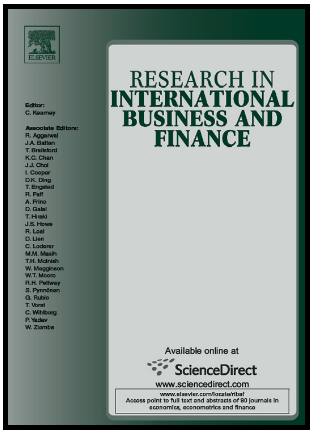

Financial Networks and Systemic Risk Vulnerabilities: A Tale of Indian Banks

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Abstract

This study identifies the nature and direction of unprecedented upheavals in the Indian banking sector which is linked to credit market asymmetry. A tail-driven network approach with a mixed sample of banks and firms exhibits the characteristics of the twin-balance-sheet syndrome. We construct the networks with a degree of interconnectedness at different quantiles and identify major systemic risk emitters and receivers. Furthermore, we find a spillover of the riskiness of deep-in-debt firms to banks. Smaller banking institutions evince a greater connection to banks and firms than larger ones. Our results are valuable for policymakers formulating financial stabilization policies and investors considering Indian markets for various opportunities.

JEL Classifications: G18, G32, C63, G01, C21, C51

Keywords: Systemic Risk, Financial Stability, Network Approach, Value at Risk, CoVaR, Indian Banks

1. Introduction

The upheavals in the Indian banking system have raised concerns about its riskiness and spillovers. The poor bank assets are linked with debt-stressed firms in the power generation, infrastructure, steel, and telecommunication sectors (Economic Survey, 2016–17). The present study assesses the connectedness among banks and deep-in-debt firms (DDFs) at their extreme tail-end risk and identifies the systemically important banks and firms. The DDFs are found to be significantly interlinked with government-owned banks (GOBs), justifying the twin-balance-sheet characteristics of the banking crisis.

In 2015, the Reserve Bank of India (RBI) performed the asset quality review (AQR) of banks, which surprised policymakers with a series of loss reporting by major banks.[1] The bad assets in the banks' balance sheets were linked to investments in power and infrastructure firms under a credit facilitation drive in the mid-2000s. This phenomenon was termed twin-balance-sheet syndrome (Economic Survey, 2016–17). Subsequently, a phase of market consolidation and regulatory restructuring began in the banking sector. The Insolvency and Bankruptcy Code (IBC, 2016), the revision of the Prompt Corrective Action (PCA) framework, and the recapitalization and merger of public sector banks were a few policy measures announced. This study examines the risk spillover patterns among banks and distressed firms and evaluates their systemic importance.

The efficiency evaluation of the Indian banking sector has been a great avenue of research using the traditional methods of data envelopment analysis and stochastic frontier analysis.

[1] Following the AQR norms, almost all the major banks reported huge losses, including Punjab National Bank (USD 761 million), Bank of Baroda (USD 458 million), and Industrial and Development Bank of India (USD 193 million). The State Bank of India (the biggest public sector bank) reported a loss of net profit of 62%. Following the incident, the stock market (Sensex-30) had major falls throughout the second week of February 2016 (February Fiasco). The panic triggered by the Indian banking crisis (2016) has then been a major concern for the banking sector and its credit conditions.

Some of them include Das and Ghosh (2009), Tabak and Tecles (2010), Ray (2016), and Rakshit and Bardhan (2022). A common consensus reveals the poor performance of public sector banks and suggests a check on their operational and cost efficiencies. Moreover, some studies provide an assessment of different financial indicators, such as asset quality (Ahmed, 2017), non-performing assets (Sengupta and Vardhan, 2017), and bank competition (Sinha and Sharma, 2018). Another strand of literature evaluates various riskiness measures of Indian banks, such as credit (Gulati et al., 2019), liquidity (Sopan and Dutta, 2018), and systemic risks (Verma et al., 2019, Ahmad et al., 2019). This study adds to systemic risk literature by including debt-ridden firms in the connectedness analysis of banks and explores the evidence of the twin-balance-sheet syndrome.

