	0.0094	EquityCF	0.0096	CashEquivalentTurnover	0.0097
ProfitToCost	0.0094	TurnovTaxRate	0.0093	FixedAssetRatio	0.0096
EquityTurnover	0.0093	CashEquivalentTurnover	0.0092	EM	0.0094
WorkingCapital	0.0091	WorkingCapital	0.0092	WorkingCapital	0.0091
TurnovTaxRate	0.0091	ProfitToCost	0.0090	ProfitToCost	0.0091
FixedAssetRatio	0.0091	FixedAssetRatio	0.0089	TurnovTaxRate	0.0085
OperatingNCFTToProfitRatio	0.0084	OperatingNCFTToProfitRatio	0.0084	ConsolidatedTaxRate	0.0082
ReceivablesToIncome	0.0080	ReceivablesToIncome	0.0078	OperatingNCFTToProfitRatio	0.0080
ConsolidatedTaxRate	0.0080	CompanyCFTTM	0.0077	OperatIncomeInCashRatio	0.0080
OperatIncomeInCashRatio	0.0079	OperatIncomeInCashRatio	0.0077	ReceivablesToIncome	0.0077
CompanyCFTTM	0.0078	FinancingNCFGrowth	0.0074	CompanyCFTTM	0.0074
FinancingNCFGrowth	0.0074	ConsolidatedTaxRate	0.0072	InterestCoverageRatio	0.0073
InterestCoverageRatio	0.0071	CashEquivalentsTurnover	0.0066	FinancingNCFGrowth	0.0069
CashEquivalentsTurnover	0.0069	InterestCoverageRatio	0.0065	CashEquivalentsTurnover	0.0068
Resellability	0.0061	Resellability	0.0058	Resellability	0.0066

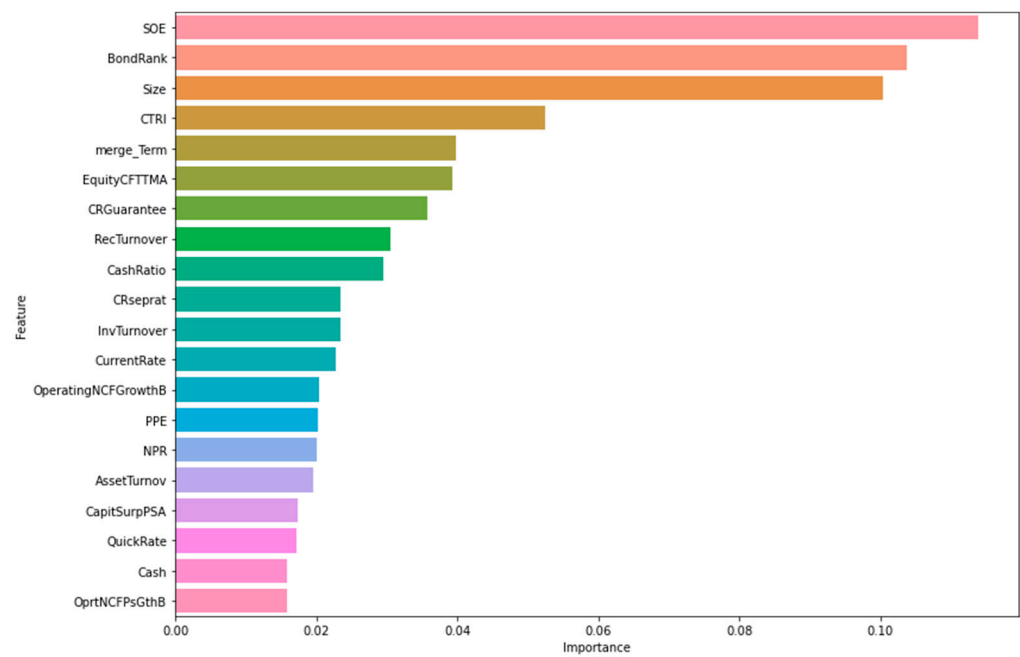


Figure A1. Top 20 permutation feature importance for predicting credit spread—final optimal model (CTRI).

