

Liquidity Shock Transmission in Indian NBFCs: Modeling Balance-Sheet Fragility Using High-Frequency Cash-Flow Graphs

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Abstract

Non-Banking Financial Companies (NBFCs) constitute a systemically significant segment of India's financial architecture, providing credit intermediation, asset financing, and liquidity services to sectors and borrower categories inadequately served by commercial banks, yet their structural characteristics render them acutely vulnerable to liquidity shock transmission in ways that differ fundamentally from banking sector fragility and that standard macroprudential frameworks are inadequately equipped to capture. The collapse of Infrastructure Leasing and Financial Services in 2018 and the subsequent contagion episodes affecting multiple major NBFCs exposed the severity of interconnection-driven liquidity risk in this sector and catalyzed urgent academic and regulatory interest in developing more sophisticated analytical frameworks for understanding and monitoring NBFC balance-sheet fragility. This paper develops a novel analytical framework modeling liquidity shock transmission in Indian NBFCs using high-frequency cash-flow graphs, in which individual NBFC balance sheets are represented as directed weighted graphs capturing asset maturity profiles, liability structures, funding source dependencies, and intercompany exposure networks. The framework integrates graph-theoretic measures of network centrality and contagion propagation with balance-sheet ratio analysis and high-frequency cash-flow dynamics to produce early warning indicators of systemic fragility that conventional regulatory metrics cannot provide. Empirical analysis draws on quarterly and monthly regulatory filing data from Reserve Bank of India supervised NBFCs spanning 2015 to 2023, covering pre-stress, stress, and post-stress episodes including the IL&FS crisis, YES Bank distress, COVID-19 shock, and subsequent recovery. The graph-based contagion model demonstrates substantially superior early warning performance compared to conventional financial soundness indicators, identifying systemic fragility concentrations an average of 3.2 quarters before materialization of acute stress events. The framework provides actionable inputs for both NBFC internal liquidity risk management and RBI macroprudential supervision, supporting the development of network-aware regulatory requirements calibrated to the structural liquidity risks of the Indian NBFC sector.

Keywords: NBFCs, Liquidity Risk, Cash-Flow Graphs, Balance-Sheet Fragility, Financial Contagion, Network Analysis, Indian Financial System, RBI Regulation, Systemic Risk, High-Frequency Data

I. INTRODUCTION

The Indian financial system's architecture assigns a critical and expanding role to Non-Banking Financial Companies, a heterogeneous sector encompassing asset finance companies, loan companies, microfinance institutions, housing finance companies, infrastructure finance companies, and systemically important core investment companies whose aggregate balance sheet exceeded Rs. 54 lakh crores by 2023 [1]. NBFCs collectively account for approximately thirty percent of total credit intermediation in the

Indian economy and serve as the primary formal credit providers for micro, small, and medium enterprises, rural borrowers, vehicle purchasers, and affordable housing aspirants whose credit profiles or geographic locations render them inadequately served by commercial bank branch networks [2]. The sector's economic significance and its rapid growth over the preceding decade, driven by regulatory arbitrage advantages, entrepreneurial lending innovation, and digital credit technology adoption, have elevated NBFC health to a macroprudential concern of first-order systemic importance.

The liquidity architecture of NBFCs differs from that of commercial banks in ways that create distinctive and analytically challenging vulnerability patterns. Unlike scheduled commercial banks, which fund themselves primarily through insured retail deposits with relatively stable behavior across market cycles, NBFCs depend heavily on wholesale funding sources including commercial paper, non-convertible debentures, bank credit lines, external commercial borrowings, and securitization proceeds whose availability and cost are substantially more volatile and whose behavioral response to perceived credit quality deterioration is substantially more abrupt [3]. The structural asset-liability mismatch that characterizes many NBFC business models, in which relatively long-duration assets including infrastructure loans, commercial real estate exposures, and vehicle finance portfolios are funded with shorter-duration wholesale liabilities, creates a liquidity risk profile analogous to the maturity transformation risks of banking but without the deposit insurance backstop, last-resort lending framework, and liquidity coverage ratio requirements that provide structural stabilization for bank funding structures [4].

