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The Nonlinear Impact of Climate Physical Risk on Bank Non-Performing Loan Ratios: Evidence from Chinese Listed Banks

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Abstract

The frequent occurrence of extreme weather exacerbates the threat of climate physical risks to financial stability. However, whether its impact on bank credit risk follows a simple linear pattern remains unclear. Based on the unbalanced panel data of 28 listed banks in China from 2010 to 2023, this paper tests the nonlinear effect of extreme precipitation on the non-performing loan rate. The results indicate a significant inverted U-shaped relationship between extreme precipitation and the non-performing loan rate, that is, the initial physical loss pushes up the risk of default, and the non-performing rate falls after exceeding the threshold, which may be affected by post-disaster policy buffering and other factors. The U-test formally confirms that the inverted U-type relationship is established within the data range (p=0.015). The effect is most significant in the two lag periods and concentrated in small banks. Large banks did not show a significant nonlinear effect due to the high degree of business dispersion. Further analysis found that small banks in areas with higher insurance coverage exhibit a more pronounced inverted U-shaped pattern, which is consistent with the theoretical expectation that insurance compensation plays a buffering role. After multiple verification of hybrid OLS, fixed effect, wild cluster bootstrap and multi-phase lag combined regression, the conclusion is robust. This study provides new micro-level evidence for the nonlinear boundaries of climate risk transmission to the banking system.

Keywords

climate physical risk, non-performing loan ratio, nonlinear effect, inverted u-shaped relationship

1. Introduction

Against the background of global warming, the threat of climate risks brought by extreme weather to financial stability cannot be ignored. In 2025, China's direct economic losses from natural disasters are as high as 241.617 billion yuan, of which floods account for 69%. Extreme weather events disrupt business operations, erode the value of collateral, and eventually worsen the quality of credit assets and bring severe tests to the banking system [1,2].

Existing studies have primarily focused on the linear transmission of climate risk, but the discussion of nonlinear effects is still in its infancy. Zaiane and Semenova found that there was a non-linear threshold between climate risk and bank liquidity creation [3]. Cortés and others confirmed that after the natural disaster, banks reallocate credit resources through the internal capital market, and the credit in the affected areas would have a phased change of increasing and then shrinking [4]. However, there are few literatures that simultaneously test the nonlinear impact of extreme weather on the non-performing loan rate and its heterogeneous boundaries in the sample of listed banks in China, and there is also a lack of explanation of the mechanism of the right decline of the nonlinear effect.

Therefore, the marginal contribution of this article is to test the inverse U-shaped effect of extreme precipitation on the non-performing loan rate for the first time in a sample of Chinese listed banks, and to use Lind & Mehlum [5] U-test to provide formal nonlinear test evidence. Second, the best window for conduction is identified for about two years through multi-phase lag test. Third, the heterogeneity boundary of the nonlinear effect is revealed from the two dimensions of bank size and regional insurance density, and provides indirect mechanical evidence for the inverted U-shaped right-hand decline.

2. Literature Review

2.1 Transmission of Climate Risk to the Banking System

The transmission path of climate physical risks to the banking system has been proven from many aspects. Guo Yitian pointed out that the assets of financial institutions face losses under the circumstances of interruption of enterprise production, damage to assets, and decline in debt repayment capacity caused by climatic physical risks [6]. Based on U.S. data, Noth and Schüwer found that natural disasters significantly weakened the stability of banks in the affected areas, and the impact was mainly transmitted through the exposure of banks' credit business in the affected areas [1]. Based on the study of the European financial system, Chabot and Bertrand proposed that climate risk is transmitted to financial institutions through the dual path of direct asset loss and indirect borrower default [2]. Based on the data of China's small and medium-sized banks, Xue et al. further confirmed that climate physical risks significantly increase the risk-taking level of banks by reducing the operating capacity and cash reserves of enterprises [7].

2.2 Direct Effects of Extreme Weather Events on Non-performing Loan Ratios

Existing studies have mainly focused on the linear transmission of climate risk to bank credit risk and financial stability. Based on the data of Chinese commercial banks, Liu et al. found that the average annual temperature increase significantly increases the credit risk of commercial banks, and small-scale banks and rural commercial banks are more sensitive to climate change [8]. Hou et al. found that extreme high temperatures and droughts have an asymmetrical impact on the non-performing loan rate of banks [9]. Deng et al. used China's rural credit cooperatives as a sample to confirm that extreme temperatures and heavy rainfall have a significant negative impact on the quality of loans and the probability of bankruptcy of rural financial institutions [10]. However, the above literature does not fully consider the possible nonlinear characteristics.

