Technological Forecasting & Social Change 206 (2024) 123490

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

The impact of climate change on credit cycles: Evidence from China's bond market

Xiaoran Kong [a], Cheng Yan Dr., Ph.D. [b,*], Kung-Cheng Ho [c,d,**]

[a] School of Finance, Shandong University of Finance and Economics, Jinan, China
[b] Essex Business School, University of Essex, Colchester, UK
[c] School of Finance, Guangdong University of Finance & Economics, Guangdong, China
[d] Zhongnan University of Economics and Law, Wuhan, China

ARTICLE INFO

Keywords:
Climate change
NDVI
Corporate bonds
Credit spreads
Economic cycles

ABSTRACT

This study examines the long-term impacts of climate change on credit spreads using a sample of A-share listed companies that issued corporate bonds between 2014 and 2020. The results indicate that the greater the climate change risk a company faces, the greater its bonds' credit spread; the secondary bond market perceives the potential harm caused by climate change. This conclusion remains valid after endogeneity treatment and robustness tests. Furthermore, mechanism testing reveals that climate change affects bond credit spreads by increasing the probability of corporate bankruptcy, profit volatility, and negative investor sentiment. The heterogeneity test considers three aspects, namely, individual enterprises' internal characteristics, creditor protection measures, and regional green finance levels. Finally, this study introduces the impact of economic cycles to test the conclusions at the macro level and closely follow the topic. Thus, we provide new evidence and perspectives for exploring the impact of climate risk on the bond market and important policy implications for green finance and the healthy development of China's bond market.

1. Introduction

Climate change is an urgent global challenge that demands immediate collective action. The 2015 Paris Agreement, which 195 countries ratified, set ambitious goals to address climate risks. The agreement aims to limit the increase in the global average temperature to within 2 degrees Celsius and even further to 1.5 degrees Celsius above pre-industrial levels. However, the current global average temperature already exceeds pre-industrial levels by approximately 1.11 degrees Celsius—dangerously close to the critical threshold. This temperature rise has resulted in extreme heat waves, heavy precipitation, storm surges, and sea-level rise, among other devastating catastrophes. Over the past two decades, over 12,000 extreme weather events have been recorded globally, and these have caused approximately 495,000 fatalities and economic losses totaling $35.4 trillion (Alam et al., 2022; Fang et al., 2023). Notably, the first 20 years of the 21st century have seen an alarming surge in climate-related disasters, with extreme weather events as the primary driving force for such occurrences (Song et al., 2022; Lang et al., 2023). Climate crises have emerged as the most significant source of uncertainty affecting social stability and the security of economic systems and exerting disruptive effects that extend beyond human safety to encompass structural transformations within the financial system. This exerts a fundamental influence on global capital allocation. Enterprises, a crucial component of the economy, face ongoing risks owing to climate change. The issue of climate financing has attracted widespread attention, prompting numerous scholars to investigate the impact of climate change on corporate governance (Pinkse and Gasbarro, 2019; Nguyen and Phan, 2020). Recognizing that climate change poses a significant threat to our planet's survival and that immediate decisive action is necessary to address this problem is crucial.

Climate change physically damages corporate facilities and production equipment, precipitating asset depreciation (Pinkse and Gasbarro, 2019). Extreme weather events further exacerbate this depreciation and reduce labor productivity, thus diminishing established input–output levels. However, companies face transition and regulatory risks stemming from policy changes and shifts in market preferences (Ren et al., 2022). Specifically, the Paris Agreement imposes limitations on the

* Correspondence to: C. Yan, 3.19 EBS, University of Essex, Colchester, UK
** Corresponding author.
E-mail addresses: cheng.yan@essex.ac.uk (C. Yan), kcho731101@163.com (K.-C. Ho).

https://doi.org/10.1016/j.techfore.2024.123490
Received 23 November 2023; Received in revised form 14 May 2024; Accepted 31 May 2024
Available online 28 June 2024

utilization of traditional energy sources. Moreover, the green objectives China announced at the 75th United Nations General Assembly included reducing peak carbon dioxide emissions before 2030 and achieving carbon neutrality before 2060 (Ho et al., 2023; Yang and Qin, 2024). In response to government environmental requirements, traditional energy assets risk being stranded (Green and Newman, 2017). Moreover, consumers' and investors' changing preferences have brought enormous uncertainty to environmentally conscious companies (Pfeiffer et al., 2018). The failure to proactively assess and adapt to climate risks in the new macro environment has hindered the smooth transition of overall development.

Climate risk, an inevitable macroeconomic disturbance, significantly affects the corporate bond market. Extreme events triggered by climate change directly damage tangible assets and operational efficiency (Green and Newman, 2017; Somanathan et al., 2021; Wen et al., 2023). Moreover, enterprises face the risk of asset depreciation owing to their transition toward sustainable development. These factors increase operational risks and the likelihood of companies violating contractual obligations (Ding et al., 2021; Odenweller, 2022; Ye, 2022). The market believes that enterprises' ability to fulfill contracts has changed, hindering companies' access to funding. Therefore, climate change may adversely affect bond financing costs. Additionally, with the intensification of climate change, profit volatility also increases. Credit spreads are highly sensitive to changes in company valuation (Vining and Boardman, 1992). When bond investors perceive an increased bond default risk, they demand an increase in the risk premium as compensation, thus increasing bond credit spreads. Finally, climate change increases information barriers and negative emotions among investors, which, in turn, guide creditors to set higher risk premiums in bond pricing (Palea and Drogo, 2020).

Against the backdrop of intensified climate change risks, examining the critical engine of direct financing for enterprises—namely, the bond market—is necessary. We selected Chinese listed companies' corporate bonds as the research object. The reasons we selected the Chinese market are as follows: First, in recent years, the corporate bond market has experienced significant growth as a prominent avenue for corporate debt financing. By the end of 2021, China recorded 4046 corporate bond issuances, amounting to an issuance size of 3.43 trillion yuan, which represents a substantial increase of over 300 times compared with the initial issuance in 2007. However, unlike shareholders, bondholders primarily emphasize a company's ability to fulfill repayment obligations, including the principal and interest, within predetermined timeframes. The capital market faces heightened risk challenges owing to evolving dynamics, such as the evolving pandemic and external uncertainties. This exacerbates conflicts between shareholders and bondholders (Rainville et al., 2022), resulting in occasional bond defaults in the Chinese market. The corresponding creditor protection system can be assumed to be unsound. Second, China is a significantly vulnerable region affected by global climate change, with rising temperatures outpacing the global average. The resulting climate-related disasters exhibit a diverse range, high frequency, and wide geographic distribution, and cause substantial economic losses (Chen et al., 2024). Considering the particularity of China's bond market and severity of climate change, protecting bondholders' legitimate rights and interests has become a critical concern in the current landscape of diligently guarding against multifaceted risk challenges and striving for high-quality capital market development.

Given these circumstances, this study examined the long-term influence of climate change on bond credit spreads using a sample of listed companies that issued corporate bonds between 2014 and 2020. The aim was to assess whether bondholders perceive a threat from macro-environmental transformations. The findings reveal a substantial increase in credit spreads for firms in regions experiencing pronounced climate change, indicating that the secondary bond market can discern the latent perils associated with climate change, potentially resulting in wealth depreciation for bondholders. To mitigate potential confounding factors, we conducted rigorous tests, and the results remained robust even after these examinations. Climate change affects bond credit spreads by increasing the probability of corporate bankruptcy, profit volatility, and negative investor sentiment. Subsequently, grouping tests were employed to investigate the impacts of ownership characteristics, firm ratings, and internal and external safeguards. Empirical evidence demonstrates that the effects of climate change on bonds are more pronounced for private enterprises and entities with lower ratings. Moreover, firm bondholders that incorporate more substantial restrictive covenant clauses and internal control mechanisms exhibit greater resilience to the adverse consequences of climate risk. In areas with high green finance levels, the secondary bond market's response to climate change is not a significant adverse reaction. Moreover, this study explicitly examined the role of the economic cycle and found that the uncertainty of economic policies amplifies the negative impact of climate risk, aggravates panic among bond investors, and widens bond credit spreads. Furthermore, a loose monetary policy has increased market liquidity and bond liquidity, thus decreasing bond credit spreads.

This study contributes to the existing literature in several ways. First, it enhances the theoretical research in the bond market domain by providing empirical evidence of macro-environmental factors. This study investigated the relationship between climate change and corporate bond spreads and found that escalating climate change risks are associated with the gradual expansion of credit spreads in the secondary bond market. The literature primarily focuses on the macro level, including financial stability considerations (Dafermos et al., 2018; Stroebel and Wurgler, 2021), the pricing dynamics of climate risk (Monasterolo, 2020), the intricacies of financial performance (Pankratz et al., 2023), environmental performance (Eleftheriadis and Anagnostopoulou, 2015), the dimensions of corporate social responsibility (Hossain and Masum, 2022), the comportment of bond yields (Huynh and Xia, 2021), and the structuring of loan terms (Huang et al., 2022). Whereas the existing literature primarily examines the impact of climate change from the perspective of firm behavior using stock market data, this study provides empirical evidence for the bond market, thus enriching relevant research in the field of climate economics.