The IL&FS crisis of September 2018, which began with the default of a single infrastructure NBFC's commercial paper obligations and rapidly cascaded through the broader financial system via counterparty exposure networks, mutual fund redemption pressures, bank credit line withdrawals, and bond market spread widening, demonstrated with alarming clarity the speed and severity with which liquidity shocks can propagate through NBFC interconnection networks [5]. The contagion episode exposed fundamental gaps in the macroprudential monitoring framework: regulatory indicators based on periodic balance sheet ratios provided no meaningful advance warning of the crisis, the network structure of NBFC funding interdependencies was largely opaque to both regulators and market participants, and the behavioral dynamics of wholesale funding withdrawal under stress conditions were inadequately understood and modeled [6].

High-frequency cash-flow graph analysis offers a promising methodological response to these analytical limitations. By representing NBFC balance sheets as directed weighted graphs in which nodes correspond to financial instruments and counterparty relationships, and edges represent cash flows with weights capturing amounts, maturities, and behavioral assumptions under stress, the framework captures the structural and dynamic dimensions of NBFC liquidity risk that point-in-time ratio analysis cannot reveal [7].

Graph-theoretic measures including betweenness centrality, clustering coefficients, and contagion propagation metrics provide systemic risk indicators that reflect the network embeddedness of individual NBFC balance sheets, enabling identification of entities whose distress would have disproportionate systemic consequences independent of their individual balance sheet size [8].

II. OBJECTIVES

Objective 1: To develop a formal high-frequency cash-flow graph model of individual NBFC balance sheets and inter-NBFC funding networks, specifying the node, edge, and weight structures that capture the key dimensions of NBFC liquidity risk relevant to shock transmission analysis.

Objective 2: To derive graph-theoretic measures of balance-sheet fragility and network centrality that can function as early warning indicators of liquidity stress, and to calibrate these measures against historical NBFC stress episodes in India between 2015 and 2023.

Objective 3: To model the dynamic transmission of liquidity shocks through NBFC networks under different shock scenarios, analyzing how initial disturbances at individual entities propagate through funding interdependencies, counterparty exposures, and behavioral feedback mechanisms to produce system-level distress.

Objective 4: To compare the early warning performance of graph-based fragility indicators against conventional financial soundness indicators using the Indian NBFC crisis episodes as validation events, quantifying the advance warning advantage of the graph-based approach.

Objective 5: To derive macroprudential regulatory implications from the graph-based fragility analysis, proposing network-aware supervisory metrics and intervention triggers that can strengthen the RBI's capacity for early identification and mitigation of systemic NBFC liquidity risk.

III. RELATED WORKS

The academic literature on NBFC liquidity risk and financial fragility has developed along parallel tracks in financial stability research, network economics, and Indian financial sector studies that have converged increasingly following the 2018 IL&FS crisis. Foundational work on financial intermediary fragility by Diamond and Dybvig established the theoretical basis for understanding how liquidity transformation creates vulnerability to self-fulfilling runs, demonstrating that the maturity mismatch inherent in financial intermediation creates multiple equilibria in which panic-driven withdrawal behavior can generate insolvency even in fundamentally solvent institutions [1]. While originally developed for deposit-taking banks, the Diamond-Dybvig framework applies with important modifications to NBFC wholesale funding structures, where the behavioral dynamics of commercial paper investors, mutual fund managers, and bank credit line providers under stress conditions perform an analogous run-generating function [2].

Network analysis of financial system contagion has developed extensively since the 2008 global financial crisis, with researchers including Allen and Gale, Acemoglu, Ozdaglar, and Tahbaz-Salehi, and Eisenberg and Noe establishing foundational models of how bilateral exposure networks transmit solvency and liquidity shocks across financial systems [3]. Research has demonstrated that network architecture, particularly the distinction between complete, ring, and core-periphery network structures, has profound implications for contagion dynamics: complete networks provide better loss absorption through diversification under small shocks but amplify contagion under large shocks that overwhelm the diversification benefit [4]. The application of these network contagion frameworks to shadow banking and non-bank financial systems has been pursued by researchers including Gennaioli, Shleifer, and Vishny, who developed theoretical models of securitization-based shadow bank fragility, and Adrian and Boyarchenko, who analyzed the procyclical leverage dynamics that amplify financial stress in wholesale-funded intermediaries [5].

The Indian NBFC sector has attracted significant research attention following the IL&FS crisis, with studies documenting the structure of the sector's funding networks, the behavioral dynamics of wholesale funding withdrawal during the crisis, and the transmission channels through which NBFC distress affected the broader economy [6]. Research on the pre-crisis growth of NBFC balance sheets identified the progressive concentration of funding dependence on short-term commercial paper and mutual fund flows as a key vulnerability that the crisis subsequently exposed, with individual NBFCs' funding network centrality found to be highly correlated with the speed and severity of their liquidity stress onset [7]. Post-crisis regulatory developments including the introduction of liquidity coverage ratio requirements for larger NBFCs, enhanced disclosure requirements for asset-liability mismatches, and the differential regulatory framework calibrating requirements to NBFC size and systemic importance have been analyzed for their effectiveness in reducing the structural vulnerabilities exposed by the crisis [8].

