

Impact of Climate Policy Uncertainty on Bank Systemic Risk: Evidence from Chinese Listed Banks

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Abstract This study empirically examines the impact of climate policy uncertainty on bank systemic risk and the underlying mechanisms, using unbalanced panel data from 36 banks over 2008–2022. The results indicate that climate policy uncertainty significantly reduces bank systemic risk. This effect operates through three key channels: increasing capital adequacy, reducing leverage, and decreasing lending to high-carbon industries. Furthermore, the risk-reducing impact of climate policy uncertainty is strengthened by greater carbon emission reductions. It is noteworthy that the effect of climate policy uncertainty on bank systemic risk follows a U-shaped pattern. The risk-reducing effect is particularly evident in larger, non-state-owned banks with strong profitability, effective risk management, and higher credit allocation to green sectors.

Keywords climate policy uncertainty; bank systemic risk; capital adequacy; leverage; carbon emission reductions; nonlinear effect

Received July 30, 2024, accepted September 2, 2025

Supported by Major Projects of Philosophy and Social Science Research in Colleges and Universities of Jiangsu Province (2023SJZD023); General Program of Social Science Foundation of Jiangsu Province (23GLB009); National Cultural Excellence Cultivation Project Special Funding Program (2021QNYC209); Fundamental Research Funds for the Central Universities (2242025S30013)

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1 Introduction

In recent years, global climate change has increasingly resulted in frequent and intense extreme weather events, posing significant challenges to human survival and socio-economic development. As a large developing country with a vast population and diverse climatic conditions, China is among the countries most severely affected by extreme weather disasters. Consequently, China plays a critical role in addressing climate change and advancing global climate governance. According to the 2024 China Climate Bulletin, in 2024, against the backdrop of global warming, the national average temperature reached 10.9 °C, the highest since 1951, while the national average precipitation was 697.7 millimeters, representing a 9.0% increase compared to the long-term average¹. The long-term cumulative effects of climate change, combined with sudden-onset extreme weather events, not only directly impact sensitive sectors such as agriculture, energy, and infrastructure, but also amplify systemic risks to the real economy through supply chain transmission mechanisms^[1,2].

To actively address climate change and its impacts, the Chinese government has formulated and implemented a series of climate-related policies. However, frequent policy adjustments during implementation and a lack of inter-sectoral coordination have notably heightened climate policy uncertainty^[3,4]. Climate policy uncertainty refers to the uncertainty among market participants regarding the timing, content, and consequences of climate policy formulation^[5]. Against the background of the current weak economic recovery and turbulent external environment, the impact of climate policy uncertainty on financial stability has also become more complex: on the one hand, it may disrupt market expectations, exacerbate the volatility of asset prices, and thus amplify financial risks^[6–8]; On the other hand, some scholars argue that such uncertainty may encourage financial institutions to accelerate their green and low-carbon transitions, potentially generating new investment opportunities and development prospects^[9,10]. At this critical stage of development, examining the mechanisms through which climate policy uncertainty affects bank systemic risk holds both theoretical value and practical significance. Particularly given that existing studies have not yet reached a consensus on its net effect, an empirical analysis grounded in the Chinese context is especially necessary. To this end, this paper investigates the impact of climate policy uncertainty on systemic risk within China's banking sector using static panel regression models, mediation effect models, and moderating effect models, aiming to uncover the underlying mechanisms. This approach not only contributes to the growing body of research on how emerging macro-level factors like climate policy uncertainty influence bank systemic risk, but also provides a scientific basis for climate policy design and financial risk management in China.

As a core component of China's financial system, banks play a pivotal role in maintaining overall financial stability. Preventing and mitigating bank systemic risk has become a key priority in preserving national financial security. Existing research has yielded substantial in-

¹China Meteorological Administration: 2024 China Climate Bulletin:
https://www.gov.cn/lianbo/bumen/202503/content_7009730.htm, visit date: 2025-5-13.

sights into the factors influencing bank systemic risk. At the micro level, several key areas have been identified. Firstly, excessive liquidity creation and rising leverage significantly amplify systemic risk^[11–13]. Secondly, differences in credit size influence risk distribution while large banks are more susceptible to systemic risk, small banks also contribute significantly to risk transmission^[14]. Thirdly, low asset quality and insufficient transparency are recognized as critical drivers of systemic risk^[15,16]. Furthermore, portfolio diversification can lead to behavioral convergence among banks, thereby increasing systemic vulnerability^[17]. Finally, the expansion of interbank business among small and medium-sized banks, coupled with maturity mismatches, intensifies risk spillovers^[18]. At the macro level, studies emphasize the influence of policy environments, unexpected shocks, and regulatory frameworks on systemic risk. Economic policy uncertainty^[19–21] and major events such as the COVID-19 pandemic^[22] have been shown to heighten banking sector instability. However, well-designed macroprudential policies^[23,24] and robust financial regulation^[25] have demonstrated effectiveness in mitigating these risks.

As global climate change becomes increasingly severe, academic research has begun to shift focus toward its impact on bank systemic risk. Studies by Song and Fang^[26], Wu, et al.^[27] and Cai and Cui^[28], based on data from China, showed that climatic events such as extreme temperatures and extreme precipitation significantly increased bank systemic risk. Curcio, et al.^[29], using climate hazard data from the United States, further validated this finding. Wu, et al.^[30] adopted a global perspective by measuring climate risk through countries' adaptive capacity to climate change, which again confirmed a significant positive relationship between climate risk and bank systemic risk, demonstrating the generalizability of this effect across international contexts. Although existing studies have examined the impact of climate change on bank systemic risk, there remained a lack of in-depth exploration regarding how climate policy uncertainty influenced such risks. Research indicated that understanding individual behaviors and organizational responses in complex environments was valuable for analyzing uncertainty^[31,32]. This analytical perspective offered useful insights into how climate policy uncertainty affected banks' risk exposure and their strategic responses. Only a few preliminary studies addressed this issue. Dai and Zhang^[33] found that climate policy uncertainty reduced banks' risk-taking levels, especially more significantly among listed banks. Liu, et al.^[10], based on data from G20 countries, confirmed that under conditions of climate policy uncertainty, banks could reduce their risk-taking through ESG investments, enhanced climate disclosure, and prudent risk management strategies, thereby effectively mitigating systemic risk. Therefore, given the limited research, further in-depth investigation into the impact of climate policy uncertainty on bank systemic risk and its underlying mechanisms could help provide banks and policymakers with more targeted and effective risk management strategies.

A review of the existing literature reveals several potential limitations in current studies. Firstly, while numerous factors influencing systemic risk in banks have been explored, relatively limited attention has been paid to climate policy uncertainty, an emerging macro-level factor within this context. Secondly, as research on the impact of climate policy uncertainty on

bank systemic risk is still in its early stages, the literature remains underdeveloped in terms of identifying the specific mechanisms through which this influence operates and lacks sufficient differentiation in the analysis of heterogeneous banking institutions. Furthermore, although a small number of studies have examined this relationship, most rely on cross-country samples and fail to fully account for China's unique financial system and policy environment.

This paper makes three key contributions to the existing literature. Firstly, in contrast to established research based on cross-country samples, this study focuses specifically on China's unique climate policy environment and banking practices to examine the impact of climate policy uncertainty on bank systemic risk. This approach not only offers a new perspective for understanding macro-policy influences on bank systemic risk but also provides empirical evidence from the Chinese context to clarify the intrinsic relationship between climate policy uncertainty and systemic risk. Secondly, unlike most existing studies that remain at the surface level of examining the effects of climate policy uncertainty, this paper explores the underlying mechanisms, through which such uncertainty affects systemic risk. It demonstrates that banks can mitigate systemic risk by increasing capital adequacy, reducing leverage, and decreasing lending to high-carbon industries in response to climate policy uncertainty. These findings offer theoretical support and practical insights for banks seeking to manage risks under uncertain climate policies. Thirdly, while previous studies often overlook the potential moderating role of climate governance factors, this paper introduces carbon emission reduction as a key moderating variable. It investigates how carbon emission reduction influences the relationship between climate policy uncertainty and bank systemic risk, thereby enriching and deepening the understanding of the mechanisms involved. Furthermore, the study explores the heterogeneous impacts of climate policy uncertainty across various dimensions, including bank ownership, size, profitability, credit operations, and risk management capacity.

