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# The Influence of Financial Institutions' Interconnectedness on Financial Systemic Risk: Evidence from Listed Chinese Financial Institutions

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***Abstract:*** *As China's capital market evolves toward a multi-tiered structure, the internal interconnectedness of the financial system has continued to strengthen. Financial innovation has accelerated market development but has also increased the potential for systemic financial risk. This paper investigates how the interconnectedness of financial institutions affects financial systemic risk in China. Using balance-sheet and stock-market trading data on 32 listed Chinese financial institutions in the banking, securities, and insurance industries from October 2010 to December 2022, the study measures systemic risk with the ΔCoVaR indicator, captures interconnectedness through the pairwise similarity of mark-to-market asset portfolios, and constructs moderating variables for high asset concentration (HHI-based) and large external shocks. Panel fixed-effects regressions reveal a dual role of interconnectedness. On the one hand, it has a risk-contagion effect: higher interconnectedness significantly raises systemic risk. On the other hand, it has a risk-sharing effect: under high asset concentration or large external shocks, interconnectedness lowers systemic risk by reducing the shock borne by individual institutions. Heterogeneity analysis shows that both effects are stronger for large institutions than for small ones, and stronger in banking than in insurance and securities. The findings offer guidance for regulators seeking to balance the robustness and fragility of financial networks in macro-prudential policy design.*

***Keywords:*** *Systemic Risk, Interconnectedness, Risk Contagion, Risk Sharing, ΔCoVaR*

## 1. Introduction

China's Central Economic Work Conference has repeatedly emphasized strengthening the prevention and resolution of financial risks and strictly guarding against the formation of regional and systemic financial risks [1]. As a core element of national security, financial security cannot be neglected: systemic financial risk must be tightly contained so that it does not escalate into broader problems, thereby safeguarding the stable operation of the economy. Achieving this requires a deep understanding of the relationship between financial security and development and precise measures to maintain the stability of the national financial system.

China's financial system contains an intricate and tightly knit network of relationships among institutions. This network provides the channels through which idiosyncratic risk can be transmitted and amplified until it evolves into systemic risk, raising the overall threat to financial stability. The existing literature has concentrated mainly on the fragility of complex inter-institutional networks—treating interconnectedness as a transmission channel for risk—and has paid less attention to the robustness of the financial system. Since the 2008 global financial crisis, the web of linkages among financial institutions has been regarded as a key trigger of systemic risk, yet the network displays both robustness and fragility: its connectivity can transmit risk and raise the probability of systemic events, but the same connectivity can also share risk and mitigate the shock borne by individual institutions. This study examines both the amplifying and the diversifying roles of interconnectedness, offers a more balanced theoretical perspective, and explores how regulators can handle the delicate trade-off between the robustness and fragility of the interconnection network.

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## 2. Literature Review

### *2.1. Research on the Interconnectedness of Financial Institutions*

Investigating the interconnectedness of financial institutions is essential for identifying and measuring systemic risk and underpins macro-prudential policy frameworks. Lin and Li [2] divide the literature into two strands: the structural approach, which studies institutions' market behavior and historical industry data to uncover intrinsic linkages and risk-transmission mechanisms, and the reduced-form approach, which applies statistical and econometric tools to market return data such as stock prices.

The structural approach rests on concrete business linkages. Acemoglu et al. [3] show theoretically that when exogenous shocks are small, dense interbank linkages disperse the shock and enhance stability, but once a shock exceeds a critical threshold the same connectivity becomes a conduit for risk propagation. Cheng et al. [4] find that heterogeneity within the financial system significantly raises both the probability and the potential losses of contagion, while Ding et al. [5] build scale-free and small-world network models from credit linkages. Iyer and Peydró [6] use the failure of a large Indian cooperative bank to provide empirical evidence that interbank relationships transmit risk, and Cai et al. [7] construct a loan-overlap interconnectedness indicator, confirming a positive effect on systemic risk while showing that greater diversification mitigates its negative externalities. In practice, however, business-linkage data are difficult to obtain and infrequently updated, limiting the approach.

