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Transfer entropy, multidimensional multiple correlation network and risk contagion of bank capital shortage

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Abstract: This paper examines the reshaping of systemic risk in China's bank-dominated financial system amid intensifying competitive homogeneity, expanding business scale, and adjustments to macro deleveraging and transition policies. Methodologically, we develop a unified measurement–network–identification framework: we employ the Relative Systemic Risk Index (SRISK) to quantify institutions' systemic contributions, balancing robustness and interpretability across leverage, size, and interconnectedness; we construct a multilayer contagion network via a threshold approach that integrates three principal channels—interbank lending, real estate, and equity markets; and we employ Spatial Durbin panel models to separate direct effects from network spillovers and to validate transmission pathways. Results show that the expansion of off-balance-sheet activities, interbank shadow credit, and on-balance-sheet regulatory arbitrage raises interbank leverage and amplifies contagion. The constructed network exhibits scale-free and small-world properties, being robust to random shocks yet vulnerable to shocks targeting central nodes, with rapid diffusion. Direct effects indicate that multiple-network centrality, capital adequacy, investor sentiment, broad money growth, and foreign-exchange deposit growth increase capital shortfall risk, while interest income, loan-to-deposit structure, nonperforming loan ratio, and foreign-exchange loan growth mitigate it. Policy implications support strengthening the dual-pillar macroprudential framework and introducing time-varying contagion damping over the financial cycle.

Key words: Relative Systemic Risk Index; Transfer Entropy; Information Contagion; Spatial Dubin Panel Model; Multi-network Centrality

1. Introduction

As competitive homogeneity deepens, business scale expands, and macro deleveraging and transition policies adjust, the probability and severity of risks facing China's commercial banks are rising. This trend coincides with the expansion of new business lines driven by financial development. The rapid growth of off-balance-sheet wealth management, together with high leverage and a shift "from the real to the virtual" among nonfinancial firms, heightens credit risk (Acharya and Thakor 2016). Concurrently, banks' expansion of interbank shadow credit and on-balance-sheet regulatory arbitrage has increased interbank leverage, amplifying risks to themselves and counterparties (Acharya et al. 2017; Acosta-Smith et al. 2020; Dinger and Hagen 2010). These risks are cumulative and latent and, in China's bank-dominated financial system, may evolve into extreme shocks triggering "black swan" events. Although the People's Bank of China has introduced measures to mitigate systemic risk, external shocks—such as geopolitical conflicts and COVID-19—have intensified global economic headwinds. As a major economy, China's financial stability is essential to its own high-quality development and to global economic and financial stability.

Systemic risk arises when multiple adverse internal and external factors accumulate unnoticed or underappreciated and, at critical junctures, resonate and become uncontained, triggering panic selling and amplifying market-wide risk and contagion. Once realized, it cannot be mitigated through diversification. Its core dynamics reflect powerful amplification and acceleration driven by scale, leverage, and dense risk interconnectedness. Accordingly, effective prudential policy requires targeted contagion oversight and identification focused on leverage, scale, and interconnectedness, the mapping of systemically important transmission channels, and the deployment of appropriate remedial tools.

A broad measurement toolkit now exists for systemic spillovers and contagion: (1) Expected Shortfall (ES) and Marginal Expected Shortfall (MES) (Acosta-Smith et al. 2020; Davydov et al. 2021); (2) Systemic Expected Shortfall (SES) (Acharya et al. 2017; Davydov et al. 2021; Acharya et al. 2012); (3) Conditional Value at Risk (CoVaR) and Incremental CoVaR (ΔCoVaR) (Adrian and Brunnermeier, 2016; Girardi and Erguen 2013; Bernardi et al. 2017); (4) the Systemic Risk Index (SRISK) and SRISK% (Acharya et al. 2012; Abedifar et al. 2017); and (5) Conditional Expected Shortfall (CoES) and Incremental CoES (ΔCoES) (Zhu et al., 2019). These approaches differ in sampling frequency, tail modeling, treatment of conditional dependence, and handling of leverage and scale, yielding method-dependent inferences about contagion intensity and attribution. Because leverage, scale, and interconnectedness are first-order drivers of systemic risk, an effective contagion metric should jointly capture these dimensions while balancing robustness and interpretability. On this basis, we adopt the Relative Systemic Risk Index as the primary measure to evaluate cross-entity and cross-market transmission.

Following a risk event, interconnections within the banking system become a key driver of risk amplification, and the resulting intertwined contagion generates a multilayered, complex network structure. From a system-wide correlation perspective, network analysis can describe the network's density, transmission path length, and structural patterns. Existing approaches to network construction focus on four categories: (1) simple dependence, such as dynamic correlations based on multivariate GARCH (Hué et al. 2019; Kristjanpoller and Minutolo 2015) and nonlinear dependence via copulas (Bernardi et al. 2017; Boako and Alagidede 2017; Huynh et al. 2020); (2) causality, including causal structures identified through VAR (Diebold and Yilmaz, 2014; Zhang et al., 2020), VECM (Billio et al. 2012), M-VAR, and nonlinear Granger causality tests (Ghysels et al. 2016; Lai and Hu 2021); (3) spatial dependence and contagion (Kelejian and Tavlas 2006; Alter and Beyer 2014; Gandy and Veraart 2017; Wang et al. 2020); and (4) informational contagion (Li et al. 2020). Informational contagion—arising from information coupling between financial institutions and markets rather than from real-sector linkages—has become a routine transmission mechanism of systemic financial risk, as illustrated by the 2008 U.S. financial crisis and the 2015 Chinese stock market crash. Crucially, the core channels of systemic financial risk also include interbank funding (especially unsecured and secured lending) and common asset valuation linkages. Therefore, a network framework that integrates at least three pathways—informational contagion, interbank lending, and common-asset dependence—more comprehensively captures the formation and propagation of systemic risk.

However, the existing literature rarely incorporates informational contagion alongside interbank lending contagion and common-asset valuation dependence within a unified analytical framework. To fill this gap, this paper uses the Relative Systemic Risk Index to measure banks' systemic contributions arising from capital shortfall risk; employs transfer entropy to capture informational contagion; uses association measures to quantify contagion intensity from interbank lending and common-asset valuation dependence; and constructs a multi-link contagion network via a thresholding approach. We then identify and validate transmission pathways using a static spatiotemporal two-way fixed-effects Spatial Durbin panel model, and conduct robustness checks with a dynamic spatiotemporal Spatial Durbin panel model.

In sum, this paper goes beyond single-metric and single-layer paradigms by establishing a unified “measurement–network–identification” loop: it employs SRISK—which jointly captures size, leverage, and interconnectedness—to quantify systemic contributions; constructs a multilayer contagion network along three principal channels—interbank, real estate, and equity markets; and, using a spatiotemporally structured Spatial Durbin panel model, separates direct effects from network spillovers while identifying the marginal impact of capital shortfall risk and the robustness of transmission pathways. This framework not only strengthens the explanatory power for systemic risk propagation, but also links measurement to actionable macroprudential instruments, yielding prioritized institution–channel intervention sequences and implementation guidance for a bank-dominated financial system.

2. Theoretical analysis

The measurement of banks’ systemic risk primarily encompasses five indicators: incremental conditional value at risk ($\Delta CoVaR$), marginal expected shortfall (MES), systemic expected shortfall (SES), incremental conditional expected shortfall ($\Delta CoES$), and the relative systemic risk index ($SRISK\%$). Among these, SRISK is non-convex, subadditive, and coherent. Unlike $\Delta CoVaR$, $\Delta CoES$, SES , and MES —which define crises via daily return thresholds— $SRISK\%$ conditions on “prolonged, sharp market declines” coupled with “system-wide capital shortfalls,” aligning more closely with systemic events and the mechanics of risk propagation. In terms of risk characterization, $\Delta CoVaR$, $\Delta CoES$, MES , and SES emphasize cross-institutional dependence, whereas $SRISK$ measures an institution’s expected capital shortfall under sustained market downturns. By jointly integrating leverage, size, and dependence proximity, $SRISK$ offers a more comprehensive comparative advantage (Cipollini et al., 2020; Brownlees et al., 2020) and is better suited to studying micro-level risk spillovers and contagion.

Most studies employing SRISK rely on bivariate dynamic conditional correlation techniques (e.g., bivariate GARCH-DCC, VAR-MGARCH-DCC), which are ill-suited to identifying the center, direction, pathways, intensity, and drivers of spillovers. Accordingly, building on $SRISK\%$ ’s crisis specification, this paper introduces a network-and-spatial econometric framework to achieve a decomposable identification of multidimensional contagion structures and maps the measurement outputs directly onto macroprudential tools to generate an institution–channel prioritized intervention list. This establishes a closed loop across crisis definition, network modeling, and policy translation, thereby enhancing both the explanatory power for systemic risk propagation and the operational viability of governance.

2.1 Definition of SRISK

Assume that there are N representative banks in the banking system. Bank i has a capital shortfall (CS) on day t :

$$CS_{it} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it} \quad (1)$$

In the formula, k denotes the capital adequacy ratio of macroprudential supervision, with the general capital adequacy ratio being 8%. A_{it} represents the total assets of the bank, which are equivalent to the sum of its capital and liabilities, while W_{it} denotes the market value of the bank’s capital, specifically the market value of the owners’ equity. Finally, D_{it} is the book value of the bank’s debt.

The return rate in the market from $t+1$ to $t+h$ is $R_{m,t+1:t+h}$. Events that pose a systemic financial risk are typically defined as $R_{m,t+1:t+h} < C$ as a result of long-term capital deficit. When C is 6 months ($h=6$), the market return rate decreases by 40% ($C=-40\%$). Subsequently, the systemic risk index ($SRISK$) of a bank is the anticipated value of long-term capital shortfall of the bank in the event of a systemic financial risk occurrence.

$$\begin{aligned} SRISK_{it} &= E_t \left(CS_{i,t+h} \mid R_{m,t+1:t+h} < C \right) \\ &= kE_t \left(D_{i,t+h} \mid R_{m,t+1:t+h} < C \right) - (1-k)E_t \left(W_{i,t+h} \mid R_{m,t+1:t+h} < C \right) \end{aligned} \quad (2)$$

The long-term marginal expected shortfall ($LRMES$) is the expected loss in total institutional equity in the event of a stock index decline of more than 40% over a six-month period.

$$LRMES_{it} = -E_{it} \left(R_{i,t+1:t+h} \mid R_{m,t+1:t+h} < C \right) \quad (3)$$

Based on the assumption of Acharya et al. (2012), when systemic risk occurs, the institution’s debt cannot be renegotiated and restructured again, which implies that the firm’s debt book remains relatively unchanged, $E_t(D_{i,t+1} \mid R_{m,t+1:t+h} < C) = D_{it}$. If $R_{i,t+1:t+h}$ is the rate of return for institution i between periods $t+1$ and $t+h$, then $W_{it} \times (1 + R_{i,t+1:t+h}) = W_{i,t+h}$. The absolute systemic risk index for an individual bank i can be written as:

$$SRISK_{it} = W_{it} \left[k \times LVG_{it} + (1-k) LRMES_{it} - 1 \right] \quad (4)$$

Where, LVG_{it} is the bank’s leverage. Equation (4) shows that $SRISK$ can be viewed as a function of three factors: the size of the bank’s capital, the level of leverage and the long-run marginal expected shortfall LRMES. Other things

being equal, the higher the size (equity), the higher the SRISK; the higher the leverage, the higher the SRISK; and the higher the LRMES, the higher the SRISK.