The assessment of systemic risk has become a norm for checking the financial health of a system.[2] The existing literature on systemic risk can be divided into three branches. The first branch focuses on calculating default probabilities using factor models (Huang et al., 2009; Kritzman et al., 2011; Billio et al., 2012; Patro et al., 2013; and Kreis and Leisen, 2018). The second branch measures the risk using spillover effects across financial institutions at different tails. Zhou (2010) provides the Systemic Impact Index and Vulnerability Index to assess the systemic importance of financial institutions. The conditional value at risk (CoVaR), developed by Adrian and Brunnermeier (2016), is a quantile-based measure of systemic risk dependence when an institution is under stress. Other prominent forms of risk measures include the marginal expected shortfall (Acharya et al., 2017), the component-expected shortfall (Banulescu and Dumitrescu, 2015), and SRISK (Brownlees and Engle, 2017). In the third branch, studies focus on measuring systemic risk using network analysis. The networks are built with the measurement of directional dependence between financial institutions. Studies in this strand include Billio et al. (2012), Diebold and Yılmaz (2014),

[2] For a detailed discussion on systemic risk, please refer to Silva, Kimura, and Sobreiro (2017)

Levy-Carciente et al. (2015), and Battiston et al. (2016). Khan and Ahmad (2022) examine the default risk of Indian banks using structural and non-structural variables and models, and distance-to-default and distance-to-capital appeared helpful in gauging the systemic risk vulnerabilities.

Constructing networks with systemic risk measures helps identify systemically important financial institutions (SIFIs). The central focus of the studies has been the US (Hautsch et al., 2015; Härdle et al., 2016) and Eurozone (Aldasoro et al., 2017; van de Leur et al., 2017; Li et al., 2018; Foglia and Angelini, 2020). A new breed of literature has developed in emerging markets such as China (Wang et al., 2018; Fang et al., 2018) and Latin America (Rivera-Castro et al., 2018). Under the emerging markets setting, this study focuses on the Indian banking sector, where limited research has been performed on systemic risk.

We employ a quantile-based network approach (Härdle et al., 2016) to rank the banks and DDFs according to their systemic importance. For DDFs, we name the ranking as prime risk emitter (PRE) and prime risk receiver (PRR) DDFs by aligning their balance sheet differences.[3] The ranking agrees with the list of defaulter firms reported in the Economic Survey (2017–18). The DDFs are found to be emitting and receiving a great amount of tail-end risk, and the risk spillover is mainly directed to the GOBs. These results are helpful for investors seeking investment opportunities in Indian markets and policymakers in identifying systemically important banking institutions. This study is important in two ways: first, it connects with an area in the banking sector of emerging markets where banks' systemic risk measurement involves various indicators and institutions and hence requires an ultra-

[3] It is noteworthy that we define PRR and PRE as those firms whose failure may spread to other large firms and may also create an adverse growth scenario for either that sector or other related sectors of the economy. Essentially, rankings of PRR and PRE reveal the "*too big to fail*" scenario.

dimensional set-up to examine. Second, the study contributes to the literature on distressed firms where borrowers' and lenders' relationships can be exhibited through networks.

The remainder of the study is organized as follows. Section 2 reviews the related literature. Section 3 explains the data and variable construction. Section 4 outlines the methodology of the tail-event-driven risk model. Section 5 contains the results and discussion. Finally, Section 6 concludes the study.

2. Related literature

There is a growing consensus on the rising need to study the systemic risk of financial institutions to safeguard economies and regions. The 2008 Global Financial Crisis (GFC) is the prime reason. Before the GFC, Bartram, Brown, and Hund (2007) quantified the systemic failure in the global banking system by using a large pool of global banks and found the significant impact of some events triggering the systemic risk. For US and European banks, Rodríguez-Moreno and Peña (2013) found the considerable role of Credit Default Swaps in modeling systemic risk using high-frequency indicators. Anginer, Demirguc-Kunt, and Zhu (2014) examined the role of market competition in augmenting systemic risk. These studies shaped the thought process of interconnectedness and financial contagion literature through different channels, and their unconventional approaches also helped the systemic literature to flourish.

