

Article

Research on Dynamic Contagion of Banking Risks and Identification of Systemically Important Institutions: Based on the HD-TVP-VAR-DY Model

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Abstract

This study focuses on analyzing the dynamic process, strength, and orientation of risk spillovers in the Chinese banking system under the exogenous shock of the COVID-19 pandemic. Using daily closing prices of 25 representative banks, it stratifies the data into three periods: pre-, during-, and post-pandemic. Employing the HD-TVP-VAR-DY model and dynamic topological directed networks, this study captures the time-varying heterogeneity of risk spillovers and identifies systemic core nodes. The findings reveal that abrupt shocks significantly exacerbate systemic fragility. The primary risk transmitters in the pre-, during-, and post-pandemic periods were CCBs, JSCBs, and CCBs, while SOCBs and RCBs were the main net risk recipients. The interbank risk propagation exhibits a structural evolution pattern of “Concentration–Decentralization–Reshaping.” In the pre-pandemic period, the network was highly concentrated, forming a directional connectedness structure from JSCBs to large banks. During the pandemic, the network underwent significant decentralization, with CMBC and SZRCB emerging as pivotal spillover sources; risk flows shifted from directional to systemic diffusion, characterized by passive absorption. Post-pandemic, the network reverted to a hierarchical-driven pattern, with BOC becoming the core risk source, and the propagation dynamics shifted from passive absorption back to active spillover dominance.

Keywords: HP-TVP-VAR-DY; COVID-19 pandemic; complex networks; risk spillovers; Systemically Important Banks; CORE risk sources



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1. Introduction

The 2008 Global Financial Crisis underlined the potential dangers of risk contagion in a global economy. Given China's bank-based financial structure, there exists an intrinsic nexus between macroeconomic instability and banking system stability. From a macro-prudential perspective, macroeconomic instability and financial fragility are deeply entwined through the asset price channel [1]. Consistent with the Efficient Market Hypothesis, fluctuations in macroeconomic variables, policy shifts, and exogenous shocks are rapidly and fully incorporated into bank stock prices and volatilities [2]. Consequently, utilizing high-frequency market data to detect risk spillovers serves not merely to gauge

micro-level linkages, but as a critical window for tracking the real-time transmission and propagation of macroeconomic stress throughout the financial system. While incorporating macroeconomic fundamentals is optimal for analyzing systemic risk, traditional indicators such as GDP and inflation are typically reported at low frequencies. This limitation creates a frequency mismatch with the rapid propagation of financial contagion. Conversely, financial market data exhibit forward-looking characteristics, effectively encapsulating investor expectations regarding future economic conditions and credit risks [1,2]. Consequently, aligning with established methodologies in the systemic risk literature [3,4], this study employs high-frequency bank stock prices. This framework facilitates the identification of real-time risk dynamics and volatility spillovers, serving as a high-frequency proxy for systemic vulnerability to broader economic shocks.

Heterogeneity in asset valuations, business models, and risk exposures leads banks to assume distinct systemic roles. An idiosyncratic shock—whether a liquidity crisis or credit event—can rapidly propagate to other institutions via interbank linkages, payment systems, and asset price volatility, precipitating a ‘domino effect.’ Such micro-level pricing cascades, triggered by exogenous macroeconomic shocks, do not merely threaten the viability of individual banks, but also jeopardize the stability of the entire banking sector and may even precipitate broader contagion across the financial system, severely disrupting real economic activity. Consequently, under conditions of extreme stress, it is imperative to accurately map the transmission pathways and evolutionary mechanisms of risk among heterogeneous institutions, thereby isolating the dominant risk sources and primary channels within the financial network.

Against this backdrop, this study utilizes the COVID-19 pandemic—a paradigmatic exogenous shock—as a structural breakpoint to investigate two core issues: (1) Amidst heightened macroeconomic turbulence, what characterizes the contagion pathways among banks of varying sizes and business models, and how do the intensity and directionality of these paths evolve over time? and (2) How does the profile of systemically important institutions shift across different regimes? Specifically, which banks emerge as core risk sources, and which serve as key transmission conduits? An in-depth examination of these questions unveils the mechanism through which macroeconomic instability translates into complex, dynamic shifts within the banking system, thereby offering a theoretical basis for the formulation of precise and effective regulatory policies.

Numerous studies have investigated systemic financial risk spillovers through diverse theoretical lenses and methodological frameworks. From a complex network perspective, Allen [5] analyzed contagion effects across the financial system utilizing interbank exposure data. Similarly, Dong [6] employed complex spillover network models to examine cross-market contagion between carbon and stock markets. Regarding tail risk, Adrian [7] introduced the seminal CoVaR model—a cornerstone of the macro-prudential perspective—to measure an individual institution’s marginal contribution to systemic distress. Subsequently, Härdle [8] proposed the TENET model, a tail-event-driven network approach based on generalized quantile regression designed to capture non-linear systemic risk contagion within high-dimensional datasets. Billio [3] further constructed connectedness networks using Principal Component Analysis (PCA) and Granger causality tests, focusing on systemic linkages among hedge funds, banks, and insurers.

Among these methodologies, network analysis has garnered significant attention. Diebold and Yilmaz [4] defined global complex networks based on generalized forecast error variance decomposition, spurring the development of numerous extended models. Notably, Antonakakis [9] proposed the Time-Varying Parameter Vector Autoregression (TVP-VAR) model. By incorporating time-varying parameters, this approach more effectively

captures dynamic linkages across different regimes and has been widely adopted [10–12]. Subsequently, the TVP-Quantile-VAR-DY model [13] was introduced to capture tail risk.

Although TVP-VAR-DY models effectively capture time-varying relationships, they remain constrained when handling high-dimensional variables. Current approaches to addressing high dimensionality fall primarily into two categories: variable selection and dimensionality reduction. Constrained by computational complexity, traditional TVP-VAR-DY models are typically limited to approximately 20 variables. Consequently, researchers often resort to omitting subsets of variables to preserve the system's time-varying properties. Alternative methods employ dimensionality reduction techniques to enhance model capacity. For instance, Demirer [14] introduced the Lasso-VAR-DY model, which uses LASSO shrinkage to compress insignificant coefficients, thereby mitigating the estimation bias inherent in traditional VAR models under high-dimensional settings. However, in the presence of high multicollinearity, the LASSO reduction process is prone to unstable coefficient identification, thereby compromising estimation efficiency. To reconcile high dimensionality with heterogeneity, Koop [15] proposed replacing traditional MCMC simulations with forgetting factors, enabling TVP-VAR models to handle dozens or even hundreds of variables. Building on this, Chen [16] further developed the HD-TVP-VAR-DY model, incorporating the Kalman filter and Elastic Net regularization for dimensionality reduction.

In summary, while recent studies have investigated dynamic risk contagion triggered by sudden events [17–19], the relevant literature remains sparse. Specifically, there is a notable absence of granular analysis regarding risk transmission pathways across heterogeneous banking institutions. Based on this, this study employs the HD-TVP-VAR-DY model to conduct a systematic analysis.

Relative to the existing literature, this study makes three primary contributions: (1) By leveraging the HD-TVP-VAR-DY model, we expand the sample to 25 banks, effectively overcoming the ‘curse of dimensionality.’ This enables a comprehensive characterization of the time-varying and moderately high-dimensional properties inherent in the complex banking network. (2) Treating the COVID-19 pandemic as a paradigmatic exogenous shock, we conduct an in-depth dissection of dynamic risk contagion across distinct temporal phases. By revealing the heterogeneity in transmission pathways—along with shifts in intensity and directionality—this study provides a precise depiction of the spillover structure, offering a vital reference for the screening and monitoring of high-risk institutions. (3) This study integrates the spillover index framework with Social Network Analysis. By analyzing network centrality metrics, we systematically identify core risk sources and critical transmission channels, thereby providing a theoretical foundation for targeted macro-prudential regulation.

