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Original Research

Climate Mirroring in Bank Credit: The Dual-Risk Resonance Effect

Weilong Xu, Xinyue Zhang°*

School of Business Administration, Liaoning Technical University, Huludao, China, 125105

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Abstract

Climate change has emerged as one of the most critical challenges of the 21st century, exerting multidimensional shocks that significantly disrupt ecological integrity and socioeconomic systems. As the core of the financial system, banks' risk governance capacity has a critical influence on both economic growth and financial stability. This study examines the distinct transmission mechanisms of physical and transition climate risks through an analysis of panel data from 189 Chinese regional commercial banks (2014-2023) using a two-way fixed effects model. Our results demonstrate that (i) both physical and transition risks significantly increase bank credit risk; (ii) long-term gradual climate change and extreme weather events increase default probabilities through climate-induced economic losses to borrowers, and (iii) transition risks impair credit quality primarily by reducing corporate solvency. We further identify insurance as an effective mitigant of weather-related credit risks and reveal spatial heterogeneity – banks in China's Hu Line transition zone face greater physical risks, while southeastern institutions are more exposed to transition risks. Based on these empirical findings, this study proposes concrete policy recommendations to strengthen the management of climate risks within the banking sector.

Keywords: climate change, regional commercial banks, credit risk, Hu Line

Introduction

Climate change has evolved from a prospective threat to an urgent problem, reshaping global ecological systems. The World Meteorological Organization (WMO) reports that the period from 2015 to 2022 was the hottest eight-year span in recorded history, with the frequency of intense heatwaves and catastrophic floods significantly surpassing 20th-century averages. Crucially, multiple climate tipping points now loom: accelerating Arctic permafrost thaw, releasing methane, systemic deterioration of Amazonian carbon sequestration capacity, and unprecedented Greenland ice sheet melt rates – nonlinear changes that may induce irreversible ecological cascades. The WMO's 2023 Global Climate Report recorded a 1.45ºC (±0.12ºC) global surface temperature anomaly relative to pre-industrial levels (1850-1900). In contrast, its 2024 update warns of persistently rising greenhouse gas concentrations, which are exhibiting increasingly irreversible, centuries-long impacts on the climate system. Scientific consensus confirms that breaching the 1.5ºC temperature threshold established by the Paris Agreement would trigger positive feedback mechanisms in the climate

*e-mail: xinyue071520@163.com
°ORCID iD: 0009-0001-2954-7216

system, leading to irreversible ecological damage and amplifying risks.

Simultaneously, climate risks are destabilizing the global economic system at unprecedented speed and scale, with cascading effects that extend beyond traditional environmental boundaries and threaten to trigger a systemic financial crisis. World Meteorological Organization (WMO, 2021) data reveal a fivefold increase in global climate disasters from 1970 to 2019, with associated economic losses soaring sevenfold to $3.64 trillion, equivalent to $202 million daily. China's Ministry of Emergency Management (2024) reports that direct economic losses from natural disasters in China reached 401.1 billion yuan in 2024. In addition to the explicit losses caused by physical risks, the implicit costs induced by transition risks are equally significant: International Energy Agency (IEA, 2020) projections indicate stranded assets in carbon-intensive sectors could total $10 trillion by 2050 and $28 trillion by the century's end, underscoring the profound structural transformations facing global markets.

In modern economic systems, the deepening coupling between the real economy and financial systems means that climate change's adverse impacts on the real economy will propagate systemic effects through financial transmission mechanisms. Recognizing this threat, the Bank for International Settlements (BIS, 2020) introduced the "green swan" framework to describe systemic financial risks arising from climate-induced extreme environmental events.

The climate governance transition has elevated climate-financial risk as an urgent research priority. Commercial banks, as key financial intermediaries, play dual roles in transmitting and absorbing these risks while maintaining economic stability. This study makes three contributions to climate finance research: Initially, it pioneers a dual-dimensional physical risk metric (incorporating both long-term gradual changes and short-term extreme events) and a tripartite transition risk framework (encompassing policy regulation, demand shifts, and technological innovation), systematically elucidating how non-economic exogenous shocks propagate to bank credit risk. Secondly, we identify a "dual-channel" transmission mechanism: physical risks directly impair collateral values through asset depreciation, whereas transition risks indirectly elevate corporate default probabilities via financial distress. Crucially, we reveal the moderating effect of climate insurance in attenuating these pathways. Ultimately, employing spatial econometric analysis along the Hu Line, we demonstrate significant regional heterogeneity – banks in transitional zones exhibit heightened sensitivity to physical risks, while southeastern institutions face greater vulnerability to transition risks. These findings provide scientific foundations for differentiated macroprudential policies and offer critical insights for refining China's climate-financial regulatory architecture.

Literature Review and Research Hypothesis

Literature Review

Climate change poses significant threats to both human habitats and quality of life, while its derivative financial risks propagate through real economic channels to the financial sector [1]. The U.S. Financial Stability Oversight Council (FSOC) formally recognized climate change as an emerging threat to financial stability in its 2021 Report on Climate-Related Financial Risk, underscoring its growing prominence in academic and policy discourse. Climate financial risk, which encompasses both the economic uncertainties caused by climate change itself and those arising from subsequent socioeconomic transitions [2], is typically classified into physical and transition risks based on their origins [3]. Physical risks, rooted in the natural manifestations of climate change, involve financial losses from acute climate events or chronic environmental shifts. Transition risks, conversely, emerge from societal responses to climate change, including policy reforms, technological disruptions, and evolving market preferences that may generate economic and financial instability.