For a long time, graph theory's pairwise connectedness and adjacency matrix were not introduced. The systemic risk analysis allowed such analysis with high-frequency data on financial markets. Acemoglu et al. (2015) found a significant role of interconnections in propagating systemic shocks to a fragile financial system and financial contagion. Anderson, Paddrik, and Wang (2019) studied the National Banking Act of 1863–1864 and its impact on the network structure and financial stability of banks in Pennsylvania. The analysis helped to understand the role of regulations. Aldasoro et al. (2017) worked on a network model that optimized risk-averse banks' lending and investments in non-liquid assets. Gai and Kapadia (2019) focused on systemically important institutions and their exposures and interlinkages across the financial system. Allen and Carletti (2013) studied panic, contagion, and foreign exchange mismatches in explaining the systemic risk characteristics of banks and found these terms relevant. We are skipping the studies mentioned above to conserve space. Using the TENET risk model, Foglia and Angelini (2020) found the interconnectedness between banks, insurance, and shadow banks in the Eurozone. The aforementioned authors showcased the "too big to fail" and "too big to interconnected" concepts, highly relevant for systemic risk analysis. Caliskan et al. (2021) examined Turkish banks and found the role of large commercial banks to be significant, accounting for more than 90%. Amor et al. (2022) developed a financial risk meter for major financial institutions and macro-variables for emerging markets. In recent studies, Mbarki et al. (2022) measured the sentiment toward systemic risk in Asia-Pacific stock markets using frequency and quantile connectedness approaches. Their episodic analysis found that the GFC, Chinese stock market turbulence, and the COVID-19 pandemic significantly impacted market sentiment spillover. Zhang et al. (2023) studied China's banking sector from 2009 to 2019 and found that the large banks faced high systemic risk and highlighted some major banks that should be considered more. Balcilar et al. (2023) showed the financial connectedness and risk transmission among MENA countries and found a strong movement between financial stress co-movements.

In summary, systemic risk literature is a well-driven research area that covers developed and emerging markets. The popularity of network models is apparent and exhibits improvement by incorporating new variables and methods to measure the degrees of interconnectedness. The introduction to ultra-high dimensional models in systemic risk analysis is another feature of the burgeoning literature. However, considering the endogenous dynamics of the Indian economy and its regulated banking sector, this study contributes substantially to the existing literature. Specifically, among studies in the Indian context, the present research constitutes a new contribution to measuring the twin-balance-sheet characteristics.

3. Data and variable construction

The study uses weekly price index data for banks and firms from March 02, 2007, to March 31, 2019. The sample of banks consists of 19 GOBs and 15 privately owned banks (POBs). The selection of DDFs is based on the leverage ratio (debt to market capitalization) and the Economic Survey (2017–2018). In 2015, most of these firms had a leverage ratio ranging between 2% and 25%, further rising to 57% in 2017. The DDFs included in the sample coincide with the list prepared by www.valueresearchonline.com and the list of the first 12 defaulters notified by the RBI.[4] The sample observations are downloaded from the Thomson DataStream for these institutions. The sample period is based on the availability of data. Following Härdle et al. (2016), Wang et al. (2017), Verma et al. (2019), and Ahmad et al. (2019), we include balance sheet variables to capture the idiosyncratic risk. These balance sheet variables include leverage, market-to-book ratio, non-performing assets (NPAs) for banks and total liabilities (firms), return on assets, and size (the frequency of balance sheet variables is annual; we use the same value for the observations of a particular year). The list of macro-variables includes short-term liquidity spread, which is the difference between the Mumbai Interbank Offered Rate (MIBOR) and 3-month treasury bill (T-bill) rate, the change in the 3-month T-bill rate, the difference between 10-year and 3-month T-bill rates, credit spread (the difference between commercial papers and 3-month T-bill rate), time-varying volatility of the representative stock market index, call money rate (CMR) for interbank borrowing and lending, and weekly equity returns of each sample bank and DDFs. Notably,