Second, amid the growing prevalence of bond default on the financial landscape, safeguarding bondholders' interests has emerged as a prominently deliberated issue in both academic and practical spheres. The existing body of literature has extensively examined the safeguarding of creditor interests through multifaceted perspectives based on credit information, family control dynamics, legal recourse mechanisms, and insurance constraints (Chu, 2017; Moro et al., 2018). However, the academic community must pay greater attention to bondholders' views and market reactions in the context of climate change. This study was based on trading data in the secondary bond market and used bond credit spreads as a measure of market response to describe bond investors' explanations of—and market reactions to—climate risk in a more effective and timely manner. This analytical approach not only contributes to expanding the extant literature concerning the protection of bondholders' interests but also imparts a distinctive avenue for comprehending bondholders' perspectives against the backdrop of evolving climatic dynamics.

Third, this study explored the potential impact of climate change on debt costs. Drawing on previous studies (Jung et al., 2018; Apergis et al., 2022), we examined the various mechanisms through which climate change can affect the creditworthiness of corporate loans and bonds. The results support Capasso et al.'s (2020) finding that climate risk exposure can negatively impact the bond market. By providing valuable insights into the cross-sectional heterogeneity of the impact of climate change, this study can help businesses understand potential risks and encourage financial regulatory agencies to consider the impact of climate change risks on loan intermediaries and corporate bond markets. This study is particularly relevant in the Chinese context considering the country's growing concern regarding global climate issues (Li et al., 2024).

The remainder of this paper is structured as follows: Section 2 proposes the research hypotheses with reference to the existing literature. Section 3 introduces the data sources, variable definitions, and model settings. Section 4 analyzes the study's empirical results. Section 5 summarizes the conclusions and proposes policy recommendations.

2. Hypothesis development

On the broader economic landscape, enterprises—as integral constituents of the socioeconomic framework—face formidable challenges regarding mitigating the adverse effects of climate change. These phenomena manifest as extreme weather events that directly damage corporate assets, precipitating value depreciation and operational interruptions (Pinkse and Gasbarro, 2019). Additionally, changes in policy direction and market preferences have brought enormous uncertainty to companies attempting to adapt to the environment (Pfeiffer et al., 2018). Most notably, considering the global, persistent, and structural dimensions of climate change, corporations encounter limitations regarding efforts to comprehensively hedge against climate risks. Such impairment and interruption adversely impact expected economic returns, thereby exacerbating operational risks.

The existing literature offers a rich body of empirical evidence in this domain. Green and Newman (2017) established the direct influence of extreme climate events on a firm's existing assets. Dafermos et al. (2018) used global data in their simulation analysis to demonstrate that climate change impairs corporate assets, diminishes profitability, and escalates loan default rates. Nguyen and Phan (2020) contended that climate change also affects asset structures, reducing firms' financial leverage and introducing higher financial constraints. Climate risks entail direct property damage for firms and adversely impact their performance. Somanathan et al. (2021) investigated the influence of rising temperatures on worker attendance rates and established a negative relationship between higher regional temperatures and worker attendance. Consequently, firms implement heat subsidies to mitigate the resulting decline in operational efficiency. Building on this research, Hong et al. (2019) and Brown et al. (2021) examined the impacts of drought and abnormal winter snowfall and presented comparable empirical findings. Poor performance induced by climate risk augments firms' operational risk and heightens the likelihood of firms breaching their contractual obligations (Ding et al., 2021). The influence of climate change on credit spread can be expounded through several interconnected channels.

First, in line with Merton (1974), a negative correlation exists between return on assets (ROA) and the credit spread. The ramifications of climate change, including extreme temperature variations and intensive precipitation events, introduce physical and transformational risks to business operations. These encompass direct impairment of economic endeavors owing to climate-induced disruptions (Green and Newman, 2017; Brown et al., 2021; Somanathan et al., 2021) and potential asset depreciation stemming from the adoption of eco-friendly transformation strategies. To ameliorate the financial losses associated with these perils, firms frequently procure emission-reduction technologies and production methodology enhancements (Bauer et al., 2012). However, these adaptive initiatives frequently entail substantial financial investments, which can potentially impede normal business operations to a certain extent (Nguyen and Phan, 2020). Consequently, such measures result in diminished financial performance and a decline in ROA. Moreover, climate change may detrimentally impact the cost of corporate bond financing. The weakened performance resulting from climate risks amplifies the operational jeopardy and the probability of contractual breaches (Ding et al., 2021). This predicament sets the stage for a reciprocal deterioration in funding accessibility and output; the heightened expenditures incurred owing to the implementation of adaptive emission mitigation strategies combined with reduced profitability accentuate the likelihood of financial vulnerabilities. Consequently, securing funds becomes significantly more daunting for enterprises.

Second, drawing on traditional financial theory, a firm's valuation is predicated upon the discounted value of anticipated future cash flows. Consequently, the credit risk is intricately linked with the issuer's financial performance and asset valuation. As the impact of climate change heightens, the volatility surrounding corporate profitability is correspondingly augmented. This dynamic aligns with Merton's (1974) conjecture that default is envisaged to transpire when the company's valuation falls below a designated threshold. Building upon this framework, Vining and Boardman (1992) delved into the nexus between corporate valuation and the credit risk associated with corporate bonds. Their analysis revealed a pronounced sensitivity of credit spreads to the volatility inherent in a company's valuation. The credit spread is characterized by the heightened rate of return necessary to compensate for the credit risk, which epitomizes the quantification of the risk premium. Typically, when bond investors discern an escalation in the likelihood of default, the demand for augmented returns as recompense for the amplified risk they assume translates to an increased risk premium, which, in turn, precipitates a rise in bond credit spreads.

The third pathway through which climate change affects credit spreads stems from investors, the key players in financial markets. Duffie and Lando (2001) proposed that credit spreads are higher when investors can rely solely on incomplete accounting information to evaluate a company's value. Creditors find it challenging to promptly obtain accurate information about enterprises' adaptation to climate change and green transformation. This apparent information asymmetry broadly encourages creditors to increase their risk premiums in the bond pricing process (Palea and Drogo, 2020). Investors can be irrational and highly sensitive to changes in their environment and are greatly influenced by emotions. When investors feel low, their risk aversion is higher, and they demand greater risk premiums, which can precipitate changes in bond yields. Climate change can cause negative emotions among investors regarding both the markets and businesses. On the one hand, climate change can cause volatility in financial markets, precipitating pessimism among investors and reducing the allocation of risky assets. On the other hand, climate change can negatively affect business operations, precipitating investors' lack of trust in corporate returns. Information asymmetry can also affect investors' evaluations, creating a demand for higher risk compensation and increased credit spreads. Based on the above discussion, this study proposed the following hypothesis:

H1a. *The more pronounced the climate change at the company's operational location, the larger its bonds' credit spread.*

From a market liquidity perspective, an inverse relationship exists between climate change risk and bond credit spreads. When the climate change risk increases, the government implements active measures by applying loose monetary and financial policies such as cuts in interest rates and reserve requirements to promote green and low-carbon development. Such macroeconomic policy regulation helps mitigate climate change risks (Annicchiarico and Di Dio, 2015, 2017). For instance, the central bank can implement a green quantitative easing policy by investing in green bonds issued by pollution-free enterprises to create a win-win situation regarding both the economy and the environment (Ferrari and Landi, 2024). Currently, interest rates in the money market are decreasing and liquidity is relatively abundant, creating arbitrage opportunities. Investors increase their credit bond holdings to obtain the term spread despite the increased risk of default owing to climate change. Overall, the default risk is controllable. This drive for arbitrage results in a significant inflow of liquidity into the bond market, outweighing the effects of climate change risk on bond credit spreads. Therefore, liquidity has a more substantial impact on reducing bond credit spreads than climate risk does, precipitating a negative net effect of climate change risks on bond credit spreads. Accordingly, we proposed the following hypothesis:

H1b. *The more pronounced the climate change at the company's operational location, the lower its bonds' credit spread.*

3. Research design

3.1. Data sources

This study examined the influence of climate change on bond credit spreads in a sample of A-share listed companies that issued bonds between January 2014 and December 2020. The existing literature highlights significant disparities in corporate and enterprise bond pricing patterns with corporate bonds exhibiting greater marketization and heightened credit risk sensitivity than their counterparts. Hence, corporate bond data were selected as this study's focal point. A systematic screening process was implemented to refine the initial sample by excluding ST and ST* listed firms and financial industry listings and removing observations with missing data.