Physical risks primarily refer to the heightened risks of increased non-performing loan ratios and asset impairments for financial institutions, stemming from global warming and extreme weather events. The dominant empirical method measures climate shocks through observable meteorological extremes, particularly temperature and precipitation deviations [4, 5]. Recent methodological advancements have transitioned to multidimensional catastrophe risk frameworks to overcome the limitations of univariate climatic indicators. This model is illustrated by Yang et al. (2024), whose frequency-based examination of natural disasters offers a thorough evaluation of physical risk transmission mechanisms in China's financial system [6]. Recent empirical studies have established methodologies for assessing climate-related financial risks using various disaster metrics. Jiang et al. (2023) examined the impacts of drought on the profitability of the banking sector [7], Lv et al. (2024) examined the impact of typhoon exposure on the risk-taking behavior of financial institutions [8], while Shen et al. (2023) quantify the severity of climate hazards through economic losses induced by disasters [9]. Researchers have developed composite risk indices to overcome the limitations of unidimensional assessment methods by incorporating multiple impact dimensions. These methodologies generally utilize weighted combinations of essential variables, exemplified by Wang et al.'s (2023) use of entropy weighting to create a comprehensive risk metric that includes economic damage, human exposure, and other significant factors [10]. Empirical evidence identifies two separate mechanisms through which extreme climate events threaten financial stability: Initially, direct channels related to corporate asset impairments [11] and household net worth erosion drive immediate deterioration in bank asset quality. Second, indirect channels – notably reduced labor productivity [12] and supply chain failures [13] – propagate systemic risk by progressively weakening borrowers' repayment ability. Following the TCFD (2016) taxonomy, physical climate risks are categorized into acute and chronic manifestations. Although the academic focus has primarily been on acute shocks, the financial ramifications of gradual climatic changes, such as global warming and sea-level rise, deserve equal scrutiny. Recent data suggests that these chronic risks significantly affect financial stability, as demonstrated by the decline in credit quality within banks' portfolios linked to assets vulnerable to sea-level rise [14].

Transition risks constitute a systemic financial peril of equal scale to physical climate hazards, stemming from global decarbonization initiatives designed to mitigate climate change and avert probable "green swan" occurrences. The transition process produces risk consequences via three interrelated factors: tightening climate policies, emerging low-carbon consumption preferences, and technological disruptions. These risks primarily manifest as financial spillovers from energy-intensive industries undergoing decarbonization. Carbon-intensive corporations demonstrate markedly elevated financial distress risk relative to sector peers [15]. The process of transmitting material credit risk occurs through financial networks [16]. The sustainability transition has altered essential business conditions for high-emission companies through (1) policy-induced increases in operational costs and (2) deteriorating asset-stranding dynamics. These combined pressures increase the likelihood of company failures, facilitating systemic risk transmission via financial channels. The decarbonization process exhibits bimodal temporal impacts – immediate regulatory compliance costs raise default likelihood through price transmission pathways [17]. In the long run, structural economic transformation will cultivate emergent industries, enhancing investment and credit demand while infusing new vigor into economic growth [18]. Recent studies primarily investigate the implications of environmental policies; for example, Li et al. (2022) illustrate the prevalence of transition "pressure effects", wherein transition risk intensifies company risk exposures and increases the likelihood of bankruptcy [19]. Furthermore, the financial impacts of transition risks also affect capital markets, as high-risk firms face notably increased financing costs, indicative of a recognized carbon risk premium in equity valuations. This pricing dynamic indicates that financial institutions with significant exposures to carbon-intensive assets are especially susceptible to transition risks. The academic literature indicates the complex effects of environmental regulations on the banking sector, highlighting both the amplification of credit risk [20] and the potential for stimulating sector development [21]. Transition risk quantification poses more significant methodological challenges than physical risk assessment, leading to the development of innovative approaches such as climate policy uncertainty indices derived from economic policy frameworks [22] and the prevalent use of carbon emissions as a direct proxy for transition risk exposure [23].

This review highlights three essential research findings in the literature on climate financial risk. The academic inquiry has primarily concentrated on macro-level analyses of climate risk measurement, the impacts on financial systems, and transmission mechanisms, largely utilizing the physical-transition risk dichotomy. Although these studies consistently demonstrate bidirectional interactions between climate and finance, there is a lack of comprehensive micro-level analyses regarding institutional vulnerabilities. Secondly, while the TCFD's (2016) acute-chronic risk classification has been adopted, research reveals a notable imbalance. The predominant emphasis on acute events tends to overlook human adaptive capacities and may lead to an overestimation of impacts. Conversely, the lack of focus on gradual changes fails to account for the potential for catastrophic disruptions. Third, the measurement of transition risk encounters methodological limitations, as existing policy-centric approaches depend on oversimplified proxies that do not adequately reflect systemic complexity. High-emission regions that rapidly adopt green technology may demonstrate lower-than-anticipated transition risks, highlighting the necessity for comprehensive assessment frameworks.

Research Hypothesis

With accelerating global climate governance transitions, climate change has emerged as a systemic risk to financial stability worldwide. As the largest developing economy, China's financial system confronts dual challenges from compounding physical and transition risks. Critically, a systematic literature review reveals two overarching research gaps: Primarily, physical risk metrics disproportionately emphasize acute shocks from extreme weather events while neglecting chronic stresses induced by long-term climatic shifts. Secondly, transition risk frameworks overemphasize the impacts of regulatory policy and inadequately integrate demand-side transitions and technological disruptions. To address these dual deficiencies, our study contributes three methodological innovations: (1) implementing the TCFD framework to decompose physical risks into acute shocks and chronic stresses; (2) developing an integrated transition risk assessment framework capturing policy interventions, market demand shifts, and technological innovation pathways simultaneously. Building on this synthesized paradigm, we propose:

H1: Banking-sector credit risk exposure exhibits statistically significant positive associations with both acute/chronic physical risks and transition risks.

Beyond this aggregate association, climate risks exhibit complex transmission linkages to bank credit quality. Focusing specifically on physical risk channels, climatic shocks threaten financial stability through two empirically established pathways: First and most directly, extreme weather events substantially impair real estate collateral values, elevating non-performing loan ratios – a relationship empirically validated by Deryugina et al. (2018) through U.S. mortgage market analysis demonstrating hurricane-induced delinquency surges [24]. Second, climate-sensitive sectors (e.g., agriculture, manufacturing) experience marked deterioration in debt-servicing capacity due to supply chain disruptions. Compounding these effects, climate hazards disproportionately affect lower-income populations via: (1) asset value depreciation and (2) heightened health vulnerabilities (e.g., vector-borne disease expansion from rising temperatures [25]), intensifying the "health-poverty" trap and undermining repayment capacity. Collectively, these mechanisms degrade borrower balance sheets, increasing default probabilities and jeopardizing banking stability [26]. This physical risk transmission logic motivates:

H2: Climate physical risks significantly increase banking-sector credit risk exposure through amplified direct asset losses.