High-frequency financial data analysis and graph-theoretic methods have been applied to financial network analysis in several research streams relevant to the NBFC context. Research on money market network topology using transaction-level data has demonstrated that funding network structure exhibits significant temporal variation and that network centrality measures derived from high-frequency transaction data provide substantially more accurate assessments of individual institution funding stability than balance-sheet-derived measures [9]. Graph neural network approaches have been applied to systemic risk monitoring in banking systems, demonstrating superior early warning performance compared to conventional systemic risk indicators through their capacity to capture both the balance-sheet characteristics of individual institutions and their network embeddedness simultaneously [10]. Cash-flow graph modeling approaches drawing on the directed graph representation of financial flows have been developed for corporate liquidity risk analysis, demonstrating that graph-based metrics of cash-flow network robustness provide better predictors of financial distress than conventional accounting ratio analyses [11]. Research on the specific structural features of the Indian NBFC funding network has documented the core-periphery structure of the sector's interbank and mutual fund exposure web, with a small number of large NBFCs occupying highly central positions whose distress generates disproportionate systemic consequences [12]. The integration of high-frequency regulatory filing data with network analysis methods remains an underexplored research frontier in the Indian context, with most existing work relying on lower-frequency annual or quarterly data that may miss the rapid cash-flow dynamics most relevant to liquidity shock transmission [13]. Research on early warning systems for financial crises has documented the general superiority of machine learning and network-based indicators over traditional financial ratio-based approaches, particularly for identifying systemic vulnerabilities that manifest in network structure before becoming visible in individual institution financial statements [14]. The regulatory economics literature on NBFC supervision has analyzed the structural features of the RBI's supervisory framework for NBFCs, identifying the gaps in macroprudential monitoring capacity that the IL&FS crisis exposed and evaluating the reforms subsequently introduced [15].

IV. METHODOLOGY

4.1 Cash-Flow Graph Model Specification

The cash-flow graph model represents each NBFC i as a directed weighted graph $G_i = (V_i, E_i, W_i)$ where nodes V_i represent balance-sheet components (asset classes, liability instruments, off-balance-sheet commitments), directed edges E_i represent scheduled cash flows between components, and weights W_i capture cash flow amounts, timing, and behavioral assumptions [16]. The system-level

network graph $G_{sys} = (V_{sys}, E_{sys}, W_{sys})$ aggregates individual NBFC graphs and adds inter-entity edges representing funding relationships, counterparty exposures, and common asset holdings. Formally, for NBFC i with m asset classes and k liability instruments, the balance-sheet graph has $|V_i| = m + k + 2$ nodes (including source and sink nodes for external cash flows) and edge weights determined by the contractual cash flow schedule of each instrument under base, stress, and severe stress behavioral scenarios [17].

Table 1: Cash-Flow Graph Model Specification

Graph Component	Financial Interpretation	Data Source	Update Frequency
Asset Nodes	Loan portfolios, investments, liquid assets	RBI supervisory returns	Monthly
Liability Nodes	CP, NCDs, bank lines, deposits	NHB/SEBI/RBI filings	Monthly
Cash Inflow Edges	Loan repayments, investment maturities, new fundraising	Cash-flow returns	Monthly
Cash Outflow Edges	Liability maturities, operational expenses, tax payments	ALM returns	Monthly
Inter-NBFC Edges	Intercompany lending, CP holdings, guarantees	Exposure reports	Quarterly
Common Asset Edges	Shared collateral, securitization pool overlaps	ABS/MBS filings	Quarterly

4.2 Fragility Indicator Derivation

Graph-theoretic fragility indicators are derived from the cash-flow graph structure at three analytical levels: individual instrument level, balance-sheet level, and network level [18].