We obtained a final sample of 2035 observations. All continuous variables were winsorized at the upper and lower 1 % levels to mitigate the influence of outliers. Financial information and daily bond trading data were sourced from the Wind and CSMAR databases. We obtained Normalized Difference Vegetation Index (NDVI) data from the MOD13A3 dataset in NASA's MODIS data repository (Didan, 2015). The government bond yield data originated from Eastmoney.com.

3.2. Definition of the variables and model construction

3.2.1. Measure of climate change

Vegetation connects with natural elements such as the atmosphere, soil, and water through photosynthesis, respiration, and other mechanisms to regulate the Earth's energy cycle. Vegetation maintains climate stability and ecosystem balance and is an essential part of the terrestrial ecosystem that supports human survival. The NDVI combines climatic information such as temperature and precipitation that reflects extreme temperature and precipitation changes at different scales and in various regions. Such information accurately represents the diversity and differences in climate change. The NDVI is a quantitative index used to characterize vegetation cover and growth status. It can monitor dynamic changes in vegetation and explain climate change events (Möllmann et al., 2020). The existing literature reports that the average annual temperature is significantly positively correlated with the annual NDVI.

Therefore, we used the annual standardized NDVI as the core explanatory variable. Based on monthly NDVI raster data obtained from the MOD13A3 dataset, this study applied the maximum synthesis method to obtain annual NDVI raster data for the 2000–2022 period. The data resolution was 1 km, and the coordinates were WGS1984. Subsequently, we processed the data by city and prefecture to facilitate matching with the addresses of corporate headquarters. The lag window width was set as 10 years because the Chinese NDVI dates back to 1998. Finally, the annual mean temperature over the past 10 years in each city where a sampled firm's headquarters is located was calculated on a rolling basis to produce a measurement of climate change risk. The larger the NDVI value, the more severe the climate change.

As a first step, we computed the historical mean and the standard deviation of the annual average NDVI separately for each city-level geographical unit based on the location of the firm's headquarters using the following equation:

$$M^W_{NDVI_{it}} = \sum\nolimits_{k=1}^{W} NDVI_{it-k} \bigg/ W, SD^W_{NDVI_{it}} = \left\{ \left[\sum\nolimits_{k=1}^{W} \left(NDVI_{it-k} - M^W_{NDVI_{it}} \right)^2 \right] \bigg/ W \right\}^{1/2} \tag{1}$$

Thereafter, we calculated the degree of fluctuation in the annual average NDVI. The lagged window width, W, is crucial because it influences the estimation of both the mean and the standard deviation. As previously mentioned, we selected a window width of 10 years as presented in Eq. (2):

$$NDVI^W_{it} = \left[NDVI_{it} - M^W_{NDVI_{it}} \right] \Big/ SD^W_{NDVI_{it}} \tag{2}$$

3.2.2. Measure of bond credit spreads

Credit spread data have been extensively used in studies examining bond market reactions (Defond and Zhang, 2014). Credit spreads represent the additional yield incorporated to compensate for credit risk and thus serve as a metric for risk premium assessment. Generally, when bond investors anticipate optimistic prospects for a company, they demand lower compensation in the form of risk premiums, which reduces credit spreads, indicating a favorable market response. Conversely, an increased credit spread suggests an adverse market reaction. We used the yield on treasury bonds with matching residual maturities to corporate bonds as the risk-free rate and defined the discrepancy between the two as the credit spreads. The credit spread of the corporate bonds (*CS*) in a given year corresponds to the mean of the credit spreads observed on valid trading days during that year. When the sample event involved multiple bonds linked to a listed company, the bonds' credit spreads were amalgamated with weights determined by their respective issuance amounts. This procedure enabled us to calculate the credit spreads for the listed company associated with the sample event (Chen and King, 2014).

3.2.3. Regression model

We used a multiple linear regression model to examine the impact of climate change on the bond market. The model's design is as follows:

$$CS_{i,t} = \beta_0 + \beta_1{}^{*} NDVI_{i,t} + \sum_k \gamma_k Control_{k,i,t-1} + \sum Year + \sum Industry + \varepsilon_i \tag{3}$$

where bond credit spread (*CS*) is the dependent variable, i represents a specific company, and β_1 denotes the core explanatory variable's regression coefficient. If the climate change risk at the company's location increases the credit spread of its bonds in the secondary market, β_1 is expected to be significantly positive; otherwise, it should be significantly negative. Drawing upon relevant studies in the bond market, we controlled for various firm- and bond-specific variables—namely, (1) *Size*: firm size, (2) *Lev*: listed companies' asset–liability ratio, (3) *ROE*: rate of return on common stockholders' equity, (4) *FirmAge*: the number of years a firm has been listed, (5) *Dual*: the integration of two positions, (6) *Top1*: the largest shareholder's shareholding ratio, (7) *Board*: the size of the board of directors, and (8) *Maturity*: the remaining term of the bond. For specific variable definitions, please refer to Table A1 in the Appendix. Additionally, we controlled for year and industry fixed effects.

4. Empirical results

4.1. Descriptive statistics

Based on the data presented in Table 1, *NDVI* exhibited positive mean and median values, indicating a consistent upward trend in temperature across all provinces, municipalities, and autonomous regions in China since 2003. For the sample companies, the average credit spread was 2.335, with a median of 1.975, a standard deviation of 1.617, and a maximum value of 8.129, highlighting substantial volatility in corporate bond credit spreads. Furthermore, the maximum and minimum values of the sample companies' asset–liability ratios were 90.7 % and 21.1 %, respectively, with an average of 58.4 %, which implies elevated financial risk and the need for improved debt-servicing capabilities among certain sampled enterprises. Simultaneously, the overall average asset–liability ratio was within a reasonable range. Additionally, the

Table 1
Descriptive statistics.

Variable	N	Mean	SD	Min	p50	Max
CS	2035	2.335	1.617	−0.006	1.975	8.129
NDVI	2035	0.015	0.013	0	0.012	0.134
Size	2035	23.86	1.385	21.21	23.71	27.85
Lev	2035	0.584	0.153	0.211	0.585	0.907
ROE	2035	0.065	0.114	−0.605	0.071	0.305
FirmAge	2035	2.934	0.318	1.946	2.996	3.526
Dual	2035	0.169	0.375	0	0	1
Top1	2035	0.379	0.160	0.078	0.363	0.803
Board	2035	2.195	0.215	1.609	2.197	2.773
Maturity	2035	2.855	1.818	0.100	2.600	8.800
Zscore w	2035	2.297	2.046	0.804	1.730	22.16
Risk_3	2035	0.018	0.019	0.002	0.013	0.250
Risk_5	2035	0.035	0.036	0.003	0.025	0.466
SentimentA	2035	0.047	0.628	−1.497	−0.043	5.660
SentimentB	2035	−0.156	1.913	−5.221	−0.002	4.326

This table displays descriptive statistics for the variables. The number of firm-year samples is 2035 over the period from 2010 to 2020. The mean, standard deviation, minimum, median, and maximum of each variable are reported. The definition of each variable is provided in the Appendix.

average net return on equity for the sample companies was 6.5 %, ranging from −60.5 % to 30.5 %, which signifies notable disparities in profitability across the sample.

4.2. Climate change and bond credit spreads

Table 2 presents the regression results in Columns (1)–(3), which sequentially present the fixed effects and control variables. According to the regression results in Column (3), which incorporates all control variables, the coefficient of the impact of climate change on corporate bond credit spreads was estimated to be 6.315, which passed the significance test at the 1 % level. Holding the other conditions constant, we found that corporate bond credit spreads increase in response to heightened climate change risk over the long term. This outcome indicates that bondholders keenly perceive the adverse impact of climate change on firm operations, resulting in a demand for increased returns and ultimately eliciting a negative market response. This result validates H1a.

Table 2
The impact of the climate change on bond credit spreads.

Dep.=	*CS*	*CS*	*CS*
	(1)	(2)	(3)
NDVI	6.129**	6.404**	6.315***
	(2.176)	(2.559)	(2.633)
Size		−0.339***	−0.352***
		(−12.227)	(−12.299)
Lev		2.683***	2.589***
		(11.164)	(10.253)
ROE		−1.870***	−1.770***
		(−10.050)	(−9.871)
FirmAge		−0.288***	−0.357***
		(−2.715)	(−3.171)
Dual		0.247***	0.124
		(2.835)	(1.474)
Top1		−1.124***	−0.920***
		(−5.293)	(−4.444)
Board		−0.404***	−0.243
		(−2.619)	(−1.630)
Maturity		−0.064***	−0.076***
		(−3.529)	(−3.978)
Constant	2.242***	11.180***	10.858***
	(40.273)	(16.924)	(13.458)
Observations	2035	2035	2035
Adjusted R^2	0.002	0.217	0.325
Year FE	No	No	Yes
Industry FE	No	No	Yes

This table reports fixed-effect panel regression estimates for the relation between climate change and bond credit spreads. The detailed definitions of the above variables are shown in the Appendix. T-statistics are given in the parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

4.3. Endogeneity test

4.3.1. The Heckman two-step method

This study examined corporate bond credit spreads exclusively among companies with publicly available bond information. The estimation results may have been biased if the sample was not randomly selected. We used the Heckman two-step method to mitigate potential endogeneity problems arising from self-selection bias. We computed the inverse Mills ratio (*IMR*) using a probit model wherein the dependent variable was inclusion in the high credit spread group (assigned a value of 1) or exclusion from it (assigned a value of 0). After incorporating the *IMR* into the regression analysis, the regression coefficients presented in Column (2) of Table 3 exhibited similar magnitudes and statistical significance as the main results.