Parallel to physical mechanisms, transition shocks exert systemic disruptions through distinct channels. Three salient pathways emerge: Most directly, policy intensification elevates compliance costs, increasing corporate leverage [27] and impairing creditworthiness, triggering asset impairment that disproportionately devalues carbon-intensive firms. Critically, given these assets' collateral function [28], market repricing heightens default probabilities via balance sheet contagion. Concurrently, transition-driven technological innovation generates dual pressures: passive adaptation erodes profitability through substitution risks, while active restructuring induces cost overruns. Simultaneously, shifting stakeholder preferences compress "brown" firms' revenues [29]. Furthermore, these effects propagate through industrial interdependencies, amplifying systemic vulnerabilities via supply chain contagion. Consequently, we posit:

H3: Climate transition risks elevate banking-system credit risk through dual channels: corporate performance deterioration and expanded risk exposure.

Complementing these risk transmission pathways, insurance markets provide critical stabilization buffers. Extreme weather events pose multidimensional threats, simultaneously damaging collateral and triggering disaster-depreciation-credit contraction cascades. Within this architecture, insurance fulfills essential functions: property coverage mitigates collateral devaluation spirals, while business continuity protection safeguards repayment capacity. Empirically validating this, U-Din et al. (2023) demonstrate comprehensive insurance's dual mechanisms – loss containment and recovery acceleration – via efficient claims resolution in Canadian banking [30]. Consequently, we propose Hypothesis 4:

H4: Insurance coverage effectively buffers extreme weather-induced credit risk shocks in the Chinese banking system.

Within China's distinctive geoclimatic context, spatial heterogeneity modulates these dynamics. Anchored by the Hu Line – a seminal socioeconomic-geographic demarcation – three interconnected dimensions emerge: First, financial architecture divergence enhances risk absorption in the southeast (sophisticated infrastructure/diversified portfolios) versus transitional zones' diminished resilience (financial market thinness). Second, ecological fragility differentials amplify physical risk exposure: transitional regions face a disproportionately higher frequency of disasters than the stable southeast. Third, industrial composition induces asymmetric vulnerabilities – transitional areas' primary-sector reliance heightens physical risk sensitivity, while the southeast's tertiary-sector concentration amplifies transition risk exposure. This multidimensional analysis leads us to propose Hypothesis 5.

H5: Credit quality in China's Hu Line transitional zone is more vulnerable to physical climate risks, whereas southeastern banks are more exposed to transition risks.

Materials and Methods

Sample and Data

The study utilizes multi-source data to ensure comprehensive coverage: meteorological data were extracted from the China Meteorological Disaster Yearbook, while macroeconomic indicators were collected from the China Statistical Yearbook and provincial statistical yearbooks. Bank-level variables were obtained from two primary sources: (1) the Wind Financial Database, and (2) official credit rating reports of regional commercial banks. Continuous variables were winsorized at the 1% and 99% levels to reduce the impact of outliers. The analysis encompasses the years 2014 to 2023, constrained by data availability. Table 1 provides comprehensive definitions of variables and the corresponding measurement methodologies.

Variable Definition

Assessment Methodology for Physical Risk

Climate physical risk is categorized into two distinct types: chronic physical risk stemming from long-term gradual climate change (*LTGC*), and acute physical risk induced by extreme weather events (*EWE*).

Current climate risk assessments predominantly rely on univariate indicators (e.g., temperature or precipitation anomalies) to measure long-term gradual climate change (LTGC). This conventional approach fails to capture critical risk amplification mechanisms

Table 1. Variable definitions.

Type	Notation	variable	Definition
Dependent Variable	*Npl*	Non-performing loan ratio	Non-performing loans/Total loans
Independent Variable	*LTGC*	Type I physical risks	Long-term gradual climate change
	EWE	Type II physical risks	Extreme weather events
	ER	Environmental regulation	Composite pollutant emission index
Control Variables	*Bsize*	Bank size	Logarithm of total assets
	Dep	Deposit-to-Asset Ratio	Deposits/Total assets
	Pcr	Loan loss provision coverage ratio	Loan loss reserves / Non-performing loans
	Ldr	Loan-to-deposit ratio	Total loans / Total deposits
	Cir	Cost-to-income ratio	Operating costs / Operating income
	Size	Firm size	ln(Total assets)
	TobinsQ	Tobin's Q	Market value/Replacement cost
	HHIB	Herfindahl-Hirschman Index	Measuring industry concentration
	Lngdp	The natural logarithm of GDP	LnGDP
	Cpi	Consumer Price Index	CPI
Robustness Metrics	*LTC*	Long-term climate change	Selected base period of 20 years
	EW	Extreme weather	Relative threshold method calculations
	TR	Transition risk	A system of indicators that encompasses three types of risk sources
Mediation Effects	*Loss*	Direct economic losses	Direct economic losses/GDP
	ZScore	Firm operational risk	Z-score
	Fpro	Firm profitability	Net income/Total assets
Moderating Effects	*Bi*	Insurance penetration	Unemployment insurance participants/Total population

stemming from temperature-precipitation interactions, as exemplified by the compounding effects that occur when rising temperatures coincide with drought conditions. Moreover, the relative importance of specific climatic factors exhibits substantial spatial heterogeneity across regions. To overcome these limitations, we develop a composite LTGC index using the entropy weighting method. This novel framework:(1) integrates both temperature and precipitation anomalies, (2) incorporates spatially varying factor weights to account for regional differences. Utilizing the methodological framework set forth by Hong et al. (2018) [31] and Ding and Sun (2022) [32], our implementation proceeds through three steps:

$$M_{temp_{it}}^{w} = \frac{\sum_{k=1}^{w} temp_{it-k}}{w} \tag{1}$$

$$SD_{temp_{it}}^{w} = \left\{ \frac{\sum_{k=1}^{w} \left(temp_{it-k} - M_{temp_{it}}^{w} \right)^2}{w} \right\}^{\frac{1}{2}} \tag{2}$$

where *W* denotes the lag window width. Subsequently, we compute a measure of volatility for the annual average temperature.

$$temp_{it}^{w} = \frac{\left[temp_{it} - M_{temp_{it}}^{w} \right]}{SD_{temp_{it}}^{w}} \tag{3}$$

A 30-year lag window was used to calculate standardized temperature and precipitation anomalies. Higher numbers indicate more extreme climatic deviations from baseline conditions in the established measures. The composite index used entropy weighting to combine temperature and precipitation anomalies while preserving their geographical sensitivities.

An evaluation index system for Type II physical risks was developed across five dimensions, based on the classification criteria for extreme climate disasters outlined in the China Meteorological Disaster Yearbook and the China Statistical Yearbook, as shown in Table 2.

