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Does Climate Policy Uncertainty Affect Bank Systemic Risk?-Empirical Evidence from China

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ABSTRACT

This study explores the impact of climate policy uncertainty (CPU) on the systemic risk of Chinese listed banks. We calculate China's CPU index from 2010 to 2022 through text analysis of newspaper articles. Using data from 42 listed banks, we document that CPU increases bank systemic risk and this impact is heterogeneous. Moreover, external shocks exacerbate the impact, while robust internal indicators and strong financial regulation reduce it. Further analysis indicates that this effect is nonlinear. This study provides several new aspects to enrich the understanding of this impact, thereby providing more comprehensive ideas for policymakers to ensure bank stability.

KEYWORDS

Climate policy uncertainty; banking; systemic risk; external risk events

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D81; G21; G28

1. Introduction

The industrialization of the global economy has resulted in the frequent occurrence of extreme natural disasters, which have significantly affected human economic activities. In response, worldwide organizations have proposed agreements for climate risk governance. These agreements aim to address the "green swan" risks1 caused by climate change. In this context, China has proposed Chinese solutions to issues of climate governance. The most recent national conference made clear that the promotion of green development and the harmonious coexistence of humans and nature are essential components of the Chinese model of modernization. The conference also proposed many major tasks, including the active promotion of carbon peaking and carbon neutrality. However, achieving this target will entail a profound and widespread systemic change in the economy and society; more policy considerations are needed to balance the impact on the economy and financial system. Climate policies exceeding expectations and the credibility of climate policies are uncertain factors that may act as transition risks, bringing uncertainty shocks to the banking system and even the financial system.

In particular, this transition risk may affect banks in the following ways. First, the uncertainty of climate policies may affect market expectations for assets in the energy, environmental, and industrial sectors, causing price fluctuations in assets held by banks and bringing direct risks. Second, China's resource endowment of "rich coal, lack of oil, and little gas" makes traditional industries high-carbon. The implementation of carbon-constrained policies will result in a reduction in the demand for fossil fuels, giving rise to the problem of "stranded assets" (McGlade and Ekins 2015; Zhang et al. 2023). Banks have cross-shareholding and credit connections with carbon-intensive industries, and this risk may be transmitted in a circular feedback manner, forming a climate Minsky moment.

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In accordance with contemporary financial theory, banks occupy a pivotal role in financial markets. Consequently, they are inevitably affected by climate policy uncertainty (CPU). However, the impact of this uncertainty on other financial sectors will also extend to banks. Therefore, it is of considerable theoretical and practical significance to study the impact of CPU on banks' systemic risk at the macro level.

In light of the frequent occurrence of extreme climate events and China's urgent need to achieve the "dual carbon" goals[2], a substantial body of literature has focused on climate finance, exploring the economic consequences of climate policies. According to this literature, climate risks can be divided into two categories: "physical" and "transition"[3]. The impact of climate policies on banks is primarily manifested through transition risks (Johannes and Jeffrey 2021). Zhang, Zhang, and Lu (2022) employed a network analysis to investigate the relationship between climate change and bank stability from the perspective of low-carbon transition. They revealed that low-carbon transition encourages banks to rely more on new energy industries than traditional energy industries. In the analysis of the risks associated with low-carbon transition, Diluiso et al. (2021) concluded that green quantitative easing policies can effectively stimulate the economy, while the decarbonization of bank balance sheets can reduce the losses incurred during financial crises. In response to the transition risk, countries generally formulate sustainable development policies. However, there lies significant uncertainty in the implementation of these policies, which may lead to opposite economic consequences. Golub et al. (2018) found that CPU greatly hinders investment in low-carbon technologies, making it more difficult for enterprises to disperse the systemic risks of increasing future emission expenditures. Gavrililidis (2021) proposed a measurement index for CPU based on text analysis, thereby providing a scientific method for subsequent quantitative research. Bouri, Iqbal, and Klein (2022) were the first to apply this indicator to empirical research on stock prices, revealing that CPU has a significant impact on asset pricing, investment strategies, and asset allocation in the capital market.