2 Theoretical Analysis and Research Hypothesis

2.1 Climate Policy Uncertainty and Bank Systemic Risk

As climate change intensifies, financial institutions are increasingly recognizing the importance of implementing preventive measures^[34]. In an environment of changing climate policy, banks, as central players in the financial system, can mitigate systemic risk through enhanced risk management practices, promotion of green innovation, and improved transparency and risk disclosure. Specifically, firstly, banks are likely to conduct more rigorous and comprehensive assessments of the extent of risk exposure and potential losses associated with climate-related assets. In response, they may adopt proactive risk management strategies such as reducing or avoiding investments in high-carbon emission industries and reallocating part of their capital to lower-risk sectors. These actions help reduce the banks' overall risk exposure and curb the likelihood of systemic risk^[33]. Secondly, banks may also accelerate the development of green financial products. In the face of heightened climate policy uncertainty, they can introduce instruments such as green bonds and sustainable investment funds, targeting environmentally

friendly and financially stable industries. Such initiatives not only support portfolio diversification and risk mitigation but also enhance asset quality and reduce the incidence and severity of non-performing loans, thereby contributing to a decline in systemic risk. Thirdly, increased climate policy uncertainty may prompt regulators to require greater transparency and more detailed risk disclosures from banks, including information on climate-related risk management strategies, loan portfolios, and risk tolerance. By improving access to relevant information, market participants can make more accurate risk assessments, which helps reduce information asymmetries and, in turn, lowers systemic risk. In summary, rising climate policy uncertainty is expected to incentivize banks to strengthen risk management, foster green innovation, and improve transparency, all of which contribute to a reduction in systemic risk. Based on this reasoning, Hypothesis 1 is proposed.

H1 Climate policy uncertainty can reduce bank systemic risk.

2.2 The Mediating Role of Capital Adequacy Level

Capital adequacy is a critical component of a bank's risk management framework. A sufficient capital adequacy level enhances a bank's ability to manage risks effectively and respond to external shocks. Climate policy uncertainty can reduce corporate cash flow, hinder R&D investment, and lower profits and productivity^[35]. These effects weaken firms' repayment capacity, increase the likelihood of defaults^[8], and raise the probability of bank credit losses. Furthermore, climate policy uncertainty may cause volatility in energy markets^[36], increasing the risk of asset depreciation for banks holding related assets. This can lead to asset illiquidity and higher financing costs. In response, banks may raise their capital adequacy levels to build stronger capital reserves, enabling them to withstand these adverse conditions. By doing so, banks can maintain operational stability and solvency in the face of widespread corporate defaults and asset value fluctuations. This also helps limit the spread of systemic risk and enhances the overall stability of the financial system. Therefore, to mitigate the challenges posed by climate policy uncertainty, banks may enhance their resilience by increasing capital adequacy, thereby reducing systemic risk. Based on this reasoning, Hypothesis 2 is proposed.

H2 Capital adequacy level plays a mediating role in the relationship between climate policy uncertainty and bank systemic risk.

2.3 The Mediating Role of Leverage Level

An increase in leverage levels indicates that banks are expanding credit^[37]. In an environment of climate policy, such credit expansion can heighten risks for banks. Specifically, it may amplify asset depreciation and loan default risks associated with the high-carbon industries. Moreover, it can trigger investors' anxiety, leading to widespread selling of related financial assets, sharp price declines, and consequently, a rise in systemic risk within the banking sector^[28]. In response, banks may choose to recapitalize and improve asset quality by reducing their leverage, namely, by decreasing holdings of risky assets in high-emission industries and directing more loans and investments toward green, clean and sustainable sectors. This shift can lower

banks' exposure to credit risk and reduce potential losses. Additionally, lowering leverage means reduced reliance on debt financing, which helps banks avoid liquidity risks arising from investors' withdrawals driven by concerns over credit quality. Overall, reducing leverage enhances the resilience and stability of banks, better safeguarding the banking system and promoting financial stability under conditions of climate policy uncertainty. Based on this reasoning, Hypothesis 3 is proposed.

H3 Leverage level plays a mediating role in the relationship between climate policy uncertainty and bank systemic risk.

2.4 The Mediating Role of Loans in High-carbon Sectors

Increased climate policy uncertainty significantly raises compliance costs for high-carbon industries, accelerating asset depreciation and increasing default risks. These effects ultimately lead to a dual impact: declining credit asset quality and reducing bank profitability^[33,38]. In response to this external shock, banks are likely to conduct more prudent assessments of climate transition risks faced by high-carbon firms^[39], and reduce the proportion of loans allocated to these sectors in their asset portfolios. This adjustment in credit structure can effectively lower banks' exposure to climate policy changes while redirecting credit flows toward green and low-carbon sectors, thereby supporting the long-term stability of banking operations. Given that loans to high-carbon industries tend to be highly concentrated and strongly correlated, reducing their share can help interrupt the transmission of risk stemming from climate policy uncertainty within the banking system, thus preventing systemic risk from emerging. Moreover, decreasing lending to high-carbon sectors may also serve as a positive market signal, indicating that banks are proactively managing climate-related uncertainties. This can enhance investor confidence and reduce the likelihood of liquidity crises. Therefore, reducing exposure to high-carbon industries improves asset quality, mitigates market volatility, and effectively curbs the accumulation of risks associated with climate policy uncertainty, ultimately lowering bank systemic risk. Based on this reasoning, Hypothesis 4 is proposed.

H4 High-carbon sector lending plays a mediating role in the relationship between climate policy uncertainty and bank systemic risk.

2.5 The Moderating Effect of Carbon Emission Reductions

According to the Intergovernmental Panel on Climate Change (IPCC), greenhouse gas emissions, primarily carbon dioxide (CO₂), are the primary cause of global warming. In response to this challenge, China's "dual-carbon" goal prioritizes carbon emission reduction as a core policy direction. An improved carbon emission reduction effect can enhance the mitigating impact of climate policy uncertainty on bank systemic risk, which is primarily achieved through three mechanisms: stabilizing market expectations, hedging transition risks, and curbing the source of environmental risk. Firstly, stronger carbon emission reduction outcomes can convey clearer policy signals to the market. This not only enhances investor confidence in government climate governance but also stabilizes market expectations, effectively reducing the stock market herd

behavior triggered by climate policy uncertainty. Consequently, fluctuations in the valuation of banks' climate-sensitive assets are dampened, lowering the likelihood of systemic financial risk. Secondly, improvements in emission reduction may prompt regulators to intensify climate-related policies. As policy stringency increases, the risk of stranded high-carbon assets rises accordingly. In response, banks may proactively adjust their asset structures based on prudential principles, gradually reducing exposure to high-carbon sectors while increasing investments in green financial instruments^[40]. Such adjustments can hedge against transition risks associated with climate policy changes and further strengthen the financial system's support for emission reduction initiatives. Thirdly, enhanced carbon emission reduction can slow the progression of climate change at its source, thereby reducing the risk of asset depreciation and operational disruptions caused by extreme weather events^[41]. This leads to improved loan quality, lower default probabilities, and greater stability within the banking system. In summary, an improved carbon emission reduction effect can reinforce the ability of climate policy to mitigate systemic risk in the banking sector through these three pathways. Based on this analysis, Hypothesis 5 is proposed.

H5 The improvement of carbon emission reduction effect moderates the relationship between climate policy uncertainty and bank systemic risk.