The reduced-form approach evaluates interconnectedness using market data such as stock and CDS prices; its advantages lie in the availability and timeliness of price data and in avoiding restrictive assumptions. Copula functions are widely used because they impose no restrictions on marginal distributions. Baur and Lucey [8] apply GARCH models on the U.S., U.K., and German markets and gold, and find that gold's safe-haven role is limited in extreme environments, while Ye et al. [9] use a quantile association regression model showing that a time-varying odds-ratio measure peaked during the subprime crisis—evidence that the crisis spread from the United States across the globe.

### *2.2. Research on Financial Systemic Risk*

More than thirty quantitative methods for assessing systemic risk [10] have emerged, mostly after 2010, and they can be grouped into micro and macro categories. Micro measures comprise Value-at-Risk (VaR)- and Expected-Shortfall (ES)-type metrics. VaR evaluates the maximum expected loss at a preset confidence level but is limited in tail events and lacks subadditivity. To capture the feedback between an institution and the system, Acharya et al. [11] propose the Marginal Expected Shortfall (MES), later combined with leverage as Systemic Expected Shortfall (SES). Adrian and Brunnermeier [12] propose CoVaR, measuring an institution's marginal contribution to system-wide risk, and, building on the capital-shortfall approach of Acharya et al. [13], Brownlees and Engle [14] develop the SRISK index, which jointly accounts for size and leverage. At the macro level, composite-index methods such as principal component analysis weight risk factors into aggregate stress indices; Tao and Zhu [15] construct a PCA-based composite index spanning seven dimensions.

### *2.3. Research on the Effect of Interconnectedness on Systemic Risk*

Inter-institutional networks play a crucial role in risk contagion. Sui et al. [16] find that the latent contagion effect of interbank networks significantly intensifies the accumulation of systemic risk in banking; Fan et al. [17] show that institutions' contributions to systemic risk are cyclical; and Jiang and Zhang [18] demonstrate that tail-risk interconnectedness among listed banks raises the probability of systemic-risk outbreaks. Because systemic risk unfolds in stages, interconnectedness can also help guard against it [19]. A growing literature therefore studies prevention and resolution: Hué et al. [20] use systemic-risk-contribution networks to identify systemically important institutions for early warning, and Li et al. [21] stress identifying risk sources precisely in the early stage so as to interrupt propagation paths. Li et al. [22] measure the systemic risk spillovers of Chinese financial institutions and discuss their channels and prevention, and Tang [23] examines the influence of correlations among financial institutions on financial systemic risk.

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## 3. Theoretical Framework and Research Hypotheses

### *3.1. Concepts and Model Setting*

Interconnectedness—sometimes called spillover or contagion—reflects the interaction and mutual influence among financial entities. When an institution is hit by a shock, interconnectedness allows risk to spread rapidly to other institutions, potentially triggering systemic financial risk [24]. Systemic financial risk is characterized by concealment during accumulation, large scale at outbreak, contagiousness through inter-institutional linkages, and destructiveness, as illustrated by the subprime crisis, which produced six consecutive quarters of negative U.S. growth and pushed unemployment to about 10 percent before evolving into a global crisis.

Following Fang and Liu [24], assume that there are N financial institutions. Each institution i holds K kinds of mark-to-market (MTM) assets with portfolio weights summing to one, plus non-MTM assets. When MTM assets are shocked, asset k suffers a loss rate $F(k) \geq 0$. The ratio of total assets to equity defines institution i's target leverage; under the regulatory framework, institutions must keep leverage within a fixed range, so when a negative shock pushes actual leverage above target, the institution sells MTM assets to repay liabilities and restore the target leverage.

### *3.2. The Risk-Contagion Effect of Interconnectedness*

When an external shock pushes institution i's leverage away from its target, the institution sells part of its MTM portfolio in proportion to pre-sale holdings. The fire sale depresses asset market values and thereby imposes losses on institution j—a negative externality that manifests as systemic risk. The loss imposed on j depends largely on the sum of the products of the asset shares the two institutions hold in common. Interconnectedness is accordingly defined as

$$I(i,j) = M(i) \cdot M(j) = \Sigma_k M(i,k) M(j,k) \quad (1)$$

Interconnectedness thus captures the similarity of asset allocations: when two institutions both hold high proportions of the same assets, their interconnectedness rises, and a fire sale by institution i imposes a correspondingly larger shock on institution j. Interconnectedness therefore plays a central role in transmitting fire-sale losses across institutions and generating systemic risk.