4.3.2. Difference in differences (DID) method applied to pilot policies related to the national big data comprehensive experimental zone

To comply with the policy direction of accelerating the development of the digital economy, Guizhou Province began constructing China's first big data comprehensive experimental zone in September 2015. In October 2016, the list of the second batch of provinces approved to build a national big data comprehensive pilot zone was released; it included two cross-regional comprehensive pilot zones, namely, Beijing–Tianjin–Hebei and the Pearl River Delta; four regional demonstration comprehensive pilot zones, namely Shanghai, Henan, Chongqing, and Shenyang; and one comprehensive pilot zone, namely, Inner Mongolia, for the coordinated development of big data infrastructure. The establishment of a national big data comprehensive pilot zone has entailed experimental exploration in areas such as big data system innovation, public data open sharing, innovative application, industry aggregation, element circulation, data center integration and utilization, and international exchange and cooperation (Razzaq and Yang, 2023).

Corporate behavior is interconnected with the external economic milieu (Gozgor and Ranjan, 2017). The advent of the digital economy has facilitated a scenario wherein clientele can circumvent conventional financing modes to access financial resources at reduced costs (Rammer and Es-Sadki, 2023; Razzaq and Yang, 2023). Subsequently, fortified by the capabilities of big data and digital technology, more streamlined production management has become attainable through data consolidation, analysis, and utilization, thereby curtailing various transaction costs intrinsic to enterprise market interactions (Xu et al., 2023). These include search, information dissemination, transportation, communication, and administration expenses. Consequently, this has impelled

Table 3
Endogeneity test: Heckman two-step regression.

Dep.=	*High_CS*	*CS*
	(1)	(2)
NDVI	–	6.386***
	–	(2.661)
IMR	–	0.293
	–	(0.839)
Controls_Heckman	Yes	–
Control variables	–	Yes
Observations	2035	2035
Adjusted R^2	–	0.325
Year FE	Yes	Yes
Industry FE	Yes	Yes

The detailed definitions of the above variables are shown in the Appendix. T-statistics are given in the parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

greater organizational efficiency and better resource allocation and augmented supply chain management proficiency, thereby boosting the efficacy of value creation (Benner and Waldfogel, 2023; Yan et al., 2023). The above attributes can significantly reinforce enterprises' preparedness for the perils climate change poses, concurrently augment the enterprises' valuation, mitigate profit volatility, and, consequently, lessen companies' susceptibility to business and credit risks as well as to the expansion of bond credit spreads.

This study used the DID methodological framework to mitigate potential confounding influences stemming from the advancement of the urban digital economy to establish a conclusive causal link between climate change and bond credit spreads. This method leveraged the experimental context the national big data comprehensive pilot zone initiative provided. China has instituted extensive big data pilot zones in 10 provinces and municipalities. Guizhou Province was incorporated into the pilot initiative in 2015, and 2016 witnessed the inclusion of Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Henan, Shanghai, Chongqing, and Guangdong.

Central to our DID approach were two key dummy variables—namely, *Treat*, representing the cities engaged in the pilot policy, and *Post*, marking the time when the policy was implemented. *Post* took a value of 1 during the policy implementation period (from 2016 onwards) and a value of 0 for other periods (pre-2016). Table 4 presents the results of the DID-based regression analysis. Notably, the positive regression coefficient associated with the DID variable (*NDVI*Treat*Post*) substantiates that the progression of the digital economy has partially mitigated the risks emanating from climate change. This underscores the role of digital economic development in shaping the dynamics of bond credit spreads.

Table 4
Endogeneity test: difference-in-difference (DID) method based on the city's digital economy development.

Dep.=	CS
	(1)
*NDVI*Treat*Post*	−10.115*
	(−1.701)
*NDVI*Treat*	1.892
	(0.640)
*NDVI*Post*	15.163***
	(3.164)
Size	−0.348***
	(−12.092)
Lev	2.586***
	(10.191)
ROE	−1.762***
	(−9.836)
FirmAge	−0.361***
	(−3.204)
Dual	0.122
	(1.457)
Top1	−0.908***
	(−4.385)
Board	−0.230
	(−1.536)
Maturity	−0.077***
	(−3.997)
Constant	10.781***
	(13.242)
Observations	2035
Adjusted R^2	0.338
Year FE	Yes
Industry FE	Yes

In this table, we use the DID method to examine the impact of comprehensive trial policy of the national big data experimental zone on bond credit spreads. The detailed definitions of the above variables are shown in the Appendix. T-statistics are given in the parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

4.4. Robustness tests

First, we selectively retained the bond with the highest issuance amount for re-estimation to mitigate the measurement errors associated with the variables. *CS-Max* represents the annual average difference between yield and maturity of the largest issued bond and that of government bonds with the same remaining maturity.

Second, following Hong et al.'s (2019) approach, we used the degree of fluctuation of the average annual temperature to depict climate change dynamics. We obtained a dataset containing the average yearly temperature from ERA5-Land, a repository published by reputable institutions such as the European Union and the European Center for Medium-Range Weather Forecasts. We derived the yearly average temperature grids based on the original monthly temperature grid data. Thereafter, we used grid calculation tools to compute the average value of each prefecture-level city's grid to ascertain the city-level yearly average temperatures. The temperature data were standardized to ensure comparability across regions and accurately capture temperature fluctuation levels. The standardized annual average temperatures (*Temp*) were rendered devoid of dimensionality and amenable to meaningful comparison.

Third, the evolving dynamics within and outside the industry over time are crucial considerations because they can impact firms' financial decision-making and governance practices. To better capture the nuances of the panel data, we used a high-dimensional fixed-effects regression model to effectively control for time-varying effects across different industry sectors. As Table 5 indicates, the regression coefficients in Columns (1)–(3) of Panel A were all statistically significant and positive, confirming the findings' robustness even after accounting for the aforementioned adjustments.

Table 5
Robustness check.

Panel A alternative measure and model			
Dep.=	*CS_Max*	*CS*	*CS*
	(1)	(2)	(3)
NDVI	4.805*	–	6.664***
	(1.752)	–	(2.652)
Temp	–	0.138***	–
	–	(3.419)	–
Control variables	Yes	Yes	Yes
Observations	2035	2035	2015
Adjusted R^2	0.297	0.327	0.323
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Industry FE*Year FE	No	No	Yes

Panel B control the impact of provinces		
Dep.=	CS	CS
	(1)	(2)
NDVI	5.303**	5.892**
	(1.982)	(2.204)
Control variables	Yes	Yes
Observations	2035	2035
Adjusted R^2	0.348	0.348
Year FE	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	No
Region FE	No	Yes

In Panel A, column (1) uses *CS_Max* as the proxy variable of bond credit spreads. Column (2) uses *Temp* as the proxy variable of climate change. Column (3) reports the regression results after using a high-dimensional fixed effect model. Panel B reports the regression results after controlling the impact of provinces. The detailed definitions of the above variables are shown in the Appendix.

Fourth, China encompasses a vast land area of 9.6 million square kilometers, the third largest globally. The country's vast territorial expanse means that it has a complex, diverse climate. China encompasses monsoon climates ranging from tropical and subtropical to temperate. Consequently, the climate change risks differ across Chinese provinces. Furthermore, the Chinese economy has strong regional characteristics. According to Jin et al. (2023), 31 provinces are divided into five main regions based on their economic development level and geographical distribution, with the most developed group being Beijing, Shanghai, Tianjin, and Guangdong, followed by Jiangsu, Zhejiang, Shandong, Fujian, and Hainan. The third most developed group of provinces comprises Hunan, Hubei, Jiangxi, Anhui, Sichuan, and Chongqing, followed by Liaoning, Jilin, Heilongjiang, Shanxi, and Inner Mongolia. The remaining provinces form the fifth most developed region. To address the impact of enterprises' geographical location, we added the following two regressions to the robustness test. Columns (1) and (2) in Panel B indicate the results of controlling for provincial and regional fixed effects, respectively. The regression results remained relatively robust.

