



# Heterogeneous Effects of Climate Risk on Risk Spillovers in China's Banking Sector

## Climate Risk and Banking Spillovers Evidence from a DY Network Model with Daily-Frequency

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**Abstract.** This study examines climate-risk transmission through China's banking sector using a daily-frequency panel of 1,231 trading days for 36 A-share listed banks (2020–2025). A Diebold–Yilmaz spillover network extracts system-wide and sector-level connectedness, while Granger causality tests and orthogonalized VAR impulse responses trace short-run causal channels of the Climate Policy Uncertainty index (CCPU) and a Natural Disasters news index. Key findings: (1) neither risk type elevates aggregate systemic spillovers; (2) CCPU shocks display a "dumbbell-shaped" heterogeneity—state-owned and rural banks are highly sensitive ( $p = 0.0007$ ), joint-stock banks immune; (3) physical-risk pathways mirror-reverse this pattern. Rural banks constitute the sole "resonance node" significant under both risk types.

**Keywords:** climate risk, banking sector risk spillover, Diebold–Yilmaz network model, Granger causality, impulse response function, cross-sectoral heterogeneity

## 1 Introduction

Climate change ranks among the most pressing systemic threats of the 21st century. The World Economic Forum's Global Risks Report 2024 places extreme weather events and climate-action failure at the top of both short- and long-horizon risk rankings for the fourth consecutive year. Beyond its direct environmental consequences, climate change transmits shocks to economic growth and financial stability through multiple channels<sup>[9][16]</sup>. International financial regulators have accordingly classified climate risk as a material source of systemic vulnerability.

China—the world's largest developing economy and carbon emitter—has accelerated its low-carbon transition since announcing the "dual carbon" targets in 2020. The banking sector, which serves as the primary conduit for credit allocation to the real economy, faces particularly acute climate-risk exposure. On the transition-risk front, loan portfolios concentrated in carbon-intensive industries (coal-fired power, steel, ce-

ment) are susceptible to stranding as emission-reduction policies tighten. On the physical-risk front, the rising frequency and intensity of extreme weather events (typhoons, torrential rainfall, flooding) pose direct threats to collateral values and agricultural-loan quality. Yet the existing literature offers limited evidence on how climate risks propagate through the intra-banking risk-spillover network, particularly at the daily frequency required to capture the short-run heterogeneous transmission dynamics of sudden climate shocks.

Prior research has advanced the understanding of climate–finance interactions, but at least three gaps persist. The most fundamental is frequency mismatch: the vast majority of studies rely on monthly or quarterly climate-risk proxies<sup>[2][6]</sup>, yet climate-policy announcements and extreme weather events are inherently abrupt, and low-frequency data cannot resolve transmission dynamics within the first one to five trading days following a shock. In addition, the analytical scope has been narrow—most work examines spillovers to broad asset classes such as equities, exchange rates, and commodities<sup>[8]</sup> or evaluates agricultural credit risk from a single-hazard perspective<sup>[6]</sup>, with little attention paid to heterogeneous propagation within the banking sector itself. The contrast between transition risk and physical risk also remains largely unexplored; their transmission mechanisms differ substantially<sup>[1]</sup>, yet no unified empirical framework has been employed for a side-by-side comparison.

This study makes three contributions aligned with its research questions. First, by performing a date-level inner join of climate indices and DY-derived spillover series on identical trading-day timestamps, a balanced daily panel of 1,231 observations is constructed, directly resolving the frequency-mismatch problem that plagues monthly or quarterly designs. Second, NET is extracted and tested separately for four bank categories, enabling quantitative identification of inter-sector sensitivity differentials. Third, the CCPU and Natural Disasters index are incorporated within a fully symmetric testing protocol, revealing the "mirror-image" transmission feature across risk types.