### *3.3. The Risk-Sharing Effect of Interconnectedness*

Equation (1) shows that interconnectedness is determined by institutions' asset portfolios. Highly concentrated asset holdings imply ineffective diversification. Raising the interconnectedness of institutions i and j makes their portfolios more similar; with total system assets held fixed, the two allocate assets evenly and jointly bear the associated risk, so each institution's asset loss is relatively small, fire sales decline, and systemic risk falls. Wang et al. [25] likewise argue that, beyond contagion, greater interconnectedness carries a risk-sharing effect: the more similar institutions' portfolios are, the stronger their risk-sharing capacity and the weaker the resulting fire-sale pressure on the system.

### *3.4. Research Hypotheses*

Interconnectedness plays a pivotal role in propagating fire-sale losses and producing systemic risk, so on average the contagion effect dominates. High asset concentration implies undiversified risk; greater interconnectedness then makes portfolios more similar, so that institutions share asset risk evenly, an effect that operates chiefly under high concentration or large shocks. Large institutions command abundant capital and broad influence, display richer asset-allocation strategies and denser linkages, and are more likely both to trigger and to disperse risk. Banking, in turn, occupies a pivotal position, and its risk shapes the whole system. These arguments yield the following hypotheses:

**H1:** Interconnectedness has a risk-contagion effect and raises the systemic risk of the financial system.

**H2a:** Under high asset concentration, interconnectedness has a risk-sharing effect and lowers systemic risk.

**H2b:** Under large external shocks, interconnectedness has a risk-sharing effect and lowers systemic risk.

**H3:** Large institutions exhibit stronger contagion and risk-sharing effects than small institutions, and

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banking institutions exhibit stronger effects than insurance and securities institutions.

## 4. Research Design

### *4.1. Sample and Data*

The sample comprises 32 listed Chinese financial institutions from October 2010 to December 2022. Over this period China's capital market changed enormously—margin trading and stock-index futures created a short-selling mechanism, and capital-account opening tightened links between domestic and foreign markets—and the sample period spans major stress events (the 2013 liquidity crunch, the 2015 stock-market crash, the 2018 China–U.S. trade frictions, and the 2020 COVID-19 shock) that materially affected institutions' risk profiles [26]. After excluding institutions with missing data or late listings, the sample contains 16 banks, 13 securities firms, and 3 insurers. Three data categories are used: financial-market data (individual and market returns from CSMAR) to construct the systemic-risk variable and asset shocks; MTM asset-holding data drawn from the notes to annual statements to construct the interconnectedness and concentration indicators; and control data (firm size, cash-flow ratio, and leverage) from the Wind database. Integrating these sources yields a balanced panel of 416 observations.

### *4.2. Variable Definitions*

**Dependent variable: systemic risk.** Building on the ΔCoVaR of Adrian and Brunnermeier [12] and following Li et al. [27], systemic risk is the difference between the financial system's conditional VaR when institution i is at its maximum-loss state and when it is at its normal (median) state:

$$\Delta CoVaR(i,t) = -[CoVaR(i,t,5\%) - CoVaR(i,t,50\%)] \quad (2)$$

**Explanatory variable: interconnectedness.** Following Fang and Liu [24], interconnectedness is the cosine similarity of pairwise MTM portfolios, averaged over counterparties:

$$IC(i,j,t) = \Sigma_k M(i,k,t)\, M(j,k,t) / [\sqrt{\Sigma_k M(i,k,t)^2} \cdot \sqrt{\Sigma_k M(j,k,t)^2}] \quad (3)$$

$$IC(i,t) = [1/(N-1)]\, \Sigma(j \neq i)\, IC(i,j,t) \quad (4)$$

where M(i,k,t) is the share of asset k in institution i's total MTM assets in period t; Equation (3) standardizes the theoretical measure in Equation (1), and Equation (4) averages institution i's pairwise interconnectedness with the other N−1 institutions.