2.3 Nonlinear Effects of Climate Risk

The study of nonlinear effects of climate risks has attracted more and more attention in recent years. Based on U.S. agricultural loan data, Liu found that the negative impact of climate shock on bank credit supply is non-linear cumulative. Small farms almost always face losses from credit channels, while large farms are less affected [11]. Based on the data of 202 rural financial institutions in China, Wang and Ma empirically found that climate risk has an inverted U-shaped impact on credit risk, but it focuses on transition risks and rural financial institutions [12]. However, there has been no research to test the nonlinear effect of extreme precipitation and its heterogeneity between different types of banks in the sample of Chinese listed banks, and there is also a lack of discussion on the mechanism of the right decline.

3. Research Design

3.1 Sample Selection and Data Sources

This paper selects China's A-share listed commercial banks as a research sample. After excluding policy banks, the unbalanced panel data of 28 listed banks from 2010 to 2023 were obtained. The extreme precipitation data comes from the climate physical risk index (CPRI) data set built by Guo et al. The data set is based on the daily observation data of the meteorological station of the National Oceanic and Atmospheric Administration of the United States. Taking 1973-1992 as the benchmark period, the number of days when the daily precipitation of each station exceeds its 95th percentile is defined as the number of days of extreme precipitation. The relative threshold method based on the historical distribution of the site itself, rather than the national unified absolute precipitation threshold, is adopted to eliminate the impact of differences in climate backgrounds in different regions on the definition of extreme precipitation. Covering the panel data of 229 cities in China from 1993 to 2023 [13]. The bank's financial data comes from the CSMAR database. The per capita financial expenditure data used in the mechanism analysis comes from the statistical yearbooks of cities, and the property insurance density data comes from the statistical yearbooks of each province.

3.2 Variable Definitions

The dependent variable is the non-performing loan rate, which is equal to the non-performing loan balance divided by the total loan balance. The core explanatory variable is the number of extreme precipitation days in the bank registration place in the two phases. The natural logarithm is taken to eliminate scale effects, and its quadratic term is generated to capture the nonlinear effect. The control variables include bank size, profitability, capital adequacy and loan growth rate, all of which are lagged by one period to alleviate endogenous problems. All continuous variables are winsorized at the 1st and 99th percentiles to eliminate the extreme value influence. The basis for choosing the two lag phases is that the impact of the first to third phases of the lag was tested in the empirical process, and it was found that the nonlinear effect was the most significant and stable in the two lag phases.

3.3 Model Specification

To examine the non-linear impact of extreme precipitation on the non-performing loan ratio, the following baseline regression model is constructed:

$$NPL_{i,t} = \alpha + \beta_1 \cdot \ln ERD_{i,t-2} + \beta_2 \cdot \left(\ln ERD_{i,t-2}\right)^2 + \gamma \cdot Controls_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{1}$$

Here, $\ln ERD_{i,t-2}$ represents the number of extreme precipitation days lagged by two periods (in logarithmic form), and $\left(\ln ERD_{i,t-2}\right)^2$ is its quadratic term. If the coefficient of the quadratic term, β_2, is significantly negative, the existence of an inverted U-shaped effect is confirmed. Pooled OLS serves as the baseline estimation method, with standard errors clustered at the bank level to address potential issues of within-group serial correlation and heteroskedasticity. In the robustness check, a fixed-effects model is employed instead of pooled OLS to further control for time-invariant, unobservable bank characteristics.

Furthermore, a negative coefficient for the quadratic term is insufficient to confirm the existence of an inverted U-shaped relationship within the data range, as the turning point may lie outside the range covered by the sample. To this end, this paper employs the U-test proposed by Lind and Mehlum to formally test for an inverted U-shaped effect. This test examines the sign of the slope at both the lower and upper ends of the data range; the inverted U-shaped relationship is confirmed to hold within the data range only if the slope is significantly positive at the lower end and significantly negative at the upper end. Furthermore, given that the 28 bank clusters fall within the "grey area" of a small number of clusters, this paper further employs the wild cluster bootstrap (using Webb’s 6-point weights and 9,999 resamples) to re-examine the core coefficients, thereby ensuring the reliability of the inference.