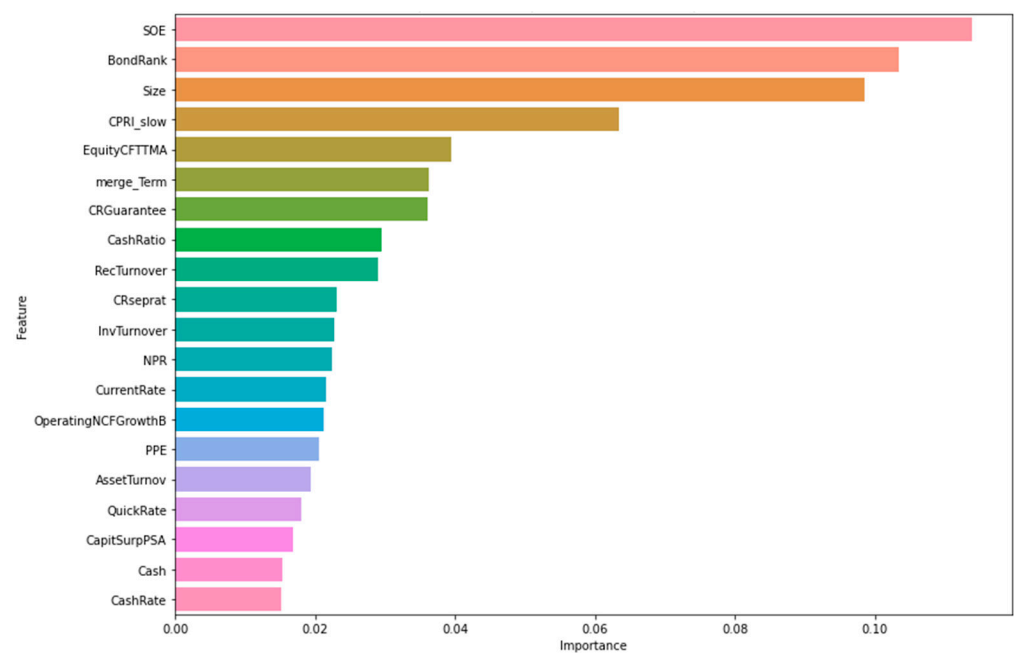


Figure A2. Top 20 permutation feature importance for predicting credit spread—final optimal model (ChroCPRI).

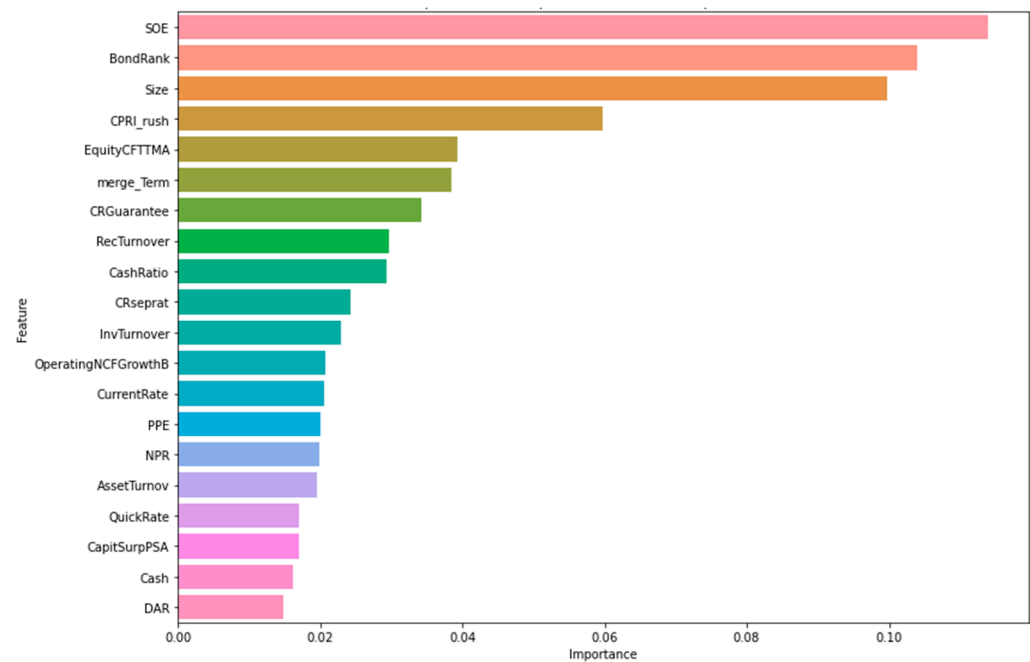


Figure A3. Top 20 permutation feature importance for predicting credit spread—final optimal model (AcuCPRI).