[4] For details, please see https://www.valueresearchonline.com/story/h2_storyview.asp?str=28001&utm_medium=vro.in (accessed on 25th October 2018). Also, please refer to page # 52, Economic Survey 2017–2018, Volume 2, Chapter 3.

the correlation structure between all the macro-variables is moderate and negative, suggesting the variables' appropriate choice. For instance, the correlation between MIBOR and CMR is 0.42, much lower than expected. We consider the news-based economic policy uncertainty index to capture global economic uncertainty. Since anecdotal events further amplify the systemic risk analysis, we consider the Punjab National Bank (PNB), which reported a maximum loss in the fourth quarter of 2015, to perform TENET. We consider February 12, 2016, as the date of the construction of the networks. The date has been identified following the adverse impact on the equity market.

Table 1 reports the full list of banks with descriptive statistics of their weekly returns. The average returns for most GOBs are negative, while most POBs exhibit positive average returns. Table 2 lists the 21 DDFs considered for the connectedness analysis. The negative average returns indicate the distressed status of these firms. The majority of the return series is leptokurtic.

[Insert Tables 1 and 2 here]

4. Empirical framework

A surge in NPAs in the balance sheets of the banks has been identified under the AQR. These bad assets are linked to their investments in the power and infrastructure sector. We capture the degree of connectedness between these sectors through the TENET risk model (Härdle et al., 2016). The model provides a measure of extreme tail risk using a large set of macro and balance sheet variables and, with the help of a network, identifies the SIFIs at different quantiles. It involves a three-step procedure. First, we calculate the riskiness of banks and DDFs using a quantile regression approach given by Adrian and Brunnermeier (hereafter AB, 2016). Second, we apply the single index model (SIM) with variable selection under a high-dimensional framework. Third, we calculate the directional spillovers using the Diebold and Yilmaz (2014) procedure.

Furthermore, we identify the top systemic risk emitter (SRE) and systemic risk receiver (SRR) based on the magnitude of these institutions' total in and out spillovers. We estimate the TENET model at 0.05 and confirm it with 0.01 for a robustness check. From a systemic risk perspective, 0.01 may have a preference over 0.05. But we discuss the 0.05 quantile because the Indian banking sector is heavily regulated. The details of these steps are explained below:

First step:

We estimate the value at risk (VaR) and CoVaR for banks and DDFs. VaR of an institution *i*, calculated for a given quantile level, $\tau \in (0,1)$ at time *t* is defined as $P(B_{i,t} \leq VaR_{i,t,\tau}) = \tau$, where $B_{i,t}$ represents the log-returns of an institution *i* at time *t*. Furthermore, the CoVaR is estimated using two-step linear quantile regression (hereafter, LQR):

$$B_{i,t} = \alpha_i + \beta_i M_{t-1} + \varepsilon_{i,t} \tag{1}$$

$$B_{j,t} = \alpha_{j|t} + \gamma_{j|i} M_{t-1} + \beta_{j|i} B_{i,t} + \varepsilon_{j|i,t} \tag{2}$$

where M_{t-1} consists of macroeconomic variables. $\gamma_{j|i}$ and β_i are the slope parameters. $\beta_{j|i}$ captures the sensitivity of the log return of an institution *j* to changes in the log return of an institution *i*. The CoVaR is obtained by augmenting VaR of institution *i* at level τ estimated in equation (3) into equation (4):

$$\widehat{VaR}_{i,t,\tau} = \hat{\alpha}_i + \hat{\beta}_i M_{t-1} \tag{3}$$

$$\widehat{CoVaR}_{j|i,t,\tau} = \hat{\alpha}_{j|t} + \hat{\gamma}_{j|i} M_{t-1} + \hat{\beta}_{j|i} \widehat{VaR}_{i,t,\tau} \tag{4}$$