## 2 Literature Review

### 2.1 Climate Risk and Financial System Stability

Bolton et al.<sup>[9]</sup> introduced the "Green Swan" concept to describe climate-induced systemic crises, highlighting the deep uncertainty and global reach that set climate risk apart from conventional financial risks<sup>[3]</sup>. The NGFS and TCFD frameworks distinguish transition risk—arising from policy shifts and asset stranding during decarbonization<sup>[17][7]</sup>—from physical risk driven by extreme weather events. Ma and Sun<sup>[4]</sup> linked typhoon intensity to coastal mortgage defaults; Do et al.<sup>[15]</sup> documented drought-driven loan-spread increases. Crucially, the two risk types interact in practice<sup>[1]</sup>, yet unified empirical comparisons remain rare.

## 2.2 Banking-Sector Risk Spillover Networks

Diebold and Yilmaz<sup>[11][12][13][14]</sup> proposed a GFEVD-based spillover framework widely applied to equity and commodity markets. Demirer et al.<sup>[10]</sup> extended it to global systemically important banks. Applications to Chinese listed banks with institution-type disaggregation, however, remain scarce—despite the sector's distinctive structure: policy-driven state-owned banks, market-oriented joint-stock banks, and regionally embedded city/rural banks, each carrying heterogeneous climate exposures.

## 2.3 Climate-Risk Spillovers to Asset Returns

Zhang et al.<sup>[8]</sup> quantified climate-shock spillovers to Chinese equities, FX, and commodities via DY networks; Ji et al.<sup>[5]</sup> examined climate-perception effects on stock markets. These studies focus on broad asset classes, leaving the banking sector—the core credit intermediary with structurally differentiated sensitivity across bank types—largely unexamined.

## 2.4 Summary and Positioning

Sector-level climate-risk spillover research on banking remains scant, constrained by frequency mismatch and the absence of transition-versus-physical comparisons within a single framework. This paper fills both gaps using a daily-frequency aligned panel integrated with DY, Granger causality, and VAR-IRF analysis.

# 3 Methodology

Risk spillovers among banks are characterized using the GFEVD-based framework of Diebold and Yilmaz<sup>[11][12][13]</sup>. An  $N$ -variable,  $p$ -th order VAR without intercept or trend is estimated via a rolling window of  $W = 150$  trading days, with a fixed lag order  $p = 1$  and forecast horizon  $H = 10$ . From the generalized variance decomposition, the unnormalized pairwise connectedness is computed and row-normalized (scaled to 100) to obtain the connectedness matrix  $d_{ij}$ . The system-wide Total Connectedness Index (TCI) and bank-level Net Directional Spillover (NET) are then defined as:

$$TCI = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N d_{ij} \tag{1}$$

$$NET_j = \sum_{i=1}^N d_{ij} - \sum_{i=1}^N d_{ji} \tag{2}$$

TCI captures the aggregate risk-interconnectedness level;  $NET_j > 0$  identifies bank  $j$  as a net risk transmitter,  $NET_j < 0$  as a net receiver.

To test whether climate-risk variables Granger-cause banking spillovers, bivariate systems are constructed with a maximum lag of 5 days and a significance threshold of  $p < 0.1$ ; all series are first subjected to ADF testing and differenced if non-stationary.

For significant climate–spillover pairs, orthogonalized VAR impulse response functions are estimated via Cholesky decomposition (AIC lag selection, 15-day horizon, 95% confidence bands at  $\pm 1.96$  SE).

## 4 Data and Variables

### 4.1 Sample Selection and Data Sources

The sample consists of 36 A-share listed commercial banks (March 2020–September 2025, 1,231 trading days), classified into state-owned major, joint-stock, city commercial, and rural commercial banks; Table 1 details the composition.

**Table 1.** Specific Classification of Banks

Bank Category	Number (Banks)	Specific Banks
<b>Large State-Owned Commercial Banks</b>	6	Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China, China Construction Bank, Bank of Communications, Postal Savings Bank of China
<b>Shareholding Commercial Banks</b>	9	Ping An Bank, Shanghai Pudong Development Bank, Huaxia Bank, China Minsheng Bank, China Merchants Bank, Industrial Bank, China Everbright Bank, Zhesang Bank, China CITIC Bank
<b>City Commercial Banks</b>	13	Ningbo Bank, Zhengzhou Bank, Qingdao Bank, Suzhou Bank, Jiangsu Bank, Hangzhou Bank, Xi'an Bank, Nanjing Bank, Bank of Beijing, Bank of Shanghai, Changsha Bank, Chengdu Bank, Guiyang Bank
<b>Rural Commercial Banks</b>	8	Jiangyin Bank, Zhangjiagang Bank, Qingdao Rural Commercial Bank, Wuxi Bank, Chongqing Rural Commercial Bank, Changshu Bank, Zijin Bank, Jiangsu Rural Commercial Bank
<b>Total</b>	36	—

