

Systemic Risk and Financial Stability in Indian Banks

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Abstract

The formation, amplification and transmission of systemic risk in Indian banks are examined by integrating dynamic panel GMM estimation, VAR, CoVaR, network analysis and Markov-switching models. The analysis uses annual bank-level and macro-financial risk variables covering 2015 to 2022 and a network sample of 24 Indian banks (11 public-sector and 13 private-sector), excluding foreign banks and institutions not represented in the analytical network. Market-based analysis over the same study period indicates that systemic risk is procyclical, time-varying and concentrated among a small group of highly connected institutions. Non-performing assets, leverage and rapid credit growth emerge as important vulnerability channels, whereas stronger capital and liquidity buffers are associated with greater resilience. VAR analysis and Granger-causality tests indicate feedback between credit growth and asset-quality deterioration. CoVaR and network measures show that systemic importance is associated not only with balance-sheet size but also with centrality and bridging positions in the banking network. Markov-switching estimates indicate stronger risk transmission during stressed regimes. The integrated framework therefore supports macroprudential surveillance, stress testing, capital and liquidity planning and early-warning assessment in the Indian banking system.

Keywords: CoVaR, Financial Stability, Indian Banking Sector, Network Analysis, Systemic Risk.

Introduction

Banks play an important role in sustainable economic growth by allocating savings, creating credit, transforming liquidity, providing payment services and transmitting monetary policy. These functions, however, also create channels for financial contagion. Interbank lending, common asset holdings, correlated funding structures and confidence effects can turn distress at an individual institution into a systemic crisis, meaning that systemic risk cannot be analyzed solely from the perspective of a single bank. Interrelationships among institutions, markets, regulation and the macroeconomy must also be considered, particularly because excessive credit expansion, weakening asset quality and liquidity pressures can intensify these linkages and generate wider losses across the financial system (1, 2). These issues are especially relevant for developing countries, where financial deepening, regulatory reform, digitalization and external shocks occur simultaneously. Capital-flow reversals, exchange-rate movements, inflation, interest-rate changes and commodity-price shocks may interact with domestic banking-sector vulnerabilities. India is particularly relevant

because its banking sector has undergone substantial structural and regulatory reform while continuing to face non-performing assets, concentration risk, liquidity risk and procyclicality. Evidence from emerging economies indicates that Basel III capital and liquidity requirements can strengthen bank stability; however, institution-level prudential ratios alone do not reveal how distress is transmitted through an interconnected banking system (3, 4). Standard measures of banking soundness include capital adequacy, liquidity, profitability, leverage, asset quality and non-performing assets. Econometric approaches, including panel-data models and Vector Autoregression (VAR), can examine persistence, feedback and macro-financial transmission. Systemic risk may also exhibit nonlinear and cross-sectional features that are not adequately captured by models that assume institutional independence or static linkages. Tail-risk measures such as CoVaR, which quantify the change in system-wide tail risk associated with distress at a specific institution, help distinguish stand-alone vulnerability from systemic contribution (5-8). A second dimension is interconnectedness, including

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direct exposures, common asset holdings, dependence on funding markets, payment links and correlated behaviour. Network measures such as degree centrality, betweenness centrality, eigenvector centrality, density and clustering can identify institutions that are systemically important because of their position in the network rather than their size alone. Network structure is especially relevant because highly central and bridging institutions can transmit contagion between otherwise weakly connected groups (9-11). Liquidity and leverage may amplify this mechanism when balance sheets expand during favourable conditions and must contract rapidly as funding liquidity dries up or asset prices fall (12, 13).

Time variation also matters: banks may behave differently in normal and stressed periods and the same balance-sheet position can have very different system-wide consequences across regimes. Structural VAR models can be used to study dynamic shocks, while Markov-switching models allow parameters or variances to change across unobserved states (14). Evidence from Europe and Asia further shows that systemic importance depends on both market-based risk and interconnectedness (15). Research on Indian banks has likewise emphasized financial-network vulnerabilities and bank-level systemic risk (16, 17), while related studies have proposed regime-sensitive and machine-learning approaches (18, 19) for forecasting systemic stress (20).

The literature remains fragmented, however, because each method captures only part of the systemic-risk process. Dynamic panel estimators address persistence, unobserved heterogeneity and endogeneity; VAR models capture feedback cycles; CoVaR measures marginal tail-risk contribution; network analysis identifies contagion channels; and regime-switching models capture state dependence. The conceptual premise of this study is therefore that systemic banking risk arises from the interaction of three mechanisms: bank-level balance-sheet vulnerabilities, time-varying interconnectedness and macro-financial shocks. Their interaction determines whether bank-level fragility is amplified and transmitted to the wider financial system.

The novel contribution of this study is the integration of these complementary mechanisms within a single empirical framework for the Indian

banking system using dynamic panel Generalized Method of Moments (GMM) estimation, VAR and Granger-causality analysis, CoVaR, network analysis and Markov-switching analysis. GMM addresses persistence and endogeneity in bank-level vulnerability; VAR captures dynamic interactions between banking and macro-financial variables; CoVaR measures marginal systemic contribution; network analysis identifies structurally important banks and potential contagion channels; and Markov-switching analysis assesses whether these relationships change during stressed periods. This integrated view provides a more complete interpretation of the formation, propagation and state dependence of systemic risk.