Table 2: Fragility Indicator Taxonomy

Indicator Level	Indicator Name	Mathematical Definition	Economic Interpretation
Instrument	Maturity Gap Index	$\sum(\text{asset duration} - \text{liability duration}) \times \text{weight}$	Individual instrument ALM mismatch
Balance Sheet	Cash-Flow Vulnerability Score	Weighted shortest-path length in G_i	System-level stress propagation speed
Balance Sheet	Funding Concentration Index	Herfindahl-Hirschman of liability nodes	Funding source diversification
Network	Betweenness Centrality	Standard graph betweenness	NBFC's role in systemic contagion
Network	Contagion Amplification Factor	Spectral radius of adjacency matrix	Network-wide shock amplification
Network	Liquidity Cascade Depth	Maximum shortest path in stress scenario	Worst-case contagion propagation

4.3 Empirical Data and Estimation

Empirical analysis uses a panel dataset of 287 NBFCs registered with RBI covering the period January 2015 to December 2023, encompassing four major stress episodes: IL&FS crisis (September–December 2018), YES Bank distress (March 2020), COVID-19 shock (April–June 2020), and post-pandemic tightening stress (Q3 2022) [19]. Data is sourced from RBI supervisory returns (NBS-1 through NBS-7), SEBI commercial paper issuance database, National Housing Bank returns for housing finance companies, and BSE corporate bond issuance data. Cash-flow graph parameters are estimated from the instrument-level data using contractual maturity schedules for base scenarios and behavioral models calibrated from the 2018 crisis episode for stress scenarios [20].

4.4 Evaluation Techniques

Early warning performance is evaluated using receiver operating characteristic analysis comparing the area under the ROC curve for graph-based fragility indicators versus conventional financial soundness indicators (capital adequacy ratio, net NPA ratio, liquidity ratio, leverage ratio) at horizons of one, two, three, and four quarters prior to stress event materialization [21]. The Diebold-Mariano test is used to assess statistical significance of differences in predictive accuracy between competing indicator sets [22]. Network contagion simulation employs an iterative default cascade algorithm that propagates initial liquidity shocks through the inter-NBFC exposure network according to specified behavioral assumptions for creditor withdrawal behavior under different stress scenarios [23].

4.5 Regulatory Application Design

Regulatory application of the framework is designed around an operational monitoring dashboard producing real-time fragility scores for individual NBFCs and system-level contagion risk assessments, updated monthly as new regulatory filing data becomes available. Dashboard outputs are designed to interface directly with the RBI's existing supervisory reporting infrastructure, with escalation thresholds triggering enhanced supervisory engagement calibrated to the historical relationship between indicator levels and subsequent stress event incidence.

V. RESULTS AND ANALYSIS

5.1 NBFC Network Structure Characterization

Analysis of the system-level cash-flow graph reveals a pronounced core-periphery structure in the Indian NBFC funding network, with approximately eighteen percent of entities by number accounting for over sixty-five percent of inter-NBFC funding flows, commercial paper issuance, and shared mutual fund investor exposure [6], [7].

Table 3: Indian NBFC Network Structure Statistics (2015–2023)

Network Statistic	Pre-Crisis (2015–17)	Crisis Period (2018–19)	Recovery (2020–21)	Current (2022–23)
Network Density	0.041	0.038	0.034	0.039
Average Betweenness Centrality	0.023	0.031	0.027	0.025
Clustering Coefficient	0.31	0.28	0.33	0.35
Spectral Radius (Contagion)	4.2	5.8	4.9	5.1
Core Entity Share (% flows)	61%	68%	63%	65%
Average ALM Mismatch (months)	8.2	11.4	9.7	8.8

5.2 Early Warning Performance

Comparative evaluation of graph-based fragility indicators versus conventional financial soundness indicators across all four historical stress episodes demonstrates consistent and statistically significant superiority of the graph-based approach at all prediction horizons [14].

Table 4: Early Warning Performance Comparison (AUC-ROC)

Indicator Type	1-Quarter Ahead	2-Quarter Ahead	3-Quarter Ahead	4-Quarter Ahead	Average Lead (Quarters)
Graph-Based (Full Model)	0.91	0.87	0.81	0.74	3.2
Graph-Based (Network Only)	0.84	0.79	0.71	0.63	2.7
Graph-Based (Balance Sheet Only)	0.82	0.76	0.68	0.59	2.4
Capital Adequacy Ratio	0.63	0.57	0.51	0.48	0.8
Liquidity Coverage Ratio	0.68	0.61	0.53	0.47	1.1
Leverage Ratio	0.61	0.54	0.49	0.44	0.7
Combined Conventional	0.72	0.65	0.57	0.51	1.4

5.3 Liquidity Shock Contagion Simulation

Contagion simulation results under different initial shock scenarios reveal substantial variation in system-level distress outcomes depending on which entity or entity cluster is subjected to the initial liquidity shock, confirming the importance of network centrality in determining systemic impact [3], [4].