2. Materials and Methods

2.1. Economic Rationale for Model Selection

This study employs the HD-TVP-VAR-DY model to dissect the risk contagion mechanisms within China's banking system. The primary rationale lies in the framework's efficacy in addressing three critical challenges often insurmountable for traditional econometric models under sudden exogenous shocks: non-linearity, moderately high-dimensional connectedness, and micro-heterogeneity.

According to Adaptive Expectations Theory, when confronted with highly uncertain exogenous shocks such as the COVID-19 pandemic, banks dynamically adjust their risk-taking behaviors and operational strategies in response to real-time information flows. In contrast, traditional linear models typically assume static risk transmission pathways throughout the sample period—an assumption that fundamentally diverges from the reality of volatile market sentiment under extreme conditions. By leveraging time-varying pa-

rameters, the proposed model accurately captures non-linear structural shifts in contagion intensity triggered by evolving market expectations, thereby providing a more authentic reconstruction of the dynamic trajectory of risk evolution. Furthermore, the modern banking industry constitutes a highly interconnected network, where institutions are deeply nested through operational linkages such as interbank lending and cross-shareholding [20]. Constrained by computational efficiency and variable capacity, traditional low-dimensional models are often compelled to exclude small- and medium-sized banks, thereby artificially truncating potential risk transmission pathways. Conversely, the HD-TVP-VAR-DY model, with its robust moderately high-dimensional processing capabilities, overcomes the bottleneck of variable scale. This ensures a holistic identification of systemic risk, effectively mitigating estimation bias resulting from the omission of critical network nodes. Additionally, grounded in Bank Heterogeneity Theory, significant disparities exist among state-owned banks, joint-stock banks, and city/rural commercial banks regarding capital structure, asset quality, and client bases [21]. By incorporating a mechanism to handle heterogeneity, this model allows the regression coefficients of individual institutions to evolve independently. This approach profoundly reflects the endogenous, differential responses of distinct financial entities when facing homogeneous external shocks.

In summary, the HD-TVP-VAR-DY model not only technically surmounts the “curse of dimensionality” but also aligns closely with the economic logic governing the banking system’s operation under extreme shocks. By integrating time-varying characteristics, moderately high-dimensional connectedness, and micro-heterogeneity into a unified framework, this model provides robust econometric support for the precise parsing of risk evolution within complex financial networks.

2.2. HD-TVP-VAR-DY Model

Traditional TVP-VAR frameworks face significant computational constraints, often termed the ‘curse of dimensionality,’ when applied to a system of 25 variables. To circumvent these limitations, this study employs the HD TVP-VAR model, an advanced extension grounded in the methodology pioneered by Koop and Korobilis. By incorporating forgetting factor approximations, this framework effectively facilitates the robust estimation of moderately high-dimensional datasets while capturing time-varying parameter heterogeneity. The general form of the model, following variable demeaning, is specified in Equation (1).

$$y_t = X_t \beta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_t) \quad (1)$$

Here, y_t denotes an $N \times 1$ vector comprising the returns of banks at time t . The term $X_t = I_N \otimes (1, y'_{t-1}, \dots, y'_{t-p})$ represents the Kronecker product matrix of the lagged variables. β_t is the vector containing all time-varying coefficients, while Σ_t defines the covariance matrix of the disturbances ε_t . The state equation is expressed as:

$$\beta_t = \beta_{t1} + \eta_t, \quad \eta_t \sim N(0, Q_t) \quad (2)$$

Involving 25 banks and a corresponding multitude of parameters, this study presents a typical high-dimensional problem. Direct estimation in such settings is susceptible to overfitting, parameter instability, and multicollinearity. These issues may compromise the reliability of the estimation results. To address these challenges, an estimation strategy integrating Elastic Net regularization with a forgetting factor Kalman filter is employed.

Initially, Elastic Net regularization is utilized for dimensionality reduction. By appending a penalty term to the conventional loss function, this technique constrains both the magnitude and number of parameters, as specified in Equation (3).

$$\hat{\beta}_{EN} = \arg \min_{\beta} \left(\|y_t - X_t \beta\|^2 + \kappa \left(\rho \|\beta\|_1 + \frac{1-\rho}{2} \|\beta\|_2^2 \right) \right) \quad (3)$$

In Equation (3), κ denotes the regularization parameter controlling the shrinkage intensity, with its optimal value determined via five-fold cross-validation. The parameter ρ ($0 \leq \rho \leq 1$) serves as the Elastic Net mixing coefficient, balancing the trade-off between L_1 and L_2 regularization. Specifically, the L_1 norm $\|\beta\|_1$ promotes sparsity, while the squared L_2 norm $\|\beta\|_2^2$ mitigates multicollinearity.

Following dimensionality reduction, parameter estimation is required. While MCMC methods are widely used in the existing literature, they rely heavily on prior distributions and suffer from computational inefficiency in high-dimensional spaces. To address these drawbacks, the Kalman Filter with a Forgetting Factor is adopted [16]. This technique incorporates a forgetting factor λ , thereby avoiding the direct estimation of the high-dimensional state covariance matrix Q_t .

The algorithm comprises two primary steps: Prediction and Update.

(1) Prediction Step

On the basis of all information available up to time $t - 1$, a prior prediction is made for the state at time t .

State Prediction:

$$\hat{\beta}_{t|t-1} = \hat{\beta}_{t-1|t-1} \quad (4)$$

Prediction Covariance Matrix:

$$P_{t|t-1} = \frac{1}{\lambda_t} P_{t-1|t-1} \quad (5)$$

As suggested by Equation (6), the uncertainty in the state prediction is contributed by two components: the inherent uncertainty of the estimation at the previous moment and the uncertainty introduced by the stochastic fluctuation of the state equation. In this model, λ_t is called the forgetting factor, taking on values strictly between 0 and 1. The faster the decay of historical data, the higher the sensitivity to new information. Following the approach of Koop [15] and Raftery [22], λ is set to 0.99.

(2) Update Step

Upon receiving new information y_t , the prior prediction is then updated to generate the posterior prediction.

Kalman Gain:

$$K_t = P_{t|t-1} X_t' (X_t P_{t|t-1} X_t' + \Sigma_t)^{-1} \quad (6)$$

State Update:

$$\hat{\beta}_{t|t} = \hat{\beta}_{t|t-1} + K_t (y_t - X_t \hat{\beta}_{t|t-1}) \quad (7)$$

Covariance Update:

$$P_{t|t} = (I - K_t X_t) P_{t|t-1} \quad (8)$$

Here, the Kalman Gain (K_t) serves as a weighting matrix, determining the influence of the new observation y_t against the prior prediction $\hat{\beta}_{t|t-1}$. This balance constitutes the core mechanism of the Kalman Filter. The State Update (Equation (7)) represents the posterior estimate, calculated as the prior estimate plus a correction term. This correction term derived from the product of the prediction error and the Kalman Gain. By incorporating new

information, the uncertainty surrounding the state estimation diminishes. $P_{t|t}$ quantifies the precision of the updated estimate $\hat{\beta}_{t|t}$.

Subsequent to the coefficient estimation, the error covariance matrix, Σ_t is updated recursively to address heteroscedasticity. Following the framework of Koop and Korobilis [15], a forgetting factor κ_2 is employed to apply exponential weighting to the squared prediction errors:

$$\hat{\Sigma}_t = \kappa_2 \hat{\Sigma}_{t-1} + (1 - \kappa_2) \hat{e}_t \hat{e}_t' \quad (9)$$

This specification enables the model to effectively capture time-varying volatility and the volatility clustering phenomena in financial time series.

Furthermore, to address the challenge of high-dimensional parameter estimation, Elastic Net shrinkage is incorporated into the recursive iteration of the Kalman filter. Although the Elastic Net is typically viewed as a static estimator, following the theoretical framework of Belmonte [23], embedding it within a state-space model is equivalent to applying a time-varying shrinkage prior. This integration theoretically guarantees the continuity of parameter evolution while ensuring numerical stability in the high-dimensional parameter space. It effectively suppresses noise and endogenously identifies the most significant risk transmission paths among banks, thereby achieving a robust balance between time-varying model flexibility and parameter parsimony.