Daily closing prices are sourced from the Wind Financial Database. Climate-risk indicators are obtained from the China Energy Finance Network (CNEFN) and include the daily China Climate Policy Uncertainty index (CCPU) and multi-dimensional climate-news indices (Natural Disasters, Climate Governance, Energy Transition, among others). All data are at daily frequency.

### 4.2 Variable Construction

Dependent variables are the system-wide TCI and sector-level NET extracted from a DY rolling-window model ( $W = 150$  days) applied to daily log returns. Explanatory variables include the China Climate Policy Uncertainty index (CCPU) as transition-risk proxy and the Natural Disasters news index as physical-risk proxy. All series are aligned via date-level inner joins, yielding 1,231 balanced daily observations.

## 5 Empirical Results and Analysis

### 5.1 Dynamic Characteristics of the Banking Risk-Spillover Network

Figure 1 displays the TCI trajectory from August 2020 to September 2025, fluctuating between 88.45% and 95.54% (mean 92.79%), with pronounced time variation aligned with major economic and climate-policy events.

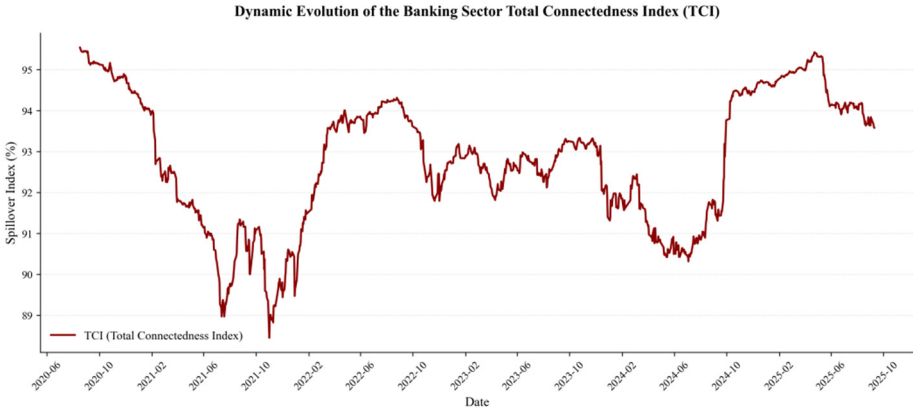


Fig. 1. Dynamic Evolution of the Total Connectedness Index (TCI) for the Banking Sector

Figure 2 compares sector-level NET dynamics: joint-stock banks serve as persistent net transmitters, state-owned banks as net receivers, while city and rural commercial banks oscillate around zero—signaling fragility under external shocks.