This paper addresses these issues through four objectives:

- a) the identification of bank and macro-financial fundamentals of systemic risk and financial instability,
- b) the analysis of the interlinkages between credit growth, asset quality and banking vulnerability,
- c) the estimation of the contribution of bank-level tail-risk and the association of centrality and bridging positions in the interbank network with systemic importance and
- d) the identification of whether the impact of balance-sheet vulnerability on interconnectedness differs for normal and stressed financial regimes.

The evidence may help inform macroprudential surveillance, conduct of stress tests, planning for capital and liquidity shortfalls and early warning systems for the Indian banking sector.

Methodology

The study uses a quantitative longitudinal framework to examine the formation, amplification and transmission of systemic risk in the Indian banking sector. It integrates dynamic panel GMM, VAR and Granger-causality analysis, CoVaR, network analysis and Markov-switching estimation to capture complementary dimensions of systemic vulnerability. Dynamic panel GMM accounts for persistence, unobserved heterogeneity and endogeneity in bank-level outcomes (21). VAR analysis captures dynamic feedback and shock transmission between banking and macro-financial variables (14, 22). CoVaR measures an institution's marginal contribution to systemic tail

risk (6, 7). Network measures identify institutional interconnectedness and potential contagion channels (9-11), while Markov-switching estimation allows these relationships to vary

between normal and high-stress financial regimes (23). Figure 1 summarizes the methodological framework.

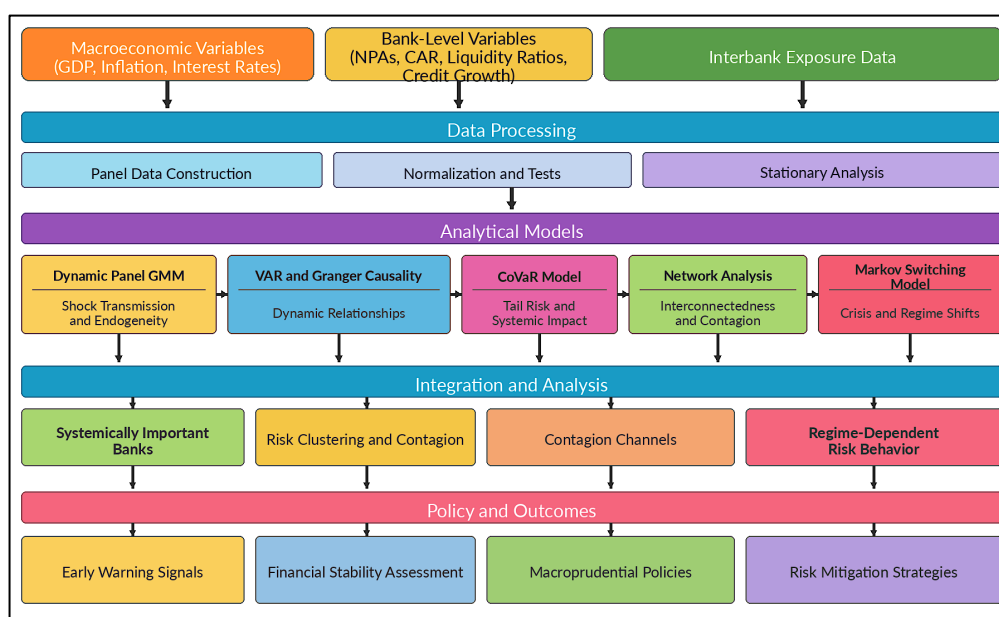


Figure 1: Methodological Framework Adopted for the Assessment of Systemic Risk in the Indian Banking Sector

The empirical window runs from 2015 to 2022. Following the annual frequency used in the time-series indicators, our bank-level and macro-financial panel is constructed on an annual basis. The analytical banking sample used in the network analysis includes 24 Indian banks: 11 public sector banks and 13 private sector banks. Public sector banks are State Bank of India, Punjab National Bank, Bank of Baroda, Canara Bank, Bank of India, Union Bank of India, Indian Bank, Bank of Maharashtra, UCO Bank, Central Bank of India and Indian Overseas Bank. Private sector banks are HDFC Bank, ICICI Bank, Axis Bank, Kotak Mahindra Bank, IndusInd Bank, Yes Bank, IDFC First Bank, Federal Bank, RBL Bank, Dhanlaxmi Bank, Karur Vysya Bank, CSB Bank and City Union Bank. Foreign banks are excluded from the bank-level analytical sample. Figures with fewer identified banks show the selected banks or informative sub-networks, while other figures depict the entire network.

Bank-level financial data are gathered from Reserve Bank of India regulatory databases, published annual reports and vetted institutional records. Core variables include non-performing asset ratios, capital adequacy, liquidity ratios, credit growth, deposit growth, return on assets,

return on equity, bank size, leverage, profitability and loan-loss provisioning. Macroeconomic variables include gross domestic product growth, inflation, policy interest rates, exchange rates and market volatility. Market-based variables are used to estimate VaR and CoVaR, while the network structure is derived from interbank exposures or empirically motivated measures of connectedness. The Reserve Bank of India's Database on Indian Economy is the primary regulatory data source (24).