**Moderating variables: high asset concentration and large shock.** Asset concentration is the Herfindahl–Hirschman index over asset classes:

$$HHI(i,t) = \Sigma_k M(i,k,t)^2 \quad (5)$$

The dummy H_HHI equals 1 when HHI is at or above the sample median and 0 otherwise. The shock variable weights asset-level loss rates by asset shares:

$$F(k,t) = -\min[R(k,t), 0]; \quad Shock(i,t) = \Sigma_k M(i,k,t)\, F(k,t) \quad (6)$$

where R(k,t) is the return of asset k, and the dummy LShock indicates a large shock. **Control variables** are firm size (lnSize), the cash-flow ratio (Cashflow), and leverage (Lev).

### *4.3. Model Specification*

To analyze the overall effect of interconnectedness on systemic risk, the baseline regression is

$$\Delta CoVaR(i,t) = \alpha + \beta \cdot IC(i,t) + \Sigma\gamma \cdot Controls(i,t-1) + \varepsilon(i,t) \quad (7)$$

Because interconnectedness magnifies the diffusion of systemic risk while risk sharing emerges only under particular conditions, the contagion effect is expected to dominate on average, so β is predicted to be positive (H1). To test risk sharing under high concentration and large shocks, interaction models are specified:

$$\Delta CoVaR(i,t) = \alpha + \beta_1 \cdot IC + \beta_2 \cdot H_HHI + \beta_3 \cdot IC \times H_HHI + \Sigma\gamma \cdot Controls + \varepsilon \quad (8)$$

$$\Delta CoVaR(i,t) = \alpha + \beta_1 \cdot IC + \beta_2 \cdot LShock + \beta_3 \cdot IC \times LShock + \Sigma\gamma \cdot Controls + \varepsilon \quad (9)$$

The coefficient of interest is $\beta_3$, the effect of interconnectedness under high concentration or a large shock; given the risk-sharing effect, $\beta_3$ is expected to be negative (H2a, H2b).

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## 5. Empirical Results

### *5.1. Descriptive Statistics*

Table 1 reports descriptive statistics for the main variables. The dependent variable ΔCoVaR has a mean of 0.015 (min 0.007, max 0.029, s.d. 0.004), indicating limited variation in systemic risk over the sample period. By contrast, the key explanatory variable IC has a mean of 0.428 (min 0.135, max 0.723, s.d. 0.140), indicating clear cross-year and cross-institution variation in interconnectedness.

*Table 1: Descriptive statistics of the main variables.*

| Variable | Obs. | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|---|
| ΔCoVaR | 416 | 0.015 | 0.004 | 0.007 | 0.029 |
| IC | 414 | 0.428 | 0.140 | 0.135 | 0.723 |
| H_HHI | 416 | 0.096 | 0.295 | 0 | 1 |
| LShock | 416 | 0.147 | 0.354 | 0 | 1 |
| lnSize | 416 | 3.311 | 0.082 | 3.043 | 3.444 |
| Lev | 401 | 0.826 | 0.136 | 0.172 | 0.966 |
| Cashflow | 416 | 0.003 | 0.096 | -0.488 | 0.242 |

### *5.2. Correlation Analysis and Multicollinearity*

Table 2 reports pairwise correlations. The correlation between interconnectedness and systemic risk is 0.226, positive and significant at the 1% level, consistent with a dominant contagion effect. Because the interaction terms embody information from both the explanatory and moderating variables, IC and the moderators are mean-centered before forming interactions. Variance inflation factor (VIF) diagnostics yield values well below 10 (mean VIF = 2), so multicollinearity is not a concern.