2.3. Construction of Risk Spillover Indices

Drawing on the insights of Primiceri [24], this study prioritizes model parsimony to ensure the stability of the Kalman filter's recursive estimation. Consequently, the optimal lag length is determined based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), the lag order for the HD-TVP-VAR model is set to $p = 4$. Drawing upon the generalized VAR framework established by Diebold and Yilmaz, variance decomposition principles are applied to construct a global complex risk network. The Generalized Forecast Error Variance Decomposition (GFEVD) method proposed by Pesaran and Shin is utilized [25]. Unlike orthogonalized decomposition, this approach remains invariant to the ordering of variables. The decomposition is mathematically expressed as:

$$d_{ijt}^H = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' \Theta_{ht} \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Theta_{ht} \Sigma_t \Theta_{ht}' e_i)} \quad (10)$$

In Equation (10), d_{ijt}^H denotes the proportion of the H-step-ahead forecast error variance of bank i at time t attributable to shocks originating from bank j . The terms e_i and e_j are defined as selection vectors, containing a value of unity at the i -th (or j -th) position and zeros elsewhere. σ_{jj} denotes the j -th diagonal element of the error variance-covariance matrix, and H represents the forecast horizon. Θ_{ht} refers to the coefficient matrices derived from the TVP-VMA (∞) representation.

Notably, since the generalized variance decomposition relaxes the assumption of shock orthogonality, the row sums of the variance decomposition matrix do not necessarily sum to unity; that is, $\sum_{j=1}^N d_{ijt}^H \neq 1$. To compute the spillover indices, row normalization of the matrix is required. The normalized variance decomposition element $\tilde{d}_{ijt}^H$ is constructed as follows:

$$\tilde{d}_{ijt}^H = \frac{d_{ijt}^H}{\sum_{j=1}^N d_{ijt}^H} \times 100 \quad (11)$$

Here, the conditions $\sum_{j=1}^N \tilde{d}_{ijt}^H = 100$ and $\sum_{i,j=1}^N \tilde{d}_{ijt}^H = N \times 100$ are satisfied.

It is crucial to clarify the interpretation of these indices. The spillover measures derived from the GFEVD framework quantify the proportion of forecast error variance of

one variable that is explained by shocks to another. Strictly speaking, this metric captures directional predictive connectedness rather than structural causality. Furthermore, in this context, we explicitly define ‘contagion’ as statistical volatility spillovers or information flows reflected in asset prices, distinguishing it from structural default chains. Therefore, terms such as ‘spillover,’ ‘transmission,’ and ‘impact’ used throughout this study refer to statistical associations and predictive dependence within the system.

Building upon this framework, several key indicators are defined to characterize the risk network structure.

First, to measure the overall intensity of risk transmission across the entire banking system, the Total Spillover Index (denoted as TCI) is constructed. This measure captures the overall systemic connectivity and is calculated as follows:

$$TCI_t = \frac{\sum_{i,j=1,i \neq j}^N \tilde{d}_{ijt}^H}{\sum_{i,j=1}^N \tilde{d}_{ijt}^H} \times 100 \quad (12)$$

Second, the cumulative risk spillover transmitted from bank i to all other institutions is quantified. This metric, denoted as TO , serves as a proxy for the bank’s systemic influence and is expressed as:

$$TO_{t,i \rightarrow \cdot} = \sum_{j=1,j \neq i}^N \tilde{d}_{ijt}^H \quad (13)$$

Third, the sum of cumulative risk spillovers received by bank i from the rest of the system is computed. This metric, denoted as $FROM$, reflects the extent to which an individual bank is affected by others and is expressed as:

$$FROM_{t,i \leftarrow \cdot} = \sum_{j=1,j \neq i}^N \tilde{d}_{jit}^H \quad (14)$$

Subsequently, the Net Spillover Index (denoted as NET) is derived by subtracting the cumulative risk received ($FROM_{i,t}$) from the cumulative risk transmitted ($TO_{i,t}$). This metric quantifies the net contribution of an individual institution to systemic risk:

$$NET_{t,i} = TO_{t,i \rightarrow \cdot} - FROM_{t,i \leftarrow \cdot} \quad (15)$$

Finally, to capture the granular bilateral transmission structure, the Pairwise Net Spillover Index is computed. Defined as the difference between gross spillovers from bank i to bank j and those from bank j to bank i , this metric is expressed as:

$$NET_{t,i \rightarrow j} = \tilde{d}_{jit}^H - \tilde{d}_{ijt}^H \quad (16)$$

3. Analysis of Dynamic Mechanisms of Banking Risk Contagion

3.1. Data and Sample Selection

3.1.1. Sample Selection and Data Sources

Following the Wind Industry Classification Standards, the Chinese listed banking sector is categorized into four distinct groups: State-owned Commercial Banks (SOCBs), Joint-Stock Commercial Banks (JSCBs), City Commercial Banks (CCBs), and Rural Commercial Banks (RCBs). For the empirical analysis, the study utilizes daily closing prices of 25 A-share listed banking institutions, spanning the period from 24 January 2017 to 31 March 2025. The rationale regarding the sampling strategy and time horizon is summarized as follows:

① To ensure a balanced and continuous panel dataset, the sample is restricted to banks listed prior to 23 January 2017. ② The selected sample substantially overlaps with the core members of the Domestic Systemically Important Banks (D-SIBs) list, as identified in the China Financial Stability Report issued by the People’s Bank of China (PBOC). Furthermore, according to official 2024 data from the National Financial Regulatory Administration (NFRA), the total assets of China’s listed banks account for approximately 70–80% of the entire banking sector. Although institutions listed in recent years were excluded, the 25 selected core banks still represent over 60% of total banking assets, thereby ensuring adequate sample sufficiency for this study. ③ The observation window encompasses three distinct phases relative to the COVID-19 pandemic: the pre-pandemic, pandemic, and post-pandemic phases. Additionally, this timeframe captures critical financial events, including the US–China Trade War, the P2P lending crisis, and volatility in US money markets. This comprehensive coverage facilitates a rigorous examination of the time-varying dynamics of intra-industry risk contagion triggered by exogenous shocks.

All the data are sourced from the Wind Database. Table 1 details the classification of the sampled banking institutions.

Table 1. Classification of the Sampled Banking Institutions.

Banking Classification	Listed Branches Institutions	Abbreviation	Banking Classification	Listed Branches Institutions	Abbreviation
State-owned Banks (abbreviated as SOCs)	Industrial and Commercial Bank of China	ICBC	City Commercial Banks (abbreviated as CCBs)	Bank of Beijing	BOB
	China Construction Bank	CCB		Shanghai Bank	BOS
	Agricultural Bank of China	ABC		Nanjing Bank	NJCB
	Bank of China	BOC		Ningbo Bank	NBCB
Joint-stock Commercial Banks (abbreviated as JSCBs)	Bank of Communications	BOCOM	Rural Commercial Banks (abbreviated as RCBs)	Hangzhou Bank	HZBANK
	China Merchants Bank	CMB		Jiangsu Bank	JSB
	Industrial Bank	CIB		Guiyang Bank	GYB
	Shanghai Pudong Development Bank	SPDB		Wuxi Bank	WXRCB
	China CITIC Bank	CITIC		Zhangjiagang Bank	ZRC
	Minsheng Bank	CMBC		Changshu Bank	CSRCB
	Everbright Bank	CEB		Suzhou Bank	SZRCB
	Ping An Bank	PAB		Jiangyin Bank	JRCB
	Huaxia Bank	HXB			

3.1.2. Descriptive Statistics and Unit Root Tests

Descriptive statistics (Table A1) reveal that the bank closing price series are characterized by heavy tails, leptokurtosis, asymmetry, and non-stationarity. Time-series plots (Figure 1) demonstrate pronounced co-movement across the 25 banks. Notably, during the 2018 US–China trade dispute, the COVID-19 pandemic (2020–2022), the domestic policy stimulus of September 2024, and the 2025 tariff escalation, stock prices exhibited synchronized and heightened volatility. From an economic perspective, such high-degree clustering suggests that systemic shocks propagate rapidly through the sector via information contagion and balance sheet interconnectedness. These synchronized fluctuations imply strong dynamic correlations, providing preliminary evidence of the complex and time-varying nature of intra-industry risk spillovers.