2.6 The Nonlinear Effect of Climate Policy Uncertainty

Although the preceding discussion highlights that rising climate policy uncertainty may reduce systemic risk in the banking sector, the impact of such uncertainty can vary significantly depending on its intensity. Existing research suggests that the relationship between policy uncertainty and financial stability is non-linear; instead, it depends on the level of uncertainty and the capacity of financial institutions to adapt^[42]. Specifically, when climate policy uncertainty is low, banks can improve their stability and mitigate systemic risk by reducing exposure to high-carbon assets, increasing allocations to green credit, and managing climate-related risk exposures, as policy directions are relatively clear. However, as climate policy uncertainty increases, banks face greater ambiguity regarding future policy directions, which leads to hesitation and misjudgment in investment decisions, asset allocation, and risk management. This dynamic significantly heightens credit and market risks^[43], which then spread through interbank credit linkages, triggering broader systemic risks. Furthermore, in environments of extreme climate policy uncertainty, market participants lose confidence in future policy expectations, leading to herd behavior in investment decisions. Such behavior amplifies stock price volatility^[44] and raises corporate default rates^[8]. These risks are transmitted to the banking system through credit channels, capital market fluctuations, and liquidity constraints, further intensifying systemic risks. Based on this analysis, this paper proposes Hypothesis 6.

H6 The impact of climate policy uncertainty on bank systemic risk follows a U-shaped pattern.

3 Data and Methodology

3.1 Empirical Model

In order to empirically test the impact of climate policy uncertainty on bank systemic risk, the following baseline regression model is established:

$$\Delta\text{CoVaR}_{i,t} = \alpha_0 + \alpha_1 \text{CPU}_t + \alpha_2 \sum \text{Controls}_{i,t} + \mu_i + \varepsilon_{i,t}, \quad (1)$$

where, the subscript i represents the listed banks and t represents the sample period. $\Delta\text{CoVaR}_{i,t}$ represents the bank systemic risk, CPU_t represents climate policy uncertainty, $\sum \text{Controls}_{i,t}$ is the collection of bank-level control variables and macro-level control variables, μ_i is the fixed effect of banks, and $\varepsilon_{i,t}$ is a random error term. It is important to note that the model construction in this study draws on the empirical approach employed by Tian and Li^[45] in their analysis of the relationship between economic policy uncertainty and bank liquidity creation. Given that climate policy uncertainty is a time-series variable, incorporating time fixed effects into the model would result in multicollinearity between the independent variable and the time fixed effect. To ensure the accuracy and validity of the estimation results, this paper does not include time fixed effect in the model specification.

3.2 Variables

3.2.1 Dependent Variable

The dependent variable in this paper is bank systemic risk. In measuring bank systemic risk, scholars have developed a relatively mature methodological framework, which mainly includes ΔCoVaR , MES and SRISK approaches^[46–49]. Among these, ΔCoVaR has become one of the mainstream methods for measuring systemic risk measurement due to its ability to effectively capture the risk contribution of financial institutions during periods of crisis^[48]. In light of its effectiveness and widespread use, ΔCoVaR is selected as the measure of bank systemic risk in this study. Adrian and Brunnermeier^[46] define it as:

$$\Pr(X^j \leq \text{CoVaR}_q^{j|i} | X^i = \text{VaR}_q^i) = q. \quad (2)$$

It is the value of risk that the whole banking system faces when a single bank i is hit. In order to consider the dynamic correlation of bank time series, this paper calculates ΔCoVaR based on the DCC-GARCH model constructed by Girardi and Ergün^[50] to measure the contribution of a single bank to the overall bank systemic risk when it generates losses. The specific calculation method is as follows:

Assume that the losses of bank i and the banking system j follow a binary normal distribution:

$$(X_t^i, X_t^j) \sim N \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} (\sigma_t^i)^2 & \rho_t^{ij} \sigma_t^i \sigma_t^j \\ \rho_t^{ij} \sigma_t^i \sigma_t^j & (\sigma_t^j)^2 \end{pmatrix} \right). \quad (3)$$

Among them, the conditional standard deviation σ_t^i , σ_t^j and the dynamic correlation coefficient ρ_t^{ij} of bank i and banking system j can be estimated by DCC-GARCH model. Accordingly,

the definition formula of Equation (2) ΔCoVaR can be rewritten as:

$$\Pr \left(\left[\frac{X_t^j - \frac{X_t^i \rho_t^{ij} \sigma_t^j}{\sigma_t^i}}{\sigma_t^j \sqrt{1 - (\rho_t^{ij})^2}} \middle| X_t^i \leq \text{VaR}_{q,t}^i \right] \leq \frac{\text{CoVaR}_{q,t}^i - \frac{X_t^i \rho_t^{ij} \sigma_t^j}{\sigma_t^i}}{\sigma_t^j \sqrt{1 - (\rho_t^{ij})^2}} \right) = q. \quad (4)$$

When bank i risks occur, the dynamics $\text{CoVaR}_{q,t}^{j|\text{VaR}_{q,t}^i}$ of the banking system can be expressed as:

$$\text{CoVaR}_{q,t}^{j|\text{VaR}_{q,t}^i} = \phi^{-1}(q) \sigma_t^j \sqrt{1 - (\rho_t^{ij})^2} + \phi^{-1}(q) \rho_t^{ij} \sigma_t^j. \quad (5)$$

Thus, the formula for calculating ΔCoVaR can be obtained:

$$\Delta\text{CoVaR}_{q,t}^{j|i} = \text{CoVaR}_{q,t}^{j|\text{VaR}_q^i} - \text{CoVaR}_{q,t}^{j|\text{VaR}_{0.5}^i}. \quad (6)$$

The data required to calculate overall bank systemic risk include the daily logarithmic returns of individual bank stocks and the daily logarithmic returns of the Shenwan bank index, which represents the banking system's rate of return. Firstly, the daily ΔCoVaR is computed, and then the annual ΔCoVaR is derived by averaging the daily values within each corresponding year. Additionally, this paper takes the absolute value of the overall bank systemic risk, with a higher absolute value indicating a greater level of systemic risk.

3.2.2 Independent Variable

The independent variable in this study is climate policy uncertainty. Many previous studies have used the U.S. climate policy uncertainty index as a proxy for climate policy uncertainty in China in their empirical analyses^[33,35,51]. However, this approach overlooks key differences between the two countries in terms of climate policy making processes, stakeholders involvement, and political dynamics, which may compromise the validity and rigor of their findings. To address this limitation, this paper follows the approaches of Sun, et al.^[52], Hu^[53], and Ma, et al.^[54], who construct the CPU index based on news articles from six major domestic media outlets: People's Daily, Guangming Daily, Economic Daily, Global Times, Science and Technology Daily, and China News Service. The index is built using a deep learning algorithm based on the MacBERT model. It effectively captures both the timing and intensity of significant climate policy announcements made by the Chinese government. A higher CPU value indicates a greater degree of climate policy uncertainty.

3.2.3 Control Variables

To effectively identify the impact of climate policy uncertainty on bank systemic risk, this paper draws on the methodologies of Borri and Di^[55], Wu, et al.^[56], Zhao and Guo^[25], Liu, et al.^[10], while controlling for bank characteristic variables and macroeconomic factors that may affect bank systemic risk, including: 1) loan-to-deposit ratio (LDR), the ratio of total bank loans to total deposits; 2) cost-to-income ratio (CIR), the ratio of a bank's operating costs to its operating income; 3) return on equity (ROE), the ratio of net profit to owner's equity; 4)

bank size (SIZE), the natural logarithm of the bank's total assets; 5) net interest margin (NIS), the ratio of net interest income to total assets; 6) non-interest income ratio (NII), the ratio of non-interest income to net operating income; 7) GDP growth rate (GDPR), GDP growth rate year-on-year; 8) inflation rate (CPI), the year-on-year growth rate of the price index; 9) deposit-reserve ratio (RD), the reserve ratio for deposits of large financial institutions.