The absolute systemic risk index for the banking sector ($SRISK_{t,total}$) is the total amount of capital that the government would have to provide to bail out the banking system from a systemic risk shock in the event of an extreme systemic risk event. The systemic risk index is additive and can be obtained by aggregating the $SRISK_{it}$ of a single bank.

$$SRISK_{t,total} = \sum_{i=1}^N (SRISK_{it})_+$$

Where $(SRISK_{it})_+$ denotes $\max(SRISK_{it}, 0)$.

The Relative Systemic Risk Index ($SRISK\%_it$), which is the share of an individual institution's systemic financial risk index to the banking sector's systemic financial risk index, can portray a certain degree of risk spillover contagion from institutions.

$$SRISK\%_it = \begin{cases} \frac{SRISK_{it}}{\sum_{i=1}^N (SRISK_{it})_+}, & SRISK_{it} > 0 \\ 0, & otherwise \end{cases} \quad (5)$$

The relative systemic risk index reflects the size of banks' contribution to the spillover contagion of risk to the financial system. The larger the value, the greater the bank's contribution to spillover contagion of systemic financial risk in the bank and the higher its systemic importance.

According to Contingent Claims Analysis (CCA), the market value of a bank's capital, W , can be viewed as a European call option with the value of the bank's assets, A , as the underlying, the book value of the liabilities, B , as the strike price, and the remaining maturity of the liabilities, $T-t$, as the holding period. Then according to the Merton model, the value of bank assets and bank capital (i.e., the market value of equity) are :

$$A_t = A_t \exp \left\{ \left(u_A - \sigma_A^2/2 \right) (T-t) + \sigma_A \sqrt{T-t} \varepsilon \right\} \quad (6)$$

$$W_t = A_t N(d_1) - B_t \exp[-r(T-t)] N(d_2) \quad (7)$$

$$d_1 = \frac{\ln(A/B) + (R + \sigma_A^2/2)(T-t)}{\sigma_A \sqrt{T-t}} \quad (8)$$

$$d_2 = d_1 - \sqrt{T-t} \quad (9)$$

Where ε is a random variable obeying a standard normal distribution and r is the discount rate, expressed as a financial market benchmark rate.

The sensitivity equation between the volatility of implied assets σ_A and the volatility of bank capital σ_W is:

$$\sigma_A = \frac{W_t}{A_t N(d_1)} \sigma_W \quad (10)$$

In terms of the bank capital volatility process, the jump diffusion GARCH model fits better than the continuous diffusion GARCH model. According to the jump diffusion GARCH model, stock market risk event shocks cause extreme changes in heterogeneous stock prices, in which stock price volatility can be decomposed into two components: continuous volatility σ_c and jump volatility σ_λ .

$$\sigma_{W_i} = \sigma_{c_i} + \sigma_{\lambda_i} \quad i = 1, 2 \quad (11)$$

On the one hand, after information contagion and stock market cofactors, bank share prices are characterized by a co-correlation between jump volatility and share price information. Thus, it is assumed that the jump volatility of bank capital is mainly derived from the bank's own jump volatility σ_{λ_i} and the associated jump volatility σ_{λ_j} , which can be obtained:

$$\sigma_{\lambda_i} = \sigma_{\lambda_i} + \beta_1 \sigma_{\lambda_j} \quad (12)$$

On the other hand, the search and dissemination of macroeconomic information, industry market information, and firm-specific information trigger synergistic changes in stock prices, and this stock price information association leads to the correlation between successive stock price fluctuations (Li Fangfang et al. 2019; etc.). It is assumed that the

continuous volatility of bank capital mainly comes from the market risk volatility σ_s , the own continuous volatility σ_{ci} and the associated continuous volatility σ_{cj} :

$$\sigma_{ci} = \sigma_{ci} + \beta_2 \sigma_s + \beta_3 \sigma_{cj} \quad (13)$$

Substituting Eq.12 and Eq.13 into Eq.11 gives the intrinsic bank capital volatility as:

$$\sigma_{wi} = (\sigma_{\lambda i} + \sigma_{ci}) + \beta_1 \sigma_s + (\beta_2 \sigma_{\lambda j} + \beta_3 \sigma_{cj}) \quad (14)$$

From equation 14, bank capital volatility consists of three components: its own continuous and jump volatility, market volatility and associated continuous and associated jump volatility of neighboring banks. Substituting Eq. 14 into Eq. 10 shows that the implied volatility of bank assets is:

$$\sigma_A = \frac{W_t}{A_t N(d_1)} (\sigma_{\lambda i} + \sigma_{ci}) + \beta_1 \sigma_s + (\beta_2 \sigma_{\lambda j} + \beta_3 \sigma_{cj}) \quad (15)$$

Bank assets consist of interbank assets V_T , common assets held V_G and other assets V_O , and bank liabilities consist of interbank liabilities D_T and other liabilities D_O .

$$V_{Ai} = V_{Ti} + V_{Gi} + V_{Qi} \quad (16)$$

$$D_i = D_{Ti} + D_{Qi} \quad (17)$$

Bank assets and liabilities are interconnected through two paths: interbank lending operations and the value linkage of holding common assets. Interbank lending is used to meet the short-term liquidity needs of banks. In a banking system consisting of two banks, their interbank lending creates equal interbank assets and interbank liabilities.

$$V_{Ti} = D_{Tj} \quad (18)$$

$$D_{Ti} = V_{Tj} \quad (19)$$

To diversify risk and pursue returns, banks have diversified portfolios of assets, and banks with similar risk preferences hold more common assets in their portfolios. In the event of a negative shock to the banking system, the sale of assets at lower prices leads to a simultaneous fall in asset prices, triggering a risk resonance covariance of revaluation fluctuations in common assets held by the two banks (e.g., real estate loans, etc.). This results in an indirect correlation of holdings of common assets mediated by changes in asset market prices. Under the asset concentration control, the asset trading market is a perfectly competitive market, and the revaluation of its common assets depends mainly on the number of sell-offs on both sides and the market price of the assets, i.e., the revaluation of a bank's common assets depends on the book value of the bank's own common assets V_{gi} and the revaluation of the other bank's common assets V_{gj} , hypothetically:

$$V_{Gi} = V_{gi} + \beta_4 V_{Gj} \quad (20)$$

Substituting Eqs.18, 19, and 20 into Eqs.16 and 17 gives the value of the bank's assets and liabilities as:

$$V_{Ai} = D_{Tj} + (V_{gi} + \beta_4 V_{Gj}) + V_{Qi} \quad (21)$$

$$D_i = V_{Tj} + D_{Qi} \quad (22)$$

According to the research on expected capital shortfall and systemic risk index SRISK, LRMES can be directly expressed by a function that includes volatility, correlation, and the expectation of the tails of the standard normal distribution:

$$\begin{aligned} LRMES_{it}^h &= -E_{it} \left(R_{i,t+1:t+h} \mid R_{m,t+1:t+h} < C \right) \\ &= \sigma_{wit}^h \beta_{2it}^h E_{t-1} \left(\varepsilon_{mt} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}} \right) + \sigma_{wit}^h \sqrt{1 - (\beta_{2it}^h)^2} E_{t-1} \left(\zeta_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}} \right) \end{aligned} \quad (23)$$

The meaning of LRMES is: at time t , the standardised residual series $(\zeta_{it}, \varepsilon_{mt})$ derived from the GARCH-DCC model, followed by a random sample with put-backs for time h , $(\zeta_{i,t+1:t+h}, \varepsilon_{m,t+1:t+h})$, and finally the conditional volatility σ_{wit}^h and σ_{mt}^h and the dynamic correlation coefficient β_{2it}^h during the period $(t+1, t+h)$ derived from the GARCH-DCC model.

The money market equilibrium interest rate is given by the LM model $M/P = b_1 Y - b_2 r$ of money market supply and demand equilibrium:

$$r = \frac{1}{b_2} \left(\frac{M}{P} - b_1 Y \right) \quad (24)$$

Where M is the nominal money supply; P is the price index; Y is the national income; and b_1, b_2 is the parameter.

2.2 Analysis of multidimensional factors and network correlations in the contagion of bank capital shortage risk

2.2.1 Multidimensional factors analysis of the contagion of bank capital shortage risk

Equations (4), (5), (7), (8), (9), (14), (21), (22), (23), and (24) constitute the core framework for analyzing the contagion of bank capital shortage risk. This risk and its transmission primarily hinge on three factors: bank capital size, financial leverage, and the long-term marginal expected shortfall (LMES). In terms of sources, they are shaped by multidimensional drivers spanning bank financial statements (internal and external), macroeconomics, monetary policy, and international finance.

i) Bank financial factors: Larger assets, shadow banking expansion, higher non-interest income share, higher capital adequacy, a higher loan-to-deposit ratio, and reduced liquidity risk collectively lower leverage and raise risk-bearing capacity. However, higher market value of bank capital tends to elevate risk-taking, increasing both shortage risk and contagion.

ii) Bank stock market factors: Elevated investor sentiment raises capital volatility and per-unit market risk premium, and inflates capital bubbles, all of which increase LMES and exacerbate shortage risk and contagion.

iii) Macroeconomic factors: During expansions, higher transaction demand for money, rising prices, and lower real money supply intensify upward pressure on interest rates. Higher rates reduce the present value of future maturing debt while increasing capital value, thereby raising shortage risk and contagion; they also lift expected returns, the unit risk premium, market co-movement volatility, and LMES, further amplifying risk and contagion.

iv) Monetary policy factors: With other conditions constant, an increase in money supply lowers money market rates, raises the present value of future maturing debt, and reduces capital value, thereby mitigating shortage risk and contagion; the converse holds.

v) International financial factors: Cross-border capital inflows expand nominal money supply over corresponding horizons and, given the term structure, lower current money market rates, reducing shortage risk and contagion.