An institution enters a specific model only when the variables required for that model are available for the relevant observation period. Bank-year observations with missing defining variables are therefore excluded rather than treated as observed values. Potential outliers, scale differences and measurement issues are addressed before estimation, for example through logarithmic scaling, winsorization, or standardization. Corporate mergers, ownership changes, entries and exits are treated as structural changes. The legal identity and ownership status of each observed institution are therefore preserved over the available period rather than back-filled to create an artificially balanced panel. Consequently, estimation samples may be unbalanced at the

model level. These rules reduce artificial continuity when the institutional structure changes. The dynamic panel model estimates the

persistence and determinants of financial instability at the bank level using the general specification given in Equation [1]:

$$FSI_{it} = \alpha FSI_{i,t-1} + \beta X_{it} + \gamma M_t + \mu_i + \tau_t + \varepsilon_{it} \quad [1]$$

Where, FSI_{it} denotes the financial-stability or systemic-risk indicator for bank i in year t ; $FSI_{i,t-1}$ is its lagged value; X_{it} is a vector of bank-specific variables; M_t is a vector of macroeconomic variables; μ_i captures unobserved bank-specific effects; τ_t represents time effects; and ε_{it} is the error term.

The lagged dependent variable captures persistence but also the endogeneity problem, motivating System GMM (21). Lagged values of endogenous variables are used internally as instruments. Hansen or Sargan tests of overidentifying restrictions and Arellano-Bond tests for first- and second-order serial correlation are used to assess model validity. Instrument proliferation is controlled because excessive

instruments can weaken specification tests and overfit endogenous variables; these diagnostic checks are therefore central to valid dynamic-panel inference (21).

The VAR analysis characterizes the relationships among banking-sector risk indicators and macroeconomic variables. The general VAR specification is given in Equation [2]:

$$Y_t = C + \sum_{p=1}^P A_p Y_{t-p} + \varepsilon_t \quad [2]$$

Where, Y_t is the vector of endogenous banking and macroeconomic variables, C is the intercept vector, A_p is the coefficient matrix at lag p , P is the maximum lag order and ε_t is the innovation vector.

Stationarity is tested and the lag order is selected using the Akaike Information Criterion, Bayesian Information Criterion and Hannan-Quinn Information Criterion. Granger-causality tests assess predictive relationships over time, while impulse-response functions and forecast-error variance decomposition can be used to evaluate the magnitude and persistence of shocks (14, 22).

CoVaR quantifies the contribution of an individual bank to systemic tail risk by comparing the system's risk when that bank is in distress with the system's risk when the bank is in its median state (6, 7). The marginal systemic-risk contribution, $\Delta CoVaR$, is expressed as the difference between these two conditional system-risk states, as given in Equation [3]:

$$\Delta CoVaR_i = CoVaR^{System|i=Distress} - CoVaR^{System|i=Median} \quad [3]$$

A larger absolute $\Delta CoVaR_i$ indicates that distress in bank i is associated with a larger deterioration in system-wide tail risk. CoVaR is interpreted together with network metrics so that market-based tail dependence can be assessed alongside structural interconnectedness. Degree centrality, weighted degree, betweenness centrality and eigenvector centrality are used together with

network density, clustering and community structure to identify highly exposed institutions and bridging positions (9-11). A Markov-switching specification allows coefficients, variances, or both to change between latent low-risk and high-risk states, with the state variable represented in Equation [4] (23):

$$S_t \in \{0, 1\} \quad [4]$$

Where, $S_t = 0$ denotes a normal or low-risk regime and $S_t = 1$ denotes a stressed or high-risk regime.

The transition probability indicates the probability of the persistence of the system in the present regime or its transition to a different regime. A regime-dependent specification can be applied to investigate whether the effect of NPA, leverage, capital adequacy, liquidity, credit growth and

network centrality differs between normal and stressed regimes (23).

The integrated framework is tested through four theory-based hypotheses:

H1: A deterioration in bank-level asset quality and increased leverage or liquidity stress are

associated with an increased contribution to systemic risk.

H2: Banks with greater network centrality or bridging positions have greater systemic importance and potential for shock transmission.

H3: Stronger capital adequacy and liquidity buffers are associated with lower systemic vulnerability especially during stress episodes.

H4: The impact of bank vulnerability and interconnectedness differs in normal and stressed financial regimes.

The data are processed, econometrically estimated, analyzed as networks and visualized using Python. Pandas and NumPy are used for data processing, Matplotlib for visualization and NetworkX for network construction and analysis. Model reliability is evaluated through specification tests, diagnostic checks, sensitivity analyses, alternative lag structures, alternative CoVaR confidence levels or estimation windows and alternative network thresholds where relevant. The results are also contextualized using recent empirical evidence on banking crises, systemic liquidity risk and systemic-risk forecasting (25-28).