3.3 Sample

This paper employs an unbalanced annual panel dataset of 36 Chinese listed banks spanning the period from 2008 to 2022 as the research sample. The sample includes six state-owned banks, nine joint-stock banks, thirteen urban commercial banks, and eight rural commercial banks. Market return data, bank financial information, and control variables are primarily sourced from the Wind database, CSMAR database, the National Bureau of Statistics, and the People's Bank of China. Data on the independent variable, climate policy uncertainty, are obtained from the International Institute for Energy Transition's Energy Finance Committee (IEFN) website. To mitigate the influence of extreme values, all continuous variables are winsorized at the top and bottom 1% levels.

3.4 Descriptive Statistics

The descriptive statistics of the variables are presented in Table 1. The mean value of ΔCoVaR is 1.734, with a minimum of 0.465, a maximum of 4.651, and a standard deviation of 0.819. These statistics indicate substantial variation in banks' contributions to systemic risk. For the climate policy uncertainty index (CPU), the minimum value is 1.363, the maximum is 3.2, the mean is 2.461, and the standard deviation is 0.447. These results suggest frequent adjustments in climate policies and a consistently high level of policy uncertainty.

Table 1 Description of main variables and descriptive statistics

Variable name	Variable symbol	Sample size	Mean value	Standard deviation	Minimum value	Median	Maximum value
Bank systemic risk	ΔCoVaR	345	1.734	0.819	0.465	1.523	4.651
Climate policy uncertainty	CPU	345	2.461	0.447	1.363	2.341	3.200
Loan-to-deposit ratio	LDR (%)	345	76.572	12.781	49.820	74.150	111.233
Cost-income ratio	CIR (%)	345	30.731	5.568	21.520	29.910	56.570
Return on equity	ROE (%)	345	14.226	4.612	6.229	13.231	25.899
Bank size	SIZE	345	28.390	1.548	25.360	28.492	31.155
Net interest margin	NIS (%)	345	2.223	0.400	1.370	2.200	3.327
Percentage of non-interest income	NII (%)	345	22.688	8.660	7.052	22.050	44.233
Economic growth rate	GDPR (%)	345	6.682	2.407	2.239	6.947	10.636
Inflation rate	CPI (%)	345	2.309	1.319	-0.683	2.125	5.900
Deposit reserve ratio	RD (%)	345	15.284	3.253	11.000	15.500	21.000

4 Empirical Results

4.1 Baseline Regression Result

Table 2 presents the baseline regression results examining the effect of climate policy uncertainty on bank systemic risk. Columns (1) to (3) display the regression outcomes for three model specifications: without control variables, with bank-level control variables only, and with all control variables included, respectively. As shown in Table 2, the coefficients of CPU are significantly negative at the level of 1% across all specifications. This finding supports Hypothesis 1, indicating that CPU can significantly reduce bank systemic risk. A potential explanation for this result is that under conditions of climate policy uncertainty, banks tend to strengthen

Table 2 Baseline regression results: The impact of climate policy uncertainty on bank systemic risk

Variable	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR
CPU	−0.903*** (0.073)	−0.639*** (0.051)	−0.734*** (0.114)
LDR		−0.007 (0.005)	−0.024*** (0.005)
CIR		0.001 (0.012)	−0.039** (0.015)
ROE		−0.055*** (0.014)	−0.013 (0.020)
SIZE		−0.584*** (0.152)	−0.481*** (0.117)
NIS		0.681*** (0.144)	0.487*** (0.160)
NII		0.025*** (0.006)	0.018** (0.007)
GDP			0.078*** (0.020)
CPI			0.037** (0.017)
RD			−0.144*** (0.018)
Constant	3.955*** (0.180)	19.109*** (4.474)	20.521*** (3.607)
Individual fixed effect	Yes	Yes	Yes
N	345	345	345
R^2	0.300	0.450	0.572
Adj R^2	0.298	0.439	0.559

Note: ***, ** and * indicate significant at 1%, 5% and 10% levels, respectively, with robust standard errors in brackets. The same below.

their risk management. Specifically, they may enhance climate risk assessment of their asset portfolios and reduce lending to high-carbon emitting industries to mitigate exposure to risk. At the same time, banks may promote green financial innovation by developing products such as green bonds and sustainable investment funds, directing capital toward environmentally friendly and sustainable sectors. These actions can help diversify risks and improve the overall stability of bank assets. Furthermore, regulators may respond to climate policy uncertainty by imposing stricter regulatory requirements. This can lead to improved transparency and risk disclosure by banks, thereby reducing information asymmetry in the market. As a result, investors and other stakeholders can better assess risks and adjust their investment strategies accordingly, which contributes to a decline in systemic risk within the banking sector.

4.2 Endogeneity

Climate policy uncertainty represents an exogenous policy impulse unlikely to be affected by bank systemic risk, and therefore does not logically exhibit a bidirectional causal relationship with it. To address potential endogeneity arising from measurement error and omitted variable bias, this study employs the instrumental variable approach. Following Mo and Liu^[57] and Huang, et al.^[58], this paper uses the U.S. climate policy uncertainty index (ACPU), constructed by Gavriilidis^[59], as an instrumental variable. Given that climate change is a global phenomenon and that there is international coordination in climate policy formulation, a strong correlation exists between China's and the U.S.'s climate policy uncertainty. At the same time, U.S. climate policy uncertainty is unlikely to have a direct impact on the stability of China's banking system. Therefore, the ACPU satisfies both the relevance and exogeneity conditions required of a valid instrumental variable.

Columns (1) and (2) of Table 3 present the regression results from the first and second stages of the endogeneity test, respectively. As shown in column (1), the U.S. climate policy uncertainty index (ACPU) is significantly and positively correlated with the Chinese climate policy uncertainty index (CPU), indicating that the instrumental variable has strong explanatory power for the endogenous regressor. The coefficient of CPU in column (2) remains significantly negative at the 1% significance level, which is consistent with the baseline regression results. This finding suggests that the main results of the paper are robust. Furthermore, the instrumental variable passes a series of diagnostic tests. The *p*-value of the Kleibergen-Paap rk LM statistic is less than 0.01, indicating no under-identification of the instrumental variable. In addition, the Cragg-Donald Wald *F* statistic is 11.278, exceeding the conventional threshold of 10, which implies that there is no issue of weak instruments. These results collectively confirm the validity of the selected instrumental variable.

4.3 Robustness Test

To further assess the robustness of the basic regression results, this study conducts additional tests by substituting both the dependent variable and independent variable and adjusting the sample period. The corresponding results are reported in Table 4.

Table 3 Endogenous processing: Instrumental variable method 2SLS regression results

Variable	(1) CPU	(2) ΔCoVaR
ACPU	0.002*** (0.000)	
CPU		-8.309*** (1.602)
LDR	0.003 (0.002)	0.017 (0.020)
CIR	-0.027*** (0.005)	-0.227*** (0.051)
ROE	-0.032*** (0.011)	-0.253*** (0.090)
SIZE	0.676*** (0.056)	5.144*** (1.273)
NIS	0.012 (0.089)	0.400 (0.628)
NII	0.005* (0.003)	0.040* (0.021)
GDPR	0.164*** (0.003)	1.308*** (0.265)
CPI	0.032*** (0.007)	0.370*** (0.093)
RD	0.052*** (0.006)	0.119 (0.082)
Individual fixed effect	Yes	Yes
N	345	345
Centered R^2		-3.161
Kleibergen-Paap rk LM		10.719***
Cragg-Donald Wald F		11.278

4.3.1 Replace the Dependent Variable

To address potential bias in the regression coefficients arising from the choice of variable measurement, this study employs alternative indicators of bank systemic risk: MES, SRISK, and quantile CoVaR ($\Delta\text{CoVaR}_{\text{quant}}$)^[60,61]. As presented in columns (1) to (3) of Table 4, the estimated coefficients of climate policy uncertainty remain significantly negative across all alternative measures. These results are consistent with the findings from the baseline regression model, confirming the robustness of the main findings.