In sum, contagion is driven by five domains—bank finance, bank equity market conditions, macroeconomics, monetary policy, and international finance—acting through three channels: capital value, financial leverage, and LMES. Hence, **hypothesis 1: risk factors are multidimensional.**

Crucially, these drivers evolve dynamically and jointly, not merely in isolated, static dimensions. Positive superposition—e.g., concurrent increases in cross-border inflows, domestic money supply, and shadow banking that raise capital value—jointly elevates shortage risk and contagion; two- or three-dimensional reinforcement can have multiplicative effects. Conversely, stable investor sentiment rationalizes the risk premium and lowers LMES; aligned improvements across the three channels jointly dampen risk and contagion. Thus, **hypothesis 2: bank capital shortage risk reflects a multidimensional factor correlation effect.**

2.2.2 Multiple interbank linkages for contagion of bank capital shortage risk

In addition, bank capital shortage risk is also manifested through interbank lending. An increase in the interbank assets of affiliated banks raises other banks' interbank liabilities, thereby increasing financial leverage and amplifying the contagion of capital shortage risk. Conversely, an increase in affiliated banks' interbank liabilities expands banks' interbank assets, elevates the market value of bank capital, and likewise heightens contagion. Therefore, the expansion of interbank lending scale strengthens the contagion of bank capital shortage risk via correlation effects.

First, banks with similar risk preferences tend to hold a higher share of common assets in their portfolios. Under stress, fire sales of common assets by affiliated banks can trigger price depreciation. If market liquidity is scarce, this may induce valuation spirals and a downward adjustment of common asset prices, resulting in substantial losses on common exposures, impairment of aggregate bank assets, and a decline in capital value. Since bank liabilities are typically not subject to negotiated restructuring, asset impairment directly reduces leverage. These mechanisms jointly affect both the incidence of capital shortage risk and the extent of contagion.

Second, increases in jump intensity and continuous volatility among affiliated banks raise intrinsic capital volatility, thereby increasing the implied volatility of bank assets, depressing asset values and capital values, and influencing capital shortage risk and its contagion. Under risk shocks, larger and more frequent jumps or higher continuous market volatility elevate the market risk premium, induce co-movement in bank equity prices, increase systemwide intrinsic capital

volatility, and further raise the implied volatility of bank assets. This sequence depresses the value of bank assets and capital and ultimately affects the level and transmission of capital shortage risk.

As a result, bank capital shortage risk is characterized by multiple interbank-link contagions, and these interbank linkages interact to form a multi-link contagion network. This leads to **hypothesis 3: the multiple interbank affiliation network is the primary feature of bank capital shortage risk contagion.**

2.2.3 Analysis of the role of multidimensional and multiple correlation networks in the contagion of bank capital shortage risk

From the above theoretical analyses, we can see that the contagion of bank capital shortage risk is driven by multidimensional factors and is materially shaped by multiple interbank correlation channels. The contagion of bank capital shortage risk is complex: multiple factors interact with multiple interbank correlation contagion mechanisms, forming a multidimensional, multi-correlation contagion network. Among these are, first, risk factors and networks arising from interbank lending, through interbank asset–liability linkages; second, information comovement in bank equity return volatility and its linkage with aggregate stock market volatility. These mechanisms are superimposed on bank capital valuation factors and long-term marginal expected shortfall, jointly influencing the level and propagation of capital shortage risk. Therefore, this paper advances Research **Hypothesis 4: the contagion of bank capital shortage risk is generated by a multidimensional, multicorrelated contagion network.**

In summary, the factors and transmission mechanisms of multidimensional–multiple correlations and bank capital shortage risk contagion are depicted in Figure 1.

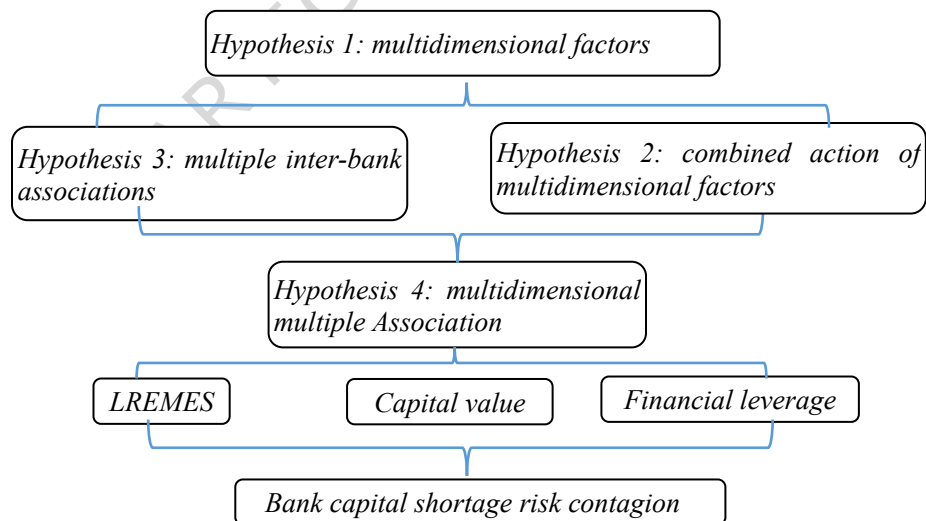


Fig. 1 Logic of proposition and hypothesis. The figure illustrates the content and contagion characteristics of bank capital shortage risk through the proposed hypotheses.

3. Method, model and variable description

3.1 Construction method of nonlinear correlated infection network

According to the theoretical analysis, the main interbank contagion channels are interbank lending contagion,

common-asset value correlation contagion, stock price volatility contagion, stock market information contagion, and market volatility linkage. The latter four can be grouped as information contagion. Given that financial risk contagion is generally nonlinear and primarily mediated by indirect, non-contractual correlation channels, its characteristics align closely with information transmission. The contagion mechanism can be represented as a complete transmission chain consisting of four elements: the source of contagion (information origin), the infected entity (information recipient), the contagion path (transmission channel), and the intermediary (media). Accordingly, drawing on Li et al. (2020), this paper uses the transfer entropy method to construct an information-contagion network for bank capital shortage risk. Transfer entropy is the core metric for information transmission, capturing its direction, intensity, and dynamics.

The transfer entropy is given by

$$TE_{j \rightarrow i}(k, l) = \sum_{x_{i,n+1}, x_{i,n}^{(k)}, x_{j,n}^{(l)}} P(x_{i,n+1}, x_{i,n}^{(k)}, x_{j,n}^{(l)}) \log_2 \frac{P(x_{i,n+1}, x_{i,n}^{(k)}, x_{j,n}^{(l)})}{P(x_{i,n+1} | x_{i,n}^{(k)}) P(x_{i,n}^{(k)}, x_{j,n}^{(l)})} \quad (25)$$

where n is the n th element of the bank in the time series of systemic risk index; x_i and x_j denote the systemic risk index of bank i and j , respectively; $P(\cdot, \cdot)$ denotes the joint distribution function of the systemic risk index variables of bank i and j ; and $P(\cdot | \cdot)$ denotes the conditional distribution function of the two variables. Parameters l and k are time series lags, which are generally considered to be Markovian in nature for time series data, and $k=l=1$ is set.

The transfer entropy value $TE_{i \rightarrow j}(k, l)$ describes the impact of bank j 's capital shortage risk on bank i , and the larger the transfer entropy value, the greater the amount of risk contagion from bank j to bank i is implied.

Taking the transfer entropy value between any two banks' systemic risk indices as an element, the original association weight matrix $\mathbf{TE}=(TE_{i \rightarrow j})_{16 \times 16}$ is obtained; then the mean value is selected as the threshold θ , and the matrix redundant association information is removed to obtain the neighborhood matrix $\mathbf{E}=(e_{ij})_{n \times n}$ of the bank's capital shortage risk contagion network, in which when $e_{ij}=1$ indicates that there exists a significantly stronger information association contagion between bank's capital shortage risks, and vice versa, $e_{ij}=0$, there is no significantly stronger association contagion.

2.2 Multi-dimensional and multiple correlation contagion validation model setting.

Theoretical analysis indicates that bank capital shortage risk is generated by multidimensional and multiple correlations. This risk exhibits both multi-path spillover–feedback contagion and mutual spillover among its constituent risk factors. Accordingly, investigating the contagion mechanism necessitates examining the established multifactor functional relationships among variables. It bears emphasis that a single-equation specification cannot adequately capture interactions across heterogeneous samples. Likewise, a non-spatial system of equations can characterize interactions among endogenous variables but cannot account for spillover–feedback correlations among exogenous variables.

The spatial Durbin model is uniquely capable of jointly capturing (i) spatial correlation among explanatory variables and (ii) correlation among exogenous explanatory variables, while also characterizing the effects of explanatory variables on other explanatory variables. Hence, the spatial Durbin model can simultaneously reflect multiple correlations and the role of multidimensional risk factors. To test the four research hypotheses and to assess both cross-sectional and time-series properties of the data, this paper uses a spatial Durbin panel model with time fixed effects and spatial fixed effects to identify the contagion-factor pathways of bank capital shortage risk. The model is specified as follows:

$$SRISK = \rho \cdot W \cdot SRISK + X \cdot \beta + W \cdot X \cdot \theta + \alpha \cdot I_n + \nu + \tau + \varepsilon \quad (26)$$

where $SRISK$ denotes the vector of banks' relative systemic risk indices. ρ is the parameter governing the spatial autocorrelation of these indices, and W is the spatial correlation (weight) matrix. I_n is the n -dimensional unit vector, which converts the scalar intercept α into vector form. X is the vector of explanatory variables, with β denoting the associated parameter vector, while θ captures the parameter on the spatially lagged explanatory variables. The specification includes time fixed effects ν and spatial fixed effects τ . The disturbance term is $\varepsilon \sim N(0, \sigma^2 I_n)$.

The model treats the contagion factor of bank capital shortage risk as the principal explanatory variable governing contagion pathways. These pathways encompass both (i) spillover channels attributable to the contagion factor itself and (ii) multiple contagion channels induced by the spatial correlation matrix. Geographic location shapes banks' exposure to policy interventions, their investment–financing preferences, and the efficiency of interbank transactions; geographic distance, in turn, is a salient determinant of information transmission.

To accommodate the “investment–financing preferences and soft-information asymmetry” arising from geographic heterogeneity, this paper uses a threshold approach to construct: (i) a geographic distance neighborhood matrix for bank headquarters, $\mathbf{A}=(a_{ij})_{16 \times 16}$; and (ii) an information-correlation contagion network matrix with respect to the systemic risk

index, $\mathbf{B}=(b_{ij})_{16 \times 16}$. We then form the joint information matrix, $\mathbf{W}=(w_{ij})_{16 \times 16}$, which yields the spatial neighborhood weight matrix used in estimation.

$$w_{ij} = \begin{cases} 1, & a_{ij} = 1 \text{ or } b_{ij} = 1 \text{ or } a_{ij} = b_{ij} = 1 \\ 0, & \text{otherwise} \end{cases} \quad (27)$$

Based on empirical verification, this spatial matrix delivers superior fit and constitutes a valid spatial weight matrix. Accordingly, we estimate the spatial Durbin panel model via maximum likelihood, obtaining parameter estimates under the specified spatial dependence structure.

3.3 Variable selection

To test the research hypotheses, we select explanatory variables from six domains spanning three dimensions, guided by a synthesis of prior findings in the literature. The selected variables and their definitions are summarized in Table 1.