Appendix B

Variable Construction and Measurement Discussion

This appendix provides a comprehensive description of the construction, economic rationale, aggregation procedures, and potential measurement errors associated with the primary climate risk variables utilized in this study: the Climate Transition Risk Index (CTRI), the Chronic Climate Physical Risk Index (ChroCPRI), and the Acute Climate Physical Risk Index (AcuCPRI).

1. Climate Transition Risk Index (CTRI)

The Climate Transition Risk Index (CTRI) at the city-year level was constructed using textual analysis of local Government Work Reports (GWRs). We collected annual GWRs from 284 prefecture-level cities in China over the period 2003–2025, yielding a baseline sample of 6130 reports after excluding missing documents. The raw texts were processed through three stages. First, we used the Python-based jieba tokenization package to segment the Chinese text. Second, non-informative words, punctuation marks, and structural particles were removed using the Harbin Institute of Technology (HIT) stopwords dictionary. Third, we counted the total occurrences of climate transition-related keywords, grouped into three policy domains:

Low-carbon, energy efficiency, and clean energy: sustainability, low-carbon, clean energy, new energy, nuclear energy, wind energy, photovoltaic, emission reduction, renewable, and circular utilization.

Dual carbon targets: carbon peaking, carbon neutrality, carbon emissions, and carbon trading.

Industrial transition and environmental regulations: environmental disclosure, environmental supervision, stranded assets, green trade, green and low-carbon, climate policy, climate governance, pollution prevention, ecological construction, ecological governance, and wetland protection.

The index is formally defined as follows:

$$CTRI_{c,t} = \left(\sum_{w \in W} \frac{Freq_{w,c,t}}{TotalWords_{c,t}} \right) \times 100 \quad (A1)$$

where $Freq_{w,c,t}$ denotes the frequency of keyword w from the climate transition wordlist W in the GWR of city c in year t , and $TotalWords_{c,t}$ is the total word count of the report. The ratio is scaled by 100 to represent a percentage.

The use of GWR keyword frequencies to proxy for transition risk is justified by three institutional characteristics of China's political economy. First, GWRs, delivered annually by mayors during the local "Two Sessions", serve as official blueprints outlining regional development priorities, industrial planning, and regulatory targets for the upcoming year. The intensity of environmental terms directly reflects the local government's commitment to climate transition. Second, a higher keyword frequency indicates subsequent increases in administrative interventions, such as stricter green building mandates, tighter environmental compliance audits, and changes in local fiscal subsidies. These local policies directly translate into transition cost shocks for real estate firms operating within that jurisdiction. Third, unlike corporate disclosure, GWRs represent binding administrative targets that affect local officials' promotion prospects due to environmental performance evaluation metrics. Thus, GWR text offers a credible, ex-ante indicator of regional regulatory pressure, which investors incorporate into primary corporate bond credit spreads.

2. Climate Physical Risk Indices

We constructed two distinct metrics to capture physical climate risk, separating gradual climatic trends (chronic risk) from sudden, disastrous events (acute risk).

2.1. Chronic Climate Physical Risk Index (ChroCPRI)

The Chronic Climate Physical Risk Index (ChroCPRI) captures long-term, progressive climatic shifts. The index was built upon the Chinese Climate Physical Risk Index (CCPRI) at the city level, which aggregates four underlying meteorological hazard metrics: (1) Extreme Low Temperature Days (LTD), which captures the standardized annual count of days where the daily minimum temperature falls below the historical baseline threshold; (2) Extreme High Temperature Days (HTD), measuring the standardized annual count of days where the daily maximum temperature exceeds the threshold; (3) Extreme Precipitation Days (ERD), indicating the standardized annual count of days with daily rainfall exceeding the historical 95th percentile; and (4) Extreme Drought Days (EED), representing the standardized annual count of days characterized by severe drought, calculated using the Standardized Precipitation Evapotranspiration Index (SPEI).

To eliminate dimensional discrepancies across the four meteorological hazards and ensure comparability across space and time, the sub-indices are aggregated using an equally-weighted standardized summation as Equation (A2):

$$ChroCPRI_{c,t} = \frac{1}{4} \sum_{k=1}^4 \frac{Event_{k,c,t} - \mu_k}{\sigma_k} \quad (A2)$$

where $Event_{k,c,t}$ represents the raw value of hazard k in city c and year t , while μ_k and σ_k denote the historical sample mean and standard deviation of hazard k , respectively.