*Table 2: Correlation matrix.*

| | ΔCoVaR | IC | H_HHI | LShock | lnSize | Lev | Cashflow |
|---|---|---|---|---|---|---|---|
| ΔCoVaR | 1 | | | | | | |
| IC | 0.226*** | 1 | | | | | |
| H_HHI | 0.191*** | -0.145*** | 1 | | | | |
| LShock | -0.178*** | -0.141*** | 0.003 | 1 | | | |
| lnSize | -0.194*** | -0.254*** | 0.166*** | 0.116** | 1 | | |
| Lev | -0.080 | -0.135*** | 0.148*** | 0.087* | 0.821*** | 1 | |
| Cashflow | 0.093* | -0.069 | 0.176*** | 0.042 | 0.316*** | 0.456*** | 1 |

*Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively (also in subsequent tables).*

### *5.3. Baseline Regression*

A Hausman test (p = 0.0163) rejects the null hypothesis, so a fixed-effects model is adopted as the main specification. Table 3 reports the baseline results for Equation (7). In column (1), the coefficient on IC is 0.005 and significant at the 1% level; adding firm and year fixed effects in column (2) leaves it significantly positive (0.006). Systemic risk therefore rises with interconnectedness, supporting H1. The mechanism is intuitive: a negative shock forces asset sales that push prices down further, so other institutions holding the same or similar assets also incur losses—loss propagation that stems from commonly held MTM assets, travels along interconnectedness, and ultimately evolves into systemic risk.

*Table 3: Baseline regression of systemic risk (ΔCoVaR) on interconnectedness.*

| Variable | (1) | (2) |
|---|---|---|
| IC | 0.005*** (3.28) | 0.006*** (3.96) |
| Lev | 0.004 (1.38) | 0.005* (1.66) |
| Cashflow | 0.007*** (3.01) | 0.005** (2.26) |
| lnSize | -0.016*** (-3.29) | -0.014*** (-2.63) |
| Constant | 0.062*** (4.29) | 0.058*** (3.44) |
| Observations | 399 | 399 |
| R-squared | 0.098 | 0.151 |
| Firm FE | No | Yes |
| Year FE | No | Yes |

*Notes: t-statistics in parentheses.*

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### *5.4. Mechanism Test: Moderating Effects*

Table 4 reports the moderation results. With asset concentration as the moderator (columns 1–2), the coefficient on IC×H_HHI is −0.008 and remains significantly negative (−0.007) under two-way fixed effects; with large shocks (columns 3–4), IC×LShock is −0.014 and remains significantly negative (−0.015). Thus, under high asset concentration or large shocks, higher interconnectedness lowers systemic risk, supporting H2a and H2b: strengthening linkages effectively disperses part of an institution's risky assets across the network so that risk is borne jointly, cushioning the shock to any single institution and shrinking shock-induced fire sales.

*Table 4: Moderating effects of asset concentration and large shocks (dependent variable: ΔCoVaR).*

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| IC | 0.006*** (3.93) | 0.006*** (3.97) | 0.006*** (3.46) | 0.005*** (2.77) |
| H_HHI | 0.003*** (4.31) | 0.002*** (2.60) | | |
| IC×H_HHI | -0.008** (-2.09) | -0.007** (-2.04) | | |
| LShock | | | 0.004** (2.25) | 0.004** (2.53) |
| IC×LShock | | | -0.014*** (-3.50) | -0.015*** (-3.64) |
| Lev | 0.004 (1.41) | 0.005 (1.62) | 0.003 (1.17) | 0.005* (1.68) |
| Cashflow | 0.005** (2.31) | 0.005** (2.29) | 0.007*** (3.25) | 0.006** (2.57) |
| lnSize | -0.017*** (-3.53) | -0.014*** (-2.63) | -0.015*** (-3.08) | -0.011* (-1.96) |
| Constant | 0.069*** (4.79) | 0.059*** (3.56) | 0.060*** (4.08) | 0.047*** (2.67) |
| Observations | 399 | 399 | 399 | 399 |
| R-squared | 0.153 | 0.155 | 0.130 | 0.181 |
| Firm FE | No | Yes | No | Yes |
| Year FE | No | Yes | No | Yes |

*Notes: t-statistics in parentheses.*

### *5.5. Robustness Checks*

To verify robustness, the systemic-risk measure is replaced with the Marginal Expected Shortfall (MES). Table 5 juxtaposes the ΔCoVaR and MES specifications. Across all specifications, the direction and significance of the coefficients are consistent: IC remains significantly positive (0.011–0.015 under MES) and the interactions IC×H_HHI (−0.019) and IC×LShock (−0.025) remain significantly negative. The main results are therefore robust to the choice of systemic-risk measure.