4.5. Economic mechanisms

The results of the previous empirical analysis suggested that investors in the secondary bond market believe that companies operating in areas experiencing severe climate change are vulnerable to adverse impacts. Consequently, they demand higher credit spreads. This section delves deeper into the underlying economic mechanisms driving this relationship.

First, we adopted the modified Z-score Altman proposed to gauge firms' vulnerability to bankruptcy. The Z-score is calculated as follows: Z-score = (0.717 × Working Capital + 0.847 × Retained Earnings + 3.107 × Earnings Before Interest and Taxes + 0.42 × Total Market Value of Stocks + 0.998 × Sales Revenue) / Total Assets. A higher Z-score indicates a lower bankruptcy risk and a correspondingly diminished likelihood of bond default. The regression results presented in Column (1) of Table 6 provide robust evidence of a negative association between *NDVI* and bankruptcy risk as represented by the Z-score. These findings reveal that an increased climate risk raises the likelihood of exceptional bankruptcy incidents. Therefore, climate change amplifies firms' vulnerability to bankruptcy, requiring higher risk premiums and, consequently, higher credit spreads.

Subsequently, we examined the level of earnings volatility over a 3-year period *(Risk*_3) and disparity between a firm's maximum and minimum industry-adjusted ROA (*ROA*) over a 5-year period (*Risk*_5) as proxies for the risk-taking level (Faccio et al., 2011). Higher *Risk*_3 and *Risk*_5 values indicate a heightened propensity for risk-taking. The regression results in Columns (2) and (3) of Table 6 evidence a positive relationship between climate change (*NDVI*) and risk-taking behavior. The coefficients were statistically significant at the 5 % level, signifying that firms respond to climate change by engaging in significantly more risk-taking. This high risk directly affects bond investors' principal repayment target.

We referred to Rhodes-Kropf et al. (2005) and Polk and Sapienza (2008) to define *SentimentA* and *SentimentB* as investor sentiment, which is the emotional premium on a company's value. When sentiment is positive (negative), investors are optimistic (pessimistic) about the company's development. A detailed definition is provided in the Appendix. Columns (4) and (5) of Table 6 indicate that even with different measurement methods, we obtained similar statistical results indicating a significantly harmful impact of climate change risk on investor sentiment. This proves that the greater the severity of the climate change enterprises face, the more negative their investors' emotions. According to the previous analysis, when investors are in a low mood, their risk aversion is high, and their demand for risk premiums increases, thus increasing bond credit spreads.

These findings reveal the economic mechanism linking climate change and credit spreads, emphasizing that climate change exacerbates the likelihood of corporate bankruptcy and the volatility of returns and triggers negative investor sentiment. Therefore, climate change poses significant challenges to bond investors regarding assurance that the principal and interest will be repaid.

4.6. Heterogeneity analysis

4.6.1. Firm characteristics' impact

State-owned enterprises (SOEs) are more likely to access local benefits, such as favorable tax policies and privileged information resources (Ren et al., 2022; Fang and Liu, 2024), which can mitigate the negative effects of climate change and enhance firm performance. Additionally, SOE bonds carry a high degree of implicit government credit, thus conveying lower bond default uncertainty to investors. Under the influence of various regulatory guidelines and management systems, bondholders exhibit greater trust in issuers, potentially diminishing the positive adjustment effect of climate change on credit spreads. The regression results presented in Columns (1) and (2) of Table 7 reveal that the coefficient of *NDVI* was significantly positive among non-SOE firms. By contrast, the same explanatory variable failed to achieve statistical significance in the SOE group.

Credit ratings are comprehensive indicators of issuers' ability to fulfill payment obligations, reflecting their financial condition, operational performance, and default risk. These ratings allow bond investors

Table 6
Economic mechanisms.

Dep.=	*Zscore*	*Risk*_3	*Risk*_5	*SentimentA*	*SentimentB*
	(1)	(2)	(3)	(4)	(5)
NDVI	−4.163**	0.007**	0.014**	−1.140*	−7.408**
	(−1.986)	(2.154)	(2.140)	(−1.820)	(−2.244)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	10.869***	0.079***	0.148***	−6.501***	0.131
	(10.752)	(7.909)	(7.872)	(−6.797)	(0.104)
Observations	2030	2035	2035	2035	2035
Adjusted R^2	0.507	0.136	0.137	0.441	0.089
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

This table shows the mediating effect results. Firm's business risk is measured by *Zscore*. The earnings volatility is measured by *Risk*_3 and *Risk*_5. Investor sentiment is measured by *SentimentA* and *SentimentB*. The detailed definitions of the above variables are shown in the Appendix. T-statistics are given in the parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 7
Impact of firm characteristics.

Dep.=	*CS*	*CS*	*CS*	*CS*
	SOE	Non_SOE	AAA-Bonds	Non_AAA-Bonds
	(1)	(2)	(3)	(4)
NDVI	−0.282	12.187***	−3.424	6.809**
	(−0.105)	(3.255)	(−0.951)	(2.292)
Control variables	Yes	Yes	Yes	Yes
Constant	7.132***	13.899***	5.110***	8.641***
	(7.815)	(9.372)	(4.489)	(6.721)
Observations	1153	882	692	1323
Adjusted R^2	0.348	0.340	0.316	0.269
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

We divide the full sample into the following sub-groups: SOE/Non_SOE, Non_-AAA/Non_AAA firms. We then re-run Eq. (3) using the sub-samples respectively. The detailed definitions of the above variables are shown in the Appendix. T-statistics are given in the parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

to assess the quality of issuers and bonds; hence, ratings facilitate information transmission. Lower credit ratings are associated with a higher probability of bond principal and interest losses; therefore, they prompt investors to demand higher risk premiums. Building on this notion, we divided the sampled companies into high-rated (i.e., AAA credit rating) and low-rated groups. The two groups' respective regression results are presented in Columns (3) and (4) of Table 7. The positive coefficients of *NDVI* in the low-rated group, which passed the 5 % significance level, indicate that climate change has a more pronounced negative impact on credit spreads under conditions of lower credit quality and higher default risk.

4.6.2. *Creditor protection considerations*

Robust contractual provisions embodying strong creditor protection are instrumental in mitigating agency conflicts between creditors and shareholders or management, thereby curtailing shareholder expropriation, debt dilution, and risky investment behavior (Dyreng et al., 2022). Previous studies have demonstrated the efficacy of restrictive bond covenants in safeguarding creditor interests, ensuring compensation only during extreme circumstances, and curbing the asset substitution strategies controlling shareholders use to exploit creditors' wealth. Following the classification that Billett et al. (2007) proposed, we applied text recognition techniques to bond offering documents to identify the presence of restrictive clauses. We defined the binary variable "restrictive clause" as 1 if restrictive contracts were present and as 0 otherwise. The empirical results presented in Columns (1) and (2) of Table 8 demonstrate a statistically significant positive relationship between climate change and credit spreads in the absence of restrictive clauses. However, we observed that this relationship became statistically insignificant when restrictive clauses were incorporated into bond contracts. This implies that comprehensive bond contracts exert a governance constraint that assuages situations detrimental to bond investors' interests.

To substantiate this potential transmission pathway, we referenced Chen et al. (2020) and the internal control index of listed Chinese firms (*Index*). A higher index value indicates superior internal control quality within a firm (Zhang et al., 2023). Based on industry-specific median values, we categorized the sample into high and low internal control groups. The grouping estimation results are reported in Columns (3) and (4) of Table 8. The regression results reveal that the coefficient lost statistical significance in the subsample characterized by stringent internal control measures (i.e., the high internal control group) but remained positive and statistically significant in the subsample with lax internal control measures. This result suggests that under rigorous internal controls, bond investors no longer interpret climate change as a signal of heightened default risk, resulting in stable credit spreads and a diminished demand for higher bond yields.

Table 8
Considerations on creditor protection.

Dep.=	*CS*	*CS*	*CS*	*CS*
	Restrictive clause = 1	Restrictive clause = 0	High_inter control	Low_inter control
	(1)	(2)	(3)	(4)
NDVI	3.264	7.651**	3.150	9.080**
	(0.978)	(2.485)	(0.990)	(2.509)
Control variables	Yes	Yes	Yes	Yes
Constant	10.666***	10.637***	11.190***	10.269***
	(9.398)	(10.146)	(10.811)	(7.651)
Observations	556	1479	1010	1025
Adjusted R^2	0.423	0.305	0.266	0.336
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

We conducted grouped regressions based on the presence of restrictive clauses in bond contracts and the strength of internal controls. We then re-run Eq. (3) using the sub-samples respectively. The detailed definitions of the above variables are shown in the Appendix. T-statistics are given in the parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

4.6.3. *Local green finance level*

The Chinese government has proposed strategic goals such as reaching peak carbon emissions before 2030 and achieving carbon neutrality before 2060 to address the environmental issues caused by climate change and economic development (Alam and Hossain, 2024). The government has also gradually promoted green finance policies and practices, actively leveraging its positive role (Sun et al., 2024). With strong government support, green finance has developed rapidly in various regions. For example, green industries receive more financial support, and green projects tilt more credit resources toward themselves (Wen et al., 2021). Therefore, we examined the impact of regional differences in green finance levels on the relationship between climate change and the bond credit spread.