Assessment Methodology for Transition Risks

The existing literature primarily examines the effects of climate and environmental regulations (*ER*) on financial risks. This paper presents the Pollutant Release Composite Index as a proxy indicator for environmental regulation to quantify exposure to transition risk, based on the risk transmission mechanism defined by "pollution-intensive regions → high policy sensitivity". This index functions as the main measure for evaluating transition risks.

The transmission mechanism of transition risks primarily functions through asset devaluation induced by carbon constraints. Commercial banks finance carbon-intensive real economy industries in China. Credit exposure risks are measured by two dimensions: (1) breadth (proportion of bank loans allocated to each industry) and (2) depth (carbon-intensity-weighted loan values that reflect sectoral CO_2 emissions within loan portfolios). We define this dual-dimensional approach using the transition risk metric, using Li et al.'s (2022) [33] methodological framework:

$$BTR_{i,t} = Ln\left(\sum_{n} CE_{n,t} * \omega_{n,i,t}\right) \tag{4}$$

$BTR_{i,t}$ denotes the climate transition risk for bank i at time t, where: $CE_{n,t}$ represents the CO_2 emissions of industry n in period t, $\omega_{n,i,t}$ is the proportion of bank i's loan exposure to industry n relative to its total loan portfolio at time t.

The three-dimensional framework created in this research solves gaps in the literature and improves transition risk assessment. Our integrated approach measures policy regulatory intensity via carbon-intensity-weighted banking sector loan exposures, low-carbon demand transition using public transportation passenger volume as a proxy for evolving consumer preferences toward sustainable consumption patterns [34], and green technological progress by measuring the absolute number of green invention patent applications and their relative proportion to total [35]. We use entropy weighting for objective aggregation to assess governmental, market, and technology forces within a single framework, allowing us to analyze transition risk transmission paths.

Bank Credit Risk

Within the multidimensional risk framework of financial institutions, credit risk emerges as the most dominant and disruptive risk dimension. Prevailing academic research predominantly analyzes bank credit risk through the credit asset quality perspective, where the non-performing loan (*NPL*) ratio has been established as the most reliable proxy for latent vulnerabilities in the banking sector. Consistent with this methodological convention, our study employs the *NPL* ratio as the core dependent variable.

Mediating Variables

Building on the theoretical framework that identifies two primary transmission mechanisms through which climate risks amplify bank credit risk, we employ the following measures: First, for regional climate shock exposure, we follow Klomp's (2014) seminal methodology by calculating the ratio of direct economic losses from natural disasters to local GDP [36]. This metric captures the relative severity of climate-related economic disruptions at the regional level. Second, for firm-level risk assessment, we adopt: (1) the Z-score as a proxy for corporate financial fragility, which quantifies the probability of business insolvency; (2) Return on assets as a key profitability metric, reflecting operational efficiency and financial health.

Table 2. Physical risk indicator system.

Type I Physical Risks			Type II Physical Risks		
Primary Indicators	Secondary Indicators	Indicator Properties	Primary Indicators	Secondary Indicators	Indicator Properties
Temperature deviation	Standard deviation of temperature	Positive	Drought Risk	Proportion of Affected Area by Drought	Positive
Precipitation deviation	Standard deviation of precipitation	Positive	Flood, Geological Disaster and Typhoon Risk	Proportion of Affected Areas by Flood, Geological Disaster and Typhoon	Positive
			Low Temperature Freezing and Snow Disaster	Proportion of Affected Area by Low Temperature Freezing and Snow Disaster	Positive
			Scale of Affected Population	Proportion of Affected Population	Positive
			Economic Loss Caused by Disaster	Direct Economic Loss	Positive

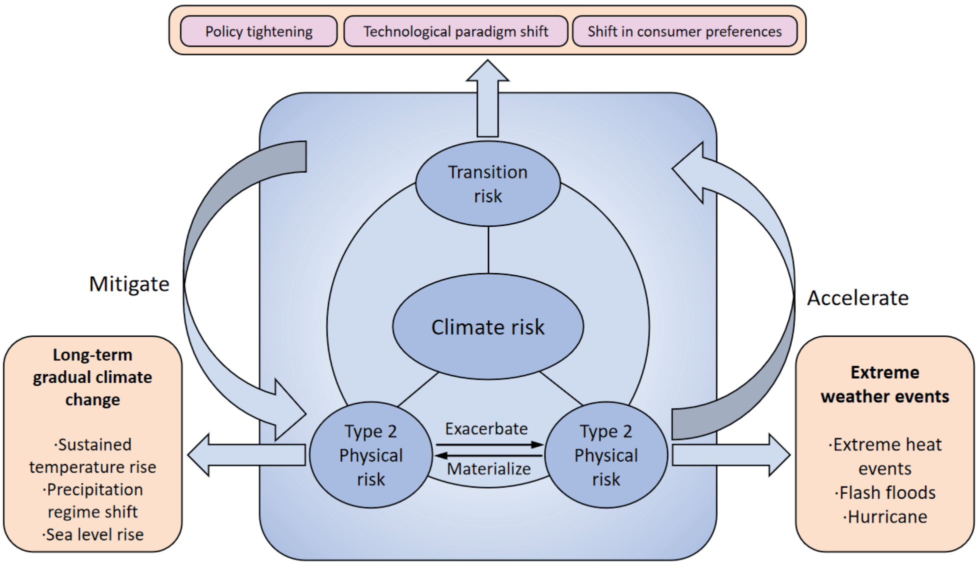

Fig. 1. Physical and transition climate risks.

Moderating Variables

Following Zhang's (2024) methodology [37], we quantify social insurance coverage as the ratio of unemployment insurance participants to the total population. This measure reflects the shock-absorbing capacity of institutional safeguards, potentially attenuating climate-related credit risk spillovers to the Chinese banking system during extreme weather episodes.

Control Variables

To enhance the precision of our analysis, we incorporated control variables at the bank, firm, and macroeconomic levels. Bank-level controls comprise Bank size (*Bsize*), Deposit-to-Asset Ratio (*Dep*), Loan Loss Provision Coverage Ratio (*Pcr*), Loan-to-Deposit Ratio (*Ldr*), and Cost-to-Income Ratio (*Cir*). Firm-level controls include Firm size (*Size*), Tobin's Q (*TobinsQ*), and the Industrial Herfindahl-Hirschman Index (*HHIB*). Macroeconomic controls consist of the natural logarithm of GDP (*Lngdp*) and Consumer Price Index (*Cpi*). Detailed variable definitions are provided in Table 1.