*Table 5: Robustness checks using MES as an alternative systemic-risk measure.*

| Variable | (1) ΔCoVaR | (2) MES | (3) ΔCoVaR | (4) MES | (5) ΔCoVaR | (6) MES |
|---|---|---|---|---|---|---|
| IC | 0.005*** (3.28) | 0.014*** (3.49) | 0.006*** (3.93) | 0.015*** (3.82) | 0.006*** (3.46) | 0.011*** (2.72) |
| H_HHI | | | 0.003*** (4.31) | 0.004*** (2.60) | | |
| IC×H_HHI | | | -0.008** (-2.09) | -0.019** (-2.00) | | |
| LShock | | | | | 0.004** (2.25) | -0.005*** (-4.16) |
| IC×LShock | | | | | -0.014*** (-3.50) | -0.025** (-2.22) |
| Cashflow | 0.007*** (3.01) | 0.012** (2.01) | 0.004 (1.41) | 0.010 (1.60) | 0.003 (1.17) | 0.013** (2.17) |
| Lev | 0.004 (1.38) | 0.013* (1.74) | 0.005** (2.31) | 0.013* (1.74) | 0.007*** (3.25) | 0.012 (1.60) |
| lnSize | -0.016*** (-3.29) | -0.113*** (-9.59) | -0.017*** (-3.53) | -0.114*** (-9.75) | -0.015*** (-3.08) | -0.111*** (-9.40) |
| Constant | 0.062*** (4.29) | 0.385*** (11.11) | 0.069*** (4.79) | 0.396*** (11.63) | 0.060*** (4.08) | 0.387*** (11.25) |
| Observations | 399 | 399 | 399 | 399 | 399 | 399 |
| R-squared | 0.098 | 0.413 | 0.215 | 0.431 | 0.130 | 0.429 |

*Notes: t-statistics in parentheses. Firm and year fixed effects are included in all columns.*

### *5.6. Heterogeneity Analysis*

Because fire-sale behavior differs across institutions of different scales, the sample is split into large

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and small institutions; because the impact of interconnectedness also differs across industries, it is further split into insurance, banking, and securities. Tables 6 and 7 report the heterogeneity results under high asset concentration and large shocks. Large institutions display a stronger contagion effect and, under large shocks, a stronger risk-sharing effect (IC×LShock = −0.029, significant for large institutions versus insignificant for small ones) than small institutions, because their resources support diverse asset-allocation strategies and dense linkages that enable coordinated responses [28]. By industry, banking shows stronger contagion and risk-sharing effects than insurance and securities: the bank IC coefficient (0.007, 1%) exceeds the others and the bank IC×LShock coefficient (−0.023) is significantly negative while the corresponding insurance and securities coefficients are not. Banking's pivotal position generates strong spillovers, and when a bank is hit, connected institutions jointly bear the risk. These results support H3.

*Table 6: Heterogeneity under high asset concentration (dependent variable: ΔCoVaR).*

| Variable | (1) Large | (2) Small | (3) Insurance | (4) Banking | (5) Securities |
|---|---|---|---|---|---|
| IC | 0.008*** (3.39) | 0.004* (1.80) | 0.003 (0.68) | 0.007*** (3.20) | 0.005** (1.99) |
| H_HHI | 0.007*** (2.91) | 0.003 (0.82) | -0.005*** (-4.98) | 0.000 (0.33) | 0.001 (0.50) |
| IC×H_HHI | -0.011 (-1.60) | -0.003 (-0.27) | -0.008 (-1.01) | 0.000 (0.04) | 0.004 (0.32) |
| Lev | 0.007 (0.60) | 0.003 (0.81) | -0.019 (-0.62) | -0.001 (-0.20) | 0.004 (1.04) |
| Cashflow | 0.017** (2.15) | 0.003 (1.20) | -0.019 (-0.96) | 0.016** (2.27) | 0.003 (1.07) |
| lnSize | -0.022** (-2.50) | -0.001 (-0.13) | -0.012 (-0.42) | -0.019** (-2.32) | -0.003 (-0.30) |
| Constant | 0.079** (2.55) | 0.015 (0.61) | 0.076 (0.93) | 0.077*** (3.07) | 0.021 (0.82) |
| Observations | 220 | 180 | 37 | 202 | 161 |
| R-squared | 0.221 | 0.044 | 0.504 | 0.154 | 0.053 |
| Firm / Year FE | Yes | Yes | Yes | Yes | Yes |