In 2016, the People's Bank of China and seven other national ministries jointly issued the *Guiding Opinions on Building a Green Finance System*, according to which green finance involves various financial products, such as green credit, green bonds, green stock indices, green development funds, green insurance, and carbon finance. This study proposes the following five different perspectives to evaluate the level of green finance in different regions at the city level: *green credit* (total environmental project loans in the province/total loans in the province), *green investment* (investment in environmental pollution control/gross domestic product), *green insurance* (income from environmental pollution liability insurance/total premium income), *green bonds* (total amount of green bond issuance/total amount of bond issuance), and *green funds* (market value of green funds/total market value of all funds). The larger the indicator, the higher the level of green finance in the region where an enterprise's headquarters are located.

Table 9 presents the regression analysis results. We found that in regions with higher green finance levels, the secondary bond market's response to climate change has evolved such that it is no longer significantly negative. This suggests that local governments have noticed climate change and implemented measures to develop green finance. By expanding its green credit market, the bond market gains a buffer against the increased risk of corporate default caused by climate change. With local governments' support, enterprises can better manage the physical and transformational risks associated with climate change.

4.7. *Further research: economic cycles and the bond market*

Climate change risk can increase bond credit spreads, and factors such as bankruptcy risk, profit volatility, and investor sentiment play a role in this process. Since bond credit spreads are closely related to economic cycles, their volatility can be affected by not only their own factors but also the macro environment and money market (Ferrari and Landi, 2024). To understand economic cycles and eliminate the impact of market liquidity on bond credit spreads as discussed in H1b, we conducted a comprehensive study from the perspectives of economic uncertainty and monetary policy.

First, during periods of substantial economic policy uncertainty, the overall probability of corporate default significantly increases, and the difficulty of accessing government assistance increases accordingly. Largescale default events are contagious and can easily trigger systemic risk. For investors, expected returns decrease significantly at this time. Widespread panic can lead to the sale of numerous bonds, driving down bond prices and increasing bond credit spreads. Drawing on Baker et al. (2016), we used the text retrieval method to conduct a statistical analysis of the *South China Morning Post*. Specifically, we estimated the proportion of articles mentioning keywords such as "economy," "policy," and "uncertainty." Subsequently, we constructed a monthly index of China's economic policy uncertainty and calculated the annual average (*EPU_1*). To avoid measurement errors, we used Davis et al.'s

Table 9
Local green finance level.

Panel A

	Green credit		Green investment		Green insurance	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
NDVI	8.716**	3.910	10.303***	2.023	8.992**	4.192
	(2.466)	(1.157)	(2.921)	(0.594)	(2.532)	(1.236)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	10.185***	10.872***	9.859***	11.388***	10.293***	10.540***
	(7.510)	(10.905)	(7.752)	(10.863)	(7.966)	(10.081)
Observations	971	1060	1008	1023	992	1039
Adjusted R^2	0.301	0.357	0.294	0.365	0.290	0.371
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	Green bonds		Green funds	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
NDVI	8.973**	3.803	7.753**	5.879
	(2.484)	(1.147)	(2.296)	(1.633)
Control variables	Yes	Yes	Yes	Yes
Constant	9.932***	11.469***	9.109***	12.624***
	(8.078)	(10.436)	(7.777)	(10.727)
Observations	1043	988	1057	974
Adjusted R^2	0.288	0.360	0.332	0.315
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

We divide the full sample into low and high subgroups based on the median level of regional green finance in the same year and industry. Then, we rerun Eq. (3) using the subsamples. Due to a lack of data on the locations of some enterprises at the city level, the sample is slightly different from the previous text. Detailed definitions of these variables are provided in the Appendix. The t-statistics are given in parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

(2019) annual China Economic Policy Uncertainty Index (*EPU_2*) to conduct a regression analysis using data obtained from the CSMAR database. We introduced an interaction term (*NDVI* × *EPU_1* or *NDVI* × *EPU_2*) between climate change risk and economic uncertainty in Model (3). Finding that the coefficient of the interaction term is significantly greater than zero would indicate that economic uncertainty performance particularly promotes the improvement effect of climate change risk on bond credit spreads. Panel A of Table 10 indicates that the coefficient of the interaction term significantly exceeded 0, suggesting that economic policy uncertainty amplifies the negative impact of climate risk, exacerbates panic among bond investors, and widens the bond credit spread.

To better understand the impact of market liquidity on bond credit spreads, we included monetary policy as a control variable in Model (3). We used the 1-year loan benchmark interest rate (*LPR*) and the annual average monthly year-on-year growth rate of M2 (*M2*) as proxy variables for monetary policy. Panel B presents the regression results after adding monetary policy as the control variable. Column (1) presents a significantly positive coefficient for the 1-year loan interest rate, indicating that a loose monetary policy increases both market and bond liquidity, which, in turn, increase the market risk appetite, resulting in the allocation of more high-risk bonds. Consequently, the requirement for a single-bond investment yield is reduced, thus decreasing bond credit spreads in the bond market. On the contrary, the results in Column (2) indicate a significantly negative coefficient for *M2*, implying that as the growth rate of the money supply increases, the bond credit spread narrows. Therefore, even after considering the impact of market liquidity, climate change risk negatively impacts the bond market, precipitating the expansion of credit spreads.

5. Conclusion

This study used a sample of A-share listed companies that issued corporate bonds between 2014 and 2020 to examine the long-term impact of climate change on bond credit spreads and test whether creditors perceive macro-environmental changes as threatening. Research has demonstrated significantly increased bond credit spreads among companies in regions experiencing severe climate change. This indicates that the secondary bond market can perceive the potential harm of climate change, which may cause losses to bondholders' wealth. To further eliminate the potential impact of other factors on the empirical results, we used the Heckman two-step and DID methods to alleviate endogeneity issues. Moreover, we conducted robustness tests using methods such as replacing key indicators and implementing high-dimensional fixed effects models. After verification, the results remained valid. Furthermore, mechanism testing revealed that climate change affects bond credit spreads by increasing the probability of corporate bankruptcy, profit volatility, and negative investor sentiment.

Additionally, the study found that climate change more significantly impacts private and poorly-rated enterprises' bonds and that bondholders with restrictive contract terms and better internal controls can better avoid the adverse effects of climate risk. In areas with high green finance levels, we observed that the secondary bond market's response to climate change evolved such that it is no longer a significant adverse reaction. By expanding the green credit market, the bond market gains a specific buffer zone to cope with the increased risk of corporate defaults caused by climate change. Further, this study explicitly examined the role of the economic cycle and found that, on the one hand, the uncertainty of economic policies amplifies the negative impact of climate risk, aggravates panic among bond investors, and widens bond credit spreads, but, on the other hand, the loose monetary policy has increased market liquidity and bond liquidity, thus decreasing bond credit

Table 10
Impact of economic cycles.

Panel A		
Dep.=	*CS*	*CS*
	(1)	(2)
NDVI	7.822***	8.162***
	(3.163)	(3.259)
EPU_1	0.003**	
	(2.534)	
*NDVI*EPU_1*	0.063**	
	(2.448)	
EPU_1		0.001**
		(2.545)
*NDVI*EPU_2*		0.032**
		(2.515)
Control variables	Yes	Yes
Constant	11.128***	11.216***
	(14.064)	(14.222)
Observations	2035	2035
Adjusted R^2	0.327	0.327
Year FE	Yes	Yes
Industry FE	Yes	Yes

Panel B		
Dep.=	*CS*	*CS*
	(1)	(2)
NDVI	6.315***	6.315***
	(2.633)	(2.633)
LPR	0.413**	
	(2.439)	
M2		−7.612**
		(−2.439)
Other control variables	Yes	Yes
Constant	13.208***	12.360***
	(11.794)	(13.631)
Observations	2035	2035
Adjusted R^2	0.325	0.325
Year FE	Yes	Yes
Industry FE	Yes	Yes

Panel A shows the moderating effect of economic uncertainty on the relationship between climate change risk and bond credit spreads. Panel B reports the results of incorporating monetary policy into the control variables. Detailed definitions of the above variables are shown in the Appendix. The t-statistics are given in parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

spreads. Even considering the impact of market liquidity, climate change risks will still harm the bond market, thus expanding credit spreads.