However, in comparison with the extensive literature on the economic consequences of climate policies, research on the consequences borne by individual banks is scarce. Furthermore, there is a paucity of research on bank systemic risk (BSR) under climate policies, which leaves us with limited understanding of the influence mechanism. In fact, climate policy risks are currently one of the most significant factors affecting bank stability. Consequently, there is an asymmetry between academic research and economic reality. Only Dai and Zhang (2023) apply the panel data of banks in China to discuss the association between CPU and the risks taken by banks. Their findings indicate that CPU significantly lowers banks' active and passive risks and raises their insolvency risks. However, the relationship between economic policy uncertainty and BSR has been extensively studied. Duan, Fan, and Wang (2022) found that economic policy uncertainty increases the level of BSR, while Lan et al. (2022) reached the opposite conclusion. It would be an interesting topic for further investigation to determine whether CPU also increases BSR.

To achieve this objective, we apply text analysis methods to calculate an index of CPU in China as an explanatory variable. In addition, we adopt the DCC-GARCH-Copula-CoVaR model to measure BSR as an explained variable. Finally, we combine the unbalanced panel data of 42 listed banks in China from 2010 to 2022 to empirically examine the impact of CPU on BSR. The results indicate that CPU increases BSR levels. This conclusion remains valid after controlling for multi-level variables, dealing with endogeneity issues by system generalized method of moments (GMM) techniques and conducting a series of robustness tests. Furthermore, the analysis reveals that CPU has a greater impact on banks in economically underdeveloped regions, banks with shorter ages, banks with lower green transformation degrees, and public banks. In addition, external shocks such as the financial crisis and the COVID-19 pandemic exacerbate this adverse impact, while better bank indicators and stronger financial regulation can reduce the risk. Finally, this study constructs a nonlinear model to further verify the positive correlation between CPU and BSR.

The main incremental contributions of this study are as follows. First, to the best of our knowledge, this is the first study to examine the impact of CPU on BSR in China. Most existing studies focus on the impact of climate risks on economic consequences at the individual level of banks, such as bank liquidity creation (Lee et al. 2022), bank performance (Li and Pan 2022), bank stability (Le, Tran, and Mishra 2023; Shabir et al. 2024), and bank risk-taking (BRT) (Dai and Zhang 2023; Liu, Li, and Sun 2024). Few studies examine banks from a systemic risk perspective. Wu et al. (2023) explored the issue of climate and BSR, but they did not consider the impact of policy uncertainty. Only Liu et al. (2023) examined the relationship between CPU and BSR, but their analysis was not based on emerging market data.

Second, scholars tend to utilize the CPU of the United States as a case study, even when the focus is on China. Furthermore, these studies merely provide descriptive language to outline the construction process (Huo, Li, and Liu 2024; Ren et al. 2024; Sun et al. 2024). In light of this, we employed a text analytical approach based on data extracted from Chinese mainstream newspapers to ascertain the level of uncertainty associated with the country's climate policy. The incremental contribution of this study lies in its detailed elucidation of the process in question through the use of formulas. This may provide valuable reference for subsequent research.

Third, we examine the impact of CPU on BSR from novel perspectives. We investigate the heterogeneity of this influence based on the degree of banks' green transformation. Additionally, we introduce multiple variables, including robust financial supervision, to elucidate the underlying mechanisms. Moreover, we further analyze this impact from a nonlinear perspective. These new aspects enrich our understanding of CPU's impact mechanism on BSR, and provide novel insights for policymakers to ensure bank stability.

This rest of this paper is structured as follows: Section 2 provides the theoretical analysis and hypotheses. Section 3 focuses on the data and methodology employed. Section 4 discusses the main empirical results. Section 5 presents the heterogeneity and other tests. Section 6 summarizes the main findings.

2. Theoretical Analysis and Hypotheses

CPU affects all financial institutions simultaneously, posing a systemic risk that is difficult for banks to circumvent. We posit that CPU affects banks within the economic system through both the policy uncertainty and climate transition risk channels.

CPU is a form of uncertainty that increases BSR by affecting their balance sheet. Policy uncertainty may increase the risk of default in bank loan agreements, leading depositors to consider factors such as the bank's future solvency, which in turn may result in a restriction of investment, thereby producing a "crowding-out effect" on bank deposits (Diamond and Dybvig 1983). Besides, an increase in policy uncertainty may result in associated banks having a lower loan loss provision ratio compared to non-associated banks (Cheng et al. 2021). Additionally, policy uncertainty may increase the risk of bank stock price collapses, thereby increasing the level of systemic risk (Yuan, Zhang, and Lian 2022).