Table 4 Robustness test

Variable	(1) MES	(2) SRISK	(3) $\Delta\text{CoVaR}_{\text{quant}}$	(4) ΔCoVaR	(5) ΔCoVaR
CPU	-0.442** (0.198)	-1.329* (0.734)	-0.426*** (0.112)		-1.191*** (0.296)
N_CPU				-1.558*** (0.260)	
LDR	-0.049*** (0.006)	-0.021 (0.027)	-0.032*** (0.004)	-0.019*** (0.006)	-0.015* (0.007)
CIR	-0.018 (0.017)	-0.064 (0.049)	-0.008 (0.011)	-0.016 (0.013)	-0.039 (0.024)
ROE	-0.006 (0.031)	0.050 (0.064)	-0.024 (0.016)	0.032 (0.026)	0.017 (0.019)
SIZE	-0.876*** (0.289)	0.817* (0.422)	-0.301 (0.189)	-0.586*** (0.114)	-0.429* (0.223)
NIS	0.907*** (0.251)	-0.515 (0.582)	0.583*** (0.150)	0.333* (0.186)	0.381*** (0.115)
NII	0.032*** (0.009)	-0.016 (0.020)	0.018*** (0.005)	0.002 (0.007)	0.010 (0.009)
GDPR	0.010 (0.039)	0.278** (0.119)	0.063*** (0.022)	-0.076*** (0.009)	-0.013 (0.055)
CPI	-0.011 (0.032)	0.063 (0.239)	-0.018 (0.018)	0.066*** (0.018)	-0.163*** (0.027)
RD	-0.186*** (0.028)	-0.073 (0.077)	-0.095*** (0.018)	-0.195*** (0.017)	-0.156*** (0.015)
Constant	33.002*** (8.192)	-12.089 (13.779)	13.598** (5.377)	29.580*** (3.257)	20.990** (6.350)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
N	345	345	345	345	209
R^2	0.537	0.066	0.512	0.586	0.253
Adj R^2	0.523	0.038	0.497	0.573	0.215

4.3.2 Alternate the Independent Variable

This study redefines the measurement of climate policy uncertainty by adopting the methodology of Gavriilidis^[59], and constructing a new climate policy uncertainty index (N_CPU) based on articles from China Economic Daily, Guangming Daily, and People's Daily. This revised index serves as an alternative indicator. The regression results are presented in column (4) of Table 4. The coefficient of climate policy uncertainty remains significantly negative at the 1% significance level, confirming the robustness of the findings.

4.3.3 Adjust Sample Interval

To exclude the potential influence of major macroeconomic shocks, specifically the global financial crisis and the COVID-19 pandemic, on bank systemic risk, this study removes bank observations from the periods 2008–2009 and 2020–2022. The regression results are shown in column (5) of Table 4. The coefficient of climate policy uncertainty remains significantly negative at 1% significance level, consistent with the benchmark regression findings.

5 Further Analysis

5.1 Influence Channel

Building on the previous theoretical analysis, this study aims to test whether climate policy uncertainty reduces bank systemic risk through three potential channels: increasing capital adequacy, decreasing leverage, and reducing loans to high-carbon industries. To examine these mediating mechanisms, the paper follows Jiang^[62] and employs a two-step mediation model for empirical verification:

$$\Delta \text{CoVaR}_{i,t} = \gamma_0 + \gamma_1 \text{CPU}_t + \gamma_2 \sum \text{Controls}_{i,t} + \mu_i + \varepsilon_{i,t}, \quad (7)$$

$$M_{i,t} = \beta_0 + \beta_1 \text{CPU}_t + \beta_2 \sum \text{Controls}_{i,t} + \mu_i + \varepsilon_{i,t}. \quad (8)$$

Among them, Eq. (8) is consistent with baseline regression Eq. (1), and the mediator variables $M_{i,t}$ are capital adequacy level (CAR), leverage level (LEV), and the share of loans in high carbon industries (HCLoan). The capital adequacy level (CAR) is defined as a ratio of net capital to total assets. Following Xu, et al.^[63], this study uses the asset-liability ratio as a proxy for the leverage level (LEV), calculated as the ratio of total liabilities to total assets. For the share of loans to high-carbon industries (HCLoan), this study following the classification in Deng, et al.^[64], which identifies mining, manufacturing, construction, electricity, heat, gas and water production and supply, and transportation, storage and postal services as high-carbon sectors. This indicator is constructed by calculating the proportion of a bank's total loans allocated to these industries relative to its overall loan portfolio. μ_i is the fixed effect of individual banks and $\varepsilon_{i,t}$ is the regression residual term.

Table 5 presents the results of the mediation analysis examining the channels through which climate policy uncertainty affects bank systemic risk. Columns (2) to (4) report the estimated mediation effects for the capital adequacy level (CAR), leverage level (LEV), and the share of loans to high-carbon industries (HCLoan), respectively.

Column (2) of Table 5 shows that the coefficient of CPU is significantly positive at the 1% significance level, indicating that climate policy uncertainty substantially enhances banks' capital adequacy levels. Capital adequacy serves as a key mechanism for banks to mitigate financial risks. It not only contributes to a bank's own operational stability but also influences the resilience of the broader banking system. Under conditions of climate policy uncertainty, high-emission firms are particularly vulnerable to frequent policy changes. For instance, stricter emission regulations or carbon taxation may raise operating costs and reduce profitability for

these firms, impairing their ability to repay loans. This increases the likelihood of credit losses and asset depreciation for banks, prompting them to strengthen their capital adequacy ratios. Furthermore, higher capital adequacy implies that banks hold larger capital buffers, enabling them to maintain solvency and operational stability in the face of widespread corporate defaults and asset value volatility^[65]. This buffer effect can mitigate the spread of systemic risk, thereby reducing overall bank systemic risk. These findings support Hypothesis 2.

Column (3) of Table 5 shows that the coefficient of CPU is significantly negative at the 1% significance level, indicating that climate policy uncertainty substantially reduces banks' leverage levels. An increase in a bank's leverage level implies greater credit expansion, which in turn raises its risk exposure^[37]. Therefore, as climate policy uncertainty increases, banks tend to adjust their capital structure and improve asset quality by lowering leverage level. Specifically, they reduce investments in high-risk assets tied to high-carbon industries and redirect credit and investment toward green, clean and sustainable sectors. This shift helps mitigate credit loss risks and enhances the banks' resilience to financial stress. Moreover, high leverage indicates a strong reliance on debt financing, making banks more vulnerable to frequent changes in climate policy. By reducing leverage, banks can decrease their dependence on debt capital and avoid liquidity risks associated with investors' withdrawals driven by concerns over credit quality. This adjustment helps prevent the spread of systemic risk within the banking system. These results support Hypothesis 3.

Column (4) of Table 5 reports a significantly negative regression coefficient for CPU at the 1% significance level, indicating that climate policy uncertainty substantially reduces the share of banks' loans to high-carbon industries. In an environment of heightened climate policy uncertainty, a large exposure to high-carbon sectors can harm banks' credit asset quality and profitability. As a result, banks proactively reduce their loan allocations to these industries in order to limit exposure to climate transition risks and maintain operational stability. Furthermore, reducing lending to high-carbon industries can effectively mitigate risk transmission arising from industry concentration and interconnectivity, thereby curbing the buildup of systemic financial risk. Additionally, such actions may signal to the market that banks are actively managing climate-related risks, which can enhance investor confidence, lower the likelihood of liquidity crises, and prevent broader financial instability. These findings support Hypothesis 4.