Bank capital-shortage risk propagates through multiple interbank correlation channels. The principal channels comprise: (i) information contagion via comovement in bank equity prices, (ii) the interbank lending channel, and (iii) the value-correlation channel arising from shared exposures to high-risk credit assets. We measure information-based contagion in capital-shortage risk using transfer entropy.

Table 1 Description of SRISK and systemic risk infection path proxy variable. Table presents the variables potentially used in Model 26, along with their definitions and calculation methods.

Variable type	Variable name	Symbol	Variable description
Explained variable	Relative systemic risk index	<i>SRISK%</i>	Spillover contagion of bank capital shortage risk
	Non-Interest Income Rate	<i>b1</i>	The robustness of bank operating income; The higher the index is, the better the value of bank assets is
On-balance sheet	Capital Adequacy Ratio	<i>b2</i>	The safety degree of micro-prudential operation of banks; The higher the index is, the safer the bank is
	Loan-to-deposit Ratio	<i>b3</i>	The liquidity matching of bank assets and liabilities, the better the index is, the lower the liquidity risk is
	Bad Loan Ratio	<i>b4</i>	Bank asset quality status, the higher the ratio is, the worse the asset quality is
Off-balance sheet	Investor Sentiment	<i>IS</i>	The product of the sign of turnover rate and return rate of bank stock trading; The higher the index is, the greater the capital bubble of banks is
	Shadow banking scale	<i>SB</i>	Equal to the sum of deposits with banks, other banks, financial balance, resale, and derivative financial assets; The larger the index is, the larger the bank's operating assets are
Macro-economic level	GDP growth rate	<i>g1</i>	The higher the economic growth is, the greater the demand for transactional money is, which will lead to an increase in interest rates
	Real estate industry loan growth rate	<i>g2</i>	Risk factors of credit asset value in high-risk industries
Policy regulation	M2 growth rate	<i>p1</i>	Measuring the central bank's monetary policy, The rapid increase of nominal currency will lead to the decline of interest rate

	The central bank's loan growth rate to financial institutions	$p2$	The prudent tendency of macro policy control, With the increase of this index, the liquidity supply in the banking system will increase, which will lead to the decline of interest rate
Multi-layered network center status	Degree centrality	$dMul$	Measure the central position of banks in multiple interbank related networks; The higher the index is, the wider the bank's correlation range is
	Betweenness centrality	$bMul$	Measure the bank's media center position and ability in the multi-industry related network; The higher the index is, the stronger the bank relevance is
International shocks	Foreign exchange deposit growth rate	$i1$	Short term cross-border capital flow shocks; The higher the index is, the more the short-term international money supply will grow and the more the total domestic money supply will increase
	Foreign exchange loan growth rate	$i2$	Long term cross-border capital flow impact; The higher the index is, the more the long-term international money supply will grow and the more the domestic long-term total money supply will increase

To test Research Hypothesis 3, we proceed in three steps. First, we estimate the interbank assets–liabilities correlation matrix using the maximum-entropy method. Second, employing correlation-coefficient and thresholding procedures, we construct four correlation layers: (a) stock-price jump-volatility correlation, (b) stock-price continuous-volatility information correlation, (c) market-fluctuation comovement correlation, and (d) common-asset value correlation. Third, we aggregate single-layer centrality measures to obtain multiplex degree centrality and multiplex betweenness (intermediation) centrality, thereby characterizing each bank's position and influence across the multilayer network. The multiplex centrality measures are defined as follows:

(i) Degree centrality index of multi-network

We use an entropy-based aggregation function to construct the multiplex centrality measure for banks in a multi-layer network, denoted d . This procedure integrates layer-specific centrality measures into a single, information-theoretically weighted index that reflects each bank's overall prominence across interdependent network layers.

$$d_i^{Mul} = \sum_{k=1}^5 \frac{d_i^k}{d_i^T} \log \left(\frac{d_i^k}{d_i^T} \right) \quad (28)$$

Where d_i^k is the degree of Bank i in the k -nd network; d_i^T is the sum of the degree centrality of Bank i in each network.

(ii) Multi-Network Intermediation Centrality Indicator

Similarly, we need to redefine the mediator centrality degree of multiple networks b .

$$b_i^{Mul} = \sum_{k=1}^5 \frac{b_i^k}{b_i^T} \quad (29)$$

Where b_i^k is the degree of intermediary centrality of bank i in the k nd network; and b_i^T is the total intermediary centrality of bank i in each network.

3.4 Sample and data

To evaluate the four research hypotheses advanced in this study, we construct a sample comprising all commercial banks listed on China's A-share market after September 2010, totaling 16 institutions, including the five systemically important banks designated by the supervisory authority. The choice of these 16 banks as the observational universe for China's systemic financial risk is motivated by three considerations: first, the banking sector accounts for more than 90% of total financial-sector assets, placing banks at the core of the national financial system and making them informative

about the macro-financial context of systemic fluctuations; second, the aggregate capital of the sampled banks exceeds 75% of the banking sector's total, conferring substantial representativeness and external validity; third, all sample banks are publicly listed, ensuring robust disclosure standards and high data availability and comparability, which are prerequisites for credible quantitative identification and intertemporal analysis.

All data are obtained from the Wind Information Database. We assemble daily market data from 2 September 2010 to 30 September 2019, covering individual bank equity prices and the CSI 300 Financials Index, for a total of 2,207 trading days. On this basis, we construct reweighted log-return series to estimate bank capital-shortfall risk and conduct subsequent network-structure analysis. In parallel, we compile a quarterly bank-level panel for the 16 institutions spanning December 2010 to September 2019, comprising 14 explanatory variables and yielding 576 observations. The data architecture is designed to identify and characterize the multidimensional and multilayer correlation structure underpinning the contagion of capital-shortage risk and its transmission mechanisms, thereby providing a rigorous empirical foundation and identification framework for hypothesis testing and robustness analysis.

Table 2 reports descriptive statistics for SRISK-related variables across three bank categories: state-owned commercial banks, joint-stock commercial banks, and city commercial banks. The sample consists of six state-owned banks, eight joint-stock banks, and two city commercial banks. Mean return indicators differ substantially across types: returns for state-owned banks are, on average, lower than those for joint-stock and city commercial banks. This pattern is consistent with heterogeneous objectives linked to their roles within the financial system: state-owned banks may prioritize macroeconomic stabilization alongside profitability.

Table 2 Summary statistics of variables. Table reports, for the 16 sample banks over the period 2010–2019, the mean, standard deviation, skewness, maximum, and minimum of the relevant raw variables.

Types	Variable	Obs	Mean	Std. dev	Skewness	Min	Max
State-owned Banks	yields	11040	0.72	0.10	0.13	0.52	1.03
	capital	11040	10747.28	4756.62	0.20	2568.25	27621.48
	liability	11040	119671.31	48447.80	-0.16	28085.58	233681.59
Joint-equity Banks	yields	17664	1.02	0.22	-0.12	0.52	1.60
	capital	17664	2332.84	1357.81	1.90	519.96	9679.38
	liability	17664	23069.22	9000.81	0.29	5366.82	47637.88
Urban Commercial Banks	yields	6624	1.06	0.13	0.60	0.79	1.43
	capital	6624	677.16	371.46	0.69	217.33	1649.15
	liability	6624	6196.64	3655.49	0.65	1361.55	15347.69

Notes: the rate of return has no unit, and the assets and liabilities are all 100 million yuan.

Table 3 Summary statistics of the bank's SRISK and main variables. Table reports summary statistics for banks' systemic risk, measured by SRISK, along with the principal covariates.

Variables	Obs.	Mean	Median	Min	Max	Std.dev
<i>SRISK%</i>	576	2.98	1.53	-10.14	20.36	4.65
<i>b1</i>	576	0.26	0.26	0.07	0.57	0.09
<i>b2</i>	576	0.13	0.12	0.09	0.17	0.01
<i>b3</i>	576	0.73	0.72	0.43	1.1	0.11
<i>b4</i>	576	1.19	1.15	0.34	2.4	0.42
<i>IS</i>	576	11.55	8.69	1.2	35.56	7.18
<i>SB</i>	576	0.06	0.05	-0.03	0.21	0.06
<i>g1</i>	576	0.12	0.13	0.08	0.2	0.03
<i>g2</i>	576	1.19	1.01	0.93	8.23	1.19
<i>p1</i>	576	7.47	7.15	6.2	9.8	0.99
<i>p2</i>	576	1.5	1.06	0.68	10.32	1.65

<i>dMul</i>	576	0.46	0.47	0.23	0.48	0.02
<i>bMul</i>	576	0.06	0.04	0.01	0.43	0.07
<i>i1</i>	576	0.15	0.12	-0.09	0.64	0.18
<i>i2</i>	576	0.08	0.07	-0.14	0.36	0.13

Liability and capital measures exhibit pronounced volatility, with liability volatility exceeding that of assets—particularly among state-owned and certain joint-stock banks. This likely reflects their function as “economic stabilizers” and core intermediaries tasked with meeting financing needs for public infrastructure and related sectors, which elevates liability fluctuations relative to capital. Moreover, the skewness of the variables is close to zero, indicating approximate normality and suitability for subsequent econometric analysis.

Table 3 reports summary statistics for banks’ systemic risk (SRISK) and key covariates. The dependent variable is bank-level SRISK. Explanatory variables include: bank fundamentals for 16 listed banks (non-interest income ratio, capital adequacy ratio, deposit-to-loan ratio, non-performing loan ratio); macro indicators (GDP growth, real-estate loan growth); policy variables (broad money growth, central bank lending to financial institutions); external shocks (y/y growth of foreign-exchange deposits and loans); multilayer network centrality (degree and betweenness on a multilayer network); and off-balance-sheet factors (shadow banking scale, investor sentiment). All series are quarterly, from the Wind Information Database and authors’ calculations.

4. Empirical results and analyses

4.1 Construction and analysis of risk network

4.1.1 Estimation results of bank capital shortage risk

Based on Eq. 1 and 2, the systemic risk index (SRISK) of each bank for the calendar year that measures the risk of bank capital shortage is calculated, and the results of its descriptive statistical analysis are shown in Table 4.

Table 4 Descriptive statistics of commercial banks' SRISK. Table presents the statistical characteristics of SRISK for 16 banks, including the mean, standard deviation, maximum, minimum, kurtosis, and skewness.