This study's significance lies in three main points. First, when responding to climate change, companies should make careful, moderate financial decisions, prioritize protecting creditors' interests, pay attention to the secondary bond market's reaction, and fulfill their duties to maintain order in the bond market. Second, efforts to address climate issues should concentrate on climate policies and encourage the development of supporting policies such as green finance to form a policy relief force. This study suggests that in areas with high green finance levels, the secondary bond market's response to climate change is rendered no longer significantly negative. As previously mentioned, by expanding the green credit market, the bond market gains a buffer zone to cope with the increased risk of corporate defaults caused by climate change. Local governments should regulate and guide companies through supportive policies such as green finance, which can promote enterprises' better management of physical and transformation risks. Third, the change in credit spread indicates that investors in China's bond market are highly sensitive to potential risk. Therefore, in the macro context of climate change, regulatory authorities need to continuously improve the primary bond market's information disclosure system and urge bond-issuing enterprises to improve the quality and frequency of information disclosure. Bond investors' rights and interests should be protected through the constraints of the secondary bond market.

Future research can continue the investigation in the following aspects with reference to the present study's limitations. Our research object comprised bond-issuing A-share listed companies, and to avoid the impact of missing data, we refined the sample multiple times. Further, future studies can, based on a theoretical foundation, expand the sample to measure the impact of climate change events more accurately. Additionally, conducting empirical research solely by collecting climate data and bond spread data from enterprises' locations may inevitably lead to the drawbacks of valuing data processing only, while neglecting mathematical deduction. Finally, future investigations can, based on our results, use evolutionary games or virtual simulation methods to support the identification and explication of the impact mechanism of existing climate change.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent

Informed consent was obtained from all individual participants included in the study.

CRediT authorship contribution statement

Xiaoran Kong: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Cheng Yan:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation. **Kung-Cheng Ho:** Writing – original draft, Validation, Resources, Formal analysis, Conceptualization.

Declaration of competing interest

All authors declare that he has no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgments

The authors were funded by the NSFC number 71903199, 72301077), "the Funda mental Research Funds for the Central Uni versities", Zhongnan University of Economics and Law (2722024EJ011), FuJian Provincial Federation of Social Sciences (Grant Number: FJ2023BF045, FJ2024B019), Guangdong Philosophy and Social Sciences Project (GD23XYJ08), Fundamental and Applied Basic Research Fund (Regional Joint Fund) of Guangdong Province in China (NO. 2021A1515110690), the Innovation and Talent Base for Digital Technology and Finance under Grant No. B21038.

Appendix A

Table A1
Variable definition.

Categories	Variable	Definition
Dependent variable	*NDVI*	normalized Difference Vegetation Index, lag window width by 10 years of standardized annual NDVI
	Temp	the fluctuation degree of average annual temperature
Independent variable	*CS*	the difference between the yield to maturity of corporate bonds and the yield to maturity of government bonds for the same maturity period.
Control variables	*Size*	natural logarithm of the firm's total assets
	Lev	total liabilities/total assets
	ROE	rate of return on common stockholders' equity
	FirmAge	the number of years the firm has been listed
	Dual	If the chairman and CEO serve concurrently, the value is 1; otherwise, take 0.
	Top1	shareholding percentage of the largest shareholder
	Board	number of board members
	Maturity	The bond's maturity period is the difference between the bond's maturity year and the year of the transaction.
Mediating variables	*Zsorce*	*Z-score* = (0.717 × working capital + 0.847 × retained earnings + 3.107 × earnings before interest and taxes + 0.42 × total market value of stocks + 0.998 × sales revenue) / total assets
	Risk_3	Level of earnings volatility over a three-year period
	Risk_5	Disparity between a firm's maximum and minimum industry-adjusted return on assets over a five-year period
	SentimentA	We use company size, leverage ratio, and profitability to fit the company's intrinsic value, and then normalize the residuals of the fitting model to obtain sentiment indicators. See Rhodes-Kropf et al. (2005) for details.
	SentimentB	We manipulate accruals as an alternative indicator of cross-sectional investor sentiment. See Polk and Sapienza (2008) for details.

Table A2
Correlation coefficient.

	CS	*NDVI*	*Size*	*Lev*	*ROE*	*FirmAge*	*Dual*	*Top1*	*Board*
NDVI	0.048**								
Size	−0.265***	−0.023							
Lev	0.136***	−0.006	0.436***						
ROE	−0.299***	0.031	0.117***	−0.181***					
FirmAge	−0.050**	−0.062***	0.160***	0.122***	−0.012				
Dual	0.097***	0.010	−0.077***	−0.050**	0.017	−0.077***			
Top1	−0.201***	0.015	0.271***	0.070***	0.075***	−0.133***	−0.121***		
Board	−0.133***	0.019	0.218***	0.094***	0.056**	0.060***	−0.188***	0.076***	
Maturity	−0.095***	0.034	0.054**	0.067***	0.067***	−0.224***	−0.062***	0.149***	0.087***

This table reports the Pearson correlation between the regression variables. The definition of each variable is provided in Appendix Table A1.
*, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Table A3
Variance inflation factor (VIF).

Variable	VIF	1/VIF
Size	1.470	0.680
Lev	1.340	0.747
Top1	1.150	0.871
FirmAge	1.130	0.882
ROE	1.100	0.911
Maturity	1.090	0.914
Board	1.090	0.916
Dual	1.060	0.942
NDVI	1.010	0.994
Mean	VIF	1.160

ROE: return on equity; NDVI: Normalized Difference Vegetation Index.

Table A4
Sample by year.

Year	Freq.	Percent
2010	25	1.23
2011	66	3.24
2012	136	6.68
2013	180	8.85
2014	199	9.78
2015	229	11.25

(continued on next page)

Table A4 (*continued*)

Year	Freq.	Percent
2016	273	13.42
2017	267	13.12
2018	244	11.99
2019	218	10.71
2020	198	9.73
Total	2035	100

References

Alam, M.B., Hossain, M.S., 2024. Investigating the connections between China's economic growth, use of renewable energy, and research and development concerning CO_2 emissions: an ARDL Bound Test Approach. Technol. Forecast. Soc. Chang. 201, 123220.

Alam, A., Du, A.M., Rahman, M., Yazdifar, H., Abbasi, K., 2022. SMEs respond to climate change: evidence from developing countries. Technol. Forecast. Soc. Chang. 185, 122087.

Annicchiarico, B., Di Dio, F., 2015. Environmental policy and macroeconomic dynamics in a new Keynesian model. J. Environ. Econ. Manag. 69, 1–21.

Annicchiarico, B., Di Dio, F., 2017. GHG emissions control and monetary policy. Environ. Resour. Econ. 67, 823–851.

Apergis, N., Poufinas, T., Antonopoulos, A., 2022. ESG scores and cost of debt. Energy Econ. 112, 106186.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.

Bauer, A., Feichtinger, J., Steurer, R., 2012. The governance of climate change adaptation in 10 OECD countries: challenges and approaches. J. Environ. Policy Plan. 14 (3), 279–304.

Benner, M.J., Waldfogel, J., 2023. Changing the channel: digitization and the rise of "middle tail" strategies. Strateg. Manag. J. 44 (1), 264–287.

Billett, M.T., King, T.H.D., Mauer, D.C., 2007. Growth opportunities and the choice of leverage, debt maturity, and covenants. J. Financ. 62 (2), 697–730.

Brown, J.R., Gustafson, M.T., Ivanov, I.T., 2021. Weathering cash flow shocks. J. Financ. 76 (4), 1731–1772.

Capasso, G., Gianfrate, G., Spinelli, M., 2020. Climate change and credit risk. J. Clean. Prod. 266, 121634.

Chen, J., King, T.H.D., 2014. Corporate hedging and the cost of debt. Finance 29, 221–245.

Chen, H., Yang, D., Zhang, J.H., Zhou, H., 2020. Internal controls, risk management, and cash holdings. Finance 64, 101695.

Chen, D., Hu, H., Wang, N., Chang, C.P., 2024. The impact of green finance on transformation to green energy: evidence from industrial enterprises in China. Technol. Forecast. Soc. Chang. 204, 123411.

Chu, Y., 2017. Shareholder litigation, shareholder–creditor conflict, and the cost of bank loans. Finance 45, 318–332.

Dafermos, Y., Nikolaidi, M., Galanis, G., 2018. Climate change, financial stability and monetary policy. Ecol. Econ. 152, 219–234.

Defond, M.L., Zhang, J., 2014. The timeliness of the bond market reaction to bad earnings news. Contemp. Account. Res. 31 (3), 911–936.

Didan, K., 2015. MODIS/Terra Vegetation Indices Monthly L3 Global 1km SIN Grid V006, NASA EOSDIS Land Processes DAAC. https://doi.org/10.5067/MODIS/MOD13A3.006.

Ding, R., Liu, M., Wang, T., Wu, Z., 2021. The impact of climate risk on earnings management: international evidence. J. Account. Public Policy 40 (2), 106818.