The risk of an institution *j* is thus calculated using macro-state variables and an estimate of the VaR of an institution *i*. The coefficient $\widehat{\beta}_{j|i}$ reflects the extent of *interconnectedness*. We compute two types of CoVaR for an institution. First, the *contribution* CoVaR is obtained by setting *j* as the whole financial system and *i* as a reference institution. It measures the influence of the institution *i* on the overall systemic risk. Second, the *exposure* CoVaR exhibits the connectedness moving from an individual institution to the whole bank system. It is obtained by setting *j* as an individual institution and i as the financial system. This measures the extent to which a single institution is affected by the system's overall risk.

Second step:

We capture the nonlinear dependency by adopting a SIM under the quantile regression framework with variable selection to estimate the CoVaR of an institution *j*. This CoVaR is calculated under a high-dimensional set-up with the asset returns of other institutions, macro-state variables, and balance sheet variables of institution *j*. The variable selection is performed with the linear least absolute shrinkage and selection operator technique.[5,6] Furthermore, a systemic risk connectedness network is obtained by applying the Diebold and Yilmaz (2014) directional connectedness framework. Mathematically:

$$B_{j,t} = f\left(\beta_{j|R_j}^T R_{j,t}\right) + \varepsilon_{j,t} \tag{7}$$

$$\widehat{CoVaR}_{j|\tilde{R}_j,t,\tau} = \hat{f}\left(\hat{\beta}_{j|\tilde{R}_j}^T \tilde{R}_{j,t}\right) \tag{8}$$

$$\widehat{D}_{j|\tilde{R}_j} = \frac{\partial \hat{f}\left(\widehat{\beta}_{j|R_j}^T R_{j,t}\right)}{\partial R_{j,t}} |_{R_{j,t}=\tilde{R}_{j,t}} = \partial \hat{f}\left(\hat{\beta}_{j|\tilde{R}_j}^T \tilde{R}_{j,t}\right) \hat{\beta}_{j|\tilde{R}_j} \tag{9}$$

where $R_{j,t} = \{X_{-j,t,}M_{t-1}, S_{j,t-1}\}$ shows the information set with k variables. $X_{-jt} = \{X_{1t}, X_{2t}, \ldots, X_{m,t}\}$ includes the returns of all institutions except the reference institution *j, and*

[5] LASSO is a popular technique and widely used in Machine Learning.
[6] For further discussion, please refer to Härdle et al. (2016).

m exhibits the number of financial institutions. $S_{j,t-1}$ consists of balance sheet indicators of institution *j*. The parameters $\beta_{j|R_j} = \left\{\beta_{j|-j}, \beta_{j|M}, \beta_{j|S_j}\right\}^T$ are defined as static with one fixed window estimation. We use the 52-week rolling window to cover one year of the trading cycle to obtain the dynamic estimates. The CoVaR, in equation (8), is named a tail-event driven network risk with a SIM (Härdle et al., 2016). It incorporates non-linearity with the influences of other institutions except for *j*, which is reflected in the shape of a link function $f(.)$. $\widehat{D}_{j|\tilde{R}_j}$ is the gradient that measures the marginal effect of covariates evaluated at $R_{j,t} = \tilde{R}_{j,t}$ and the component-wise expression is $\widehat{D}_{j|\tilde{R}_j} = \left\{\widehat{D}_{j|-j}, \widehat{D}_{j|M}, \widehat{D}_{j|S_j}\right\}^T$. $\widehat{D}_{j|-j}$ shows the spillover effects across financial institutions and characterizes their networks. For connectedness analysis, we consider only the partial derivatives of institution *j* for other financial institutions, $\widehat{D}_{j|-j}$, and ignore partial derivatives regarding macro-variables, $\widehat{D}_{j|M}$, and the institution's characteristic variables, $\widehat{D}_{j|S_j}$. Since the primary purpose is to exhibit the connectedness among the institutions in the network analysis.