2.2. Acute Climate Physical Risk Index (AcuCPRI)

The Acute Climate Physical Risk Index (AcuCPRI) measures sudden, high-impact natural disasters. We retrieved the provincial-level direct economic loss from natural hazards (including floods, typhoons, landslides, and storms) compiled by the Chinese Research Data Services (CNRDS) database. To address the heavy right-skewness of the distribution of direct financial damages, we applied a natural logarithmic transformation as Equation (A3):

$$AcuCPRI_{p,t} = \ln(DirectLoss_{p,t} + 1) \quad (A3)$$

where $DirectLoss_{p,t}$ represents the direct economic loss (in RMB 100 million) in province p and year t .

Notes

- ¹ First, we established a random forest every 10 steps within 1 to 200 trees to obtain different cross-validation scores (see Figure 4). Figure 4 shows that the mathematical maximum of the cross-validation score is achieved at 191 estimators ($R^2 = 0.7314$). We performed 5-fold cross-validation recursively over 357 features, which requires fitting random forest models $5 \times 357 = 1785$ times. Therefore, using 191 trees to train the model would lead to prohibitive training times. We observed from Figure 4 that the learning curve flattened significantly after 30 estimators. Considering the overall program running efficiency, further stepwise validation was conducted between 30 to 40 trees to obtain the cross-validation scores for each tree, as shown in Figure 5. Finally, we chose 38 trees for model training.
- ² A bond rating of AAA scores 6, AA scores 5, AA scores 4, AA-scores 3, A scores 2, A scores 1, and the rest score 0.

References

1. Nordhaus, W.D. Economic growth and climate: The carbon dioxide problem. *Am. Econ. Rev.* **1977**, *67*, 341–346.
2. Dell, M.; Jones, B.F.; Olken, B.A. Temperature shocks and economic growth: Evidence from the last half century. *Am. Econ. J. Macroecon.* **2012**, *4*, 66–95. [\[CrossRef\]](#)
3. Hsiang, S.; Kopp, R.; Jina, A.; Rising, J.; Delgado, M.; Mohan, S.; Houser, T. Estimating economic damage from climate change in the United States. *Science* **2017**, *356*, 1362–1369. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Tankov, P.; Tantet, A. Climate Data for Physical Risk Assessment in Finance. 2019. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3480156&__cf_chl_rt_tk=E9AmLbaMKHV38LbY5gH6mdbP_UgvvkWrWO6cs9p_tjE-1784439068-1.0.1.1-vNZbG2cSBID6uEoUa3L9rPdA509OI1iTxE9Kg7C4kA (accessed on 9 October 2025).
5. Semieniuk, G.; Campiglio, E.; Mercure, J.F.; Volz, U.; Edwards, N.R. Low-carbon Transition Risks for Finance. *Wiley Interdiscip. Rev. Clim. Change* **2021**, *12*, e678.
6. Giglio, S.; Kelly, B.; Stroebe, J. Climate finance. *Annu. Rev. Financ. Econ.* **2021**, *13*, 15–36. [\[CrossRef\]](#)
7. Hugon, A.; Law, K. Impact of Climate Change on Firm Earnings: Evidence from Temperature Anomalies. 2019. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3271386 (accessed on 11 September 2025).