Results and Discussion

The results indicate that systemic risk in Indian banks is dynamic and procyclical, reflecting the joint influence of bank-level vulnerabilities, macro-financial conditions and interconnectedness. The dynamic-panel patterns associate higher non-performing assets, leverage and rapid credit growth with greater vulnerability, whereas stronger capital and liquidity buffers are associated with lower vulnerability. This direction is consistent with recent Indian evidence showing that concentration, cyclical lending, earnings volatility and asset-quality deterioration can reinforce banking fragility (28) and with evidence that similarity in Indian banks' credit exposures can create clusters through which common stocks are amplified (29). The VAR and Granger-causality results further indicate predictive feedback between credit growth and asset quality: faster

credit growth precedes deterioration in asset quality, while higher non-performing loans precede weaker credit growth as provisioning and balance-sheet repair constrain lending. This interpretation is broadly consistent with crisis-forecasting evidence (25), but Granger causality is predictive rather than structural; the results should therefore not be interpreted as proof of a one-way causal mechanism.

The CoVaR and network results suggest that systemic risk is concentrated among a relatively small number of highly connected banks. Systemic importance, however, is not determined by size alone; a bank may also be important because it occupies a central or bridging position in the network. This pattern is consistent with earlier evidence on Indian banking networks (16) and with recent Indian evidence showing that financial interconnectedness rises during crisis periods and that banks can act as net transmitters of risk within the wider financial system (30). It is also consistent with recent multi-layer network research showing that network position can identify systemic importance beyond conventional size-based measures (31). At the same time, the present network definition, sample and annual observation frequency differ from those studies, so bank-specific rankings should not be compared directly. The Markov-switching results further indicate that the associations of leverage, asset quality, liquidity and capital adequacy with systemic risk strengthen in stressed regimes, which is consistent with evidence that funding and market-liquidity interactions can amplify stress through forced balance-sheet adjustment and adverse price dynamics (26).

Figure 2 reports the systemic-risk contribution of selected banks in terms of ΔCoVaR . A larger absolute value indicates a larger deterioration in system-wide tail risk when a bank moves from its median state to a distress state. The concentration visible in the figure should therefore be interpreted jointly with balance-sheet size, market relevance and network position rather than as a stand-alone ranking of overall bank importance.