Model

Baseline Regression Model

This study begins with an empirical analysis based on historical data to examine the impact of climate risk on bank credit risk. Specifically, we employ the following model to conduct an in-depth analysis of the magnitude and direction of physical risk effects:

$$Risk_{i,t} = \alpha + \beta_1 Climate_{r,t} + \beta_2 bank_{ctrls_{i,t}} + \beta_3 macro_{ctrls_{r,t}} + u_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

where i, t, and r index banks, years, and cities respectively; $Risk_{i,t}$ measures the credit risk of a bank i in year t; $Climate_{i,t}$ is climate risk in the headquarters city r of bank i; $bank_{ctrls_{i,t}}$ and $macro_{ctrls_{i,t}}$ are vectors of bank-level and regional-level controls; u_i and λ_t denote bank and year fixed effects.

Mechanism Test Model

We extend model (1) by utilizing a stepwise regression method to develop the subsequent mediation effect model:

$$Loss_{i,t} = v_0 + v_1 Climate_{r,t} + v_2 Lngdp_{r,t} + v_3 Cpi_{r,t} + \lambda_t + \varepsilon_{i,t} \quad (6)$$

$$Risk_{i,t} = \gamma_0 + \gamma_1 Loss_{i,t} + \gamma_2 Climate_{r,t} + \gamma_3 bank_{ctrls_{i,t}} + \gamma_4 macro_{ctrls_t} + u_i + \lambda_t + \varepsilon_{i,t} \quad (7)$$

Model (6) analyzes the transmission mechanisms through two distinct variables: *Loss*, which quantifies direct economic losses attributable to climate change, and *Climate*, which encompasses both chronic and acute physical risks. Extreme weather events (*EWE*) include direct loss components; thus, we utilize the extreme weather (*EW*) indicator to measure the second dimension of physical risk.

Due to the inability to directly match micro-level data between banks and enterprises, this study adapts the methodological framework of Ge et al. (2021) [38] to implement a two-stage analytical approach. The first stage employs the firm-level model (5) to assess climate risk impacts on corporate operational performance, specified as:

$$Firm_{i,t} = \alpha + \beta_1 Climate_{s,t} + \beta_2 Size_{i,t} + \beta_3 TobinQ_{i,t} + \beta_4 HHIB_{i,t} + \beta_5 Lngdp_s + \lambda_t + \gamma_i + u_{i,t} \tag{8}$$

The subscripts t, i, s denote time, enterprise, and region, respectively. Firm represents the relevant variables at the enterprise level, and the size and significance of β_1 determines the degree of the impact of climate risk on the business situation of the enterprise.

Since model (8) already controls for individual firm and time fixed effects, the $\widehat{\beta_1}$ captures the variation in business conditions of firms at the regional level due to climate risk after excluding firm and macro-environmental factors. Therefore, a new estimator is defined in the area and time dimensions, which is used to link the 1-stage and 2-stage models.

$$\widehat{Firm_{s,t}} = \widehat{\beta_1} \times Climate_{s,t} \tag{9}$$

We replace the estimate $\widehat{Firm_{s,t}}$ with $Climate_{s,t}$ in the baseline model to obtain the following 2-stage regression model (10). According to the sign and significance of the coefficient φ_1 in this model, we can finally identify the indirect mechanism by which climate risk affects bank credit risk by influencing firms' operational capability.

$$Risk_{i,t} = \varphi_0 + \varphi_1 \widehat{Firm_{s,t}} + \varphi_2 bank_{ctrls_{i,t}} + \varphi_3 macro_{ctrls_{r,t}} + u_i + \lambda_t + \varepsilon_{i,t} \tag{10}$$

Moderated Regression Analysis

To examine how insurance coverage moderates the impact of extreme weather on bank credit risk, we augment model (1) by introducing interaction terms.

$$Risk_{i,t} = \alpha + \beta_1 Climate_{r,t} + \beta_2 Bi_{r,t} + \beta_3 Climate_{r,t} * Bi_{r,t} + \beta_4 bank_{ctrls_{i,t}} + \beta_5 macro_{ctrls_{i,t}} + u_i + \lambda_t + \varepsilon_{i,t} \tag{11}$$

where $Bi_{r,t}$ denotes the insurance coverage rate in the bank i headquarters city r, and the interaction term β_3 captures its moderating effect. Other variables follow model (1).

Results

Baseline Regression

Based on the results of the regression analysis conducted in Stata 16, it can be concluded that all three climate risk indicators significantly increase the credit risk exposure of commercial banks (Table 3). Extreme weather events (*EWE*) display a more noticeable influence at 0.979, significant at the 1% level, which can be attributed to their unpredictable qualities (Column 2). Long-term gradual climate risk (*LTGC*) illustrates a coefficient of 0.745 (Column 1), but extreme weather events (*EWE*) reveal a more prominent effect. According to the data presented in Column 3, transition risk (*ER*) has a considerable impact of 0.787, which indicates that carbon-intensive assets are being repriced on a systemic level. Therefore, Hypothesis 1 (H1) is supported.

Robustness Tests

To ensure the reliability of our findings, we conduct comprehensive robustness checks through two

Table 3. Baseline regression results.

Variables	*Npl* (1)	*Npl* (2)	*Npl* (3)
LTGC	0.745**		
	(0.290)		
EWE		0.979***	
		(0.127)	
ER			0.787***
			(0.241)
Dep	0.128**	0.122**	0.135**
	(0.057)	(0.056)	(0.057)
Ldr	0.005***	0.004***	0.006***
	(0.001)	(0.001)	(0.001)
Bsize	-0.157***	-0.132***	-0.146***
	(0.042)	(0.041)	(0.042)
Cir	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)
Pcr	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Lngdp	-0.576**	-0.708***	-0.789***
	(0.233)	(0.223)	(0.228)
Cpi	0.091***	0.070**	0.087***
	(0.033)	(0.032)	(0.033)
Constant	12.335*	17.672**	18.672**
	(7.361)	(7.120)	(7.315)
bank	YES	YES	YES
year	YES	YES	YES
N	1486.000	1486.000	1486.000
R^2	0.523	0.542	0.524