To ensure stationarity and mitigate the impact of disparate data scales, daily closing prices are converted into logarithmic returns using the following formula:

$$r_{it} = 100 \times (\ln P_{it} - \ln P_{i,t-1}) \quad (17)$$

where P_{it} denotes the closing price of bank i at time t . Descriptive statistics and unit root test for the logarithmic returns of the 25 sampled banks are summarized in Table 2.

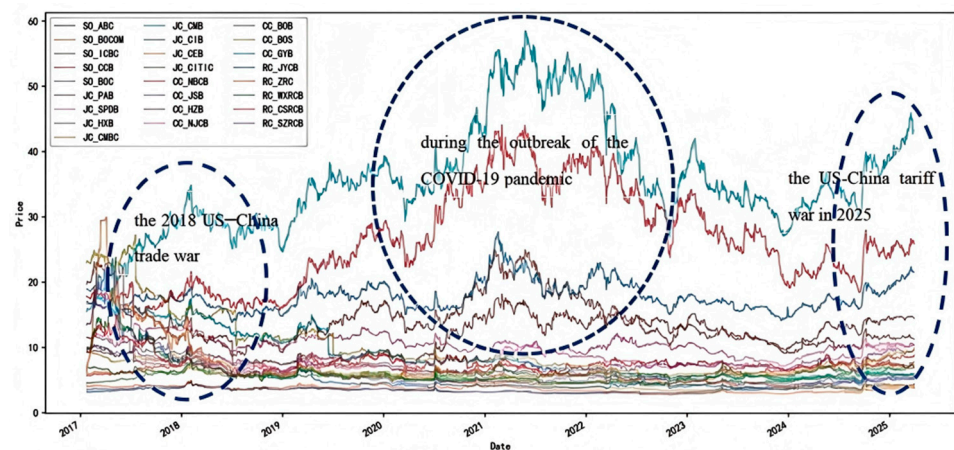


Figure 1. Time series trend charts of 25 banks.

Table 2. Descriptive Statistics and Stationarity Tests of Daily Logarithmic Returns.

Bank	Mean	sd	Skew	Kurtosis	t-Statistic	Bank	Mean	sd	Skew	Kurtosis	t-Statistic
SO_ABC	0.025	1.105	−0.262	7.608	−31.4067	CC_NBCB	0.019	2.115	−0.280	9.559	−31.6988
SO_BOCOM	0.011	1.124	−0.631	8.915	−30.0552	CC_JSB	0.000	1.454	0.019	4.895	−31.6462
SO_ICBC	0.021	1.159	0.037	5.859	−30.2101	CC_HZB	−0.016	2.114	−5.038	94.335	−31.6369
SO_CCB	0.023	1.333	−0.075	6.086	−30.346	CC_NJCB	−0.006	1.777	−4.694	99.250	−32.7405
SO_BOC	0.023	1.074	0.001	10.264	−30.8892	CC_BOB	−0.026	1.175	−2.971	49.633	−31.3527
JC_PAB	0.010	1.954	0.312	3.063	−30.7334	CC_BOS	−0.043	1.743	−10.047	191.369	−31.8431
JC_SPDB	−0.024	1.285	−1.274	22.874	−30.697	CC_GYB	−0.049	1.621	−5.789	141.958	−30.7403
JC_HXB	−0.019	1.255	−1.924	36.772	−30.8705	RC_JRCB	−0.040	2.042	−0.290	11.057	−30.2936
JC_CMBC	−0.044	1.192	−1.996	42.483	−30.707	RC_ZRC	−0.020	2.383	0.099	7.489	−28.2276
JC_CMB	0.042	1.820	0.209	2.380	−31.72	RC_WXRCB	−0.027	2.013	0.262	6.940	−29.6379
JC_CIB	0.012	1.584	0.108	4.596	−31.106	RC_CSRB	−0.014	2.012	0.150	5.068	−31.6726
JC_CEB	−0.004	1.324	0.347	6.705	−30.2886	RC_SZRCB	−0.047	2.046	−1.026	17.903	−33.0097
JC_CITIC	0.001	1.517	0.279	8.057	−30.856						

Note: The t-Statistic denotes the Augmented Dickey–Fuller (ADF) test statistic with a lag order of 1. All statistics are significant at the 1% level ($p < 0.01$).

As shown in Table 2, although volatility remains low across most banks, higher fluctuations are observed in RCBs and CCBs. Regarding distributional characteristics, all series exhibit significant skewness and leptokurtosis. Furthermore, each series has a mean centered around zero, with no evident trend or seasonality, as illustrated in Figure A1. The ADF test results further reject the null hypothesis of a unit root at conventional significance levels. Consequently, all series are confirmed as stationary, thereby validating the feasibility of the subsequent empirical modeling.

To evaluate the impact of the COVID-19 pandemic on China's banking system risk across different phases, this study further partitions the sample into three distinct periods. To enhance the statistical rigor of this periodization and address the inherent limitations of time-varying parameter models in capturing discrete systemic mutations, the Bai–Perron [26] multiple structural break test is applied to the arithmetic mean sequence of log-returns for the 25 sample banks (Figure 2).

Empirical results identify four significant structural breaks across the full sample period. Aligning with the research focus, two pivotal breakpoints—4 February 2020 and 11 November 2022—were selected due to their close synchronicity with the onset and resolution of the pandemic shocks. Furthermore, by incorporating major shifts in national containment policies, 2 January 2020 and 8 December 2022 were designated as the final thresholds for periodization. By integrating quantitative detection with qualitative contextual analysis, the study interval is divided into three distinct phases (pre-, during-, and post-pandemic), as detailed in Table 3.

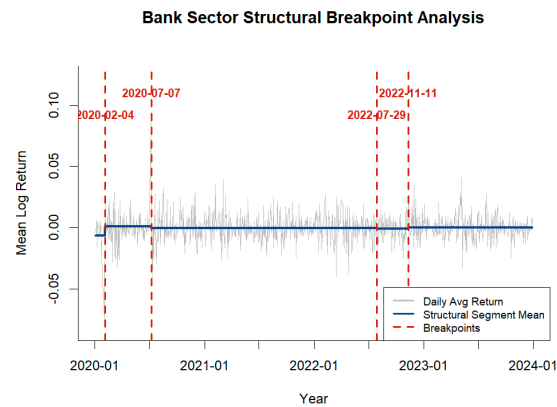


Figure 2. Average bank structural breakpoint analysis.

Table 3. Principles for Sample Stage Classification.

Phase	Time Phase	Rationale
pre-pandemic	24 January 2017– 31 December 2019	The pre-outbreak phase of the COVID-19 pandemic.
during-pandemic	2 January 2020– 8 December 2022	The rapid transmission phase of the COVID-19 pandemic.
post-pandemic	9 December 2022– 31 March 2025	After 8 December 2022, mandatory nationwide mass PCR screening ceased (excluding Hong Kong, Macao, and Taiwan) to be replaced by voluntary PCR tests (“Yuan Jian Jin Jian”). Thus, the nation shifted to a fully opened normalized stage, which marked the end of the extensive anti-pandemic campaign.

3.2. Dynamic Evolution of Interbank Risk Transmission and Systemic Importance Analysis

With the COVID-19 pandemic serving as the focal exogenous shock, this section systematically dissects interbank risk spillovers across three distinct phases. Furthermore, it scrutinizes the intricate transmission dynamics of systemic risk within the banking industry.