Third step:

This step involves the identification of SIFIs through the systemic risk relevance of each firm. We measure a specific firm's total in and out connections weighted by market capitalization and define two indices for systemic risk. The SRR Index is the weighted sum of incoming links for an institution. For an institution *j*,

$$SRR_{j,s} = MC_{j,s}\left\{\sum_{i\in k_s^{IN}} \left(|\widetilde{D}_{j|i}^{s}|.MC_{i,s}\right)\right\} \tag{10}$$

The SRE index is defined as the weighted sum of outgoing links for an institution. For a firm *j*:

$$SRE_{j,s} = MC_{j,s}\left\{\sum_{i\in k_s^{OUT}} \left(|\widetilde{D}_{i|j}^{s}|.MC_{i,s}\right)\right\} \tag{11}$$

where k_s^{IN} and k_s^{OUT} are the group of institutions connected with the reference institution j through IN (incoming) and OUT (outgoing) connections at window s, respectively. $MC_{i,s}$ is the market capitalization of an institution i at the starting point of window s. $|\widetilde{D}_{j|i}^{s}|$ and $|\widetilde{D}_{i|j}^{s}|$ are absolute partial derivatives representing the directional connectedness between firms i and j.

5. Results

We perform a TENET analysis with the banks and DDFs and capture significant connectedness among these institutions. We consider the PNB as a reference institution. Figure 1 (Panel A) plots the total connectedness among the banks and firms under consideration at the 5% quantile. In addition, it plots the average penalization parameter Lambda (λ) obtained in the variable selection in the SIM framework. The total connectedness is high during 2008–10 with bank-financed countercyclical policies to contain the contagion. The penalization parameter also sharply rose in this period. The banks were involved in extending the stimulus packages and evergreening of loans to DDFs, which were able to access credit despite their losses. The rise in total connectedness in 2014–15 coincides with the reallocation of the spectrum and mining contracts (Ahmad et al., 2019). The rise in connectedness implies a better credit market outlook and limited credit market imperfections. The subsequent dip in the connectedness measure suggests the arrival of new reforms in the banking sector. The AQR revealed the abundance of bad assets in the banks' balance sheets and made the ground for new regulations. The share of call money and *Certificate of Deposits*, which accounted for 71% of the total short-term interbank market in March 2012, significantly declined to 36% in March 2016. This decrease in the connectivity ratio is reflected in the total connectedness measure. The post-2016 period shows an upward trend in total connectedness due to PCAs, improved credit market outlooks, bank consolidation, and recapitalization measures under Indradhanush Yojana. Panel (B) of Figure 1 shows the total connectedness and average Lambda at 1% quantile, and we observe that the trend is the same as the 5% quantile. The connectedness is relatively higher for the 1% quantile and remains the same, more or less.

[Insert figures 1–3 here]

We divide the sample of institutions into three groups: GOBs, POBs, and DDFs. We capture these three groups' total in- and out-connectedness separately at 5% and 1%, respectively. In Figure 2, Panels A and B show the total connectedness at 5% and 1% quantiles, respectively. Furthermore, in Figure 3, Panels A and B show the total out-connectedness (outgoing links) at 5% and 1%, respectively. We consider a rolling window of 52 weeks, corresponding to one year's weekly returns, to obtain the time-varying estimates of in- and out-connectedness. The incoming links indicate that the riskiness of POBs is substantially lower than DDFs and GOBs. The DDFs receive comparatively higher impacts of shocks to the banks and other stressed firms. The observed trend is similar to total connectedness and can be similarly linked to the events. The outgoing links reveal the DDFs as major risk transmitters among the three groups.

The POBs are identified as the least risky. In the post-2016 period, the total out-connectedness from GOBs is on the surge, while DDFs exhibit a declining trend. Implementing the IBC and the revision of the PCA framework brings a surge in the connectedness measure of the banks. Moreover, the government's demonetization decision catalyzed the nuances in the banking sector. (Sengupta et al., 2016; Sengupta and Vardhan, 2017). These figures reveal the phases of poor performance of all three groups and agree with the rescue measures taken by the RBI (FSR, June 2016). The connectedness links at the 1% quantile also reflect similar trends and, in some periods, are more pronounced than the 5% quantile.