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

complementary approaches: (1) alternative variable construction: We first assess the sensitivity of our climate variable measurements to the choice of the baseline period. Climate anomalies are highly sensitive to the reference period, which can introduce bias if not properly accounted for. To mitigate this, we recalculate standardized temperature and precipitation anomalies using two distinct reference periods: the conventional 30-year baseline (1984-2013) and a shorter but more recent 20-year baseline (1993-2013). The latter captures recent climatic shifts more precisely, reducing potential distortion from earlier outliers. These recalculated anomalies are then integrated into long-term climate change indicators using entropy weighting, a method that objectively assigns weights based on informational value, minimizing subjective bias. For extreme weather (*EW*) measurement, we employ the relative threshold method developed by Ren et al. (2010) [39], which accounts for China's pronounced regional climatic diversity. Unlike absolute thresholds, this approach defines extremes relative to local historical conditions, ensuring cross-regional comparability. Similarly, we reconstruct our transition risk (*TR*) indicators by applying entropy-weighted integration across three critical dimensions – policy, demand, and technology – to produce a more balanced and representative composite measure. (2) Restricted Sample Analysis: Second, we address potential confounding effects from municipalities with unique administrative and economic characteristics. Specifically, we exclude the four directly controlled municipalities (Beijing, Tianjin, Shanghai, and Chongqing) from our sample. These cities exhibit distinct financial, policy, and developmental attributes that may not generalize to other regions. By omitting them, we test whether our baseline results hold for a more homogeneous subset of provinces. As summarized in Table 4, all climate risk coefficients remain statistically significant across both alternative variable specifications and restricted samples. The consistency of these estimates underscores the robustness of our baseline findings, reinforcing confidence in their validity.

Mechanism Tests

Table 5 (Columns 1-4) displays the regression results for models (6) and (7). The positive coefficients for both climate indicators in Columns (1) and (3) are statistically significant, indicating that climate change incurs substantial economic costs for affected entities. Columns (2) and (4) indicate that these direct economic losses lead to a notable increase in bank credit risk. The findings demonstrate that direct economic losses serve as a key transmission channel through which climate risks are propagated to the banking sector, thereby verifying Hypothesis 2.

Table 6 presents the two-stage regression results, revealing consistent climate risk transmission channels. The first-stage estimates demonstrate statistically significant climate-driven increases in corporate

Table 4. Robustness check results.

Variables	Alternative Variable Specifications			Excluding Direct-Controlled Municipalities		
	Npl (1)	*Npl* (2)	*Npl* (3)	*Npl* (4)	*Npl* (5)	*Npl* (6)
LTC	0.594**					
	(0.276)					
LTGC				0.722**		
				(0.317)		
EW		0.978***				
		(0.236)				
EWE					1.081***	
					(0.139)	
TR			0.925***			
			(0.215)			
ER						1.786***
						(0.508)
Control Var	YES	YES	YES	YES	YES	YES
bank	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES
N	1486.000	1486.000	1486.000	1383.000	1383.000	1383.000
R^2	0.522	0.527	0.527	0.512	0.533	0.515

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

Table 5. Transmission mechanism through direct economic losses.

Variables	*Loss* (1)	*Npl* (2)	*Loss* (3)	*Npl* (4)
LTGC	0.033***	0.501*		
	(0.003)	(0.303)		
EWE			0.008***	0.912***
			(0.003)	(0.236)
Loss		7.028***		7.409***
		(2.592)		(2.474)
Control Var	YES	YES	YES	YES
bank	YES	YES	YES	YES
year	YES	YES	YES	YES
N	1580.000	1486.000	1580.000	1486.000
R^2	0.225	0.525	0.152	0.530

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

operational risk across both Z-score (*ZScore*) and profitability (*Fpro*) measures. Second-stage results confirm that these firm-level impairments propagate to the banking sector, with the constructed corporate risk measure showing a significant negative association with loan performance. This empirical evidence establishes that climate transition risks systematically amplify credit risk in the regional banking sector by deteriorating local firms' operational fundamentals, thereby supporting Hypothesis 3 (H3).

Moderated Regression Analysis

Columns (1) and (2) of Table 7 indicate a significant negative relationship between the breadth of insurance coverage and banks' non-performing loan (*NPL*) ratio. Additionally, the significantly negative coefficient for the interaction term between insurance coverage breadth and extreme weather implies that broader insurance coverage mitigates the adverse impact of extreme weather on banks' credit risk, thereby supporting Hypothesis 4 (H4).

Heterogeneity Analysis

The regression findings indicate notable regional variation in exposure to climate risk. Columns (1) and (3) indicate that banks in the Hu Huanyong transition zone encounter significantly heightened physical climate risk. Columns (2) and (4) indicate that southeastern

Table 6. Climate risk transmission via corporate channel.

Variables	The first stage		The second stage	
	Fpro (1)	*ZScore* (2)	*Npl* (3)	*Npl* (4)
ER	-0.044**	-1.647*		
	(0.019)	(0.943)		
$\widehat{Fpro}$			-9.399***	
			(2.792)	
$\widehat{ZScore}$				-0.251***
				(0.075)
N	2327	13857	2321	13857
Control Var	YES	YES	YES	YES
Bank	YES	YES	YES	YES
year	YES	YES	YES	YES

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

Table 7. Insurance coverage as a risk mitigation mechanism.

Variables	*Npl* (1)	*Npl* (2)
Bi	-3.912***	-4.351***
	(1.436)	(1.414)
Stew		2.154***
		(0.343)
*Bi*Stew*		-8.451***
		(2.063)
Control Var	YES	YES
bank	YES	YES
year	YES	YES
N	1486.000	1486.000

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

banks exhibit greater susceptibility to transition risk. As shown in Table 8, the findings highlight the uneven distribution of climate-related financial vulnerabilities across regions, thereby providing empirical support for Hypothesis 5 (H5).

Discussion

Empirically validated evidence demonstrates that climate change poses material and systemic threats to China's financial stability. To mitigate these risks, coordinated efforts are imperative: financial regulators must develop climate stress-testing frameworks, ESG rating agencies should enhance their disclosure standards, and banks need to integrate physical and transition risks into their governance structures.

Crucially, to design such targeted interventions, a granular understanding of risk transmission mechanisms is essential. Delving into these pathways, our analysis reveals two distinct channels with profound regulatory implications: Physical risks directly degrade borrower repayment capacity, while transition risks erode capital buffers through carbon asset stranding. More critically, the pronounced geographical distribution of these risks shows that banks along the Hu Huanyong Line are disproportionately vulnerable to physical shocks, whereas their southeastern counterparts bear heavier transition burdens. This stark spatial divergence directly exposes two critical regulatory gaps: first, homogeneous supervisory metrics fail to capture regional disparities, necessitating spatially differentiated regulatory architectures; and second, conventional stress testing inadequately accounts for complex interdependencies between risk factors. Collectively, these findings establish that spatially granular supervision is imperative for reconciling carbon neutrality ambitions with financial stability imperatives.