Bank	Abb.	Mean	Std.dev	min	Max	Skewness	kurtosis
Bank of Communications	BCM	3198.47	1108.62	-1243.13	5423.89	-0.72	3.62
Industrial and Commercial Bank of China	ICBC	9766.65	6365.82	-5987.48	21437.48	-0.06	2.13
China Construction Bank	CCB	9098.54	5729.65	-9087.17	18329.16	-0.76	3.32
Bank of China	BOC	8085.59	3076.72	-1351.9	13919.29	-0.89	3.46
Agricultural Bank of China	ABC	9931.95	4334.66	-3795.07	17394.39	-0.93	4.3
Shanghai Pudong Development Bank	SPDB	1585.72	1792.28	-23598.1	3194.53	-5.08	9.05
Ping An Bank	PAB	-1022.32	2985.55	-24448.6	2364.03	-2.66	6.84
HSBC Bank	HXB	415.59	871.48	-2515.67	1616.03	-1.32	4.03
China Minsheng Banking Corp.	CMBC	71.48	3110.71	-25524.6	3147.37	-2.51	5.58
China Merchants Bank	CMB	2103.67	2980.48	-32486	5370.57	-4.1	7.08
China Industrial Bank	CIB	1027.45	1877.98	-17291.3	3447.3	-4.03	6.32
China Everbright Bank	CEB	1388.86	518.5	-539.47	2612.9	-0.75	3.77
CITIC Bank	CITICB	2245.73	812.87	-1730.83	3550.79	-1.47	5.27
Bank of Ningbo	BNB	276.67	263.58	-937.66	856.07	-0.27	4.06
Bank of Nanjing	BNJ	-20.79	585.03	-2261.39	916.17	-1.42	4.57

Bank of Beijing	BJB	-554.66	1970.57	-8697.57	1541	-1.95	6.2
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As can be seen from Table 4, the standard deviation of *SRISK* index of all banks is larger and the degree of dispersion is higher. Among them, the mean level of *SRISK* is high and the degree of dispersion is relatively large for ICBC, CCB, BOC and ABC among state-owned banks, and SPDB, CMB and CIB among joint-stock banks, and the systemic risk indexes of these banks changed dramatically from September 2010 to September 2019, and regarding the positive and negative directions of the median, the changes are all long term expected capital gap is positive, i.e., the systemic risk index is continuously increasing. It is noteworthy that PAB, BNJ and BJB have negative mean *SRISK* levels, have capital surpluses in the sample interval in general, and are operating in a stable and favorable development, but the relative degree of dispersion is still high; while CMBC has the lowest positive mean *SRISK* level, but the greatest degree of dispersion, and is operating in a more stable way, which makes it less likely to be a source of systemic risk for banks.

4.1.2 Estimation results and analyses of bank capital shortage risk contagion

To measure bank capital shortage risk contagion, according to equation 5, we calculated the annual relative systemic risk index *SRISK%* of 16 banks during the period from 2010Q4 to 2019Q3 to measure bank capital shortage risk contagion, and gave the results of the ranking from the largest to the smallest, see Table 5.

Table 5 Ranking results of banks' relative systemic risk index *SRISK%* from 2010 to 2019. The table lists, by year (2010–2019), the rankings of *SRISK%*—a relative measure of systemic risk—for 16 banks, and reports each bank's average rank and the change in rank over the period.

Bank	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average	Increase
ICBC	7	3	3	1	1	4	3	2	1	1	2.6	6
ABC	9	1	2	3	3	2	1	1	3	3	2.8	6
BOC	1	2	4	4	4	1	2	4	4	4	3.0	-3
CCB	14	4	1	2	2	3	4	3	2	2	3.7	12
BCM	2	5	5	5	5	5	5	5	6	5	4.8	-3
CITIC	5	7	8	7	8	7	6	7	7	7	6.9	-2
SPDB	3	6	7	8	7	6	8	8	13	12	7.8	-9
CEB	6	8	11	9	10	9	9	10	8	9	8.9	-3
CMB	16	15	6	6	6	15	10	6	5	6	9.1	10
CIB	13	9	10	14	9	11	12	11	9	8	10.6	5
HXB	4	10	12	10	13	10	11	12	12	14	10.8	-10
CMBC	15	14	9	16	12	8	7	9	11	15	11.6	0
BNB	12	12	13	11	15	16	15	13	10	11	12.8	1
BNJ	10	11	14	13	16	14	14	15	14	13	13.4	-3
PAB	8	16	16	15	11	13	16	16	15	10	13.6	-2
BJB	11	13	15	12	14	12	13	14	16	16	13.6	-5

Table 5 shows that ICBC, ABC, CCB, BOC, and BCM consistently rank in the top five of the relative systemic risk index. This pattern indicates that, considering leverage, size, and interconnectedness, these institutions constitute the systemically important core of China's banking sector. The rankings align closely with the global systemically important banks (G-SIBs) list, suggesting that the parameter-adjusted *SRISK* framework—incorporating an 11.5% macroprudential capital ratio—provides an effective measure of systemic risk in the Chinese context. By contrast, urban commercial banks generally exhibit low relative systemic risk and do not face material long-term expected capital shortfalls, implying limited system-wide impact.

Over the sample period, CCB and CMB rose markedly in the rankings—by 12 and 10 places, respectively—signaling a notable increase in their systemic risk contributions that warrants supervisory attention. Conversely, HXB

and SPDB experienced the largest declines—10 and 9 places—consistent with effective prudential management and oversight.

4.1.3 Analysis of the overall structure of the nonlinear information-linked contagion network

On the basis of the previously measured relative systemic risk indices, and recognizing contagion and spillovers as core dimensions of systemic risk, this paper uses transfer entropy per Equation (25) to delineate the transmission pathways of systemic risk across banks. We further apply a thresholding criterion to construct a nonlinear information network of capital shortfall risk in China's banking sector. The results are presented in Figure 2.

According to Figure 2, the nonlinear information network of banks' capital shortfall risk exhibits a density of 0.67 with 161 directed connections, indicating a highly dense network and a tightly knit correlation structure. Table 6 reports descriptive statistics for the network characteristics of Chinese banks' systemic risk and the associated capital shortfall risk indices. The SRISK figures are averages computed from quarterly observations over the entire sample period.

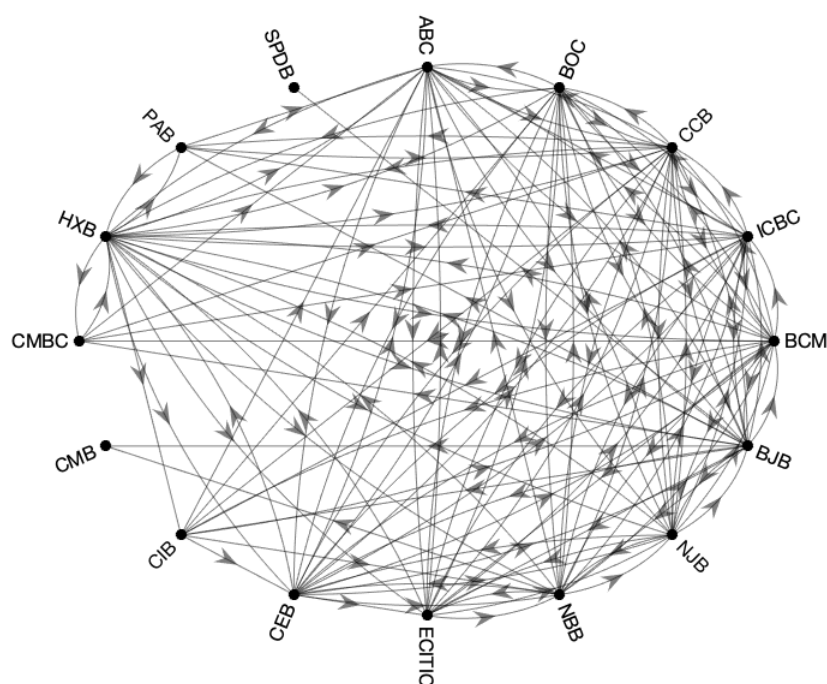


Fig. 2 The non-linear information association network of China's banking systemic risk. Figure depicts a nonlinear information network of capital shortfall risk in China's banking sector, constructed via transfer entropy and a thresholding rule; nodes represent banks, and directed edges indicate the direction and intensity of risk transmission within a densely interconnected system.

Table 6 indicates a highly concentrated degree distribution among the top five banks, while most banks exhibit low degrees consistent with a power-law distribution; this pattern is characteristic of a scale-free network. The clustering coefficient is 0.793, implying a 79.3% likelihood that any two banks' systemic-risk correlation neighborhoods overlap. This reflects strong local cohesion, dense and intersecting contagion paths, bidirectional and multidirectional transmission, and the absence of fully isolated nodes. The nonlinear information-linked contagion network for banks' capital shortfall risk has an average path length of 1.33 and a compactness of 0.83, consistent with small-world properties. The network is tightly connected and structurally compact, implying that a financial shock can diffuse across the system with at most one intermediary. Pudong Development Bank and China Merchants Bank maintain only one and two links, respectively, suggesting relatively greater structural independence in risk, a lower likelihood of serving as initial sources of systemic risk, and potentially smaller, slower losses under extreme stress. The network diagram further shows that state-owned banks possess substantially more connections than joint-stock banks. Urban commercial and other banks also maintain numerous links, primarily with state-owned and urban commercial peers. These patterns support a preliminary inference that state-owned banks occupy a dominant position within the systemic risk network.

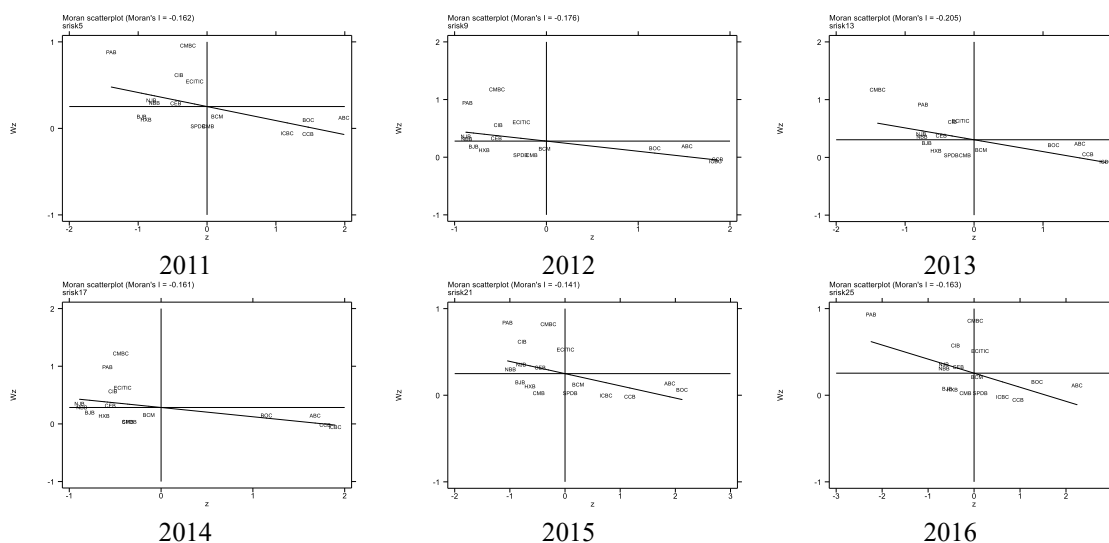
Table 6 Network centrality and SRISK calculation results. Table summarizes Chinese banks' centrality metrics in the nonlinear information network—out-/in-degree, closeness, betweenness, and eigenvector centrality—along with the corresponding average SRISK values.