Furthermore, CPU affects the level of BSR through transition risk. In terms of external factors, China's resource endowment in coal has made the economy highly carbon-intensive. As important financial intermediaries, banks have cross-shareholding and mutual investment with traditional energy industries, and these correlations will enable the easy transmission of the asset stranding risk of energy companies to banks (McGlade and Ekins 2015; Zhang et al. 2023). Concurrently, the traditional energy and transportation industries, constrained by carbon emissions pressure, will pursue low-carbon transformation, which will result in increased costs, reduced profits, and the depreciation of related positions held by banks (Johannes and Jeffrey 2021). With regard to internal factors, climate transition risk will elevate BSR through various channels. Climate transition risk will negatively impact bank performance through the channel of inhibiting bank loan scale (Li and Pan 2022). Climate change will significantly increase the level of BSR spillover through asset volatility and credit quality (Wu et al. 2023). Furthermore, climate risk will inhibit bank loan supply and affect the stability of bank operations by reducing bank risk appetite and deposits (Li and Wu 2023). Therefore, we propose the following hypothesis:

H1a: Increased CPU increases the level of BSR.

CPU may also reduce BSR, with typical support coming from the theory of creative destruction. This theory posits that innovation is the continuous internal renewal of economic structures, which entails the destruction of the old and the creation of the new (Aghion, Antonin, and Bunel 2021; Schumpeter 1911). In this theory, policy consists of “creation” and “destruction” elements (Kivimaa and Kern 2016). When the creation element is dominant, it manifests itself in positive effects on banks. Some scholars have put forward ideas consistent with the creation-destruction theory. Liu et al. (2023) find that CPU can reduce BSR by prompting banks to provide more transparent disclosure of climate information and by shifting their investment concepts to a low-carbon economy. Similarly, Li and Wu (2023) argue that active restructuring of credit business and innovation of credit products by commercial banks can enhance the stability of banks under climate risk. Cepni et al. (2023) demonstrate that greater environmental, social, and governance-related investment by banks can enhance the diversification of their portfolios, thereby reducing the adverse impacts of climate policies. Liu, Li, and Sun (2024) illustrate that digital transformation can effectively mitigate the adverse impact of CPU on BRT. Given the argument above, we propose the following hypothesis:

H1b: Increased CPU reduces the level of BSR.

There are significant differences in ownership attributes, geographical location, and customer base among banks. Therefore, the impact of CPU may also vary. For example, large state-owned commercial banks usually have a large market share and sufficient capital reserves, and may require more loan loss provisions as systemically important banks. As such banks also have a national implicit credit guarantee (Zhang and Wang 2020), they have relatively strong risk resistance. In addition, banks in economically underdeveloped regions may have a narrower business scope that relies more on industries supported by traditional energy sources such as coal and oil. In contrast, banks in economically developed regions have a broader business scope, involving more high-technology industries that are less affected by climate risks, thereby ensuring more diversified income. Consequently, the profitability of banks in economically developed regions can be better guaranteed and is more stable (Maghyereh and Yamani 2022). Furthermore, banks with a longer operating history may possess more sophisticated risk management mechanisms and a larger pool of professional and technical talent, enabling them to more effectively navigate external policy risks. In light of this, we propose the following hypothesis:

H2: CPU has a heterogeneous effect on the level of BSR.

3. Methodology

3.1. Data Description and Sources

Since 2010, the Chinese government has formulated a series of climate policies to promote the transformation of economic growth and realize sustainable development. Given the time lag in the impact of climate policies, we have chosen 2010 to 2022 as our sample interval. Listed banks play a significant role in China’s financial system, with their total assets exceeding 265 trillion yuan, accounting for approximately 84% of the total assets of China’s commercial banks and 67% of the listed companies by the end of 2022, according to data released by the China Banking Association. Besides, listed banks have stock market returns through which systemic risks can be measured. Therefore, we selected 42 listed banks, including 6 state-owned banks, 9 joint-stock commercial banks, 17 city commercial banks, and 10 rural commercial banks. In view of the usage of bank financial data in empirical analysis, we set the data frequency at the quarterly level. The stock market returns data and bank financial data are sourced from the CSMAR database (https://data.csmar.com/.) and the macro-level data from the China National Bureau of Statistics (https://www.stats.gov.cn/). In accordance with the conventions of academic research, the data were preprocessed as follows. First, samples with severe missing financial indicators or abnormal indicators were filtered out. Second, we truncated the data to mitigate the adverse impact of outliers on the results. Third, the data were standardized to eliminate the impact of differences in measurement scales. Finally, we obtained an unbalanced data set with 1,270 observations.