3.2.1. Analysis of Aggregate and Localized Spillovers

The analysis commences with the total spillover index at the aggregate level, as depicted in Figure 3.

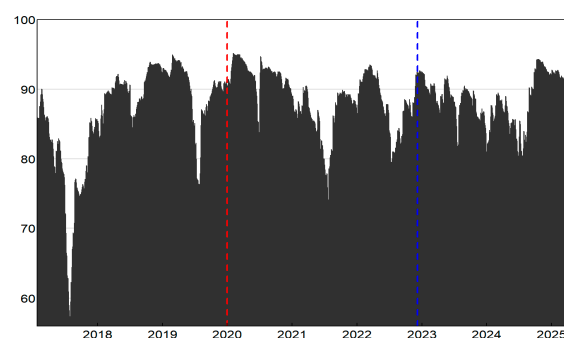


Figure 3. Dynamic Evolution of the Total Spillover Index. Note: In Figure 3, vertical reference lines delineate three distinct temporal phases: the pre-pandemic period (situated to the left of the red line), the pandemic period (bounded by the red and blue lines), and the post-pandemic period (extending to the right of the blue line). This temporal demarcation is consistently applied throughout the subsequent analysis.

Figure 3 illustrates that, prior to 2018, total risk spillovers within the banking sector remained relatively subdued, albeit exhibiting significant volatility. However, the post-2018 era marked a pronounced shift. Driven by economic deceleration, financial deleveraging,

and US–China trade tensions, risk transmission channels widened, causing the spillover index to rise and persist at elevated levels. In 2020, the COVID-19 pandemic induced a severe macroeconomic shock, resulting in widespread industrial stagnation and corporate liquidity constraints. Consequently, the total spillover index fluctuated at a high plateau of approximately 95. During the post-pandemic recovery, industries faced structural bottlenecks, including labor shortages and supply chain disruptions. When compounded by the geopolitical conflicts of 2023 and heightened RMB exchange rate volatility, the index rebounded to surpass the 95 threshold following a brief decline. Subsequently, driven by policy interventions and enhanced risk mitigation mechanisms, the index retreated rapidly to the 94 level. Nonetheless, it remains significantly above the baseline levels observed in the pre-2018 era.

Based on the classification in Table 1, the dynamics of total spillovers (TO) and spill-ins (FROM) for each bank category are examined.

Figure 4 illustrates distinct heterogeneity in risk spillovers across banking categories throughout the pre-pandemic, pandemic, and post-pandemic phases. For SOCBs, total spillovers remained a relatively high baseline (approximately 80) prior to the pandemic. Although this level declined during the crisis, it rebounded in the post-pandemic phase following a mid-2023 trough, yet failed to fully recover to pre-pandemic highs. Conversely, JSCBs exhibited an upward trajectory prior to the outbreak. During the pandemic, despite short-term fluctuations, spillovers persisted at elevated levels (averaging 87), positioning JSCBs as the primary risk contributors among the four groups. In the post-pandemic era, these spillovers recovered rapidly, eventually surpassing pre-pandemic levels. CCBs displayed considerable volatility before the pandemic. Prior to August 2018, spillovers remained below 65; however, driven by the confluence of economic transformation and financial deleveraging, the index subsequently surged past 80. A notable decline occurred during the pandemic relative to late 2019, followed by a sluggish post-pandemic recovery characterized by substantial volatility. Finally, RCBs maintained low spillover levels with a downward trajectory prior to the pandemic. A distinct drop from late-2019 levels was observed during the pandemic, while post-pandemic spillovers stabilized at a relatively low baseline.

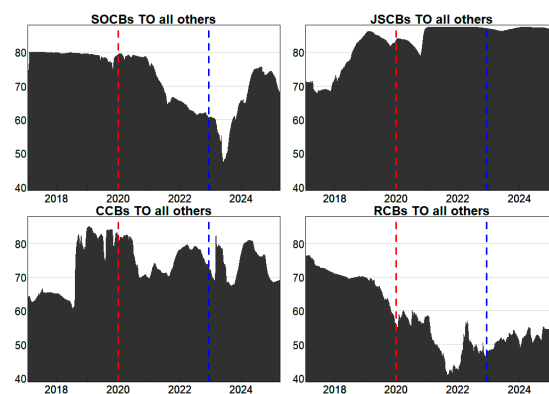


Figure 4. Dynamic Evolution of TO across Different Banking Categories.

Figure 5 illustrates the total spill-in indices (FROM) across distinct banking categories.

As illustrated in Figure 5, the post-2018 period is characterized by a broad elevation in incoming spillovers (FROM) across the banking industry. Among the various cohorts, SOCBs and JSCBs exhibit the most pronounced volatility. The heightened sensitivity of SOCBs to external risk transmission is attributed to their designation as Systemically Important Banks, as well as their dense interbank linkages. Similarly, the rising risk exposure of JSCBs reflects structural frictions that impede the expansion of interbank transactions,

thereby accelerating capital spillovers and escalating operational risks. Conversely, CCBs and RCBs remained relatively insulated during the pre-pandemic period, primarily due to their segmented client bases. Following the onset of COVID-19, the severe shock to the real economy triggered an initial surge in spill-ins, followed by a sharp retrenchment. Meanwhile, the expansion of digital banking facilitated a swift resurgence in risk inter-connectedness. Throughout this turbulent phase, aggregate spillover intensity remained elevated. Notably, CCBs experienced a substantial decline in inward spillovers during the pandemic. This trend is attributed to the deterioration in creditworthiness among SMEs and service sectors, which were disproportionately impacted by the outbreak. Consequently, the strategy of strategic credit contraction and strengthened risk management protocols contributed to a sharp reduction in high-risk interbank trading and inward spillovers. In the post-pandemic era, a rapid rebound in inward risk spillovers is observed across the broader banking sector.

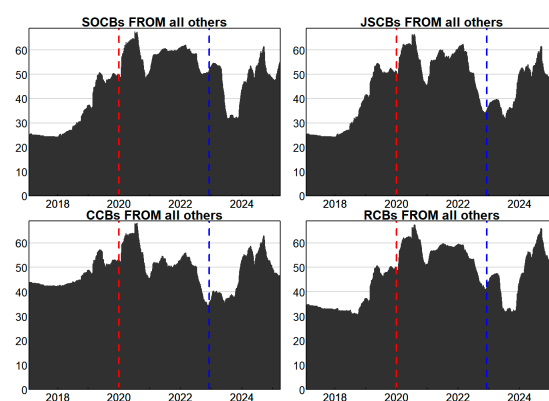


Figure 5. Dynamic Evolution of FROM across Different Banking Categories.

Taking together, SOCBs and JSCBs consistently occupy a dominant position within the risk network. Particularly during economic downturns, these large institutions shoulder the policy mandate of ‘stabilizing growth’ through credit expansion; this concomitant balance sheet enlargement objectively amplifies risk resonance within the system. Conversely, CCBs and RCBs exhibit relatively subdued risk spillover levels, with a notable contraction observed during the pandemic. This trend is primarily attributable to the stringent regulatory crackdown on shadow banking and the deepening of financial deleveraging campaigns in recent years. Such structural divergence suggests that while large banks serve as the primary conduits for systemic risk transmission, small and medium-sized banks—due to their exposure to vulnerable micro and small enterprises—are more prone to becoming localized accumulation points for credit risk. Consequently, under external shocks, these institutions may trigger micro-level feedback loops through credit contraction.

3.2.2. Analysis of Interbank Spillover Intensity and Directionality

This section investigates the magnitude and dynamics of risk transmission across distinct banking categories. Two analyses employing two key metrics—namely, Net Spillovers (NET) and Pairwise Net Spillovers (Pairwise-NET)—were performed, as visualized in Figures 6 and 7, respectively.

Figure 6 illustrates the dynamic trajectories of net risk spillovers across banking categories, explicitly revealing the heterogeneity of institutional roles and their structural shifts within the systemic risk network surrounding the pandemic.