Bank	Out degree	In-degree	In-Closeness centrality	Out-Closeness centrality	Betweenness centrality	Eigenvector Centrality	SRISK
BCM	12	10	31.25	83.33	6.87	0.29	3072.20
ICBC	12	10	31.25	83.33	6.98	0.30	9344.38
CCB	12	12	32.61	83.33	12.10	0.30	8537.29
BOC	10	11	31.92	75.00	2.89	0.28	7712.87
ABC	8	13	33.33	68.18	6.76	0.30	9394.06
SPDB	0	1	31.25	6.25	0.00	0.03	1501.73
PAB	3	4	27.27	51.72	0.00	0.13	-901.50
HXB	13	12	32.61	88.24	16.60	0.30	378.05
CMBC	4	3	27.27	53.57	0.00	0.16	-153.87
CMB	0	2	34.09	6.25	0.00	0.05	1806.77
CIB	5	5	28.30	55.56	0.00	0.23	931.80
CEB	10	10	31.25	75.00	2.27	0.28	1337.40
CITICB	7	10	31.25	62.50	0.25	0.26	2133.29
BNB	10	10	31.25	71.43	7.83	0.28	258.26
BNJ	10	10	31.25	75.00	1.12	0.26	-36.88
BJB	15	8	30.00	100.00	23.33	0.31	-633.33

4.2 Analysis of empirical results on multidimensional contagion factors and multiple pathways

4.2.1 Statistical analysis of spatial correlation

To test the four hypotheses, we conduct spatial correlation analyses of SRISK. We compute Moran's I and its temporal trend to assess whether bank capital shortfall risks exhibit spatial dependence over time and to identify the direction of that dependence. Finally, we visualize the spatial correlation using Moran's I scatter plots; the results are reported in Figure 3.



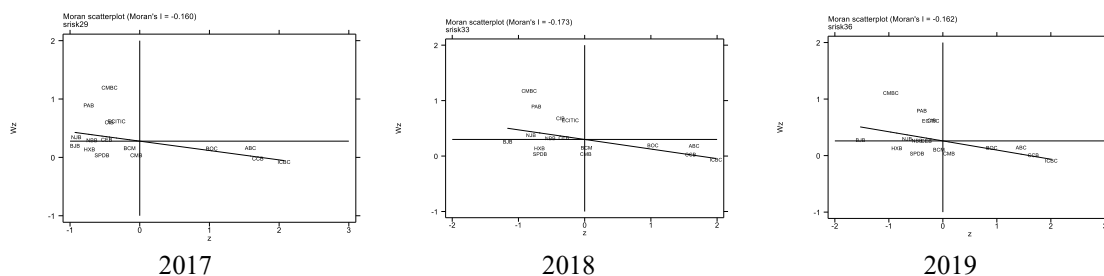


Fig. 3 Moran scatter chart of systemic risk index (SRISK) from 2010 to 2019. Figure presents yearly Moran's I scatter plots for banks' SRISK, illustrating the strength and direction of spatial dependence over time.

Table 7 Moran value of systemic risk index (SRISK) from 2011 to 2019. Table shows consistently significant negative spatial dependence at the 1% level.

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Moran's I	-0.162	-0.176	-0.205	-0.161	-0.141	-0.163	-0.160	-0.173	-0.162

Note: The Moran values in the table are significant at the significant level of 0.01.

The spatial correlation analysis of banks' relative systemic risk index (Figure 3; Table 7) shows a significant negative spatial autocorrelation in SRISK during 2010–2019. To identify the appropriate spatial process, we first estimate a multiple linear regression by least squares, then apply Lagrange multiplier tests and report the LM statistics. The results are provided in Table 8.

Table 8 Spatial econometric model identification test. Table indicates that LM-Error and R-LM-Error are highly significant, while LM-Lag is significant but R-LM-Lag is not.

Test	Test statistic value
LM-Lag	130.9767***
R- LM-Lag	0.1729
LM-Error	188.3145***
R- LM-Error	54.4211 ***

Table 8 shows that the LM-Lag and LM-Error tests reject the null of no spatial autocorrelation, the R-LM-Lag test is insignificant, and the R-LM-Error test rejects the null. These results indicate spatial dependence not only in the dependent variable but also in the error process for the transmission of banks' capital shortfall risk; hence, a spatial Durbin panel model is adopted to trace the transmission path of systemic risk. The spatial diagnostics also provide preliminary support for Hypothesis 2 (capital shortfall risk reflects multidimensional factor correlations) and Hypothesis 3 (interbank affiliation networks are the primary channel of contagion). Furthermore, Hausman and LR tests favor a spatial Durbin panel model with two-way fixed effects (time and space) at the 5% significance level.

4.2.2 Construction and descriptive analysis of multi-networks

To test Hypothesis 3—that the multiple interbank affiliation network is the primary feature of capital shortfall risk contagion—we construct a multilayer interbank contagion network. Prior studies indicate that interbank lending, stock price information comovement, and real estate business exposures are key drivers of common asset value fluctuations and, hence, of interbank risk contagion. These three channels, together with the nonlinear information linkage in banks' capital shortfall risk, constitute the principal contagion paths and give rise to a complex interbank contagion structure. To characterize the data and network architecture, we employ the maximum entropy method to construct (i) the interbank lending matrix; use the Pearson correlation to measure (ii) the information linkage in stock price fluctuations and (iii) the comovement of real estate asset value fluctuations; and, under thresholding, plot the corresponding stock information and real estate correlation networks. Consistent with the above, we compute (iv) the nonlinear information matrix of capital shortfall risk using transfer entropy and visualize the associated nonlinear information network. Finally, we integrate the four layers via a weighted average to obtain the Multi-network, as depicted in Figure 4.

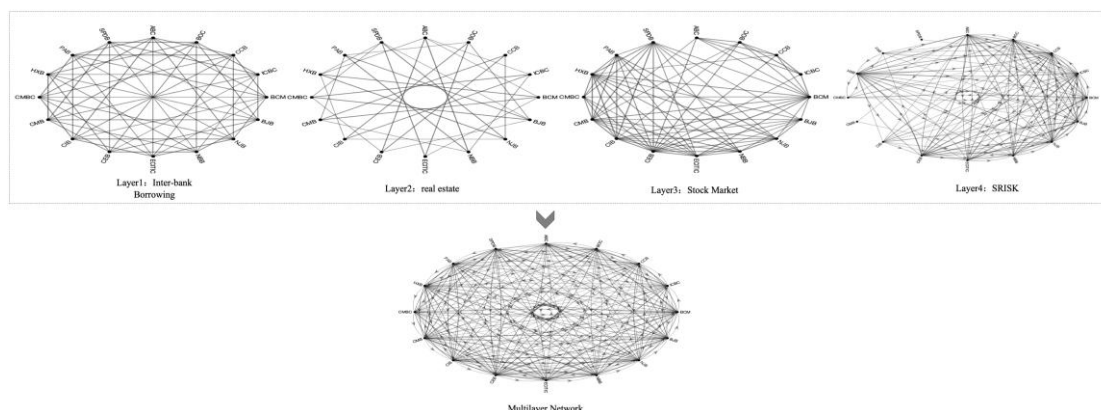


Fig. 4 Four single association networks and multiple association networks. Figure presents four single-layer association networks—interbank lending, real estate, stock market information, and capital shortfall risk—and their integrated multilayer “Multi-network,” illustrating the primary contagion channels and their combined structure.

Figure 4 presents four network layers: Layer 1 depicts asset–liability linkages from interbank lending; Layer 2 shows correlations in banks’ real estate loan values; Layer 3 captures information linkages in banks’ stock return fluctuations; and Layer 4 displays nonlinear information linkages in banks’ capital shortfall risk (SRISK). All graphs are edge-weighted, with edge thickness denoting the strength of association between nodes. The upper panels highlight pronounced heterogeneity in banks’ multiple linkages, confirming significant multidimensional interbank connections.

Banks obtain funds via financial markets and interbank lending to ease liability pressures. When interbank activity exceeds a threshold, asset–liability mismatches can emerge, generating liquidity risk. Layer 1 indicates that China’s interbank asset–liability network is stable and symmetric. Lending and borrowing ties are strong, without signs of excessive expansion. Affiliation in deposit and loan business is largely bilateral and shaped by information asymmetry. Because state-owned commercial banks are government controlled, joint-stock and city commercial banks prefer them as counterparties, yielding a symmetric structure between state-owned banks and other banks. Real estate loan values exhibit the weakest correlations. As a pillar industry and a core credit line for banks, real estate has recently been steered by the “housing for living, not for speculation” policy, fostering healthy, stable development; correspondingly, Layer 2 exhibits the lowest comovement in real estate loan asset values.

Compared with Layers 1 and 2, the stock price information network (Layer 3) is the densest. Correlations are concentrated among joint-stock banks; state-owned banks exhibit the lowest stock return volatility, followed by city commercial banks. The correlation structure of stock return volatility thus reveals heterogeneity across bank types. Stock market linkages expand the channels and likelihood of interbank risk correlation, making Layer 3 the most connected. Layer 4 is the directed nonlinear information network of banks’ systemic risk (SRISK), constructed from the transfer-entropy matrix of relative systemic risk. It exhibits marked concentration and asymmetry in both linkages and directions. Concentration arises because systemic risk associations cluster around state-owned and city commercial banks, while joint-stock banks appear to maintain stronger self-discipline under the “prevent and resolve major risks” policy. State-owned banks, despite policy emphasis, may be weakened by broader social and developmental obligations. Asymmetric transmission implies distinct sender and receiver roles, with significant role heterogeneity in risk propagation.

Overall, the linkage patterns in each dimension are consistent with the classification, development trajectory, and theoretical analysis of China’s banking sector, supporting Hypothesis 3: multiple interbank affiliation networks are the primary feature of capital shortfall risk contagion.

The multi-network, formed by integrating Layers 1–4, represents the comprehensive affiliation network after superimposing contagion channels. The overall structure appears stable, with limited differentiation in pairwise correlations. This suggests that once systemic risk emerges, interbank transmission becomes effectively uncontrollable, and the notion of systemically important banks is less salient. Although edge weights imply differences in the speed and intensity of transmission, these differences are modest.

To assess role and transmission heterogeneity under multi-channel contagion, we compute centrality measures on the directed, weighted multi-network obtained via additive integration. The metrics include degree centrality (out- and in-degree), closeness centrality (out- and in-closeness), betweenness centrality, and eigenvector centrality. Results are reported in Table 9. Degree centrality: A larger degree implies a broader scope of risk contagion for a node. Closeness centrality: A larger value indicates that a node can more readily form associations with others.