4. Empirical Results

4.1 Baseline Regression and Robustness Tests

Results of the baseline regression and robustness checks regarding nonlinear effects. In Model 1 (pooled OLS), the coefficient for the linear term is 0.128 ($p < 0.05$) and the coefficient for the quadratic term is -0.035

($p < 0.05$), preliminarily indicating the existence of an inverted U-shaped effect. The Lind & Mehlum (2010) U-test formally confirmed the existence of an inverted U-shaped relationship within the data range: the slope at the left end was significantly positive (0.128, p=0.015), the slope at the right end was significantly negative (-0.172, p=0.007), and the overall test rejected the null hypothesis of monotonicity or a U-shaped relationship (p=0.015). The inflection point is located at ln_ERD = 1.81, corresponding to approximately six days of extreme precipitation. This indicates that the defect rate peaks at a moderate level of extreme precipitation duration but declines as the duration increases further, forming an inverted U-shaped curve. The coefficient of the quadratic term was re-examined using the wild cluster bootstrap; the resulting bootstrap p-value of 0.018 is highly consistent with the p-value based on conventional clustered standard errors (0.016), confirming the robustness of the baseline findings even with a small number of clusters.

In Model 2 (fixed effects), the coefficient of the linear term was 0.117 (p<0.10), and the coefficient of the quadratic term was -0.027 (p<0.10), with the direction consistent with significance. The U-test passed at the 10% level (p=0.067), and the bootstrap p-value was 0.091. This indicates that the inverted U-shaped effect is not driven by cross-sectional differences among banks but rather exists within-bank variation over time. In Model 3, after replacing the variable with the CPRI composite climate index, none of the coefficients were statistically significant; this indicates that the observed non-linear effect is specific to extreme precipitation rather than a result of broader climate-related risks.

Multicollinearity diagnostics indicate that the centered VIFs for all control variables in the baseline model are below 2 (mean: 3.38); the VIFs for the linear and quadratic terms are approximately 15 due to structural correlation, which falls within the normal range for models incorporating quadratic terms.

Table 1: Robustness Tests of the Nonlinear Effect on the Non-Performing Loan Ratio

	(1)	(2)	(3)
	Pooled OLS	Fixed Effects	Alternative Measure of CPRI
L2_ln_ERD	0.128**	0.117*	
	(0.056)	(0.065)	
L2_ln_ERD_sq	-0.035**	-0.027*	
	(0.014)	(0.015)	
L_ln_Size	-0.058	0.118	-0.052
	(0.036)	(0.167)	(0.035)
L_ROA	-0.170	-0.481**	-0.165
	(0.228)	(0.229)	(0.226)
L_CAR	0.001	-0.003	0.000
	(0.016)	(0.019)	(0.017)
L_LoanGrowth	-2.599***	-1.505***	-2.521***
	(0.554)	(0.448)	(0.560)
L2_CPRI			-0.028
			(0.032)
L2_CPRI_sq			0.001
			(0.001)
U-test p-value	0.015	0.067	
Bootstrap p-value	0.018	0.091	
N	408	408	408
R^2	0.393	0.422	0.386

*Notes: Clustered standard errors at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Year fixed effects are included in all specifications. The U-test p-value is obtained from the inverted U-shaped relationship test proposed by Lind and Mehlum (2010). The Bootstrap p-value is derived from a wild cluster bootstrap procedure (Webb six-point weights, 9,999 replications) for testing the coefficient of the squared term.*

Table 2 reports the results of a joint regression incorporating multiple lags. Only the quadratic term at the two-period lag is significantly negative at the 10% level (coefficient = -0.022, $p < 0.10$), whereas the quadratic terms at the one-period and three-period lags are statistically insignificant; this rules out alternative explanations based on the arbitrary selection of lag periods and confirms the existence of an optimal identification window of approximately two years for the transmission of extreme weather effects to bank asset quality. This time-lag characteristic aligns with economic intuition: following extreme precipitation, it takes time for corporate production, operations, and debt-repayment capacity to deteriorate significantly, while the recognition of non-performing loans by banks also involves processes such as delinquency, collection, and write-offs.