Overall, it is apparent that there are a lot of similarities in the estimates of 5% and 1% quantiles. The extreme quantile estimates are nuanced and capture all the major turning points relevant to our analysis. For brevity, we analyze and discuss the results at 5% quantile; however, the results at 1% are available upon request.

We follow Diebold and Yilmaz (2014) to prepare a network with directional connectedness. Figure 4 (Panel A) shows the overall pairwise connectedness among the banks and DDFs at 5% quantile. The node's size represents the magnitude of overall interconnectedness, and the edge indicates the extent of pairwise directional connections: $DC_{j|i}^{s} = |\widehat{D}_{j|i}^{s}|$. The DDFs are found to be more strongly connected among themselves than banks. JPA exhibits the strongest directional risk spillovers to JPV. Other pairs of firms with significant connections are LANCO to GVKP, IVRCL to ALOK and LANCO, JPA to GMR and PUNJ, and JPV to JPA. Strong connections are found among banks at the 5% quantile level from OBC to UBI, UBI to OBC, and UCO to DENA. We have considered the pairwise connections with a magnitude of 20 or more for the network analysis owing to the higher range of pairwise connections.

[Insert Figure 4 (panels A–E) here]

We plot the interbank TENET at the 5% quantile in Figure 4 (Panel B). We observe similar interbank connectedness at both quantiles. Canara Bank (CANB) is observed with maximum linkages with other banks and exhibits strong connections to Karur Vyasa Bank, Federal Bank, Karnataka Bank, SBI, and UCO Bank. Other significant pairs include BOMH to CUB and ICICI, SYNB to IDBI, and UCO to SIB. The smaller banks are strongly connected to other small banks. POBs exhibit limited interdependence compared to GOBs. The significant connectedness among GOBs is associated with their larger share in credit expansion (see Sengupta, Sharma, and Thomas, 2016). Figure 4 (Panel C) shows the interconnectedness among sample DDFs at the 5% quantile. The prominent linkages are found from JPV to SRES, MTNL, and AMTEK and from VIDEO to GMR, PUNJ, ABGS, and JYOTIS. Other connected pairs are JPA to ABGS, SRES to RAIN, and IVRCL to RAIN. The pairs with strong connections are consistent at both quantile levels.

In addition, we examine the pairwise connectedness networks from banks to DDFs (Panel D) and DDFs to banks (Panel E) to determine the extent of connectedness. The underlying reason for the twin-balance sheet crisis has been the high connectedness between banks and stressed firms. We identify the more vulnerable pairs with systemic symptoms using networks. From a systemic risk analysis perspective, such networks are valuable. Figure 4 (Panel D) shows the strongest connectedness from SYNB to MTNL, followed by OBC to ORCHID, KARB to JYOTIS, and DCB to GITAJ. Similarly, from DDFs to banks (Panel E), the JPA shows strong connectedness with CANB, VIJB, ICICI, ALLA, IOB, DHAB, INDB, IDBI, and ANDB. Similarly, SRES is connected with YES, GITAJ to CBOI, and IVRCL to FEDB. The anecdotal evidence suggests that JPA has exposure to CANB, IDBI, and ICICI.[7] Furthermore, we examine the directional connectedness of the top 10 banks and firms.

Tables 3 and 4 report the total directional connectedness measures (To All and From All) of the top 10 banks and firms. At the 5% quantile (Table 3, Panel A), OBC tops the list in emitting the risk to other banks and DDFs with a connectedness measure of 789.30, which is followed by YES (566.02), UBI (445.30), and SYNB (363.36). The recipients of risks are identified with “from all” connectedness measures (Table 4, Panel A). YES (399.05) receives the maximum spillovers from other banks and DDFs at the 5% quantile, followed by BOI (371.18), UBI (370.84), and PNB (354.64). A common feature of the banks in the recipients' list is their high gross NPAs to gross advances ratio. Some private banks, such as DCB,