5.2 The Moderating Effect of Carbon Emission Reduction

To examine the moderating effect of carbon emission reduction effect on the relationship between climate policy uncertainty and bank systemic risk, this study employs carbon emission intensity reduction (CO₂ Reduction) as a measure of the carbon emission reduction effect². A decline in carbon emission intensity refers to a reduction in carbon intensity within a given year compared to the previous year (carbon emission intensity = total CO₂ emission/GDP). A larger

²Data source: <https://iea.blob.core.windows.net/assets/3c8fa115-35c4-4474-b237-1b00424c8844/CO2Emissionsin2022.pdf>.

Table 5 Test of influence channels: Regression results of the mediation effect model

Variable	(1) ΔCoVaR	(2) CAR	(3) LEV	(4) HCLoan
CPU	-0.734*** (0.114)	1.984*** (0.353)	-0.617*** (0.198)	-0.033*** (0.012)
LDR	-0.024*** (0.005)	-0.018 (0.020)	-0.029** (0.011)	-0.002** (0.001)
CIR	-0.039** (0.015)	-0.076 (0.052)	0.044* (0.023)	0.005*** (0.001)
ROE	-0.013 (0.020)	-0.103** (0.046)	0.120*** (0.035)	-0.003** (0.001)
SIZE	-0.481*** (0.117)	-1.614*** (0.450)	0.501 (0.364)	-0.002 (0.016)
NIS	0.487*** (0.160)	0.160 (0.337)	-0.497*** (0.173)	0.032** (0.015)
NII	0.018** (0.007)	-0.011 (0.014)	-0.012 (0.008)	-0.000 (0.001)
GDPR	0.078*** (0.020)	-0.285*** (0.071)	0.098* (0.040)	0.006** (0.002)
CPI	0.037** (0.017)	0.095 (0.057)	0.004 (0.032)	0.004** (0.001)
RD	-0.144*** (0.018)	-0.219*** (0.059)	0.023 (0.030)	0.007*** (0.002)
Constant	20.521*** (3.607)	64.442*** (14.705)	79.689*** (10.511)	0.220 (0.481)
Individual fixed effect	Yes	Yes	Yes	Yes
N	345	345	345	345
R^2	0.572	0.545	0.718	0.822
Adj R^2	0.559	0.532	0.710	0.817

decline indicates a more pronounced reduction in carbon emissions. The following moderating effect model is constructed:

$$\Delta\text{CoVaR}_{i,t} = \delta_0 + \delta_1\text{CPU}_t + \delta_2\text{CO}_2\text{Reduction}_t + \delta_3\text{CPU}_t \times \text{CO}_2\text{Reduction}_t + \delta_4 \sum \text{Controls}_{i,t} + \mu_i + \varepsilon_{i,t}. \quad (9)$$

To address potential multicollinearity arising from the inclusion of interaction terms, this study applies a mean-centering procedure. The results of the moderating effect analysis for carbon emission reduction are presented in Table 6. As shown, the coefficient of the interaction term $\text{CO}_2 \text{ Reduction} \times \text{CPU}$, which captures the joint effect of climate policy uncertainty and the magnitude of decline in carbon emission intensity, is significantly negative at the 1% significance level. The results indicate that an improvement in carbon emission reduction strengthens

Table 6 Moderation effect and nonlinear effect

Variable	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR
CPU	-0.934*** (0.073)	-5.128*** (0.135)	-5.014*** (0.449)	-4.055*** (0.499)
CO ₂ Reduction $\times$ CPU	-16.862*** (1.708)			
CO ₂ Reduction	1.214 (0.845)			
CPU ²		0.887*** (0.032)	0.888*** (0.087)	0.711*** (0.112)
LDR	-0.006 (0.005)		-0.015*** (0.004)	-0.024*** (0.005)
CIR	-0.028*** (0.010)		-0.031*** (0.012)	-0.041*** (0.014)
ROE	0.012 (0.015)		-0.037** (0.015)	-0.010 (0.019)
SIZE	0.209* (0.112)		-0.277** (0.115)	-0.363*** (0.103)
NIS	0.197** (0.094)		0.649*** (0.135)	0.420** (0.162)
NII	-0.001 (0.006)		0.020*** (0.006)	0.015** (0.007)
GDPR	0.045* (0.022)			0.012 (0.022)
CPI	-0.186*** (0.020)			0.087*** (0.021)
RD	-0.101*** (0.019)			-0.087*** (0.014)
Constant	-1.710 (3.501)	8.804*** (0.137)	17.142*** (3.265)	20.577*** (3.304)
Individual fixed effect	Yes	Yes	Yes	Yes
<i>N</i>	345	345	345	345
<i>R</i> ²	0.666	0.425	0.536	0.584
Adj <i>R</i> ²	0.654	0.422	0.524	0.571

the negative effect of climate policy uncertainty on bank systemic risk. Enhanced carbon emission reduction can boost investor confidence in the government's capacity to manage climate governance, stabilize market expectations, and reduce valuation fluctuations in banks' climate-sensitive assets caused by herd behavior in the stock market. At the same time, better carbon emission reduction outcomes often lead to stricter climate regulations, which encourage banks

to reduce exposure to high-carbon assets and increase green investments as a hedge against transition risks. Furthermore, improved carbon emission performance can lower the likelihood of extreme weather events, enhance corporate repayment capabilities, reduce bank loan losses, and ultimately strengthen banking system stability. These findings support Hypothesis 5.

5.3 Nonlinear Effect

To further investigate whether a nonlinear relationship exists between CPU and Δ CoVaR, this paper extends the analysis by re-estimating Eq. (1) with the inclusion of a quadratic term for climate policy uncertainty (CPU^2). The revised model is specified as follows:

$$\Delta\text{CoVaR}_{i,t} = \eta_0 + \eta_1\text{CPU}_t + \eta_2\text{CPU}_t^2 + \eta_3 \sum \text{Controls}_{i,t} + \mu_i + \varepsilon_{i,t}. \quad (10)$$

In this model, we assess whether a U-shaped or inverted U-shaped relationship exists between CPU and Δ CoVaR, based on the statistical significance and sign of η_1 and η_2 .

The results of the nonlinear tests are presented in columns (2) to (4) of Table 6. As shown, regardless of whether micro-level or macro-level control variables are included, the regression coefficient of CPU remains significantly negative, while the coefficient of CPU^2 is consistently and significantly positive. This pattern suggests a U-shaped relationship between CPU and ΔCoVaR , indicating that the effect of CPU on ΔCoVaR initially decreases and then increases. To further validate this U-shaped relationship, we employ the three-step U-test procedure proposed by Lind and Mehlum^[66], the results of which are reported in Table 7. The estimated slope on the left side of the curve is negative, while the slope on the right side is positive. These slopes show opposing directions and statistical significance, which is consistent with the characteristics of a U-shaped relationship. The inflection point is estimated at 2.853, which lies within the observed sample range [1.363, 3.200]. Moreover, the overall U-test is significant at the 5% level, further supporting the presence of a U-shaped association between CPU and ΔCoVaR . Specifically, when CPU is below 2.853, an increase in CPU is associated with a reduction in ΔCoVaR ; however, once this threshold is exceeded, the effect becomes positive, thereby confirming Hypothesis 6.

When CPU is low, banks can promptly adjust their strategic direction in response to clear policy guidance, reduce exposure to high-carbon assets, and increase support for green finance. These actions enhance their risk resilience and reduce the likelihood of systemic risk. However,

Table 7 U-test results

Indicator	Lower bound	Upper bound
Slope	-2.117***	0.493**
<i>t</i> -value	-10.167	2.025
Interval	1.363	3.200
Extremum point	2.853	
Return sample interval	[1.363, 3.200]	
Overall inspection level	$t = 2.03^{**}$ ($p = 0.025$)	

when CPU rises to a high level, banks face increased uncertainty regarding future policy directions, leading to hesitation or biased decision-making. This uncertainty intensifies credit and market risks, which can propagate through credit networks and evolve into systemic risk. At the same time, fluctuations in market sentiment driven by CPU may encourage herd behavior, further amplifying stock price volatility and corporate default risks. These risks are transmitted to the banking system through multiple channels, such as credit markets, capital markets, and liquidity conditions, thereby further intensifying systemic risks.