Beyond regulatory frameworks, market-based diagnostic tools exhibit parallel deficiencies. Complementary to the identified regulatory gaps, our examination of prevailing ESG rating frameworks identifies three material shortcomings that severely compromise their diagnostic value: (1) undifferentiated bundling of physical and transition risks, (2) failure to account for geographical vulnerability variations, and (3) omission of insurance-based mitigation evidence. These limitations, mirroring the regulatory blind spots, collectively undermine ESG ratings' precision in assessing institutional climate resilience. Building upon this diagnosis, our findings provide a robust empirical basis for designing next-generation ESG frameworks incorporating risk-typed differentiation and spatial granularity – a paradigm shift from compliance-based reporting to genuinely predictive risk modeling.

Equally critical are deficiencies in risk quantification methodologies. Extending the critique of conventional approaches, our investigation into stress testing identifies three fundamental weaknesses: First, scenario

Table 8. Heterogeneous effects across the Hu Line.

Variables	Hu Line Transition Zone		Southeastern Transition Zone	
	Npl (1)	*Npl* (2)	*Npl* (3)	*Npl* (4)
EW	0.959***		0.676***	
	(0.315)		(0.130)	
ER		0.934***		1.815**
		(0.305)		(0.807)
Control Var	YES	YES	YES	YES
bank	YES	YES	YES	YES
year	YES	YES	YES	YES
N	313.000	313.000	1092.000	1092.000

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

designs inadequately distinguish between instantaneous weather shocks and cumulative climate changes. Second, pervasive spatial oversimplification generates materially biased risk metrics. Third, static model specifications ignore feedback loops mediated by insurance. These insights collectively establish the microfoundations for next-generation testing frameworks, which must integrate spatiotemporal heterogeneity and adaptive mechanisms. Such advancements are indispensable for realistically assessing banking resilience in the face of climate uncertainty.

Conclusions

Our empirical analysis, utilizing a two-way fixed effects model on panel data encompassing 189 local commercial banks across 30 Chinese provinces (2014-2023), provides robust evidence that climate risk constitutes a material threat to financial stability in China. We demonstrate that both physical risks (chronic climate change and extreme weather events) and transition risks significantly elevate banks' credit risk exposure. Notably, the acute nature and constrained buffering capacities associated with extreme weather events result in more pronounced impacts on credit quality compared to gradual climate change, while transition risk manifests heightened destructiveness primarily through the revaluation of high-carbon assets. Mechanism analysis confirms that these risks impair bank credit quality by deteriorating the underlying economic conditions and debt service capabilities of borrowers. Crucially, our findings identify expanded insurance coverage as an effective adaptation strategy, mitigating the adverse credit risk consequences of extreme weather by facilitating risk transfer. Furthermore, significant spatial heterogeneity exists along the Hu Line: banks operating in the transitional zone exhibit heightened sensitivity to physical risks, particularly extreme weather, whereas those in the southeastern region face greater exposure to transition risks. These results underscore the imperative for regionally differentiated, risk-specific prudential policies and adaptation mechanisms to safeguard China's financial system against the multidimensional vulnerabilities posed by climate change.

Policy Implications

Empirically grounded policy recommendations are proposed to strengthen China's climate-financial governance framework, specifically targeting enhanced systemic resilience and supervisory effectiveness in response to intensifying climate-related risks.

Within the regulatory domain, policymakers should prioritize two critical enhancements to strengthen climate resilience. First, capital adequacy and risk provisioning requirements must be calibrated according to geospatial variations in climate risk exposure. This differentiation should account for distinct risk profiles between regions, such as the transitional zone along the Hu Huanyong Line – characterized by heightened physical risk vulnerability – and southeastern areas facing greater transition risks. Such regionally tailored metrics would prevent systemic distortions inherent in uniform regulatory approaches. Second, regulatory authorities need to advance stress testing methodologies through dynamic co-assessment models that quantify cross-contagion effects between physical and transition risks. These enhanced models should incorporate multi-risk shock scenarios featuring synchronized risk factor interactions, thereby establishing institutional safeguards that simultaneously reconcile carbon neutrality objectives with financial stability while mitigating systemic instability resulting from regional imbalances.

In parallel with reforms for market instruments, transforming ESG ratings into effective risk-signaling tools requires two methodological advancements. First, rating methodologies should fundamentally restructure climate risk assessment by mandating disaggregation of exposures into physical risks (including both extreme weather events and progressive changes) and transition risks. Each category must receive differentiated weighting coefficients reflecting its distinct financial materiality. Second, embed geospatial and mitigation analytics: Integrate sub-national risk exposure mapping into rating methodologies while quantifying the loss-absorption efficacy of risk transfer mechanisms (e.g., insurance penetration) within institutional resilience metrics.

Concurrently, for risk assessment frameworks, stress testing systems must evolve through two critical innovations. First, models should systematically embed risk mitigation instruments – including climate-linked derivatives and insurance products – to quantify endogenous moderating effects on financial shocks. Second, a complex systems-oriented methodology should be developed to assess bank resilience, specifically designed to pinpoint critical transmission nexuses and systemic fragility points within climate risk contagion networks. These enhancements would transform stress testing from static compliance exercises into anticipatory resilience diagnostics.

Conflict of Interest

The authors declare no conflict of interest.

References

1. STROEBEL J., WURGLER J. What do you think about climate finance? Journal of Financial Economics. **142** (2), 487, **2021**.
2. BATTISTON S., MANDEL A., MONASTEROLO I., SCHUTZE F., VISENTIN G.A. Climate stress-test of the financial system. Nature Climate Change. **7** (4), 283, **2017**.