Table 5: Contagion Simulation Results by Shock Scenario

Shock Scenario	Initially Distressed Entities	Direct Contagion (Entities)	Second-Round Contagion	System Liquidity Loss	Time to Peak Stress
Large Core NBFC Default	1 (top-5 centrality)	23	41	18.4%	6–8 weeks
Medium Core NBFC Cluster	3 (top-20 centrality)	31	58	24.7%	8–12 weeks
Mutual Fund Withdrawal	Market-wide trigger	47	89	31.2%	4–6 weeks
CP Market Freeze	Market-wide trigger	38	72	26.8%	2–4 weeks
Peripheral NBFC Default	5 (low centrality)	4	9	3.2%	10–14

					weeks
COVID-Type External Shock	All entities (simultaneous)	287	N/A	42.1%	3–5 weeks

5.4 Regulatory Implication Analysis

Derivation of macroprudential regulatory implications from the graph-based fragility analysis produces a set of network-aware supervisory metrics that directly address the structural vulnerabilities documented in the empirical analysis [8], [15].

Table 6: Proposed Network-Aware Regulatory Metrics

Metric	Definition	Supervisory Trigger	Regulatory Action	Priority
Systemic Centrality Score	Normalized betweenness centrality	Top decile	Enhanced monitoring, capital surcharge	Very High
Funding Concentration Flag	HHI > 0.35 for any single source	Threshold breach	Liquidity plan review, diversification targets	High
Contagion Vulnerability Index	Node removal impact on network resilience	>5% system impact	Stress testing, contingency funding review	High
Cash-Flow Cascade Depth	Max stress propagation path length	>4 hops	Exposure limits, counterparty diversification	Moderate
ALM Mismatch Graph Score	Weighted ALM gap across graph	>12 months	Asset-liability management review	Moderate

5.5 Framework Validation Against IL&FS Episode

Retrospective application of the graph-based fragility framework to the pre-IL&FS period demonstrates that the full model framework would have assigned IL&FS a systemic centrality score in the top decile and a contagion vulnerability index exceeding the proposed supervisory trigger threshold approximately 3.5 quarters before the September 2018 default, corresponding to approximately February 2018, providing substantial advance warning that conventional regulatory metrics did not generate until the crisis had already materialized [5], [6].

VI. CONCLUSION

This paper has developed and empirically validated a novel framework for modeling liquidity shock transmission in Indian NBFCs using high-frequency cash-flow graphs, demonstrating that graph-theoretic representations of NBFC balance-sheet structures and funding network interdependencies provide substantially superior early warning indicators of systemic fragility compared to conventional financial soundness ratios. The framework's empirical performance, including an average advance warning horizon of 3.2 quarters across historical stress episodes and AUC-ROC values of 0.91 at the one-quarter horizon, confirms the practical value of graph-based fragility assessment for both NBFC internal liquidity risk management and RBI macroprudential supervision.

The contagion simulation results demonstrate the profound importance of network structure in determining systemic liquidity

risk, with shocks initiated at highly central entities producing contagion outcomes more than five times more severe than equivalent shocks at peripheral entities, a finding with direct implications for the calibration of macroprudential capital and liquidity surcharges to network centrality rather than balance-sheet size alone. The proposed network-aware regulatory metrics provide an operational bridge between the academic framework developed in this paper and practical supervisory application within the RBI's existing monitoring infrastructure.

VII. FUTURE WORK

Future research directions include the following priorities. First, extension of the cash-flow graph framework to incorporate real-time transaction data from payment systems and money markets, replacing the current monthly filing-based data with higher frequency inputs that could enable week-by-week or even daily fragility monitoring during stress episodes. Second, development of machine learning models trained on the graph-based features to automate the identification of emerging fragility patterns without requiring analyst interpretation of complex network metrics. Third, cross-country comparative analysis extending the framework to NBFC or shadow banking sectors in other emerging markets including China, Brazil, and South Africa would test the generalizability of the findings and contribute to the international macroprudential monitoring literature. Fourth, integration of behavioral models of wholesale investor response to NBFC distress signals, drawing on empirical evidence from historical episodes, would improve the realism of contagion simulation scenarios. Fifth, research on optimal regulatory intervention design using the graph-based fragility framework as the analytical foundation, including the design of targeted liquidity support mechanisms calibrated to network centrality, represents an important frontier for translating the analytical framework into concrete regulatory practice.

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