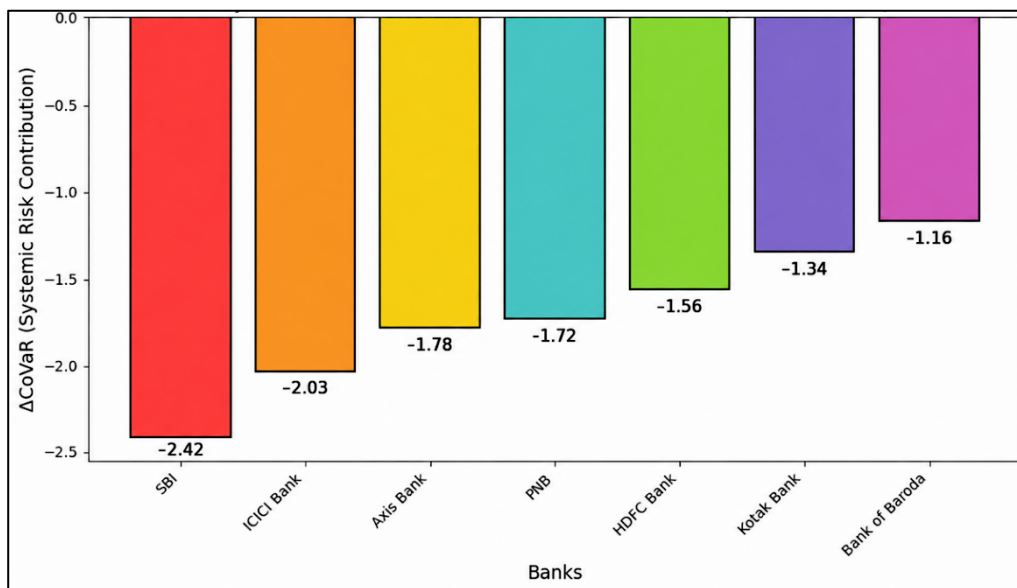


Figure 2: Systemic Risk Contribution of Indian Banks Based on CoVaR Estimates

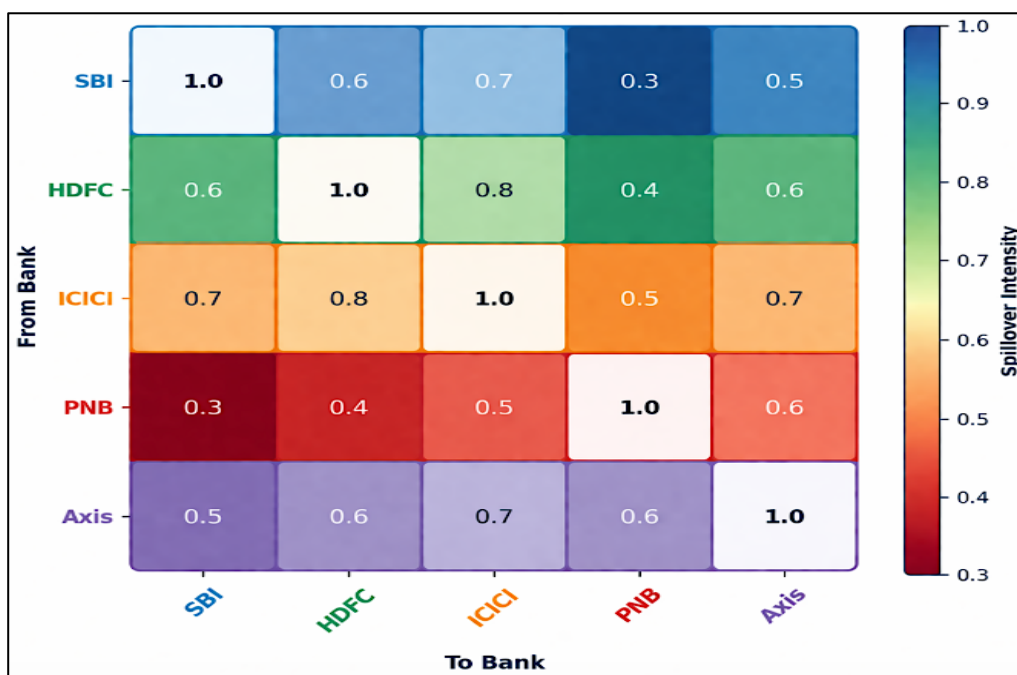


Figure 3: Interbank Risk-spillover Matrix in the Indian Banking Sector

Figure 3 presents the interbank risk-spillover matrix for the selected banks. Larger cell values indicate stronger spillover relationships. These relationships need not be symmetric because stress can propagate through shared borrowers, portfolio correlations, common funding conditions and common responses to macroeconomic shocks. The matrix therefore supports a network interpretation of contagion rather than a simple bilateral one: a shock to a highly connected institution can spread more rapidly and through more indirect channels than a shock to a peripheral institution. This interpretation is consistent with

recent evidence that common credit exposures and network connectedness can amplify systemic vulnerability in Indian banking (29, 30).

Figure 4 shows the annual movement of key banking-risk indicators from 2015 to 2022. Asset quality, capital adequacy, credit growth and liquidity do not move in parallel, indicating that risk accumulation and resilience operate through different channels and at different speeds. The stronger capital and liquidity position observed alongside changing credit and asset-quality conditions is consistent with evidence from emerging economies that regulatory capital and

liquidity requirements can improve bank stability (4). At the same time, systemic-liquidity research shows that adequate institution-level buffers do not eliminate contagion risk when common funding shocks trigger simultaneous asset sales

(26). The time-series results therefore complement the dynamic-panel findings by showing why both balance-sheet buffers and system-wide transmission channels need to be monitored.

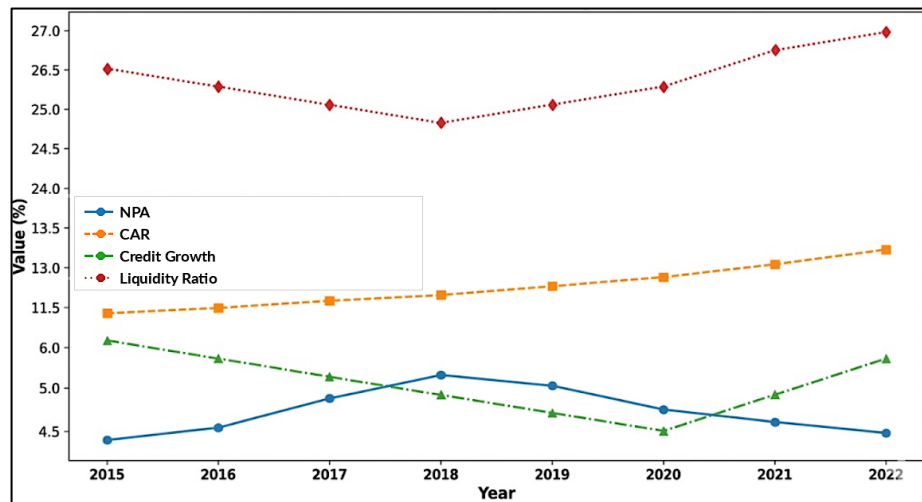


Figure 4: Time-Series Trend of Key Banking-risk Indicators in the Indian Banking Sector

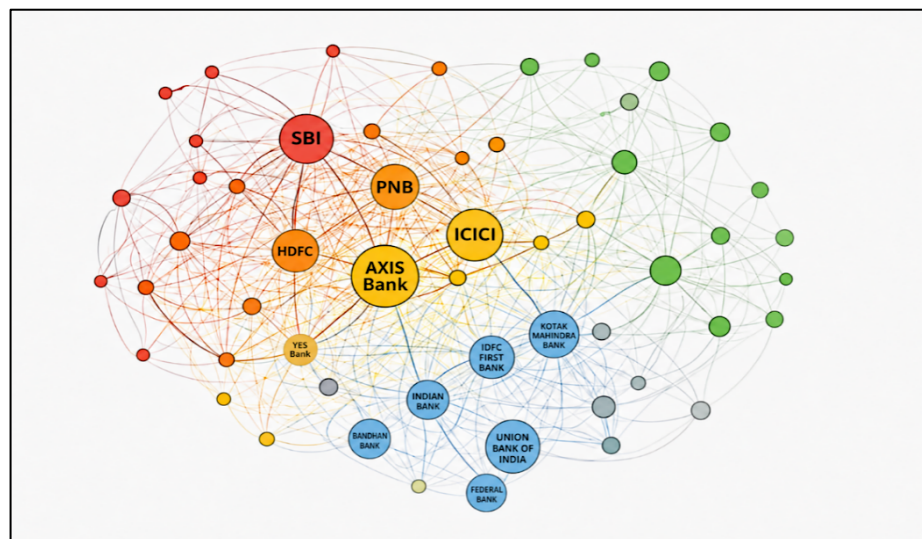


Figure 5: Interbank Network Structure of the Indian Banking Sector

Figure 5 represents the interbank network as nodes (banks) and edges (the defined exposure or connectedness relationships). The structure is broadly consistent with a core-periphery interpretation, in which institutions with greater systemic-importance measures lie closer to the core and have denser links, increasing their potential to transmit or absorb shocks. Peripheral