Table 2: Results of the Joint Regression with Multiple Lagged Terms

	(1)
	NPL
L1_ln_ERD	-0.043
	(0.058)
L1_ln_ERD_sq	0.009
	(0.014)
L2_ln_ERD	0.073*
	(0.041)
L2_ln_ERD_sq	-0.022*
	(0.011)
L3_ln_ERD	0.067
	(0.045)
L3_ln_ERD_sq	-0.013
	(0.012)
L_ln_Size	-0.037
	(0.034)
L_ROA	-0.135
	(0.223)
L_CAR	0.006
	(0.015)
L_LoanGrowth	-2.111***
	(0.564)
N	380
R^2	0.443

Notes: Clustered standard errors at the bank level are reported in parentheses. Year fixed effects are included in all regressions.

4.2 Heterogeneity Analysis

The inverted U-shaped effect does not exist across the board for all banks. Table 3 reports the results of the heterogeneity regression grouped by bank size. For the small bank group, the coefficient for the linear term is 0.119 ($p < 0.10$) and the coefficient for the quadratic term is -0.032 ($p < 0.10$); the inverted U-shaped effect remains significant, and the U-test is passed at the 5% level ($p = 0.047$). In the large bank group, however, the coefficients for both the linear and quadratic terms are close to zero and entirely statistically insignificant.

This divergence reveals a significant structural boundary: due to high geographic concentration and limited risk-cushioning capacity, small banks are far more sensitive to localized extreme precipitation than large banks. The advantages of large-scale assets and business diversification enjoyed by large banks serve as an effective buffer against climate risk, preventing systemic fluctuations in asset quality caused by extreme weather events in any single region. It should be noted that the Suest cross-equation test indicates the difference in quadratic coefficients between large and small banks has not reached statistical significance ($\chi^2 = 1.65$, $p = 0.200$), suggesting that this pattern of heterogeneity requires further confirmation with a larger sample. However, the two groups exhibit a clear divergence in the qualitative patterns of nonlinear effects: the U-test is significant for small banks ($p = 0.047$), whereas the result is entirely insignificant for large banks. This finding aligns with the conclusion drawn by A dataset to measure global climate physical risk [8] that small banks are more sensitive to climate change, and echoes the findings of Xue et al. [7] regarding the heightened sensitivity of rural commercial banks to climate shocks.

Furthermore, the wild cluster bootstrap test for the small-bank subsample reveals a bootstrap p-value of 0.111 for the quadratic term—higher than the conventional p-value of 0.081—suggesting that the term is marginally significant within a more rigorous inference framework. To alleviate the problem of insufficient degrees of freedom caused by too many year dummy variables in the subsample (the F-statistic shows missing values), this paper merges the 14 year dummy variables into 4 period dummy variables (2010-2012/2013-

2015/2016-2019/2020-2023). The direction and significance of the core coefficient remain consistent—and indeed strengthen (β_2 = -0.038, p = 0.020)—while the F-statistic returns to a normal level (33.57), confirming that the conclusion does not depend on the specific form of the time fixed effects.

Table 3: Heterogeneity Analysis of the Nonlinear Effect

	(1)	(2)
	Large Banks	Small Banks
L2_ln_ERD	-0.025	0.119*
	(0.075)	(0.068)
L2_ln_ERD_sq	0.004	-0.032*
	(0.021)	(0.018)
L_ln_Size	0.104	-0.260***
	(0.095)	(0.066)
L_ROA	0.147	-0.416**
	(0.372)	(0.191)
L_CAR	-0.074**	-0.027
	(0.030)	(0.024)
L_LoanGrowth	-2.385**	-2.148***
	(1.014)	(0.473)
U-test p-value	—	0.047
N	212	196
R^2	0.585	0.459

Notes: Clustered standard errors at the bank level are reported in parentheses. All specifications control for year fixed effects. A seemingly unrelated estimation (SUEST) test is conducted to compare the squared-term coefficients across groups. The test statistic is χ^2 = 1.65 (p = 0.200).