8. Pankratz, N.; Bauer, R.; Derwall, J. Climate change, firm performance, and investor surprises. *Manag. Sci.* **2023**, *69*, 7352–7398. [\[CrossRef\]](#)
9. Bolton, P.; Kacperczyk, M. Do investors care about carbon risk? *J. Financ. Econ.* **2021**, *142*, 517–549. [\[CrossRef\]](#)
10. Choi, D.; Gao, Z.; Jiang, W. Attention to global warming. *Rev. Financ. Stud.* **2020**, *33*, 1112–1145. [\[CrossRef\]](#)
11. Ilhan, E.; Sautner, Z.; Vilkov, G. Carbon tail risk. *Rev. Financ. Stud.* **2021**, *34*, 1540–1571.
12. Chen, Y.; Mamon, R.; Spagnolo, F.; Spagnolo, N. Stock market returns and climate risk in the US. *J. Multinatl. Financ. Manag.* **2025**, *77*, 100887. [\[CrossRef\]](#)
13. Faccini, R.; Martin, R.; Skiadopoulos, G. Dissecting climate risks: Are they reflected in stock prices? *J. Bank. Financ.* **2023**, *155*, 106948. [\[CrossRef\]](#)
14. Peng, P.; Guo, Y.; Huang, D.; Wang, H. Climate change risk and bond risk premium. *Int. Rev. Financ. Anal.* **2025**, *97*, 103885. [\[CrossRef\]](#)
15. Ma, F.; Guo, Y.; Luo, Q.; Zhong, J. Forecasting corporate bond returns amid climate change risk: A dynamic forecast combination approach. *J. Int. Money Financ.* **2025**, *154*, 103324. [\[CrossRef\]](#)
16. Cang, H.; Li, C. Corporate climate risk and bond credit spreads. *Financ. Res. Lett.* **2024**, *67*, 105741. [\[CrossRef\]](#)
17. Painter, M. An inconvenient cost: The effects of climate change on municipal bonds. *J. Financ. Econ.* **2020**, *135*, 468–482. [\[CrossRef\]](#)
18. Allman, E. Pricing climate change risk in corporate bonds. *J. Asset Manag.* **2022**, *23*, 596–618. [\[CrossRef\]](#)
19. Bernstein, A.; Gustafson, M.T.; Lewis, R. Disaster on the horizon: The price effect of sea level rise. *J. Financ. Econ.* **2019**, *134*, 253–272. [\[CrossRef\]](#)
20. Nguyen, D.D.; Ongena, S.; Qi, S.; Sila, V. Climate change risk and the cost of mortgage credit. *Rev. Financ.* **2022**, *26*, 1509–1549. [\[CrossRef\]](#)
21. Cho, C.; Yang, J.; Jang, B. Climate policy uncertainty and its impact on real estate market dynamics: A sectoral and regional analysis. *PLoS ONE* **2024**, *19*, e0311688. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Eren, E.; Merten, F.; Verhoeven, N. *Pricing of Climate Risks in Financial Markets: A Summary of the Literature*; BIS Papers: Basel, Switzerland, 2022.
23. Seltzer, L.H.; Starks, L.; Zhu, Q. *Climate Regulatory Risk and Corporate Bonds (No. w29994)*; National Bureau of Economic Research: Cambridge, MA, USA, 2022.
24. DiMaggio, P.J.; Powell, W.W. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *Am. Sociol. Rev.* **1983**, *48*, 147–160. [\[CrossRef\]](#)
25. Scott, W.R. *Institutions and Organizations: Ideas, Interests, and Identities*; Sage Publications: London, UK, 2013.