institutions are not insulated from contagion because indirect links, common exposures and shared funding or payment channels can transmit stress across the network. This interpretation aligns with recent Indian evidence that interconnectedness and credit-exposure clustering are relevant for systemic vulnerability (29, 30).

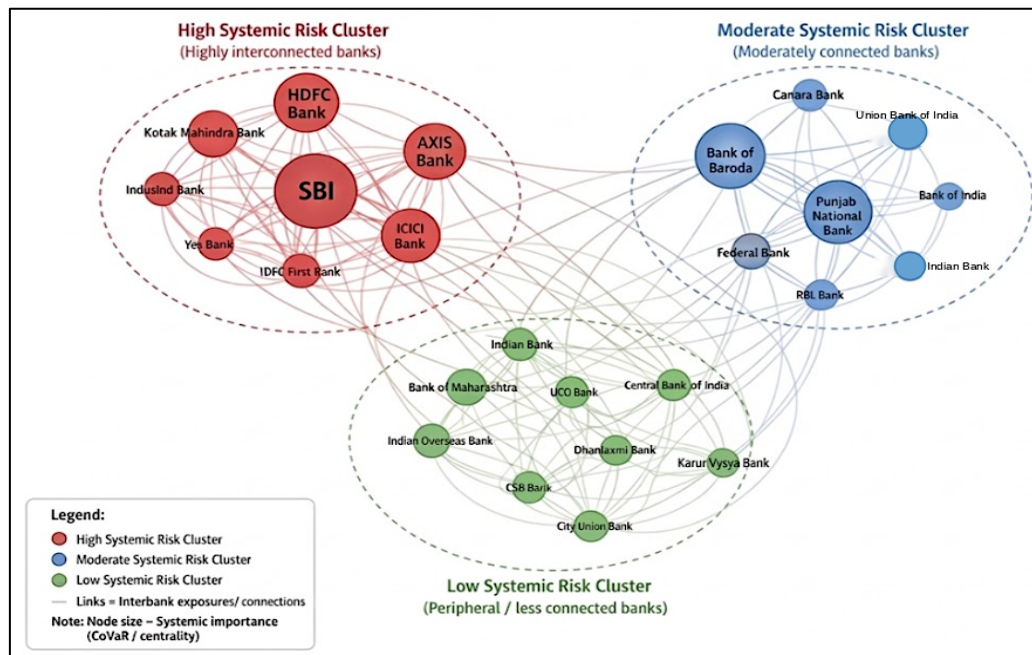


Figure 6: Systemic-risk Clustering Among Banks Based on Network Connectivity

Figure 6 indicates that banks are not equally positioned within the system: highly interconnected institutions form a core cluster, intermediary institutions connect the core with other groups and less connected banks lie closer to the periphery. Within-cluster linkages can generate correlated stress, while bridging institutions can transmit shocks between clusters.

Recent multi-layer network evidence similarly shows that transaction concentration and network position affect the systemic importance of financial institutions (31). The clustering result therefore supports the view that macroprudential surveillance should combine institution-level vulnerability with network position rather than relying on size alone.