3.2. Empirical Model

Linear regression is employed to examine the impact of CPU on BSR, which can be expressed as:

$$RISK_{i,t} = \alpha_0 + \alpha_1 CPU_t + \gamma X_{i,t} + \lambda Y_{i,t} + \eta Z_{i,t} + \mu_i + \varepsilon_{i,t} \quad (1)$$

where the subscripts $i = 1, \ldots, N$and $t = 1, \ldots, T$ represent the bank institutions and time, respectively. $RISK_{i,t}$ is the explained variable, which refers to BSR. CPU_t is the explanatory variable, referring to CPU. The coefficient α_2 indicates the degree of BSR. It is affected by CPU and is expected to have a significantly positive sign. $X_{i,t}, Y_{i,t}, andZ_{i,t}$ represent control variables at the institution, industry, and macro level, respectively, which includes return on equity (*ROE*), quality of earnings (*QOE*), asset liability ratio (*ALR*), loan loss reserve adequacy ratio (*LLRA*), loan-to-deposit Ratio (*LDR*), banking industry prosperity index (*PI*), GDP growth (*GDP*), and M2 growth (*M2*). μ_i refers to the fixed effects for banks and $\varepsilon_{i,t}$ is the residual. Given that the CPU index is a time series indicator, fixing the time effect in equation (1) will result in multicollinearity problems and lead to estimation distortion. Therefore, the model does not fix the time effect. The specific definitions and measurements of all of the variables are provided in Appendix A.

3.3. Descriptive Statistics[4]

Tables 1 present the descriptive statistics of the main variables. As illustrated in Table 1, the standard deviation of BSR during the sample period is 0.8520, with a maximum value of −0.3914 and a minimum value of −4.7642, reflecting individual differences. CPU exhibits a maximum value of 113.7370, a minimum value of 9.6155, and a standard deviation of 26.9664, indicating some fluctuations across quarters. Its median is 27.2917, which is smaller than the mean of 38.3721, suggesting a typical right-skewed distribution. The differences in each control variable are within reasonable limits.

Table 1. Descriptive statistics.

Variable	Mean	P50	SD	Max	Min
Risk	−1.7360	−1.5933	0.8520	−0.3914	−4.7642
CPU	38.3721	27.2917	26.9664	113.7370	9.6155
ROE	9.8828	9.1450	5.3122	24.8000	2.1200
QOE	7.8818	8.4240	2.0015	10.5510	0.5660
ALR	9.2976	9.2970	0.1210	9.6130	9.0300
LLRA	5.5516	5.0185	2.2791	13.0180	2.3624
LDR	7.3392	7.2330	1.3526	10.8700	4.0020
PI	7.1906	7.0400	0.7718	8.7200	5.8300
GDP	2.3120	7.1892	11.8382	19.0626	−29.9085
M2	2.8594	2.6898	1.3545	6.4918	0.9255

Note: In the empirical section, in order to eliminate the adverse effects of the differences in scale, this paper standardizes all the variables in the model. However, given that the mean and standard deviation of each variable tend to be the same after the standardized treatment, the data used in the descriptive statistics are the original data.

4. Empirical Results

4.1. Estimation Results of Primary Model

Table 2 represents the primary model results based on equation (1). From column (1) to column (4), control variables are added by different levels. The estimation results of each column remain stable in the process of stepwise regression, suggesting that the results are valid. The coefficients of the *RISK* terms are all greater than 0 and statistically significant at the 1% level, indicating that the increase in CPU will increase the level of BSR. This supports H1a. This is because CPU can exacerbate BSR through two channels: policy uncertainty (Cheng et al. 2021; Yuan, Zhang, and Lian 2022) and transition risk (McGlade and Ekins 2015; Zhang et al. 2023).