Duffie, D., Lando, D., 2001. Term structures of credit spreads with incomplete accounting information. Econometrica 69 (3), 633–664.

Dyreng, S.D., Hillegeist, S.A., Penalva, F., 2022. Earnings management to avoid debt covenant violations and future performance. Eur. Account. Rev. 31 (2), 311–343.

Eleftheriadis, I.M., Anagnostopoulou, E.G., 2015. Relationship between corporate climate change disclosures and firm factors. Bus. Strateg. Environ. 24 (8), 780–789.

Faccio, M., Marchica, M.T., Mura, R., 2011. Large shareholder diversification and corporate risk-taking. Rev. Financ. Stud. 24 (11), 3601–3641.

Fang, X., Liu, M., 2024. How does the digital transformation drive digital technology innovation of enterprises? Evidence from enterprise's digital patents. Technol. Forecast. Soc. Chang. 204, 123428.

Fang, M., Njangang, H., Padhan, H., Simo, C., Yan, C., 2023. Social media and energy justice: a global evidence. Energy Econ. 125, 106886.

Ferrari, A., Landi, V.N., 2024. Whatever it takes to save the planet? Central banks and unconventional green policy. Macroecon. Dyn. 28 (2), 299–324.

Gozgor, G., Ranjan, P., 2017. Globalisation, inequality and redistribution: theory and evidence. World Econ. 40 (12), 2704–2751.

Green, J., Newman, P., 2017. Disruptive innovation, stranded assets and forecasting: the rise and rise of renewable energy. J. Sustain. Financ. Invest. 7 (2), 169–187.

Ho, K.C., Shen, X., Yan, C., Hu, X., 2023. Influence of green innovation on disclosure quality: mediating role of media attention. Technol. Forecast. Soc. Chang. 188, 122314.

Hong, H., Li, F.W., Xu, J., 2019. Climate risks and market efficiency. J. Econ. 208 (1), 265–281.

Hossain, A.T., Masum, A.A., 2022. Does corporate social responsibility help mitigate firm-level climate change risk? Financ. Res. Lett. 47, 102791.

Huang, H.H., Kerstein, J., Wang, C., Wu, F., 2022. Firm climate risk, risk management, and bank loan financing. Strateg. Manag. J. 43 (13), 2849–2880.

Huynh, T.D., Xia, Y., 2021. Climate change news risk and corporate bond returns. J. Financ. Quant. Anal. 56 (6), 1985–2009.

Jin, Z., Li, Y., Liang, S., 2023. Confucian culture and executive compensation: evidence from China. Corp. Gov. 31 (1), 33–54.

Jung, J., Herbohn, K., Clarkson, P., 2018. Carbon risk, carbon risk awareness and the cost of debt financing. J. Bus. Ethics 150, 1151–1171.

Lang, Q., Ma, F., Mirza, N., Umar, M., 2023. The interaction of climate risk and bank liquidity: an emerging market perspective for transitions to low carbon energy. Technol. Forecast. Soc. Chang. 191, 122480.

Li, H., Tang, M., Cao, A., Guo, L., 2024. How to reduce firm pollution discharges: does political leaders' gender matter? Technol. Forecast. Soc. Chang. 204, 123432.

Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. J. Financ. 29 (2), 449–470.

Möllmann, J., Buchholz, M., Kölle, W., Musshoff, O., 2020. Do remotely-sensed vegetation health indices explain credit risk in agricultural microfinance? World Dev. 127, 104771.

Monasterolo, I., 2020. Climate change and the financial system. Ann. Rev. Resour. Econ. 12, 299–320.

Moro, A., Maresch, D., Ferrando, A., 2018. Creditor protection, judicial enforcement and credit access. Eur. J. Financ. 24 (3), 250–281.

Nguyen, J.H., Phan, H.V., 2020. Carbon risk and corporate capital structure. Finance 64, 101713.

Odenweller, A., 2022. Climate mitigation under S-shaped energy technology diffusion: leveraging synergies of optimisation and simulation models. Technol. Forecast. Soc. Chang. 178, 121568.

Palea, V., Drogo, F., 2020. Carbon emissions and the cost of debt in the eurozone: the role of public policies, climate-related disclosure and corporate governance. Bus. Strateg. Environ. 29 (8), 2953–2972.

Pankratz, N., Bauer, R., Derwall, J., 2023. Climate change, firm performance, and investor surprises. Manag. Sci. 69 (12), 7352–7398.

Pfeiffer, A., Hepburn, C., Vogt-Schilb, A., Caldecott, B., 2018. Committed emissions from existing and planned power plants and asset stranding required to meet the Paris Agreement. Environ. Res. Lett. 13 (5), 054019.

Pinkse, J., Gasbarro, F., 2019. Managing physical impacts of climate change: an attentional perspective on corporate adaptation. Bus. Soc. 58 (2), 333–368.

Polk, C., Sapienza, P., 2008. The stock market and corporate investment: a test of catering theory. Rev. Financ. Stud. 22 (1), 187–217.

Rainville, M., Unlu, E., Wu, J.J., 2022. How do stronger creditor rights impact corporate acquisition activity and quality? J. Bank. Financ. 144, 106625.

Rammer, C., Es-Sadki, N., 2023. Using big data for generating firm-level innovation indicators-a literature review. Technol. Forecast. Soc. Chang. 197, 122874.

Razzaq, A., Yang, X., 2023. Digital finance and green growth in China: appraising inclusive digital finance using web crawler technology and big data. Technol. Forecast. Soc. Chang. 188, 122262.

Ren, X., Zhang, X., Yan, C., Gozgor, G., 2022. Climate policy uncertainty and firm-level total factor productivity: evidence from China. Energy Econ. 113, 106209.

Rhodes-Kropf, M., Robinson, D.T., Viswanathan, S., 2005. Valuation waves and merger activity: the empirical evidence. J. Financ. Econ. 77 (3), 561–603.

Somanathan, E., Somanathan, R., Sudarshan, A., Tewari, M., 2021. The impact of temperature on productivity and labor supply: evidence from Indian manufacturing. J. Polit. Econ. 129 (6), 1797–1827.

Song, Y., Zhang, B., Wang, J., Kwek, K., 2022. The impact of climate change on China's agricultural green total factor productivity. Technol. Forecast. Soc. Chang. 185, 122054.

Stroebel, J., Wurgler, J., 2021. What do you think about climate finance? J. Financ. Econ. 142 (2), 487–498.

Sun, Y., Jia, R., Razzaq, A., Bao, Q., 2024. Social network platforms and climate change in China: evidence from TikTok. Technol. Forecast. Soc. Chang. 200, 123197.

Vining, A.R., Boardman, A.E., 1992. Ownership versus competition: efficiency in public enterprise. Public Choice 73 (2), 205–239.

Wen, H., Lee, C.C., Zhou, F., 2021. Green credit policy, credit allocation efficiency and upgrade of energy-intensive enterprises. Energy Econ. 94, 105099.

Wen, J., Zhao, X.X., Fu, Q., Chang, C.P., 2023. The impact of extreme weather events on green innovation: which ones bring to the most harm? Technol. Forecast. Soc. Chang. 188, 122322.

Xu, Y., Yuan, L., Khalfaoui, R., Radulescu, M., Mallek, S., Zhao, X., 2023. Making technological innovation greener: does firm digital transformation work? Technol. Forecast. Soc. Chang. 197, 122928.

Yan, Z., Sun, Z., Shi, R., Zhao, M., 2023. Smart city and green development: empirical evidence from the perspective of green technological innovation. Technol. Forecast. Soc. Chang. 191, 122507.
Yang, Y., Qin, H., 2024. The uncertainties of the carbon peak and the temporal and regional heterogeneity of its driving factors in China. Technol. Forecast. Soc. Chang. 198, 122937.
Ye, L., 2022. The effect of climate news risk on uncertainties. Technol. Forecast. Soc. Chang. 178, 121586.
Zhang, W., Qin, C., Zhang, W., 2023. Top management team characteristics, technological innovation and firm's greenwashing: evidence from China's heavy-polluting industries. Technol. Forecast. Soc. Chang. 191, 122522.

Xiaoran Kong is an Associate Professor in Economics and Finance from Shandong University of Finance & Economics, who published dozens of papers in international journals such as Pacific-Basin Finance Journal.

Cheng Yan is an Associate Professor inFinance fromUniversity of Essex, who published dozens of papers in international journals such as Management Science, Journal of Corporate Finance, Energy Economoics, Technological Forecasting & Social Change, etc.

Kung-Cheng Ho is an Associate Professor in Economics and Finance from Guangdong University of Finance & Economics, who published dozens of papers in international journals such as Journal of Corporate Finance, Energy Economoics, Technological Forecasting & Social Change, etc.