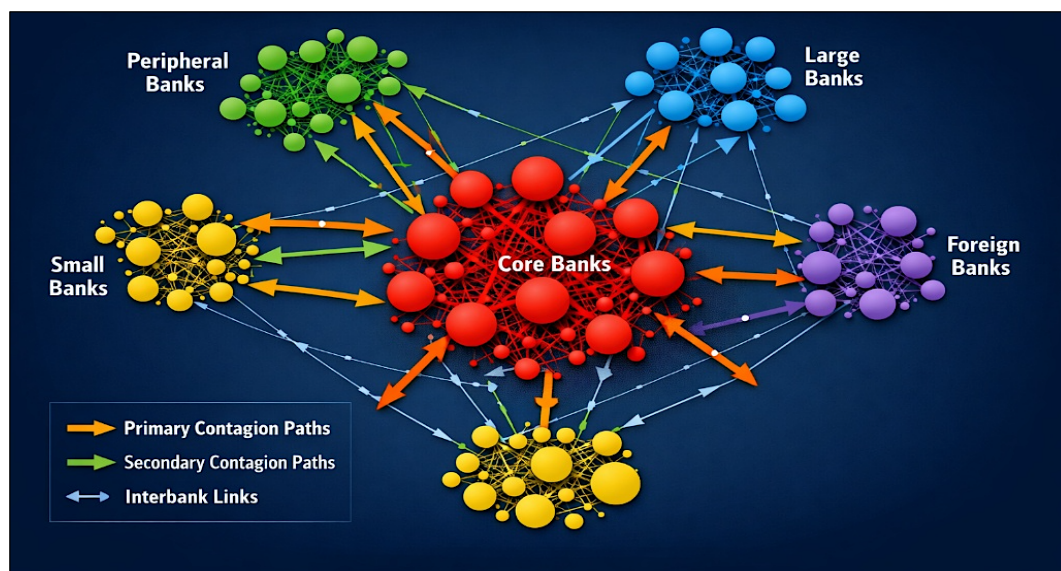


Figure 7: Contagion Pathways and Interconnectedness in the Banking Network

Figure 7 provides a simplified representation of contagion channels in the banking system. Connections are densest around the core group, while intermediate and peripheral groups remain linked through several direct and indirect paths. This helps explain how shocks originating in

central institutions can reach a wider set of banks through common exposures, funding links and confidence channels. The figure should nevertheless be interpreted as a structural representation of possible transmission pathways rather than as evidence of a specific causal

ordering. These pathways illustrate why betweenness centrality complements size-based measures of systemic importance. A comparatively smaller bank can still matter systemically if it connects otherwise weakly connected clusters and therefore becomes a bridge for contagion. Network centrality thus provides structural information that is not contained in stand-alone balance-sheet measures, an interpretation consistent with recent work emphasizing network-based identification of systemically important institutions (30, 31).

In Figure 8, larger nodes represent more central and influential banks, whereas smaller nodes

represent more peripheral institutions. Comparing Figures 2 and 8 shows that CoVaR and network centrality capture related but distinct dimensions of systemic importance: CoVaR measures marginal tail-risk contribution, while network centrality identifies structural positions through which shocks may propagate. Their partial convergence strengthens the systemic-risk interpretation, while any divergence is also informative because a bank may have high market-based tail dependence without occupying the most central network position, or vice versa.

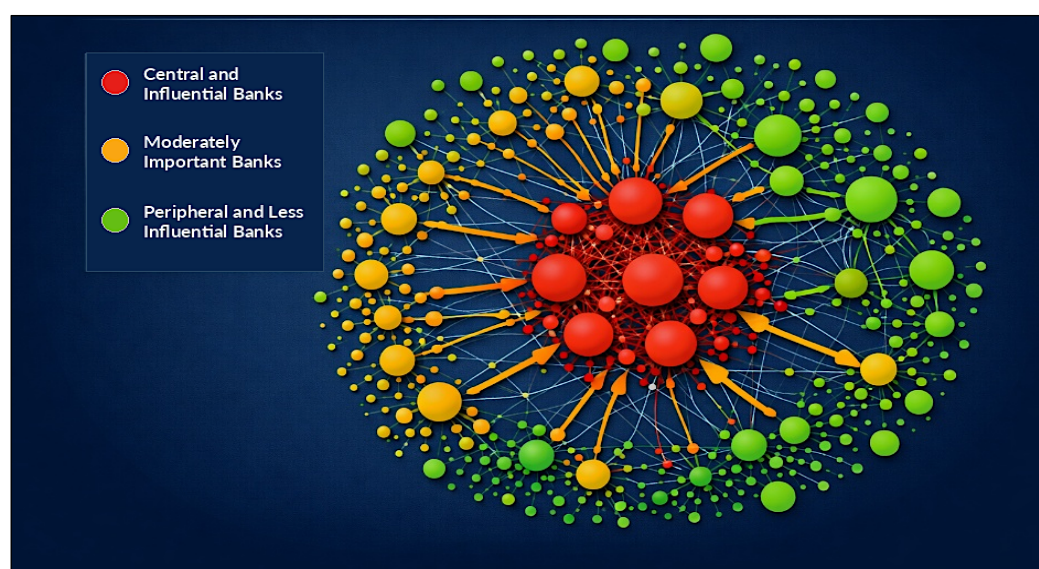


Figure 8: Visualisation of Bank-level Risk Centrality and Network Influence

The hypothesis-oriented interpretation is based on the direction and consistency of the empirical patterns across the integrated models. These hypotheses are interpreted cautiously because the manuscript does not present a complete table of coefficient estimates, confidence intervals and p values for every model. Accordingly, the discussion emphasizes convergent patterns across methods rather than claiming precise effect sizes that are not reported.

The evidence is consistent with H1: weaker asset quality and higher leverage are associated with greater systemic vulnerability, while rapid credit growth appears to amplify risk through the credit-quality channel. This is consistent with recent Indian evidence linking cyclical lending, asset quality and concentration to bank fragility (28) and with credit-exposure clustering as a channel for common-shock transmission (29).

The network and CoVaR patterns are consistent with H2: banks in central or bridging network

positions appear more systemically important and potentially more capable of transmitting shocks between clusters. Recent Indian connectedness evidence reaches a similar conclusion that systemic-risk contributions and network connectedness interact dynamically, especially during periods of stress (30).

The results provide broad support for H3, as stronger capital adequacy and liquidity are associated with lower vulnerability and greater capacity to absorb shocks without distressed asset sales or sharp lending contractions. This direction is consistent with evidence from emerging economies that Basel III capital and liquidity requirements can support bank stability (4), although the effect of liquidity should remain context-sensitive because system-wide funding shocks can still generate fire-sale externalities (26).