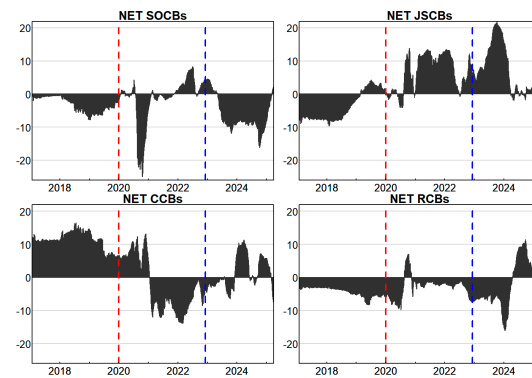


Figure 6. Dynamic Evolution of Net Spillovers across Different Banking Categories.

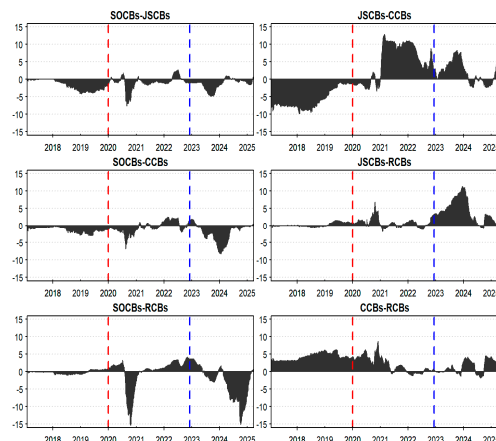


Figure 7. Dynamic Evolution of Pairwise Net Spillovers between Banking Categories.

First, SOCBs exhibit the distinct characteristics of a ‘Systemic Stabilizer.’ For the majority of the sample period, the net spillover indices for SOCBs remain predominantly negative, underscoring their structural position as net risk recipients. Notably, during the initial COVID-19 outbreak in 2020 and subsequent turbulent phases, SOCBs displayed profound negative spillovers. This reflects the ‘counter-cyclical adjustment’ mandate assumed by large state-owned banks under the macro-prudential framework. Underpinned by robust capital buffers and implicit government guarantees, SOCBs proactively absorbed tail risks emanating from smaller banks and the real economy during the crisis, thereby smoothing systemic volatility. Second, while JSCBs fluctuated near zero prior to 2020, this year marks a definitive structural breakpoint. Thereafter, their net spillovers shifted sharply positive and sustained elevated levels, positioning them as the dominant net risk transmitters in the system. This transition is attributed to their aggressive balance sheet expansion strategies combined with higher market-oriented risk appetite. Amidst monetary easing, JSCBs actively sourced wholesale funding through interbank liabilities to chase high-yield assets via credit expansion. This model of ‘active liability management plus aggressive expansion’ rendered them the primary source for the outward propagation of liquidity shocks and credit risks. Third, CCBs experienced a drastic reversal from ‘Shadow Banking Participants’ to ‘Risk Absorbers.’ Prior to 2020, CCBs were primary net risk transmitters; however, following the outbreak, their net spillovers rapidly inverted to negative values. Given that CCBs primarily serve vulnerable Small- and Medium-sized Enterprises (SMEs), the concentration of credit defaults during the economic downturn compelled CCBs to passively absorb these endogenous risks, thereby suppressing their risk transmission capacity through credit contraction. Finally, RCBs persisted in a net recipient state for an extended period but exhibited a notable positive rebound after 2024. This

suggests a hierarchical lag in risk transmission. RCBs acted as passive risk bearers during the initial stages of the crisis. The subsequent rebound likely reflects new risk exposures arising from credit deepening driven by rural revitalization policies.

Figure 7 provides a granular view of pairwise risk transmission pathways, capturing shifts in both intensity and directionality across different phases.

The interaction between JSCBs and CCBs exhibits a decisive structural reversal. Specifically, the JC-CC subplot identifies 2020 as a distinct watershed. Prior to the pandemic, JSCBs predominantly functioned as net risk recipients from CCBs. This pattern reflected the pre-regulatory dynamic, where smaller banks transmitted risks upward through shadow banking channels. However, post-2020, JSCBs rapidly pivoted to become aggressive net risk transmitters to CCBs. This reversal highlights intensified ‘liquidity stratification’ within the interbank market. In an environment characterized by post-pandemic monetary easing alongside stringent regulation, JSCBs—distinguished by their high market orientation and aggressive asset expansion—have played a pivotal role. These institutions source wholesale funding from large banks and cascade liquidity down to the lower tiers of the market (CCBs) through interbank lending and bond investments. Second, the relationship between SOCBs and JSCBs reaffirms the former’s role as a systemic anchor. The net spillover for LS-JC remains predominantly negative, confirming the structural status of SOCBs as systemic risk stabilizers that absorb shocks from risk-taking institutions. Finally, the interaction between CCBs and RCBs displays a rigid geographic hierarchy. The net spillover for CC-RC remains consistently positive throughout the sample period, indicating a unidirectional outflow of risk from CCBs to RCBs. This trend reflects a ‘Core–Periphery’ geographic dependency. Typically situated in provincial capitals or economic hubs, CCBs occupy a central node in regional financial networks, whereas RCBs operate primarily at the county level. Consequently, capital and risk naturally permeate from regional financial centers to the hinterlands, establishing a stable geographic cascade effect.

3.3. Robustness Checks

To validate the reliability of the empirical findings, robustness tests are conducted on key model parameters. First, the lag order is adjusted from the baseline of 3 to alternative orders of 1 and 2. Second, the forgetting factor is recalibrated from 0.99 to 0.95. The new dynamic total spillover indices derived using the different model parameters are shown in Figure 8.

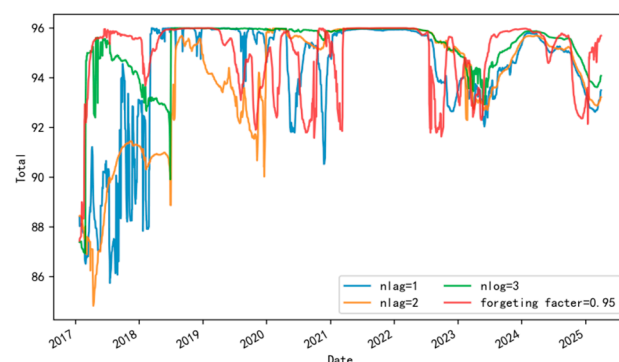


Figure 8. Comparison of Total Spillover Indices under Alternative Model Specifications.

Figure 8 illustrates that the variation in lag orders and forgetting factors produces only marginal differences in the magnitude of the total spillover indices. Despite minor quantitative deviations, the estimated series remain highly comparable. Crucially, the temporal evolution exhibits a consistent pattern across all model specifications. This alignment corroborates the robustness and validity of the empirical framework.

4. Dynamic Identification and Assessment of Systemically Important Financial Institutions

4.1. Analysis of Systemic Importance Across Banking Categories

To provide an intuitive visualization of systemic importance within the banking industry, network topology analysis is employed to characterize the structural features of the risk network. Figure 9 illustrates the evolution of systemic importance across the pre-pandemic, pandemic, and post-pandemic phases. In these topological graphics, nodes represent distinct banking categories. The size of each node is proportional to its weighted out-degree centrality; consequently, larger nodes identify institutions serving as primary sources of risk spillovers. Regarding the connecting edges, they signify net risk spillovers between institutions: red edges denote a net risk export from node i to node j , while blue edges indicate a net risk import. Furthermore, the edge thickness corresponds to the absolute magnitude of the net spillovers, with thicker edges implying more intense risk transmission.