With respect to the control variables, the *QOE* terms are all positive and significant, which implies that the earnings quality is positively associated with BSR. This demonstrates that banks with higher earnings quality behave as larger banks in China. Larger banks may exhibit higher levels of systemic risk, consistent with established research (Berger, Roman, and Sedunov 2020; Davydov, Vähämaa, and Yasar 2021). The *ROE* term is significant and negative, indicating that banks with higher *ROE* have lower systemic risk (Duan, Fan, and Wang 2022). Higher *ROE* ensures the stability of banks' income in times of risk. The *LDR* terms are positively correlated with BSR, indicating that banks with high gearing have a higher level of systemic risk. Thus, a higher *LDR* poses more risk of default for banks as creditors, and the inability to recover principal and interest can affect bank stability.

The results of the macro control variables are consistent with Wu et al. (2023). The *GDP* term indicates that the guidance of industrial policies, as well as the increase in the scale and concentration of bank loans, may increase systemic risks in the process of China's economic growth. Moreover, the *M2* term implies that sufficient market liquidity can provide banks with richer sources of funds, which can reduce BSR.

4.2. Robustness Checks

To further confirm the robustness of the primary results, we employ different approaches including the substitution of explained and explanatory variables, controlling for additional factors and

Table 2. Climate policy uncertainty and bank systemic risk.

	Model (1)	Model (2)	Model (3)	Model (4)
CPU	0.3525***	0.1176**	0.1194**	0.1425***
	(0.0327)	(0.0497)	(0.0496)	(0.0486)
ROE		−0.0225	−0.0153	−0.1349***
		(0.0284)	(0.0292)	(0.0355)
QOE		0.1352***	0.1358***	0.1394***
		(0.0428)	(0.0424)	(0.0414)
ALR		−0.0793	−0.0749	−0.0430
		(0.0698)	(0.0679)	(0.0674)
LLRA		0.0473	0.0504	0.0743
		(0.0592)	(0.0583)	(0.0559)
LDR		0.2783***	0.2766***	0.2296***
		(0.0777)	(0.0763)	(0.0719)
PI			−0.0281	0.0372
			(0.0427)	(0.0414)
GDP				0.1370***
				(0.0283)
M2				−0.1092***
				(0.0293)
Bank fixed-effects	Yes	Yes	Yes	Yes
No. of observations	1270	754	754	754
No. of banks	42	42	42	42
Adjusted R^2	0.3130	0.3718	0.3713	0.3923

Note: The standard errors (in parentheses) are clustered at the bank level. *, **, *** denote statistical significance at 0.1, 0.05 and 0.01 levels, respectively.

Table 3. Robust test.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
CPU	0.1364***	0.1888***	0.1666***	0.1639***		0.2772***	1.9852***	0.1092**
	(0.0497)	(0.0473)	(0.0446)	(0.0461)		(0.0614)	(0.1747)	(0.0479)
CPU_PD					0.1425***			
					(0.0486)			
EPU_CHN						−0.1427***		
						(0.0340)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	754	754	754	754	754	754	257	725
No. of banks	42	42	42	42	42	42	25	42
Adjusted R^2	0.3863	0.4264	0.3930	0.4720	0.3923	0.4031	0.5623	0.3956

Note: The standard errors (in parentheses) are clustered at the bank level. *, **, *** denote statistical significance at 0.1, 0.05 and 0.01 levels, respectively.

filtering samples by criteria. The results are reported in Table 3. In line with Zhu et al. (2019) idea of replacing the explanatory variables, we apply different functions to calculate BSR, such as Gaussian copula, Clayton copula, and SJC copula, as shown in column (1) (4). As the *People's Daily* is the largest newspaper in China and is highly consistent with national policies, we replace the explanatory variable with CPU based on the *People's Daily* as shown in column (5). In the column (6), we add China's economic policy uncertainty index as a control variable to the primary model to eliminate the effect of economic policy uncertainty. In light of the potential impact of strong financial regulation on the estimation results, we select the sample before 2018 for robustness analysis5. Moreover, we exclude the data during the financial crisis to eliminate extreme situations (Liu, Li, and Sun 2024). The results are shown in columns (7) and (8), respectively. The coefficients of the *CPU* terms are all significantly positive at the 1% level, thereby confirming the robustness of the primary model.