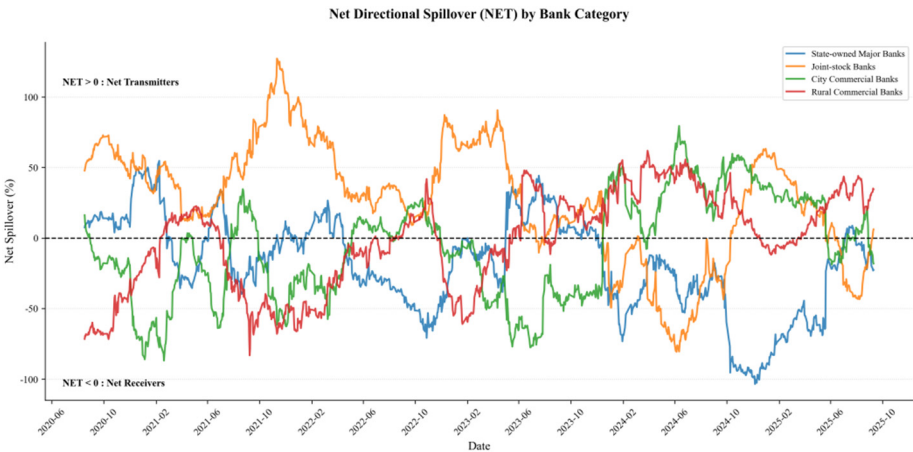


Fig. 2. Comparison of Net Directional Spillovers (NET) Across Four Major Sectors

### 5.2 Granger Causality Tests: CCPU and Banking-Sector Spillovers

Table 2 reports the Granger causality test results for CCPU on each spillover indicator, scanning lags 1 through 5 with a significance cutoff of  $p < 0.1$ .

**Table 2.** Granger Causality Tests of CCPU on Banking Sector Spillovers

Independent Variable	Dependent Variable	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Minimum p-value	Significant
CCPU	TCI	0.4673	0.5417	0.3494	0.4798	0.5300	0.3494	No
CCPU	Major state-owned banks	0.2250	0.0007***	0.0023***	0.0065***	0.0062***	0.0007	Yes
CCPU	Shareholding Banks	0.5096	0.8333	0.8805	0.9121	0.8852	0.5096	No
CCPU	City Commercial Banks	0.0807*	0.2055	0.2568	0.3152	0.3562	0.0807	Yes
CCPU	Rural Commercial Bank	0.5620	0.0007***	0.0014***	0.0013***	0.0016***	0.0007	Yes

Note: \*\*\*, \*\*, and \* denote significance levels of 1%, 5%, and 10%, respectively.

CCPU fails to Granger-cause TCI at any lag (minimum  $p = 0.3494$ ); short-run climate-policy uncertainty does not trigger system-wide panic but propagates through sector-specific channels. At the sector level, CCPU strongly leads the NET of state-owned major banks and rural commercial banks (both  $p = 0.0007$  at lag 2, remaining below 0.01 at lags 3–5)—the former due to massive carbon-intensive SOE exposures, the latter due to deep embeddedness in local high-carbon SMEs. Joint-stock banks are immune (minimum  $p = 0.5096$ ), reflecting diversified portfolios and agile asset reallocation.

### 5.3 Impulse Response Analysis of CCPU Shocks

Orthogonalized VAR impulse response functions are estimated for each significant climate-spillover pair identified in Table 2. The dynamic propagation trajectories are depicted in Figures 3–5.

1. Figure 3 shows that a one-S.D. CCPU shock induces a significant positive NET deviation for state-owned banks, peaking at days 2–3 and reverting to zero by approximately day 10.

2. Figure 4 reveals a similar but faster and larger response for rural commercial banks, peaking on day 2 and converging by days 6–8.

3. Figure 5 indicates a weaker response for city commercial banks, with confidence bands overlapping zero at several horizons—consistent with their marginal Granger significance ( $p = 0.0807$ ).

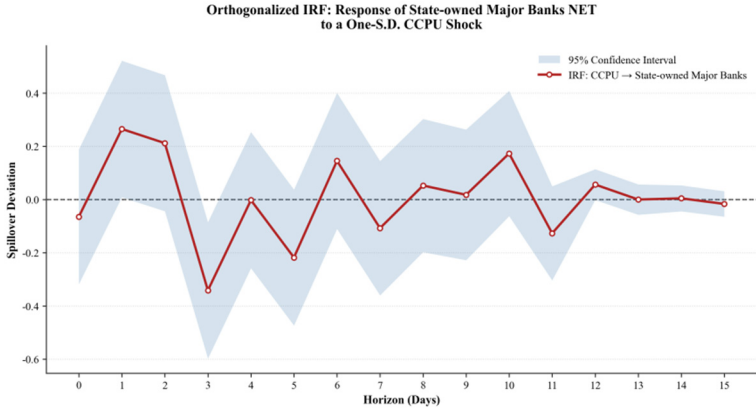


Fig. 3. Dynamic Impulse Response (IRF) of State-Owned Major Banks to the CCPU Shock