From Table 9, out- and in-degrees are broadly similar across nodes, implying that banks that emit more risk also tend to absorb more risk. CEB, BCM, HXB, CMB, and CIB rank in the top 5 of 16 on both active transmission (out) and reception (in), exceeding the mean and thus acting as “dominant players” in systemic risk transmission. (Closeness centrality values in Table 9 are normalized by Ucinet for comparability.) ICBC, CCB, and SPDB exhibit mild asymmetries between spillovers and spillbacks, but the differences are small; other banks show nearly identical out- and in-closeness. CMB, SPDB, BOC, ABC, PAB, and BNB have relatively low closeness centrality, suggesting they receive transmitted risk later than peers. Overall, cross-bank differences in closeness are limited, indicating no pronounced variation in ease of transmission. Banks with high overall centrality also display high out-closeness, implying that the magnitude of systemic contagion is proportional to the ease of contagion, with bilateral exposures amplifying risk propagation.

Table 9 Centrality Analysis of Multiple Network. Table reports centrality metrics—out/in-degree, out/in-closeness, betweenness, and eigenvector—along with standard deviations for 16 banks in the multilayer network, enabling comparison of their relative importance in systemic risk transmission.

bank	Out degree	in-degree	in-Closeness centrality	Out-Closeness centrality	betweenness centrality	Eigenvector Centrality
BCM	17	16	100.00	100.00	0.60	0.28
ICBC	11	11	100.00	93.75	0.53	0.20
CCB	12	12	100.00	93.75	0.45	0.20
BOC	13	13	93.75	93.75	0.30	0.23
ABC	13	13	93.75	93.75	0.38	0.22
SPDB	15	15	88.24	93.75	0.38	0.26
PAB	14	14	93.75	100.00	0.53	0.23
HXB	17	17	100.00	100.00	0.60	0.29
CMBC	13	13	88.24	88.24	0.30	0.22
CMB	16	16	100.00	100.00	0.60	0.28
CIB	16	16	100.00	100.00	0.60	0.27
CEB	18	18	100.00	100.00	0.60	0.30
CITICB	14	14	100.00	100.00	0.60	0.24
BNB	14	15	93.75	93.75	0.30	0.26
BNJ	15	15	100.00	100.00	0.60	0.26
BJB	14	14	100.00	100.00	0.60	0.25
standard deviation	1.93	1.86	4.36	3.84	0.13	0.03

Betweenness centrality quantifies the role of nodes as “connecting intermediaries.” As shown in Table 9, under extreme risk, 75% of banks have betweenness above the mean. Thus, most banks function as risk transmitters, and strong intermediation effects are pervasive, further facilitating network-wide contagion. Banks with strong intermediation span all three major categories—state-owned, joint-stock, and city commercial—indicating that differences in capital-funding structures do not materially affect the intermediation role in risk transmission; systemic risk exhibits cross-category contagion. Effective prevention therefore requires a system-wide perspective on banking risk.

Eigenvector centrality incorporates the centrality of neighbors in addition to a node’s own centrality. According to Table 9, except for BCM, eigenvector centrality for state-owned banks lies below the mean, suggesting that, under multi-channel contagion, their transmission is more robust (i.e., less reliant on highly central neighbors) than that of other banks. Overall, however, inter-bank differences in centrality remain modest.

In sum, analysis of node centralities in the multi-network and the standard deviations of these indicators (last row of Table 9) shows no pronounced dispersion across banks. Hence, under multiple risk-related contagion, banks’ systemic importance is generally high and relatively homogeneous.

4.2.3 Empirical analysis on the risk contagion path of bank capital shortage

According to the theoretical framework, this section uses a static spatial panel Durbin model to examine contagion channels of bank capital shortfall risk along six dimensions: multi-network linkages, on-balance-sheet factors, off-balance-sheet factors, macroeconomic conditions, policy variables, and international shocks. The model is estimated by maximum likelihood, with results reported in Table 8. The model fit is strong ($R^2 = 0.8170$). The spatial autoregressive coefficient ($\rho = -0.7733$) is significant at the 1% level, indicating pronounced negative spatial dependence in capital shortfall risk. Capital shortfalls at neighboring banks exert adverse effects on target banks, implying spatial spillovers of “risk transfer,” consistent with high–low and low–high spatial clustering. These findings provide strong support for Hypothesis 3.

The OLS estimates in Column (1) of Table 10 show that, *ceteris paribus*, higher multi-network degree centrality raises the likelihood of capital shortfall risk; greater network position thus implies larger risk contribution and faster transmission. Regarding off-balance-sheet factors, investor sentiment (IM) increases systemic risk, whereas the scale of shadow banking (SB) is not significant. These results indicate that, even without extra-bank variables, the determinants of capital shortfall contagion are multi-dimensional and interact, supporting Hypotheses 1 and 2.

The full-sample static spatial Durbin estimates in Column (2) indicate that, when multiple channels are considered, contagion propagates significantly through the interbank loan network, the real-estate credit network, and intermediary nodes in the stock-market association network, again supporting Hypothesis 3. In this specification, multi-network degree centrality is not significant, but multi-network betweenness centrality is significant, implying that intermediary banks accelerate contagion, especially under stress. At the micro level, neighboring banks’ non-interest income (b1) and loan-to-deposit ratio (b3) elevate a bank’s systemic risk, while neighbors’ capital adequacy (b2) mitigates it. Competition and adverse selection may induce greater risk-taking when sectoral capital adequacy is strong, increasing the long-run capital gap and the probability of systemic risk. Off-balance-sheet factors of neighboring banks are insignificant. Macroeconomically, neighbors’ support for real-estate development (g2) is strongly positively related to systemic risk, suggesting real estate as a common-asset conduit. Central bank lending to banks (p2) is insignificant. Under international shocks, foreign-exchange deposits (i1) and foreign-exchange loans (i2) significantly raise systemic risk. Overall, with multi-bank associations, multi-dimensional drivers and their interactions remain significant, reinforcing Hypotheses 1 and 2; given the validity of Hypothesis 3, Hypothesis 4 (multi-dimensional, multi-association contagion) is also supported.

From the direct-effect estimates in Column (3) of Table 10, even after accounting for the multilayer structure of stock-market, real-estate credit, and interbank lending networks, the significance and signs of contagion drivers are consistent with the bank-level analysis. The direct transmission of systemic risk operates through interbank lending, real-estate credit, and stock-market association networks. At the micro level, higher non-interest income ratio, loan-to-deposit ratio, and non-performing loan ratio tend to moderate, to some extent, the onset and diffusion of systemic risk, whereas higher capital adequacy amplifies it. For off-balance-sheet factors, investor sentiment significantly increases systemic risk, while shadow banking remains insignificant. Macroeconomic development shows no direct effect. By contrast, monetary growth at the policy level directly and materially intensifies systemic risk. Regarding international shocks, foreign-exchange deposits and loans exhibit opposite effects—deposits mitigate while loans exacerbate systemic risk—with the positive effect of foreign-exchange loans dominating. Controlling the volume of foreign-exchange lending is therefore critical for systemic-risk prevention.

Table 10 Regression results of the static SDPM with dual fixed effects in space and time. Table reports OLS and static SDPM estimates—with direct, indirect, and total effects—for multi-layer network status and bank-, macro-, policy-, and external-shock variables, quantifying their contributions to systemic risk transmission.

Path	factors	OLS	SDPM	Direct effect	Indirect effect	Total effect
		(1)	(2)	(3)	(4)	(5)
Multi-layered network	<i>dMul</i>	5.85*	-1.90	6.36*	-4.63	1.73
center status	<i>bMul</i>	0.02	38.31***	-1.73	23.71***	21.97***
On-balance	<i>bl</i>	-8.62***	29.01**	-10.04***	22.99**	12.95*

sheet	<i>b2</i>	74.10***	-186.16**	84.78***	-149.82***	-65.05*
	<i>b3</i>	-3.65*	27.67**	-5.00***	18.70**	13.71*
	<i>b4</i>	-1.54***	0.53	-1.63***	1.01	-0.62
Off-balance	<i>IM</i>	0.06***	0.01	0.06***	-0.02	0.04
sheet	<i>SB</i>	-0.13	-17.67	0.75	-10.51	-9.76
Macro-	<i>g1</i>	—	39.80	-176.00	240.00	222.00
economic	<i>g2</i>	—	76.83*	-33.39	77.55*	44.16*
level						
Policy	<i>p1</i>	—	-49.1***	21.43***	-304***	-282.57***
regulation	<i>p2</i>	—	5.79	-1.94	30.87	28.93
International	<i>i1</i>	—	-53.40*	27.96*	-398.00*	-370.04*
shocks	<i>i2</i>	—	65.7***	-202.00***	487.00***	285***
Spatial rho		-0.77***				
sigma2_e		3.17***				

Notes: The significance level of the test quantity is indicated by *, which respectively represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The indirect-effect estimates in Column (4), capturing spillover contagion, are consistent with the direct-effect results of the spatial Durbin model. Spatial transmission operates through interbank lending, real-estate credit, and stock-market association networks, interacting with bank-level, macroeconomic, policy, and foreign-exchange dimensions. The total effect combines direct and spillover effects. Column (5) shows that the total-effect estimates broadly align with the spatial-correlation and indirect-effect results in terms of signs, significance, and magnitudes. The decomposition indicates that spillover contagion generally dominates the direct effect. The spatial contagion path runs through intermediary banks in the interbank, real-estate credit, and stock-market association networks, with multi-network betweenness centrality remaining significant. Under foreign-exchange shocks, both deposits and loans significantly affect systemic risk—deposits mitigate, while loans exacerbate risk. Off-balance-sheet factors—investor sentiment and shadow banking—are not significant in the total effect.

4.2.4 Further analysis

Given clustering and serial correlation in the banks' relative systemic risk index and its determinants, we augment equation (26) with the first-order lag of the dependent variable $\ln(SRISK)$ as an explanatory variable. We then specify a dynamic spatial Durbin panel model and estimate the parameters by log-maximum likelihood. Estimation results are reported in Table 11.

The dynamic spatial Durbin panel model attains ($R^2 = 0.8548$), exceeding the static spatial panel model, indicating better model adequacy and higher estimation precision. The coefficient on the first-order lag of $SRISK$ is 1.07 and significant at the 1% level, evidencing strong intertemporal persistence: current systemic risk rises with its prior level. The spatial autoregressive coefficient is -0.75 (1% level), confirming significant multi-path transmission and supporting Hypothesis 3.

Table 11 Dynamic verification results of the path of infectious factors. Table reports dynamic SDPM estimates—including the lagged $SRISK$ term and spatially lagged covariates—quantifying direct and spatial effects of network status, bank fundamentals, macro, policy, and external shocks on systemic risk.