3. BOLTON P., KACPERCZYK M. Do investors care about carbon risk? Journal of Financial Economics. **142** (2), 517, **2021**.
4. PAN M., LIU H.Y., CHENG Z.S. The impact of extreme climate on commercial banks' risk-taking: Empirical evidence from Chinese regional commercial banks. Journal of Financial Research. (10), 39, **2022.**
5. XIA Y.G., ZHANG Y.M., LIU L.P. Extreme climate and commercial bank risk-taking: An empirical study based on 152 regional commercial banks in China. Insurance Studies. (6), 15, **2023**.
6. YANG Z.H., LI D.C., CHEN Y.T. Research on "Green Swan" risks in financial markets: A dual perspective of physical and transition risks. Management World. **40** (2), 47, **2024**.
7. JIANG H., YI Y. Drought shocks and bank performance: An empirical study from the perspective of green credit. Finance Forum. (7), 35, **2023**.
8. LV Y.B., LI Z.S., GUO Y.C. Advancing against the wind: Typhoon disasters and bank risk-taking behavior. Journal of Financial Research. **523** (1), 19, **2024**.
9. SHEN Y., SHE K.W., XU X. Climate risk and bank earnings management: A financial regulation perspective. Journal of Financial Research. (7), 116, **2023**.
10. WANG Y., WANG W.W. The impact of environmental disasters on bank default rates: Theoretical and empirical analysis. Journal of Financial Research. (12), 38, **2021**.
11. RAN M.D., ZHENG Y., WANG C.L. The impact of extreme climate risk on corporate cross-regional investment. Chinese Journal of Management. **21** (11), 1708, **2024**.
12. GRAY C.L., MUELLER V. Natural disasters and population mobility in Bangladesh. Proceedings of the National Academy of Sciences. **109** (16), 6000, **2012**.
13. LI L., WU S.M., CHEN Z.Z. Extreme weather risk and macroeconomic fluctuations: A dual perspective of network connectedness and spatial spillover effects. Journal of Financial Research. (9), 58, **2023**.
14. BERNSTEIN A., GUSTAFSON M.T., LEWIS R. Disaster on the horizon: The price effect of sea level rise. Journal of Financial Economics. **134** (2), 253, **2019**.
15. CHEN G.J., WANG J.Q., ZHAO X.Q. The impact of climate transition risk on corporate default rates. Journal of Management Science. **36** (3), 144, **2023**.
16. JAVADI S., MASUM A.A. The impact of climate change on the cost of bank loans. Journal of Corporate Finance. **69**, 102019, **2023**.
17. KABIR M.N., RAHMAN S., RAHMAN M.A., ANWAR M. Carbon emissions and default risk: International evidence from firm-level data. Economic Modelling. **103**, 105617, **2021**.
18. ZHANG T., HOU Y.H., QU X.X., ZHANG Z.Q. Carbon cycle, climate change and financial risks: A DSGE model approach. China Population, Resources and Environment. **33** (8), 1, **2023**.
19. LI J.C., WANG W.W. What drives corporate risk-taking under environmental regulation: "Transition incentives" or "survival pressure"? China Population, Resources and Environment. **32** (8), 40, **2022**.
20. HUANG B., PUNZI M.T., WU Y. Do banks price environmental transition risks? Evidence from a quasi-natural experiment in China. Journal of Corporate Finance. **69**, 101983, **2021**.
21. LUO Z., QI B.C. Environmental regulation's dual effects: Industrial relocation/upgrading and banking sector co-development – Evidence from water pollution control in the Yangtze River Basin. Economic Research Journal. **56** (2), 174, **2021**.
22. GAVRIILIDIS K. Measuring climate policy uncertainty. SSRN. **2021**.
23. CHEN Y., ZHANG D., WU F., JI Q. Climate risks and foreign direct investment in developing countries: the role of national governance. Sustainability Science. **17** (5), 1723, **2022**.
24. DERYUGINA T., KAWANO L., LEVITT S. The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. American Economic Journal: Applied Economics. **10** (2), 202, **2018**.
25. ROCKLOV J., DUBROW R. Climate change: an enduring challenge for vector-borne disease prevention and control. Nature Immunology. **21** (5), 479, **2020**.
26. CAMPIGLIO E., DAFERMOS Y., MONNIN P., RYAN-COLLINS J., SCHOTTE G., TANAKA M. Climate change challenges for central banks and financial regulators. Nature Climate Change. **8** (6), 462, **2018**.
27. NGUYEN J.H., PHAN H.V. Carbon risk and corporate capital structure. Journal of Corporate Finance. **64**, 101713, **2020**.
28. UESUGI I., MIYAKAWA D., HOSONO K., ONO A., UCHIDA H. The collateral channel versus the bank lending channel: Evidence from a massive earthquake. Journal of Banking & Finance. **170**, 107315, **2025**.
29. KABIR M.N., RAHMAN S., RAHMAN M.A., ANWAR M. Carbon emissions and default risk: International evidence from firm-level data. Economic Modelling. **103**, 105617, **2021**.
30. U-DIN S., NAZIR M.S., SHAHZAD A. Money at risk: climate change and performance of Canadian banking sector. Journal of Economic and Administrative Sciences. **39** (2), 273, 2023.
31. HONG H., LI F.W., XU J. Climate risks and market efficiency. Journal of Econometrics. **208** (1), 265, **2019**.
32. DING Y.G., SUN Q.X. The impact of climate risk on China's agricultural economic development: Heterogeneity and mechanism analysis. Journal of Financial Research. (9), 111, **2022**.
33. LI S., PAN Z. Climate transition risk and bank performance: Evidence from China. Journal of Environmental Management. **323**, 116275, **2022**.
34. ZHENG Q.Q., WAN L., WANG S.Y., LI J., WU J., SONG M.L. Can environmental regulation induce green lifestyles? Evidence from China. Systems Engineering - Theory & Practice. **43** (4), 941, **2023**.
35. DONG Z.Q., WANG H. Urban wealth and green technology adoption. Economic Research Journal. **56** (4), 143, **2021**.
36. KLOMP J. Financial fragility and natural disasters: An empirical analysis. Journal of Financial Stability. **13**, 180, **2014**.
37. ZHANG Q.J., ZHAO Z.S., MENG X.X. Extreme weather and regional financial risks: Amplification or neutralization? Journal of Modern Finance. **29** (9), 59, **2024**.
38. GE X.Y., ZHUANG J.L., LIU Y. Trade policy uncertainty and commercial bank risk: Evidence from the corporate operations channel. China Industrial Economics. (8), 133, **2021**.
39. REN G.Y., CHEN Y., ZOU X.K., ZHOU Y.Q., WANG X.L., JIANG Y., REN F.M., ZHANG Q. Definition and trend analysis of integrated extreme climate indices. Climatic and Environmental Research. **15** (4), 11, **2010**.