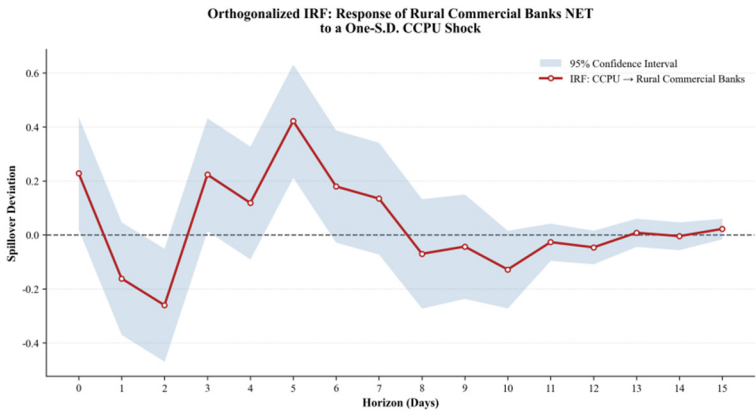


Fig. 4. Dynamic Impulse Response (IRF) of CCPU Shocks on Rural Commercial Banks

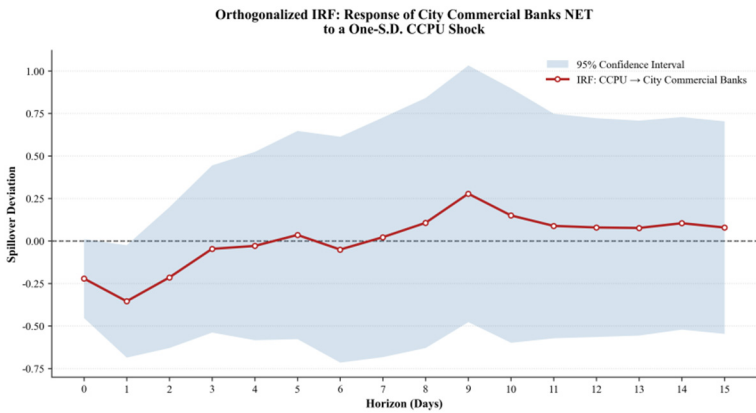


Fig. 5. Dynamic Impulse Response (IRF) of CCPU Shocks to City Commercial Banks

#### 5.4 Heterogeneity Analysis: The "Dumbbell-Shaped" Shock Structure

CCPU impacts exhibit a "dumbbell-shaped" heterogeneity: state-owned major banks ( $p = 0.0007$ ) and rural commercial banks ( $p = 0.0007$ ) are the most sensitive, city commercial banks intermediate ( $p = 0.0807$ ), and joint-stock banks immune ( $p > 0.5$ ). State-owned banks are exposed top-down through carbon-intensive legacy portfolios; rural banks bottom-up through high-carbon SME and agricultural clients. Joint-stock banks' diversified credit mix and flexible asset management absorb localized policy shocks.

### 6 Robustness Checks

#### 6.1 Substituting the Climate-Risk Proxy: Physical Risk (Natural Disasters)

To assess robustness, the Natural Disasters news index is substituted for CCPU and all Granger tests re-estimated. The TCI-level conclusion holds: physical risk likewise fails to Granger-cause aggregate spillovers (minimum  $p = 0.1741$ ). A "mirror-image reversal" emerges at the sector level—Natural Disasters significantly affects joint-stock banks ( $p = 0.0363$ ) and rural banks ( $p = 0.0238$ ) but not state-owned or city commercial banks, confirming that the heterogeneous transmission structure is robust across climate-risk types.

### 7 Conclusions and Policy Implications

Three findings emerge from a daily panel of 1,231 trading days for 36 A-share banks. Neither climate-risk type elevates system-wide TCI; shocks propagate through sector-differentiated channels. CCPU exhibits "dumbbell-shaped" heterogeneity—state-owned and rural banks are most sensitive ( $p = 0.0007$ ), joint-stock banks immune. Physical risk reverses the pattern, striking joint-stock and rural banks instead. Rural banks are the sole "resonance node" significant under both risk types. Stress tests should accordingly be differentiated by bank category, with rural banks designated as priority targets. Limitations include the absence of macro controls, lack of mediating-variable identification, and a nationwide rather than regionalized physical-risk proxy.

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