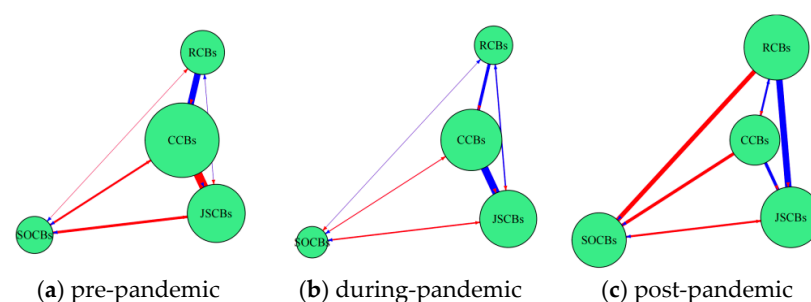


Figure 9. Risk Network Topologies within the Banking Sector across Different Periods.

As demonstrated in Figure 9, distinct risk spillover topologies emerge among banking categories across the three phases. During the pre-pandemic, CCBs were identified as the core source of risk contagion. Dominant transmission pathways originated from CCBs, targeting SOCBs and JSCBs, alongside a notable unidirectional flow from JSCBs to SOCBs. Amid the pandemic, CCBs retained their prominence as a primary risk transmitter, with JSCBs emerging as a secondary source. Key network dynamics included bidirectional spillovers between CCBs and SOCBs, unidirectional transmission from JSCBs to SOCBs, and distinct transmission chains flowing from RCBs to CCBs and, subsequently, from CCBs to JSCBs. In the post-pandemic era, the topological center shifted, with RCBs becoming the core risk source, followed by JSCBs as a secondary transmitter. Primary outflow channels were characterized by net risk transmission from RCBs to SOCBs, cascading further from SOCBs to CCBs.

4.2. Bank-Level Assessment of Systemic Importance in Different Periods

To provide a granular analysis of systemic importance, this subsection evaluates 25 individual banks using a dynamic risk network framework. This approach scrutinizes the evolution of core risk sources and transmission pathways across distinct phases. Figure 10 depicts the complete network architecture, revealing pronounced heterogeneity in the intensity and structure of interbank spillovers.

To isolate critical transmission channels and dominant risk emitters, a filtered network topology is constructed (Figure 11). In this visualization, significant pathways are highlighted in yellow, while core risk sources are distinguished in orange. The filtering threshold is established as follows: ‘critical pathways’ comprise edges within the top 20th percentile of weights, and the four institutions exhibiting the highest centrality rankings are designated as core risk sources.

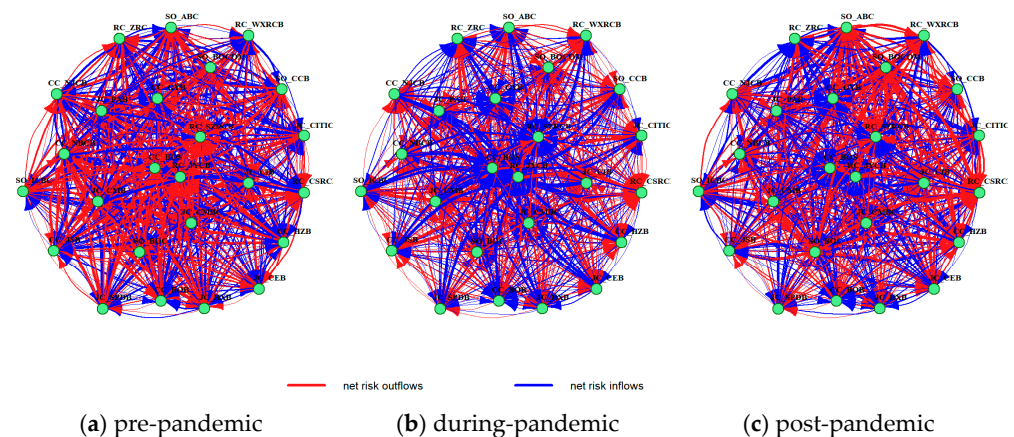


Figure 10. Complex Interbank Risk Network Topology.

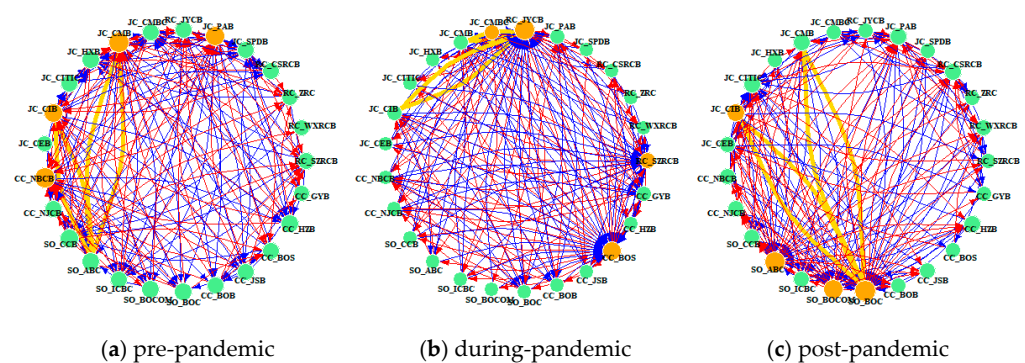


Figure 11. Filtered Interbank Risk Network Topology.

Figure 11 explains critical transmission pathways, offering intuitive understanding insights into the evolving characteristics and trends of interbank risk transmission. Prior to the pandemic, red lines (net risk outflows) clustered predominantly around JSCBs, while blue lines (net risk inflows) converged on SOCBs. This configuration indicates a dominant transmission vector from JSCBs to SOCBs. During the pandemic, the distribution of red edges became markedly dispersed. A significant proliferation of red edges associated with RCBs and CCBs signals their emergence as major risk transmitters; specifically, Minsheng Bank exhibited pronounced outward spillovers. Concurrently, an increased density of blue edges targeting these banks highlights their heightened risk intake. Notably, the distribution of edges became more uniform, reflecting decentralization of the risk network. Crucially, transmission during this period was characterized primarily by risk absorption. In the post-pandemic phase, network activity reconcentrated around JSCBs and SOCBs, underscoring their role as primary risk transmitters. Furthermore, the recurrence of blue edges converging on SOCBs emphasizes their significant exposure to interbank risks, with the overall transmission dynamic being predominantly driven by risk outflows.

Table 4 summarizes the systemic importance rankings and identifies critical transmission pathways corresponding to the top 20th percentile of weighted edges, illustrating the dynamic migration of risk centers across different banking tiers.

As illustrated in Table 4, the findings demonstrated highlight the clear changes that have occurred in the rankings and transmission channels over the three periods. In the pre-pandemic, it is clear that the core risk sources included CMB, NBCB, PAB, and CIB, which comprised mainly JSCBs and CCBs, with high intensity of risk output. The major transmission paths during that period came from both CIB and CMB, and the paths pointed towards the ABC. This indicates that the ABC had a major role as a risk recipient. During the pandemic, JRCB, BOS, CMBC, and SZRCB were identified as the primary core risk

sources. These banks are constituents of the RCBs and CCBs. This result further reinforces the view of the significantly effect of the systemic shock on the client bases of RCBs and CCBs. It should be noted that JRCB can be viewed as a representative case. The main paths of this period remained centered on the outflows of risks from JRCB to CMB and CIB. In the post-pandemic period, BOC, ABC, BOCOM, and CIM have been identified as core risk sources. The major risk transmission channels have been found to be risk outflows from BOC to CMB and risk outflows from BOC to CIB.

Table 4. Rankings of Systemic Importance and Key Transmission Pathways (Top 20% Weighted Edges).