Variables	coefficient	Variables	coefficient
$SRISK\%(-1)$	1.07***	<i>cons</i>	40.31***
<i>dMul</i>	0.95	$w1 \times dMul$	-2.91***
<i>bMul</i>	3.02**	$w1 \times bMul$	4.89***
<i>b1</i>	-10.99***	$w1 \times b1$	0.75**
<i>b2</i>	70.01***	$w1 \times b2$	-15.65***
<i>b3</i>	-3.79***	$w1 \times b3$	0.99**

<i>b4</i>	-1.86***	<i>w1 × b4</i>	-0.06
<i>g1</i>	-12.06	<i>w1 × g1</i>	-2.86**
<i>g2</i>	-0.55**	<i>w1 × g2</i>	0.05***
<i>p1</i>	0.79*	<i>w1 × p1</i>	-0.15***
<i>p2</i>	0.11	<i>w1 × p2</i>	0.00
<i>i1</i>	1.56	<i>w1 × i1</i>	-0.04
<i>i2</i>	-20.42***	<i>w1 × i2</i>	1.60***
<i>IM</i>	0.05***	<i>w1 × IM</i>	0.00
<i>SB</i>	0.18	<i>w1 × SB</i>	0.00

Contagion pathways continue to link bank-level management, multi-network centrality, macroeconomic conditions, policy stance, and foreign-exchange exposures to systemic risk, consistent with the static analysis and reinforcing the empirical identification of channels. At the micro (bank) level, the non-interest income ratio, loan-to-deposit ratio, and non-performing loan ratio display negative direct effects but positive spatial spillover and contagion effects. By contrast, the capital adequacy ratio shows a positive direct effect and a negative spatial spillover effect, with a stronger overall impact. Conclusions regarding network position, macroeconomic variables, policy variables, foreign-exchange variables, and off-balance-sheet factors align with the static spatial panel results. Hence, after controlling for dynamics and unobserved heterogeneity, the dynamic specification preserves the core findings of the static model. The evidence thus supports a persistent multi-dimensional, multi-network contagion mechanism for bank capital shortfall risk, validating all four research hypotheses.

5. Conclusions and policy implications

Scale, leverage, and interconnectedness are the defining attributes of systemically important banks and primary sources of systemic financial risk. Accordingly, this study employs the relative systemic risk index to quantify banks' capital shortfall risk contributions and transfer entropy to capture the information-contagion effect of those contributions. Using a threshold approach, we construct a contagion network of capital shortfall risk contributions, then embed both a common-asset-value network and an interbank-lending network to form a multilayer contagion matrix. We successively specify static and dynamic two-way fixed-effects spatial Durbin panel models, and design multiple-relation centrality and multiple-relation betweenness centrality to characterize banks' multilayer network positions. Within this framework, we examine the factor pathways of capital shortfall risk contribution contagion. The principal conclusions and implications are as follows.

i. Based on the Relative Systemic Risk Index, the Industrial and Commercial Bank of China, Agricultural Bank of China, China Construction Bank, Bank of China, and Bank of Communications exhibit higher levels and larger contributions to capital shortfall risk. From the perspectives of leverage, size, and proximity, these five institutions are systemically important within China's banking sector. In addition to strengthened micro- and macro-prudential oversight, these banks should be subject to supplementary, cross-institutional capital requirements to promote more resilient operations.

ii. The network of capital shortfall risk contributions is highly dense, with tight information linkages, strong node cohesion, and intersecting transmission paths. First, the degree distribution follows a power law, indicating a scale-free structure: the network is robust to random shocks yet vulnerable to shocks targeting central nodes. To mitigate vulnerability arising from scale-free properties, supervisory authorities should enhance micro-prudential oversight and impose additional capital buffers on highly connected central institutions. Second, the network exhibits a short characteristic path length, high clustering, and rapid, broad diffusion—typical of small-world structures. Regulators should therefore closely monitor shocks tied to systemically important institutions and factors, implement forward-looking prudential measures, and promptly dampen incipient risks once extreme events are detected. Strengthening the risk-absorption capacity of transmission hubs can curb spillovers and constrain network contagion.

iii. Direct effects indicate that banks' capital shortfall risk rises with multiple-network centrality, the capital adequacy ratio, investor sentiment, broad money growth, and foreign-exchange deposit growth. By contrast, the interest income ratio, loan-to-deposit ratio, non-performing loan ratio, and foreign-exchange loan growth exert significant negative direct effects. The contagion of capital shortfall risk displays significant negative spatial autocorrelation and intertemporal dependence across locations. With respect to indirect (spillover and contagion) effects, multiple-network

betweenness centrality, the non-interest income ratio, the deposit-loan ratio, real-estate loan growth, and foreign-exchange loan growth generate significant positive spillovers; in contrast, the capital adequacy ratio, broad money growth, and foreign-exchange deposit growth exhibit significant negative spillover and contagion effects. Policy should therefore reinforce the dual-pillar framework of monetary–fiscal regulation and macro-prudential policy: sharpen the alignment of policy and financial-stability objectives, broaden the toolkit, strengthen countercyclical buffers, and safeguard the systemic-risk boundary atop robust micro-prudential standards. In addition, a time-varying damping mechanism for contagion coefficients over the financial cycle should be introduced to reduce the diffusion and amplification capacity of financial networks, enhance the absorption and mitigation capabilities of systemically important institutions, network hub intermediaries, and systemically vulnerable institutions, and ultimately restrain—or even halt—network spillover and contagion of banks’ capital shortfall risks.

Ethical Approval

This manuscript does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent

This article does not contain any studies with human participants performed by any of the author.

Competing interests

A conflict exists in the submission of this manuscript that S., Y. P. on the paper is the member of this journal’s editorial board. We have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Conceptualization, Wang, Z. and Wei, W.; methodology, Wang, Z. and Wang, Y.; software, Wang, Z. and Wei, W.; formal analysis, Wang, Z. and Wei, W.; investigation, Wang, Z., Wei, W., Wang, Y. and Song, Y.; resources, Song, Y.; data curation, Wei, W.; writing—original draft preparation, Wei, W. and Wang, Y.; writing—review and editing, Wang, Z. and Song, Y.; visualization, Wei, W. and Wang, Y.; supervision, Wang, Z. and Song, Y.; project administration, Wang, Z.; funding acquisition, Wang, Z. All authors have read and agreed to the published version of the manuscript.

Data Availability

The dataset for the empirical analysis can be derived from Wind Information Database.

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References

- Abedifar P, Giudici P, Hashem SQ (2017) Heterogeneous market structure and systemic risk: evidence from dual banking systems. *Journal of Financial Stability* 33: 96-119
- Acharya VV, Engle R, Richardson M (2012) Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks. *American Economic Review* 102: 59-64

- Acharya VV, Pedersen LH, Philippon T, Richardson MP (2017) Measuring Systemic Risk. CEPR Discussion Papers 29: 85-119
- Acharya VV, Thakor AV (2016) The dark side of liquidity creation: Leverage and systemic risk. *Journal of Financial Intermediation* 28: 4-21
- Acosta-Smith J, Grill M, Lang JH (2020) The Leverage Ratio, Risk-Taking and Bank Stability. *Journal of Financial Stability*
- Adrian T, Brunnermeier MK (2016) CoVaR. *American Economic Review* 106: 1705-1741
- Aldasoro I, Alves I (2018) Multiplex interbank networks and systemic importance: An application to European data. *Journal of Financial Stability* 35: 17-37
- Alter A, Beyer A (2014) The dynamics of spillover effects during the European sovereign debt turmoil. *Journal of Banking & Finance* 42: 134-153
- Bernardi M, Durante F, Jaworski P (2017) CoVaR of families of copulas. *Statistics & Probability Letters* 120: 8-17
- Billio M, Getmansky M, Lo AW, Pelizzon L (2012) Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104: 535-559
- Boako G, Alagidede P (2017) Examining evidence of shift-contagion in African stock markets: A CoVaR-copula approach. *Review of Development Finance* 7: 142-156
- Brownlees C, Chabot B, Ghysels E, Kurz C (2020) Back to the future: backtesting systemic risk measures during historical bank runs and the great depression. *Journal of Banking & Finance* 113: 105736
- Cipollini F, Giannozzi A, Menchetti F, Roggi O (2020) The beauty contest between systemic and systematic risk measures: Assessing the empirical performance. *Journal of Empirical Finance* 58: 316-332
- Davydov D, Vhmaa, S, Yasar S (2021) Bank liquidity creation and systemic risk. *Journal of Banking & Finance*, 123: 106031
- Diebold FX, Yılmaz K (2014) On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182: 119-134
- Dinger V, Hagen JV (2010) Does interbank borrowing reduce bank risk? *Journal of Money, Credit and Banking* 41: 491-506
- Gandy A, Veraart LAM (2017) A Bayesian methodology for systemic risk assessment in financial networks. *Management Science* 63: 4428-4446.
- Ghysels E, Hill JB, Motegi K (2016) Testing for Granger causality with mixed frequency data. *Journal of Econometrics* 192: 207-230
- Girardi G, Erguen AT (2013) Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance* 37: 3169-3180.
- Hué S, Lucotte Y, Tokpavi S (2019) Measuring network systemic risk contributions: a leave-one-out approach. *Journal of Economic Dynamics and Control* 100: 86-114
- Huynh TLD, Nasir MA, Nguyen SP, Duong D (2020) An assessment of contagion risks in the banking system using non-parametric and copula approaches. *Economic Analysis and Policy* 65: 105-116
- Kelejian HH, Tavlas GS, Hondroyannis G A (2006) Spatial Modelling Approach to Contagion Among Emerging Economies. *Open Economies Review* 17: 423-441
- Kristjanpoller W, Minutolo MC (2015) Gold price volatility: a forecasting approach using the artificial neural network-GARCH model. *Expert Systems with Applications* 42: 7245-7251
- Lai Y, Hu Y (2021) A study of systemic risk of global stock markets under COVID-19 based on complex financial networks. *Physica A: Statistical Mechanics and its Applications* 566: 125613

-
- Li F, Wei W, Wang Z (2020) A comprehensive recognition research of systemic import local government: A perspective of individual risk and information infection risk. *The Theory and Practice of Finance and Economics* 41: 78-85.
- Morelli D, Vioto D (2020) Assessing the contribution of China's financial sectors to systemic risk. *Journal of Financial Stability* 50: 100777
- Wang Z, Lv S, Mao X (2014) A study on effectiveness of CoVaR calculation methods based on risk spillover features. *Economic Review* 24: 148-160
- Wang Z, Zhao Q, Zhu M, Pang T (2020) Jump Aggregation, Volatility Prediction, and Nonlinear Estimation of Banks' Sustainability Risk. *Sustainability* 12: 8849
- Zhang W, Zhuang X, Wang J, Lu Y (2020) Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network. *The North American Journal of Economics and Finance* 54: 101248
- Zhu B, Zhou X, Liu X, He K, Wang H, He K, Wang P (2019) Exploring the risk spillover effects among china's pilot carbon markets: a regular vine copula-CoES approach. *Journal of Cleaner Production* 242: 118455