5.4 Bank Heterogeneity Analysis

5.4.1 Heterogeneity of Bank Property Rights

To examine whether the effects of climate policy uncertainty on bank systemic risk vary depending on ownership type, the sample is divided into state-owned banks and non-state-owned banks, with separate regressions conducted for each group. The results are reported in columns (1) and (2) of Table 8. It is evident that climate policy uncertainty exerts a more pronounced dampening effect on systemic risk in non-state-owned banks. This heterogeneity may be attributed to several factors. Compared to non-state-owned banks, state-owned banks often benefit from implicit government guarantees and possess greater market power^[67]. Prior to climate policy adjustments, they typically maintain higher capital reserves and stronger risk-resistance capabilities. As a result, they can respond more swiftly to policy changes, which mitigates the impact of climate policy uncertainties. In contrast, non-state-owned banks are more sensitive to market volatility and investor sentiment, making them more vulnerable to such uncertainties. This also suggests that these banks have greater potential to reduce systemic risk through proactive measures. Moreover, non-state-owned banks tend to place a higher emphasis on maintaining their reputation and ensuring a stable business environment in order to secure continuous financial support. Consequently, they are more likely to implement preventive measures and risk management strategies, resulting in a more pronounced reduction in systemic risk.

5.4.2 Heterogeneity of Bank Size

To examine the heterogeneity by bank size, this study categorizes banks into large and small based on the mean value of total assets, with separate regressions conducted for each group. The results are presented in columns (3) and (4) of Table 8. The findings show that for large banks, the coefficient of CPU is significantly negative at the 1% level, whereas for small banks, the coefficient remains negative but is not statistically significant. This suggests that climate policy uncertainty has a more pronounced dampening effect on systemic risk in large banks compared to small banks. A possible explanation is that large banks typically have more diversified funding sources, broader business operations, and higher credit ratings. As a result, they are better positioned to increase capital reserves and liquidity in response to climate policy uncertainty, thereby reducing the likelihood of systemic risk. Additionally, large banks generally possess more advanced and comprehensive risk management systems, enabling

Table 8 Analysis of bank heterogeneity

Variable	(1) ΔCoVaR state-owned	(2) ΔCoVaR non-state	(3) ΔCoVaR large-scale	(4) ΔCoVaR small-scale	(5) ΔCoVaR higher profit	(6) ΔCoVaR lower profit
CPU	-0.763* (0.318)	-0.570*** (0.156)	-0.738*** (0.157)	-0.146 (0.175)	-0.973*** (0.288)	-0.291 (0.204)
LDR	0.018 (0.044)	-0.026*** (0.005)	-0.021*** (0.007)	-0.007 (0.009)	-0.026** (0.010)	-0.009 (0.006)
CIR	-0.064 (0.105)	-0.043*** (0.014)	-0.073** (0.027)	-0.057** (0.026)	-0.075** (0.027)	-0.013 (0.017)
ROE	-0.156** (0.049)	-0.002 (0.023)	-0.064** (0.025)	-0.039* (0.019)	-0.042 (0.025)	0.051* (0.030)
SIZE	-2.287** (0.740)	-0.594*** (0.127)	-1.371*** (0.202)	-0.786*** (0.225)	-0.322 (0.301)	-0.988*** (0.299)
NIS	1.126 (0.690)	0.273* (0.139)	0.819** (0.287)	0.036 (0.225)	0.765** (0.312)	0.059 (0.178)
NII	0.028 (0.019)	0.012 (0.008)	0.034*** (0.007)	-0.001 (0.012)	-0.001 (0.020)	0.002 (0.006)
GDPR	0.043 (0.054)	0.057** (0.026)	0.047 (0.030)	-0.009 (0.029)	0.013 (0.093)	0.023 (0.041)
CPI	-0.035 (0.034)	0.051*** (0.017)	-0.084** (0.036)	0.093*** (0.022)	0.058** (0.026)	0.069 (0.074)
RD	-0.041* (0.018)	-0.170*** (0.024)	-0.114*** (0.015)	-0.169*** (0.026)	-0.188*** (0.044)	-0.169*** (0.022)
Constant	73.399** (24.023)	24.229*** (3.925)	47.980*** (6.233)	28.320*** (6.158)	19.786* (10.164)	32.480*** (8.463)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	77	268	185	160	151	194
R^2	0.637	0.588	0.496	0.630	0.591	0.588
Adj R^2	0.582	0.572	0.467	0.605	0.562	0.566

them to promptly monitor and assess various risks associated with climate policy uncertainty. This allows for timely implementation of risk mitigation strategies, thus helping to prevent the emergence of systemic risk.

5.4.3 Heterogeneity of Bank Profitability

To explore the heterogeneity in bank profitability, this study categorizes banks into high-profitability and low-profitability groups based on the mean return on equity. Separate regressions are conducted for each group. The results are presented in columns (5) and (6) of Table 8. It is evident that, in the high-profitability group, the regression coefficient of CPU is sig-

nificantly negative at the 1% level. In contrast, the coefficient of CPU remains negative but is not statistically significant in the low-profitability group. These findings suggest that climate policy uncertainty exerts a more pronounced dampening effect on systemic risk in highly profitable banks compared to less profitable ones. A possible explanation is that banks with higher profitability typically maintain stronger capital and liquidity positions, enabling them to better withstand the adverse impacts of climate policy uncertainty. Furthermore, such banks often enjoy a stronger market reputation and institutional standing, which fosters greater confidence among customers and investors in their ability to manage regulatory and policy changes. This helps reduce credit and liquidity risks associated with climate policy uncertainty. In addition, highly profitable banks generally have more diversified business structures, allowing them to spread climate-related risks across different sectors and activities. This diversification facilitates effective risk balancing and control, thereby enhancing overall banking system stability.

5.4.4 Heterogeneity of Banks' Green Credit Operations

To examine the heterogeneity in banks' green credit operations, this paper categorizes banks based on the mean value of their green credit ratios and conducts separate regressions for banks with high and low green credit allocations. The results are presented in columns (1) and (2) of Table 9. Notably, the regression coefficients for CPU in the case of high green credit allocation banks are significantly negative at the 1% significance level, whereas those for low green credit allocation banks are not statistically significant. This suggests that climate policy uncertainty has a more pronounced dampening effect on systemic risk in banks with higher green credit allocations. A possible explanation for this finding is that banks with substantial green credit portfolios are typically more responsive to climate policies and are better equipped to integrate environmental considerations into their lending decisions. These institutions also tend to possess stronger risk management frameworks. When faced with heightened climate policy uncertainty, such banks can adjust their green asset allocations promptly and develop innovative green financial instruments. By directing credit toward policy-supported sectors such as renewable energy, energy efficiency, and environmental protection, these banks enhance overall asset quality, reduce credit risk exposure and non-performing loan rates. Moreover, diversified investments across sustainable sectors help lower inter-institutional risk correlations, thereby mitigating the buildup and transmission of systemic risk.