*Notes: t-statistics in parentheses.*

*Table 7: Heterogeneity under large shocks (dependent variable: ΔCoVaR).*

| Variable | (1) Large | (2) Small | (3) Insurance | (4) Banking | (5) Securities |
|---|---|---|---|---|---|
| IC | 0.007*** (3.01) | 0.004* (1.73) | -0.001 (-0.26) | 0.007*** (3.14) | 0.006*** (2.65) |
| LShock | 0.009** (2.56) | -0.002 (-0.49) | -0.002 (-0.17) | 0.007* (1.76) | 0.004 (0.50) |
| IC×LShock | -0.029*** (-3.07) | -0.002 (-0.23) | 0.001 (0.02) | -0.023** (-2.17) | -0.016 (-0.89) |
| Lev | -0.017 (-1.50) | 0.002 (0.49) | -0.014 (-0.29) | -0.001 (-0.17) | 0.003 (0.85) |
| Cashflow | 0.022*** (2.75) | 0.004 (1.47) | -0.028 (-1.06) | 0.016** (2.34) | 0.004 (1.40) |
| lnSize | -0.030*** (-3.26) | 0.006 (0.78) | -0.028 (-0.52) | -0.020** (-2.47) | 0.005 (0.61) |
| Constant | 0.127*** (4.10) | -0.007 (-0.30) | 0.125 (0.82) | 0.078*** (3.06) | -0.006 (-0.22) |
| Observations | 220 | 180 | 37 | 202 | 161 |
| R-squared | 0.205 | 0.095 | 0.101 | 0.185 | 0.113 |
| Firm / Year FE | Yes | Yes | Yes | Yes | Yes |

*Notes: t-statistics in parentheses.*

## 6. Conclusions

Frequent global financial crises in recent years and rapid financial innovation have intensified the accumulation and amplification of market risk. Against this backdrop, the empirical analysis yields three conclusions. First, interconnectedness has a risk-contagion effect: higher inter-institutional interconnectedness raises the level of systemic financial risk. Second, when the financial system exhibits high asset concentration or experiences large external shocks, interconnectedness has a risk-sharing effect that lowers systemic risk. Third, the contagion and risk-sharing effects are stronger for large institutions than for small ones, and stronger for banking than for insurance and securities. Interconnectedness is thus a double-edged sword whose net effect depends on system conditions; regulation should manage—rather than simply minimize—network linkages, balancing the robustness and fragility of financial networks in macro-prudential policy design.

## References

*[1] Zhang S. Building a firm line of defense against systemic financial risk to accelerate the construction of a financially strong country[J]. Agricultural Development and Finance, 2024(2): 86-88.*
*[2] Lin D, Li Y. Measuring the interconnectedness of listed Chinese financial institutions and analyzing its determinants[J]. Statistical Research, 2019, 36(4): 50-59.*
*[3] Acemoglu D, Ozdaglar A, Tahbaz-Salehi A. Systemic risk and stability in financial networks[J].*