4.3. Endogeneity Issues

The current level of systemic risk may be influenced by the prior period of variables and there may exist endogenous relationships between explained and explanatory variables. At the same time, omitted variables and measurement error may cause estimation bias. In view of this, we employ differential GMM and systematic GMM methods to conduct dynamic panel regressions to deal with the endogeneity problem (Arellano and Bond 1991; Li and Pan 2022). The United States' CPU with one period lag is chosen as an instrumental variable. This is because it is not only highly correlated with China's CPU but also does not directly contribute to BSR in China.

$$RISK_{i,t} = \alpha_0 + \alpha_1 RISK_{i,t-1} + \alpha_2 CPU_t + \gamma X_{i,t} + \lambda Y_{i,t} + \eta Z_{i,t} + \mu_i + \varepsilon_{i,t} \quad (2)$$

where the systemic risk of the bank *i* in year *t-1* ($RISK_{i,t-1}$) is brought into the model as an explanatory variable. The meaning of other terms is equal to equation (1). Table 4 represents the estimation results.

In Table 4, columns (1)(2) and (3)(4) are the differential GMM and system GMM methods, respectively. The weight matrix of columns (1) and (3) is the unit matrix, while that of columns (2) and (4) is the minimum variance matrix obtained by iteration. The estimation results indicate that the *L.RISK* term in each column is significantly positive, suggesting that the level of BSR is influenced by the previous period, which means there is an inertia effect. The *CPU* terms are also significantly positive, indicating that the level of systemic risk will be amplified by the impact of CPU. This confirms H1a. After conducting the requisite checks, the values of the *AR (1)* are all significant at the 0.05 level while the *AR (2)* terms are insignificant, indicating that the disturbances have no serial correlation (Liu, Li, and Sun 2024). The p-values of the Hansen test demonstrate that the choice of instrumental variables is reasonable and valid.

Table 4. Endogeneity analysis.

	Model (1)	Model (2)	Model (3)	Model (4)
L.RISK	0.3406***	0.3859**	0.3275***	0.3228***
	(0.0723)	(0.1878)	(0.0505)	(0.0842)
CPU	0.1701***	0.1546*	0.1920***	0.2306***
	(0.0359)	(0.0869)	(0.0396)	(0.0517)
Controls	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes
No. of observations	328	328	712	712
No. of banks	28	28	42	42
AR (1)	0.015	0.044	0.023	0.030
AR (2)	0.192	0.244	0.517	0.436
Hansen-P	1.000	1.000	1.000	1.000

Note: The standard errors (in parentheses) are clustered at the bank level. *, **, *** denote statistical significance at 0.1, 0.05 and 0.01 levels, respectively.

5. Discussion

5.1. Heterogeneity Analysis

There are geographical differences among banks owing to the varying levels of economic development across regions. To examine the heterogeneous effects, we divide the full sample into two groups, depending on whether the regional economy was better developed (better developed in column (1), otherwise in column (2)). Table 5 shows that the coefficient of the *CPU* term in column (2) is significantly positive at the 5% level, while the coefficient in column (1) is not significantly positive. It can be inferred that banks in economically undeveloped regions are more susceptible to the effects of CPU. This may be due to the simpler industrial structure, which includes a larger share of carbon-intensive manufacturing firms. Therefore, they may encounter difficulties in their operations when faced with CPU. For instance, some of the machines may become inoperable owing to the firms' inability to meet the requirements of the new policy, or the price of carbon emissions may result in operational difficulties. Moreover, the exploration of green transformation of the industrial structure will require a significant investment of capital. The banks in these regions have a close business relationship with these enterprises. Consequently, the issue of stranded assets will be transmitted to the banks along with their assets and liabilities, which makes them more susceptible to the risk of climate policies (Dunz, Naqvi, and Monasterolo 2021). Conversely, economically developed regions have a more complete industrial structure, which is more knowledge- and technology-intensive, so banks are less likely to be affected by climate policies.