5.4.5 Heterogeneity of Banks' Risk Management Capabilities

To examine the heterogeneity in banks' risk management capabilities, this paper uses the non-performing loan (NPL) ratio as a proxy variable for risk management capability. Banks are divided into two groups, those with strong risk management capability and those with weak risk management capability, based on the sample mean of the NPL ratio. Separate regressions are then conducted for each group, with results reported in columns (3) and (4) of Table 9, respectively. In this context, a higher NPL ratio indicates weaker risk management capability, and vice versa. The results indicate that for both banks with strong and weak risk management

Table 9 Analysis of bank heterogeneity

Variable	(1)	(2)	(3)	(4)
	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
	High green credit allocation	Low green credit allocation	Strong risk management capability	Weak risk management capability
CPU	−0.927*** (0.229)	−0.054 (0.133)	−0.686*** (0.214)	−0.427* (0.211)
LDR	−0.032*** (0.010)	−0.016** (0.006)	−0.017 (0.012)	−0.021** (0.008)
CIR	−0.052** (0.019)	−0.021 (0.022)	−0.050** (0.023)	−0.039 (0.029)
ROE	−0.098** (0.038)	0.037* (0.021)	−0.029 (0.030)	−0.028 (0.045)
SIZE	−0.662** (0.271)	−0.530*** (0.177)	−0.592** (0.231)	−1.203*** (0.284)
NIS	1.340*** (0.252)	0.330** (0.157)	0.131 (0.245)	0.717* (0.363)
NII	0.039*** (0.010)	0.007 (0.008)	0.006 (0.013)	0.023** (0.010)
GDPR	0.103** (0.045)	−0.043* (0.024)	0.074* (0.038)	0.022 (0.037)
CPI	−0.057 (0.043)	−0.091 (0.065)	0.069* (0.026)	−0.021 (0.040)
RD	−0.095** (0.038)	−0.107*** (0.032)	−0.143*** (0.037)	−0.130*** (0.031)
Constant	25.818*** (7.887)	19.267*** (5.881)	24.408*** (6.848)	40.470*** (6.602)
Individual fixed effect	Yes	Yes	Yes	Yes
N	112	184	177	168
R^2	0.562	0.212	0.517	0.606
Adj R^2	0.518	0.166	0.488	0.581

capabilities, the CPU regression coefficient is significantly negative. However, the coefficient for banks with strong risk management capabilities is -0.686 , while that for banks with weak risk management capabilities is -0.427 . This suggests that the dampening effect of climate policy uncertainty on systemic risk is more pronounced among banks with stronger risk management capabilities. Banks with robust risk management frameworks typically possess more comprehensive environmental risk assessment systems and a wider array of risk management tools. These institutions are better able to accurately assess the risk exposure and potential losses associated with climate-related assets. In response to climate risks, such banks tend to increase their green

investment portfolios by reducing or avoiding holdings in high-carbon sectors, thereby lowering overall risk exposure. Additionally, their stronger capital buffers and improved disclosure mechanisms further enhance their resilience to shocks, resulting in a more significant dampening effect on systemic risk during periods of policy uncertainty.

6 Discussion

Following Yin, *et al.*^[68], this paper contrasts the existing literature in terms of research perspectives, underlying mechanisms, and analyses of heterogeneity, highlighting its theoretical contributions and practical insights.

Firstly, a significant portion of the existing literature focuses on the impact of climate change on bank systemic risk, largely agreeing that climate change exacerbates such risks^[26–30]. Most of these studies adopt an “outcome-oriented” perspective on climate risk, emphasizing its positive association with systemic risk in the banking sector. This paper extends the current understanding of the relationship between climate risk and financial stability by introducing climate policy uncertainty, an external institutional factor that has not been extensively examined. It reveals that banks are not merely passive recipients of risk during policy shifts but may actively adjust their strategies based on forward-looking risk management to reduce exposure and suppress the accumulation of systemic risk. By doing so, the study offers a new theoretical framework for examining how financial institutions respond behaviorally to uncertain environments. This insight aligns with the findings of Liu, *et al.*^[10], while further refining and expanding upon them in terms of contextual scope and underlying mechanisms.

Secondly, regarding the mechanisms at play, existing studies suggest that climate policy uncertainty reduces bank systemic risk through ESG investments, climate disclosure, and prudent risk-taking strategies^[69]. However, these studies primarily rely on cross-country samples and emphasize common mechanisms under the global convergence of climate policy environments. In contrast, this paper focuses on China’s unique climate policy environment and financial structure, identifying a distinct set of impact pathways. Specifically, within China’s institutional context, banks facing climate policy uncertainty tend to proactively adjust their business structures, for instance, by increasing capital adequacy ratios, reducing leverage, and decreasing credit allocation to high-carbon industries, thereby effectively mitigating the accumulation of systemic risk. This not only enriches the understanding of how climate policy uncertainty affects bank systemic risk but also highlights the critical role of the institutional environment in shaping banks’ green transition paths, offering new analytical insights for future research.

Furthermore, this study incorporates climate governance factors into the analytical framework, revealing their moderating role—a dimension that has received limited attention in prior literature. Moreover, existing studies have primarily focused on the linear relationship between climate policy and economic or financial variables, overlooking the potential for nonlinear effects. This study builds on that foundation by examining the nonlinear relationship between these factors and verifying it through empirical analysis, thereby broadening the scope of re-

search in terms of both perspective and methodology. Regarding heterogeneity analysis, this paper provides an in-depth examination of how climate policy uncertainty differentially affects the systemic risk of various types of banks. This approach offers more targeted risk management recommendations for financial regulators and banking institutions.

7 Conclusion

Using unbalanced panel data from 36 Chinese listed banks over the period 2008 to 2022, this paper examines the impact of climate policy uncertainty on bank systemic risk. The empirical results show that climate policy uncertainty significantly reduces bank systemic risk, a finding that still holds after endogeneity treatment and a series of robustness tests. Further mechanism analysis reveals that climate policy uncertainty dampens bank systemic risk through three key channels: by increasing capital adequacy ratios, reducing leverage levels, and decreasing lending to high-carbon industries. Moreover, a stronger carbon emission reduction effect enhances the negative relationship between climate policy uncertainty and bank systemic risk. It is noteworthy that the effect of climate policy uncertainty on bank systemic risk follows a U-shaped pattern. Heterogeneity analysis shows that the dampening effect is more pronounced in non-state-owned banks, large banks, banks with stronger profitability, higher green credit allocation, and better risk management capabilities.

8 Implications

Based on the aforementioned findings, this paper proposes three implications:

Firstly, banks should enhance their monitoring and assessment of climate risks and related policy uncertainties, establishing robust climate information disclosure mechanisms. By closely tracking climate policy adjustments and changes, banks can promptly identify potential risks and opportunities, enabling more informed investment and financing decisions. Additionally, timely disclosure of climate-related information to the market and investors can guide support for and investment in low-carbon industries and related technologies, fostering green finance development and minimizing bank losses while avoiding systemic risk.

Secondly, financial regulators should intensify supervision of the banking sector to mitigate the impact of climate policy uncertainty. This includes requiring banks to increase capital reserves by raising capital adequacy levels, optimizing asset quality through reduced leverage, and decreasing credit investments in high-carbon industries. Regulators should also formulate climate risk management strategies and conduct regular risk assessment and stress tests. These measures will improve banks' awareness of prevention and resilience against risks, reducing the adverse impacts of climate policy uncertainty and curtailing the spread of risks throughout the financial system.

Thirdly, governments should incentivize banks to extend credit support for climate protection projects to facilitate carbon reduction. Through financial subsidies and loan guarantees, governments can encourage banks to offer credit services such as green loans, green bond financ-

ing and credit guarantees. Such support would target emerging low-carbon technology research and development, green infrastructure construction, ecological environmental protection, and disaster prevention and control projects. This approach aims to reduce the occurrence of extreme climate events at their source and prevent negative repercussions on the real economy and financial institutions.

9 Limitations and Future Research Directions

This study has certain limitations. The current sample is restricted to listed banks and excludes non-listed banks and other financial institutions. Future research should expand the sample to include a broader range of financial entities, including different types of banks and non-bank financial institutions, to better assess how climate policy uncertainty affects financial system stability. Moreover, greater attention should be given to the growing role of digital technologies in this area^[66]. Tools such as big data analytics and artificial intelligence offer promising avenues for accurately assessing and managing climate-related financial risks. Exploring how these technologies can assist various financial institutions in responding to climate policy uncertainty could yield valuable insights into enhancing the resilience of the financial system as a whole.

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