4.3 Mechanism Analysis: Explaining the Decline on the Right Side of the Inverted U-shaped Relationship

The benchmark regression confirms that extreme precipitation has an inverted U-shaped impact on the non-performing loan rate of banks. A key issue is: Why did the non-performing loan rate fall after the extreme rainfall exceeded the inflection point? This article puts forward the post-disaster policy buffering hypothesis to explain and provide indirect evidence.

When extreme precipitation is at a medium and low level, the disaster losses have not reached the threshold of the government's large-scale rescue. Enterprises and farmers mainly rely on their own funds to absorb the losses, and the damage to debt repayment capacity is directly transmitted to the rise in the non-performing rate of banks. However, when extreme precipitation exceeds a certain intensity, the economic losses caused by it reach the response threshold of local governments and insurance systems, and the multi-level risk buffer mechanism is activated. On the one hand, local governments inject resources through emergency financial allocations, special funds for post-disaster reconstruction, tax exemptions and loan forbearance policies to help the affected borrowers recover their production and operation capabilities. On the other hand, insurance payouts directly covers some of the asset losses of the disaster-stricken enterprises, reducing their cash flow gap, thus maintaining the ability to repay bank loans. The two channels work together to partially hedge the marginal credit risk impact after extreme precipitation exceeds the threshold.

This article provides indirect evidence from the dimension of regional insurance density. The sub-samples of small banks were divided into high insurance density groups and low insurance density groups according to the median of property insurance density in the region, and the nonlinear effect was estimated respectively. If the insurance payouts serve as a buffer, it is expected that the decline on the right side of the inverted U-shaped should be more significant in areas with high insurance coverage.

The results in Table 4 are consistent with this expectation. In the group of small banks with high insurance density, the coefficient for the linear term of extreme precipitation is significantly positive (β_1 = 0.166, p = 0.006), while the coefficient for the quadratic term is significantly negative (β_2 = -0.051, p = 0.002); a U-test confirms the inverted U-shape within the data range (p = 0.003), and the wild cluster bootstrap p-value is 0.013. In the low insurance density group, however, neither the linear nor the quadratic term was significant (β_1=0.078, p=0.488; β_2=-0.016, p=0.587), and no inverted U-shaped pattern was detected. A comparison between the two groups indicates that in regions with more comprehensive insurance coverage, the credit risk mitigation effect following extreme precipitation events that exceed the threshold is more pronounced.

The Suest cross-equation test indicates that the difference between the quadratic coefficients of the two groups is not statistically significant ($\chi^2 = 1.29$, $p = 0.256$), and the p-value for the joint test of differences in linear and quadratic terms is 0.219. Therefore, the current evidence provides only indirect support: while the two groups exhibit a clear divergence in the qualitative pattern of nonlinear effects, this difference is not statistically sufficient to rigorously reject the null hypothesis that the coefficients for the two groups are identical.

Table 4: Evidence on the Indirect Mechanism by Insurance Density Groups
(Small Banks, Time Fixed Effects)

	(1)	(2)
	High Insurance Density	Low Insurance Density
L2_ln_ERD	0.166***	0.078
	(0.054)	(0.109)
L2_ln_ERD_sq	-0.051***	-0.016
	(0.014)	(0.029)
L_ln_Size	-0.259***	-0.238*
	(0.040)	(0.121)
L_ROA	-0.693***	-0.393
	(0.212)	(0.293)
L_CAR	-0.007	-0.039
	(0.020)	(0.031)
L_LoanGrowth	-0.962***	-2.410**
	(0.317)	(0.882)
U-test p-value	0.003	—
Bootstrap p-value	0.013	—
N	104	92
R^2	0.623	0.405
F	57.41	71.78

Notes: The sample is restricted to small banks, defined as banks with total assets below the sample median. Time fixed effects are specified using four subperiods: 2010–2012, 2013–2015, 2016–2019, and 2020–2023. Clustered standard errors at the bank level are reported in parentheses. The SUEST joint test yields $\chi^2 = 3.04$ ($p = 0.219$).