26. Cui, J.; Dai, J.; Wang, Z.; Zhao, X. Does environmental regulation induce green innovation? A panel study of Chinese listed firms. *Technol. Forecast. Soc. Change* **2022**, *176*, 121492. [\[CrossRef\]](#)
27. Baldauf, M.; Garlappi, L.; Yannelis, C. Does climate change affect real estate prices? Only if you believe in it. *Rev. Financ. Stud.* **2020**, *33*, 1256–1295. [\[CrossRef\]](#)
28. Brandt, L.; Li, H. Bank discrimination in transition economies: Ideology, information, or incentives? *J. Comp. Econ.* **2003**, *31*, 387–413. [\[CrossRef\]](#)
29. Song, Z.; Storesletten, K.; Zilibotti, F. Growing like china. *Am. Econ. Rev.* **2011**, *101*, 196–233. [\[CrossRef\]](#)
30. Han, P.; Hu, Y. Dose the bond with government implicit guarantee usually have the lower capital cost? An empirical study on the bonds of the state-owned enterprises and the local financing platforms. *J. Financ. Res.* **2015**, *3*, 116–130. (In Chinese)
31. Lin, J.Y.; Cai, F.; Li, Z. Competition, policy burdens, and state-owned enterprise reform. *Am. Econ. Rev.* **1998**, *88*, 422–427.
32. Fang, H.; Shi, J.; Zhang, G. Ownership Type, Information Quality, and Corporate Bond Pricing: The Empirical Evidence from Capital Market in China. *J. Financ. Res.* **2013**, *4*, 170–182. (In Chinese)
33. Zhou, H.; Lin, W.; Li, G.; Wang, H. Research on the Impact of Information Asymmetry on the Credit Risk of Chinese Corporate Bonds—Based on the Data of Chinese Corporate Bonds in 2008–2011. *Account. Res.* **2012**, *12*, 36–42. (In Chinese)
34. Bhagat, S.; Bolton, B. Corporate governance and firm performance. *J. Corp. Financ.* **2019**, *58*, 142–168. [\[CrossRef\]](#)
35. Liu, L.; Du, Y. An Empirical Research on the Relationship between Corporate Governance and the Quality of Accounting Information. *Account. Res.* **2003**, *2*, 28–36. (In Chinese)
36. Zhou, H.; Zhou, C.; Lin, W.; Li, G. Corporate governance and corporate bond credit spreads: An empirical study of China's corporate bonds from 2008 to 2016. *Account. Res.* **2018**, *5*, 59–66. (In Chinese)
37. Wu, S.; Chen, Z. Bond default early warning model based on financial and non-financial information: Empirical evidence from machine learning methods. *J. Xiamen Univ.* **2023**, *73*, 108–121. (In Chinese)
38. Zheng, Y.; Wu, S. Research on bond default warning model based on financial and non-financial information: Empirical analysis and application of Fisher model and Logistic model. *Financ. Account. Mon.* **2023**, *44*, 22–29. (In Chinese)
39. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
40. Wei, M.; Lai, J.; Zhang, H. Implicit guarantee, financial intermediaries' governance and information efficiency of corporate bond market. *Nankai Bus. Rev.* **2017**, *20*, 30–42. (In Chinese)
41. Alfaro, L.; Asis, G.; Chari, A.; Panizza, U. Corporate debt, firm size and financial fragility in emerging markets. *J. Int. Econ.* **2019**, *118*, 1–19. [\[CrossRef\]](#)
42. Liu, L.; Yuan, C. The Impact of Local Climate Attention on Corporate Bond Credit Spreads. *Nankai Econ. Stud.* **2025**, *2*, 61–80. (In Chinese)
43. Guo, K.; Ji, Q.; Zhang, D. A dataset to measure global climate physical risk. *Data Brief.* **2024**, *54*, 110502. [\[CrossRef\]](#) [\[PubMed\]](#)
44. He, F.; Ren, X.; Wang, Y.; Lei, X. Climate risk and corporate bond credit spreads. *J. Int. Money Financ.* **2025**, *154*, 103297. [\[CrossRef\]](#)
45. Jiang, T. Mediating Effects and Moderating Effects in Causal Inference. *China Ind. Econ.* **2022**, *5*, 100–120.
46. Zhai, S.; Han, X.; Zhang, X.; Chen, X. Can Digital Finance Reduce the Risk of Corporate Debt Default? *Account. Res.* **2022**, *2*, 117–131. (In Chinese)
47. Safiullah, M.; Phan, D.H.B.; Kabir, M.N. Green innovation and corporate default risk. *J. Int. Financ. Mark. Inst. Money* **2024**, *95*, 102041. [\[CrossRef\]](#)
48. Boermans, M.; Bun, M.J.; Van der Straten, Y. *Funding the Fittest?: Pricing of Climate Transition Risk in the Corporate Bond Market*; De Nederlandsche Bank NV: Amsterdam, The Netherlands, 2024.
49. Ruan, Q.; Li, C.; Lv, D.; Wei, X. Going Green: Effect of green bond issuance on corporate debt financing costs. *N. Am. J. Econ. Financ.* **2025**, *75*, 102299. [\[CrossRef\]](#)
50. Bartik, A.W.; Bertrand, M.; Cullen, Z.; Glaeser, E.L.; Luca, M.; Stanton, C. The impact of COVID-19 on small business outcomes and expectations. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 17656–17666. [\[CrossRef\]](#) [\[PubMed\]](#)
51. Leland, H.E.; Pyle, D.H. Informational asymmetries, financial structure, and financial intermediation. *J. Financ.* **1977**, *32*, 371–387. [\[CrossRef\]](#)
52. Besanko, D.; Thakor, A.V. Collateral and rationing: Sorting equilibria in monopolistic and competitive credit markets. *Int. Econ. Rev.* **1987**, *28*, 671–689. [\[CrossRef\]](#)
53. Lu, C.L.; Chen, H.C.; Chou, R.K.; Lin, C.Y. Debt capacity, cash holdings and financial constraints. *J. Bus. Financ. Account.* **2024**, *51*, 2020–2054.
54. Tang, D.Y.; Yan, H. Market conditions, default risk and credit spreads. *J. Bank. Financ.* **2010**, *34*, 743–753. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.