Phase	Rank	Core Risk Source	Risk Outflow Intensity	Rank (Path)	Key Transmission Pathway	Transmission Intensity
Pre-pandemic	1	CMB	40.70124	1	CIB→ABC	3.294849
	2	NBCB	39.93517	2	CMB→ABC	3.292593
	3	PAB	34.85628			
	4	CIB	33.24386			
During-pandemic	1	JRCB	42.31553	1	JRCB→CMB	2.335893
	2	BOS	33.98259	2	JRCB→CIB	2.326020
	3	CMBC	18.58274			
	4	SZRCB	18.57193			
Post-pandemic	1	BOC	46.10428	1	BOC→CMB	3.016431
	2	ABC	40.39261	2	BOC→CIB	3.006325
	3	BOCOM	33.76634			
	4	CIB	24.97696			

In the pre-pandemic phase, core risk sources were predominantly concentrated among JSCBs (e.g., CMB, PAB, CIB) and leading CCBs (e.g., NBCB). The critical transmission pathways, notably CIB→ABC and CMB→ABC, indicate a dominant risk vector flowing from JSCBs to SOCBs. This pattern aligns with the prevailing market characteristics of regulatory arbitrage and aggressive interbank leveraging. During the pandemic, the risk epicenter shifted significantly downward. RCBs (e.g., JRCB, SZRCB) and CCBs (e.g., BOS) emerged as core risk sources, with JRCB ranking first. The transmission pathways transitioned to flow from RCBs to JSCBs (e.g., JRCB→CMB). This shift underscores the asymmetric impact and structural vulnerability exposed by the crisis. As smaller regional banks are heavily exposed to vulnerable Small- and Medium-sized Enterprises (SMEs), the deterioration in asset quality triggered a concentration of credit risk at the grassroots level, which subsequently propagated upward to interconnected joint-stock banks. In the post-pandemic phase, SOCBs (e.g., BOC, ABC, BOCOM) regained their top rankings, re-establishing their structural dominance. The key pathways reversed to flow from SOCBs to JSCBs (e.g., BOC→CMB). This structural reversion reflects the “pro-growth” policy mandate assumed by large state banks during the recovery. As they ramped up credit expansion to stabilize the economy, these institutions once again acted as the central hubs for injecting liquidity and credit into the system, thereby becoming the primary sources of risk spillovers.

5. Discussion and Conclusions

Drawing upon the preceding empirical analysis, the principal findings are summarized below:

(1) The pandemic exerted a profound shock on the banking industry. The magnitude of total spillovers remained significantly elevated during and after the pandemic compared to the pre-pandemic period, signaling a heightened level of systemic risk following the external shock.

(2) The banking system exhibits distinct heterogeneity and time-varying dynamics. Prior to the pandemic, CCBs and JSCBs functioned as primary net risk transmitters. Specifically, CCBs emerged as the core risk source, channeling risk primarily toward SOCBs and JSCBs. Following the outbreak, JSCBs and CCBs retained their roles as core sources, directing risk transmission paths largely toward SOCBs. Conversely, SOCBs and RCBs functioned predominantly as net risk recipients. Pairwise spillover analysis further corroborates that SOCBs consistently absorb net risk spillovers from the other three banking categories.

(3) The analysis of systemic importance across 25 individual banks reveals pronounced structural shifts in core risk sources. Pre-pandemic risk concentration was driven by CMB, NBCB, PAB, and CIB. During the pandemic, the risk epicenter migrated to JRCB, BOS, CMBC, and SZRCB. In the post-pandemic phase, systemic dominance reverted to BOC, ABC, BOCOM, and CIB.

Based on the empirical evidence, a differentiated regulatory framework is proposed. For SOCBs, the priority is to enhance risk-buffering capacities. Maintaining robust capital adequacy ratios is a prerequisite for mitigating the inherent vulnerability of these institutions as primary risk recipients. Conversely, for JSCBs and CCBs, the regulatory focus must shift to monitoring risk transmission channels. It is advisable to establish tailored liquidity management indicators while curbing the expansion of high-risk businesses. Regarding RCBs, strengthening cooperative risk defense mechanisms at the county level is essential. Furthermore, risk-isolation mechanisms should be reinforced to insulate these banks from broader sector volatility. Additionally, a dual-track ‘Risk Source–Transmission Pathway’ approach should be adopted to adapt to dynamic shifts in core risk sources, specifically by setting inter-institutional exposure limits to control critical transmission channels. Collectively, these measures aim to enhance the forward-looking capability and efficiency of financial regulation.

While this study provided a detailed examination of the dynamic evolution of risk spillovers and identified core transmission pathways under exogenous shocks, certain limitations merit acknowledgement. First, financial markets are characterized by inherent asymmetry—a feature not explicitly incorporated into the current modeling framework. Furthermore, the methodological approach relies primarily on point estimation, presenting spillover indices without accompanying confidence intervals or significance tests. These constraints represent potential avenues for further theoretical and empirical refinement in future research.

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Data Availability Statement: All data have been uploaded to Science DB (<https://doi.org/10.57760/sciencedb.29260>). The other original data can be obtained from the authors upon reasonable request (34049@sdwu.edu.cn).

Conflicts of Interest: The author Zhenyan Qin was employed by the company Jimo District Bureau of Statistics. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Appendix A

Table A1. Descriptive Statistics and Stationarity Tests of Daily Price.

Bank Name	Mean	sd	Skew	Kurtosis	se	t-Statistic	Bank Name	Mean	sd	Skew	Kurtosis	se	t-Statistic
SO_ABC	3.572	0.561	1.099	0.924	0.013	−0.5255	CC_NBCB	26.135	7.454	0.453	−0.857	0.167	−1.8705
SO_BOCOM	5.665	0.861	0.437	−0.573	0.019	−1.1411	CC_JSB	7.247	1.054	0.881	0.314	0.024	−2.0092
SO_ICBC	5.284	0.648	0.641	0.223	0.015	−1.7597	CC_HZB	12.374	3.237	0.753	1.172	0.073	−2.5485
SO_CCB	6.707	0.785	0.742	0.589	0.018	−2.2805	CC_NJCB	9.022	1.27	0.315	−0.792	0.028	−3.0712
SO_BOC	3.724	0.581	1.154	0.997	0.013	−0.1402	CC_BOB	5.569	1.312	1.52	2.114	0.029	−3.7181
JC_PAB	13.396	3.585	1.137	0.809	0.08	−1.9579	CC_BOS	9.997	4.754	1.694	2.222	0.107	−2.7939
JC_SPDB	9.963	2.241	0.583	0.16	0.05	−3.0181	CC_GYB	8.793	3.64	0.885	−0.576	0.082	−1.6884
JC_HXB	7.01	1.562	0.991	0.457	0.035	−2.8769	RC_JRCB	5.491	3.298	3.182	10.931	0.074	−1.9916
JC_CMBC	5.318	1.69	0.735	−0.63	0.038	−2.191	RC_ZRC	6.696	3.925	2.988	10.408	0.088	−2.1642
JC_CMB	35.592	8.486	0.584	0.031	0.19	−2.1956	RC_WXRCB	6.457	2.359	3.408	14.112	0.053	−2.6118
JC_CIB	17.79	2.146	1.061	1.37	0.048	−2.7937	RC_CSRCB	7.652	1.405	2.206	5.884	0.032	−2.782
JC_CEB	3.638	0.461	−0.1	−1.046	0.01	−2.502	RC_SZRCB	6.238	3.04	2.707	7.184	0.068	−2.3913
JC_CITIC	5.742	0.763	0.083	−0.884	0.017	−2.6461							

Note: The t-Statistic denotes the Augmented Dickey–Fuller (ADF) test statistic with a lag order of 1. All statistics are insignificant at the 5% level ($p > 0.05$).

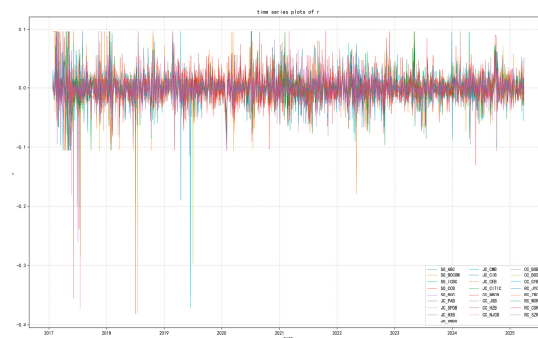


Figure A1. Logarithmic Return Time Series Plot.

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