The Markov-switching patterns are consistent with H4: leverage, non-performing assets, liquidity

and interconnectedness become more consequential in stressed regimes, supporting a regime-dependent interpretation of systemic risk. This accords with recent evidence that connectedness intensifies during crisis periods in the Indian financial system (30). The magnitude of state-specific effects, however, should be interpreted from the underlying model estimates rather than inferred from the figures alone.

Practical Implications and Recommendations

The findings have several implications for banking supervision and financial-stability policy. Macroprudential oversight can complement conventional balance-sheet indicators with CoVaR and network-centrality measures to identify institutions that contribute disproportionately to tail risk or occupy important bridging positions, even when they are not the largest banks. Supervisory stress tests should incorporate contagion channels and regime-dependent scenarios rather than assess institutions only in isolation. Capital and liquidity planning should also account for the interaction between balance-sheet vulnerability and network centrality. Early-warning systems should jointly monitor non-performing assets, leverage, credit growth, liquidity and network position because these indicators capture different stages of risk accumulation and transmission. Finally, recovery and resolution planning should consider indirect contagion across clusters, particularly when distress originates in a highly interconnected institution.

Limitations

The main limitation is that the annual bank-level panel from 2015 to 2022 is suitable for studying medium-term balance-sheet dynamics and macro-financial developments but cannot fully capture high-frequency changes in market stress. CoVaR estimates depend on the return series, confidence level and estimation window; VAR estimates depend on stationarity assumptions and lag selection; and dynamic panel GMM is sensitive to instrument choice and instrument count. Network results also depend on how interbank or connectedness relationships are defined and may not represent all contractual bilateral exposures. Markov-switching results depend on the number and specification of latent regimes. In addition, figures showing selected banks or sub-networks

should not be interpreted as complete rankings of all institutions. Future research could use higher-frequency market data, more granular bilateral exposure data and additional sources of systemic risk such as cyber, climate, FinTech and geopolitical shocks.

Conclusion

This study develops an integrated framework for examining systemic risk in the Indian banking system using dynamic panel GMM, VAR and Granger-causality analysis, CoVaR, network analysis and Markov-switching estimation. The evidence indicates that systemic risk is time-varying and procyclical and is associated with balance-sheet vulnerability, macro-financial conditions, tail-risk spillovers and network interconnectedness during 2015-2022. Important vulnerability channels include non-performing assets, leverage and rapid credit growth, whereas stronger capital and liquidity buffers are associated with greater financial resilience.

The findings also show a predictive interrelationship between credit growth and deteriorating asset quality and a concentration of systemic importance among a subset of banks. CoVaR and network measures are complementary: CoVaR captures marginal contribution to system-wide tail risk, while network measures identify structurally important institutions and potential contagion channels. The network evidence therefore suggests that interconnectedness and not balance-sheet size alone, should be considered in macroprudential surveillance.

The Markov-switching analysis indicates stronger risk transmission during stressed regimes, underscoring the limitations of fixed-parameter interpretations in volatile periods. The methodological contribution of the study is the joint representation of bank vulnerability, macro-financial feedback, tail dependence, network structure and regime shift within one systemic-risk framework. The combined evidence supports integrated early-warning, stress-testing, capital, liquidity and network-monitoring tools for assessing financial stability in the Indian banking system.

Abbreviations

AIC: Akaike Information Criterion, BIC: Bayesian Information Criterion, CAR: Capital Adequacy Ratio, CoVaR: Conditional Value-at-Risk, GDP:

Gross Domestic Product, GMM: Generalized Method of Moments, NPA: Non-Performing Asset, RBI: Reserve Bank of India, VaR: Value-at-Risk; VAR: Vector Autoregression.

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Author Contributions

Borigam Venkateshwarlu: Conceptualization, Literature Review, Methodology, Data Collection, Data Analysis, Interpretation of Results, Writing - Original Draft, Rajyalaxmi M: Research Supervision, Methodological Guidance, Critical Review, Interpretation of Findings, Writing - Review and Editing, Suman Kumar N: Research Supervision, Methodological Guidance, Critical Review, Interpretation of Findings, Writing - Review and Editing. All authors reviewed and approved the final version of the manuscript and agreed to be accountable for the work.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this study.

Data Availability

The data supporting the findings of this study were compiled from Reserve Bank of India regulatory databases, published bank reports and other verified institutional sources described in the Methodology. The processed dataset used for the analysis is available from the corresponding author upon reasonable request, subject to the terms of the original data sources.

Declaration of Artificial Intelligence (AI) Assistance

The authors acknowledge the use of generative AI to assist in the paraphrasing of certain parts of the manuscript. All content generated through AI was critically reviewed, edited and verified by the authors to ensure accuracy, originality and

compliance with academic standards. The authors take full responsibility for the integrity and validity of the manuscript.

Ethics Approval

This study is based on secondary banking, financial, macroeconomic and market data obtained from regulatory databases, published financial statements and institutional sources. It did not involve human participants, personal interviews, questionnaires, clinical procedures, or animal experiments. Therefore, formal human- or animal-research ethics approval was not applicable.

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