Second, based on the median of the bank age, we divide the full sample into two groups: startups and established. Columns (3) and (4) of Table 5 present the heterogeneous impact of CPU on these two types of banks, respectively. The results indicate that the coefficient of the CPU term of the startup group is significantly positive at the 1% level, whereas that of the established group is not significant. This means that banks with shorter established times are more susceptible to the risk of CPU. We

Table 5. Heterogeneity analysis.

	Location		Bank age		Green transformation		Ownership		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
CPU	0.0829	0.2278**	0.1959***	0.0112	0.1347**	0.0669	0.1779***	0.1269*	0.1055
	(0.0604)	(0.0739)	(0.0602)	(0.0617)	(0.0523)	(0.1184)	(0.0516)	(0.0641)	(0.0656)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	531	223	388	366	526	228	634	460	414
No. of banks	31	11	21	21	21	21	34	26	24
Adjusted R^2	0.3748	0.3848	0.3437	0.3955	0.4624	0.2238	0.4226	0.4156	0.3164

Note: The standard errors (in parentheses) are clustered at the bank level. *, **, *** denote statistical significance at 0.1, 0.05 and 0.01 levels, respectively.

suggest that this phenomenon arises mainly because banks with longer ages have accumulated more risk management, internal control, and professional talents, thereby becoming more resilient to external risks. However, banks with shorter ages are more vulnerable owing to the relatively small scale and scope of their business and the insufficient diversification of their sources of income because of the limitation of their years of operation.

Third, we use text analysis to construct a bank green transition index based on financial statements. Banks are categorized into two groups based on the mean value of this index during the sample period. The results are presented in columns (5) and (6) of Table 5. The CPU term of column (5) is significantly positive at the 5% level. This suggests that banks with a lower degree of greening transformation are more vulnerable to shocks from CPU. This is because banks' greening transition supports green energy production and promotes a stable low-carbon transition (Horky and Fidrmuc 2024). It can also incentivize green innovation and support the structural transformation of energy-intensive firms by providing them with targeted loans (Chang et al. 2024). Thus, firms will have more stable solvency in the face of CPU, thereby supporting the stability of associated banks.

Finally, we analyze the heterogeneity of banks with different ownership. We adopt the "identification strategy" approach by removing state-owned, public, and local banks from the full sample to create three groups for model estimation. The estimation results are shown in columns (7) to (9) of Table 5. If the coefficient of the *CPU* term is smaller than that of the full sample, the systemic risk level of the category of banks removed is more severely affected by CPU. According to Table 5, the coefficient of the *CPU* term in column (7) is 0.1779, larger than that of the primary model (0.1425). This implies that the systemic risk level of state-owned banks is less exposed to CPU. The coefficient of the *CPU* term in column (8) is 0.1269, smaller than that of the primary model, suggesting that public banks are exposed to greater shocks. This situation may occur for three reasons. First, state-owned banks are generally of larger size. Larger banks have greater business capacity and resources, which makes them more stable in their operations (Wu et al. 2023). Second, state-owned banks are systemically important and are required by the supervisory authorities to strictly comply with the regulatory requirements of the capital adequacy ratio (8%) and the core capital adequacy ratio (4%). Therefore, when facing external risk, they have a "buffer" against risks and usually do not face capital replenishment pressure that exceeds their tolerance range. Third, state-owned banks have an invisible credit guarantee from the government. The government intervenes and provides administrative support with the objective of consolidating the position of large state-owned banks in order to achieve the goal of "big but cannot fail" (Dong, Hou, and Ni 2021).

These results indicate that the impact of CPU is more pronounced for banks in economically undeveloped regions, banks with a shorter age, banks with a lower degree of greening transformation, and public banks. This evidence supports H2.

5.2. Moderating Effect

The preceding findings indicate that the increase in CPU will exacerbate BSR, and this impact has heterogeneous effects. This section further examines whether this impact is influenced by internal and external bank factors.

To test for the moderating effect, an intersection term is introduced. In the case of BRT, the model can be written in the form of equation (3).

$$RISK_{i,t} = \alpha_0 + \alpha_1 CPU_t + \alpha_2 CPU_t \times BRT_t + \gamma X_{i,t} + \lambda Y_{i,t} + \eta Z_{i,t} + \mu_i + \varepsilon_{i,t} \tag{3}$$

The coefficient of the cross-multiplier term α_2 is of interest because its significance indicates the presence or absence of a moderating effect. The direction of this effect is determined by the sign of the coefficient.