ISSN 2616-5902 Vol. 8, Issue 10: 6-13, DOI: 10.25236/AJBM.2026.081002

*American Economic Review, 2015, 105(2): 564-608.*
*[4] Cheng X, Wu J, Liao S. A study of contagion in the financial system from the perspective of network analytics[J]. Neurocomputing, 2017, 264: 42-49.*
*[5] Ding D, Han L, Yin L. Systemic risk and dynamics of contagion: A duplex inter-bank network[J]. Quantitative Finance, 2017, 17(9): 1435-1445.*
*[6] Iyer R, Peydró J L. Interbank contagion at work: Evidence from a natural experiment[J]. Review of Financial Studies, 2011, 24(4): 1337-1377.*
*[7] Cai J, Eidam F, Saunders A, et al. Syndication, interconnectedness, and systemic risk[J]. Journal of Financial Stability, 2018, 34: 105-120.*
*[8] Baur D G, Lucey B M. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold[J]. Financial Review, 2010, 45(2): 217-229.*
*[9] Ye W, Luo K, Liu X. Time-varying quantile association regression model with applications to financial contagion and VaR[J]. European Journal of Operational Research, 2017, 256(3): 1015-1028.*
*[10] Gong M, Song T. Research on methods for identifying systemic risk[J]. Studies of International Finance, 2010(5): 90-96.*
*[11] Acharya V V, Pedersen L H, Philippon T, et al. Measuring systemic risk[J]. Review of Financial Studies, 2017, 30(1): 2-47.*
*[12] Adrian T, Brunnermeier M K. CoVaR[J]. American Economic Review, 2016, 106(7): 1705-1741.*
*[13] Acharya V V, Engle R, Richardson M. Capital shortfall: A new approach to ranking and regulating systemic risks[J]. American Economic Review, 2012, 102(3): 59-64.*
*[14] Brownlees C T, Engle R F. SRISK: A conditional capital shortfall measure of systemic risk[J]. Review of Financial Studies, 2017, 30(1): 48-79.*
*[15] Tao L, Zhu Y. Monitoring and measuring systemic financial risk: A study based on China's financial system[J]. Journal of Financial Research, 2016(6): 18-36.*
*[16] Sui C, Tan Z, Wang Z. A network-based method for measuring banking systemic risk[J]. Chinese Journal of Management Science, 2016(5).*
*[17] Fan X, Wang D, Fang Y. Measuring and supervising financial institutions' systemic risk contributions in China: Marginal risk contribution and leverage[J]. Nankai Economic Studies, 2011(4).*
*[18] Jiang H, Zhang J. Tail-risk network interconnectedness of commercial banks and systemic risk: Evidence from Chinese listed banks[J]. Finance & Trade Economics, 2018(8).*
*[19] Zhang H, Shi C, Jin H, et al. Measuring and early-warning models of systemic financial risk: A survey[J]. Modern Management Science, 2019(9).*
*[20] Hué S, Lucotte Y, Tokpavi S. Measuring network systemic risk contributions: A leave-one-out approach[J]. Journal of Economic Dynamics and Control, 2019, 100: 86-114.*
*[21] Li Z, Liang Q, Fang Y. Monitoring and early warning of cross-sector systemic risk spillovers in China based on downside and upside ΔCoES[J]. Journal of Financial Research, 2019(2).*
*[22] Li Z, Zhu M, Li Y, et al. Systemic risk spillovers of Chinese financial institutions: Measurement, channels, and prevention[J]. Journal of Financial Research, 2023(4): 55-73.*
*[23] Tang S. Study on the influence of financial institutions' correlation on financial systemic risk[D]. Shanghai: University of Shanghai for Science and Technology, 2024.*
*[24] Fang Y, Liu J. Bank interconnectedness and systemic financial risk: Contagion or sharing?[J]. Journal of Financial Research, 2023(6): 57-74.*
*[25] Wang G, Xu Z, Xie C. Interconnectedness and systemic risk contributions of Chinese financial institutions: A tail-risk spillover network perspective[J]. Journal of Management Sciences in China, 2022, 25(5): 109-126.*
*[26] Ouyang Z, Zhou X. Backtesting and interconnectedness of systemic risk of Chinese financial institutions: Evidence from MES and ΔCoVaR[J]. Chinese Journal of Management Science, 2021 (online first).*
*[27] Li J, Fang Y, Jing Z. Measuring banking systemic risk in Belt and Road partner countries[J]. Journal of Hohai University (Philosophy and Social Sciences), 2024, 26(1): 104-117.*
*[28] Benoit S, Colliard J E, Hurlin C, et al. Where the risks lie: A survey on systemic risk[J]. Review of Finance, 2017, 21(1): 109-152.*