It should be noted that there may be other explanations for the fall on the right side of the inverted U-shaped: First, supervision and tolerance. After a major natural disaster, bank regulators may relax the criteria for the identification of non-performing loans or allow loan extensions, so that the non-performing rate on the books is underestimated. Second, the write-off effect. Extreme disasters may prompt banks to accelerate the write-off of confirmed bad debts, but instead reduce the stock of non-performing loans. Third, credit contraction. Post-disaster banks may significantly tighten credit injection, and the contraction of total loans may partially offset the rise in non-performing loans. The sample results of the insurance density in this article help to distinguish the above explanation to a certain extent: if the decline is purely driven by regulatory tolerance or write-off, the effect should not depend on the level of insurance density, but actual data shows that only areas with high insurance density have a significant reverse U-shaped decline. This differential model is more inclined to support the insurance compensation buffer mechanism than the above alternative explanation. Of course, this article cannot completely exclude the joint effect of alternative channels. This limitation needs to be identified by future research using more microscopic disaster compensation data and bank loan ledger data.

4.4 Extended Analysis: the Transmission Boundary of Green Credit

In order to further examine the transmission boundaries of climate risks in different dimensions of banking behavior, this paper examines the impact of extreme precipitation on the proportion of green credit in banks. In stark contrast to the inverted U-shaped effect of the non-performing loan rate, the linear and nonlinear effects of extreme precipitation on the proportion of green credit are not significant, and the interaction between large banks and regional banks is also unstable. This null result is unlikely to be driven by data quality issues, but may be because the green credit allocation of listed banks is driven by policy assessment and long-term strategic planning, and is less sensitive to short-term climate shocks in a single region. This comparison reveals the transmission boundaries of climate risk. The impact can affect banks' risk indicators and total credit, but it is difficult to change the green strategic direction driven by policy assessment.

5. Conclusions

This article takes 28 listed banks in China as a sample to empirically test the nonlinear impact of extreme precipitation on the non-performing loan rate of banks. The study found that: First, there is a significant inverse U-shaped relationship between extreme precipitation and non-performing loan rate, which has been officially confirmed by U-test (p=0.015) and remains stable under wild cluster bootstrap (p=0.018). The initial physical loss increases the risk of default, but when the extreme degree exceeds the threshold (about 6 days), the non-performing loan ratio declines. The effect reached its peak when it was delayed by two periods, reflecting the transmission window of about two years. Second, the inverted U-shaped effect is concentrated in small banks. Large banks do not show significant nonlinear effects due to the high degree of business dispersion, which shows that the size of banks is a key buffer factor for climate risk transmission. Third, small banks in areas with high insurance density present a clearer and more stable inverted U-shaped model (U-test p=0.003), which is consistent with the theoretical expectation that insurance compensation plays a buffer role, but this indirect evidence does not yet constitute a strict verification at the level of causal identification. Fourth, extreme precipitation has no significant impact on the proportion of green credit, revealing the behavioral boundaries of climate risk transmission.

Based on the above findings, this article puts forward the following policy suggestions: First, financial regulators should integrate climate risks into the differentiated regulatory framework, paying special attention to the fluctuations in the asset quality of small banks in extreme climate events. Using the transmission window of about two years found in this paper, we will establish a forward-looking early warning mechanism, that is, after the occurrence of extreme precipitation, small banks in high-exposed areas will be required in advance to increase the provision coverage rate or tighten the credit approval standards in high-disaster areas. Second, improve the disaster insurance system. The indirect evidence in this article shows that the credit risk mitigation effect of banks in areas with high insurance coverage is more significant, suggesting that expanding the coverage of property insurance will help reduce the possibility of extreme weather events amplifying the risk of the financial system through banking channels. Third, small banks should adjust their credit strategies in a timely manner within the two-year window period after extreme weather to strengthen risk buffering capacity building.

The limitations of this study are: First, the sample only covers listed banks, and can be expanded to non-listed small and medium-sized banks in the future to enhance the generalizability of the findings. Second, limited by the total amount of data, it is difficult to accurately capture the post-disaster special investment and insurance compensation flow such as macro indicators such as general public budget expenditure and insurance density used in this paper, resulting in the failure to find a significant positive correlation in the first stage of the mechanism test. Future research can use more microscopic disaster relief allocation data and insurance claim data to make a more direct causal identification of the post-disaster policy buffer mechanism. Third, although the Suest test shows that the coefficient difference between large and small bank groups and between high and low insurance groups has not reached the conventional statistical significance level, there is a clear qualitative differentiation between the two groups in the nonlinear effect model, and the data of larger samples and longer spans is expected to provide stronger statistical support for these heterogeneity models.

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