In terms of internal moderators, we examine four indicators: bank risk-taking (*BRT*), bank income diversification (*HHI*), bank capital adequacy (*CAR*), and bank interest recovery rate (*IRR*). In terms of

Table 6. Moderating effect.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
CPU	0.1095**	0.1115***	5.2372***	−0.3203	0.1182**	1.2160***	−0.2266
	(0.0440)	(0.0400)	(1.2304)	(0.3115)	(0.0465)	(0.1276)	(0.1509)
CPU×BRT	−0.0652*						
	(0.0379)						
CPU×HHI		−0.0576*					
		(0.0314)					
CPU×CAR			−0.3488***				
			(0.0920)				
CPU×IRR				−0.3122*			
				(0.1606)			
CPU×Risk					1.7281***		
					(0.1268)		
CPU×Fr						−1.1485***	
						(0.1091)	
CPU×Covid							0.4111***
							(0.1482)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	754	743	127	39	754	754	754
No. of banks	42	42	16	5	42	42	42
Adjusted R^2	0.3939	0.3993	0.4701	0.3824	0.4444	0.4493	0.4106

Note: The standard errors (in parentheses) are clustered at the bank level. *, **, *** denote statistical significance at 0.1, 0.05 and 0.01 levels, respectively.

external moderators, we consider three indicators financial crisis *(Risk)*, financial regulation *(Fr)*, and COVID-19 *(Covid)*.[6]

According to Table 6, it can be seen that the four internal moderators have a negative influence on BSR. This means that bank risk-taking, bank income diversification, bank capital adequacy, and bank interest recovery rate can dampen the adverse impacts of climate policy uncertainty. The results also show that the financial crisis and COVID-19 can intensify this effect, while strong financial regulation can mitigate it.[7] These findings are consistent with our expectations.[8]

6. Conclusion

The high-quality development of the Chinese economy is closely related to the promotion of green transformation. The design of a good low-carbon transition strategy in line with China's national conditions is of great significance in controlling BSR and ensuring the stable operation of the banking system. Meanwhile, the normal functioning of banks also contributes to the stability of the financial system. However, there is little research on the impact of climate policies on BSR. In light of the above, this study calculates a CPU index for China based on text analysis and empirically investigates the effect of CPU on BSR based on the data of listed banks. The findings indicate that CPU can significantly increase the level of BSR, with heterogeneous effects. The moderating effect demonstrates that external shocks can exacerbate the impact, while robust internal indicators and strong financial regulation can reduce the risk.

The findings have theoretical value and policy significance for maintaining the stability of the bank system under the "dual carbon" goals. First, policy makers should base their decisions on China's energy and resource endowments and steadily promote carbon peaking and carbon neutrality strategies on the concept of "establishing before breaking" to maintain the relative stability of climate policies. Second, macroeconomic policies should be employed to facilitate banks' green transformation. This entails the implementation of a green evaluation system and transformation incentive measures. Finally, banks' capacity to respond to CPU should be enhanced, with a view to reducing their sensitivity to transformation risks. This will ensure the continued provision of financial support for the real economy.[9]

Notes

1. The Bank for International Settlements first proposed the concept of “green swans” in 2020, which refers to the unpredictable and irreversible risk caused by increasing greenhouse gases that affects the economy, society, environment, and geopolitics.
2. On September 22, 2020, China first proposed the dual carbon goals, which refer to achieving carbon peak by 2030 and carbon neutrality by 2060, at the UN meeting.
3. Physical risk refers to the direct economic and financial losses caused by extreme climate events, while transition risk refers to the risks caused by asset stranding issues resulting from policy changes and other factors in the low-carbon transition.
4. The correlations of the main variables can be found in Appendix B.
5. Financial regulation has tightened since 2018 with a series of policy documents jointly issued by Chinese financial regulatory authorities.
6. The explanation of internal and external moderators can be found in Appendix C.
7. A detailed discussion of the results of moderating effect can be found in Appendix D.
8. We also conduct a further research of nonlinearity test, which can be found in Appendix E.
9. A detailed policy suggestion can be found in Appendix F.

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