[7] The Jaipraakash Associates defaults ₹2,897 crore on principal and interest repayments. Source: https://www.thehindubusinessline.com/companies/jaiprakash-associates-defaults-2987-crore-on-principal-and-interest-repayments/article65277972.ece

DHAB, and KARB, are also on the list. The ranking reveals that smaller banks are more strongly connected than larger banks and seek considerable attention during policy formulation. This finding disagrees with the notion that large banks are only vulnerable to systemic shocks, as has been found by Caliskan et al. (2021) and Amor et al. (2022) for Turkey and emerging markets, respectively.

Similarly, the major risk transmitter DDFs are listed in Table 3 (Panel B) with their connectedness score. JPA (1570.31) and IVRCL (1351.99) are prominent firms in risk transmission. Other firms emitting significant risks are ABAN (920.48), GITAJ (872.24), and LANCO (863.11). According to the "from all" connectedness measure (Table 4, Panel B), GITAJ (611.14) receives maximum spillovers from banks and other DDFs. Other major recipients are LANCO (483.92), GVKP (434.99), and JPA (434.77). This ranking of DDFs agrees with the list of the first 12 defaulters notified by the RBI on June 13, 2017 (Economic Survey, 2017–18). The DDFs operating in infrastructure and real estate exhibit more connectedness than other sectors. The large-sized DDFs are at the top of the list of risk emitters and receivers, unlike the banks, which are consistent with their overleveraging and access to credit.

Table 5 presents the prominent pairwise connections found in the TENET analysis at the 5% quantile. We report separate rankings for the connection between banks (Panel A), between DDFs (Panel B), from banks to DDFs (Panel C), and from DDFs to banks (Panel D). Moreover, the two-way connection between OBC and UBI is the highest among the interbank connections. OBC's connections with other banks (PNB, BOI, ANDB, and SYNB) appear in the top-10 list. The high connectedness of OBC at the interbank level matches Verma et al. (2019) and attracts further investigation at the micro level. Other major interbank pairwise connections are YES to INDUS, UCO to DENA, and YES to AXIS. Among the DDFs, the spillover from JPA to JPV is the highest of all pairwise connections and is visible in the overall connectedness network (Figure 4, Panel A). Other prominent connections between DDFs are JPA to GMR, JPA to PUNJ, IVRCL to ALOK, and LANCO to GVKP. From banks to DDFs, the connectedness is captured from SYNB to MTNL, OBC to ORCHID, and KARB to JYOTIS, consistent with their lending to these institutions. JPA is found to be highly linked to banks, and its six pairwise spillovers with banks are listed among the top 10 DDFs to bank connectedness. Other DDFs with high spillover to banks are GITAJ to CBOI and SRES to YES. These pairs are consistent with the aforementioned overall interconnectedness network (Figure 4). The interbank connectedness measure captures the banks recommended for PCA due to their unsustainable losses. The connectedness between banks and DDFs can be linked to their corresponding loan exposure. Scrutiny is strongly recommended between firms as sectoral dependence is a visible case.

[Insert Tables 3–5 here]

Furthermore, we evaluate the systemic importance of banks and DDFs following the third step of the TENET framework. Table 6 reports the top 10 banks in the SRE ranking (Panel A) and the top 10 DDFs in the PRE ranking (Panel B) at the 5% quantile. Similarly, Table 7 lists the top 10 SRR banks (Panel A) and top 10 PRR DDFs (Panel B) at the 5% quantile. YES, ICICI and AXIS are identified as top systemic risk emitters at the 5% quantile, while HDFC, AXIS, and ICICI lead the list of systemic risk receivers. The RBI publishes the list of domestic systemically important banks (D-SIBs) as a part of its Financial Stability Report and has identified SBI, ICICI, and HDFC as D-SIBs in its previous reports. The ranking of SRR and SRE identified in the TENET analysis includes the D-SIBs. The ranking also suggests that YES, BOB, AXIS, and KOTAK should be included as "*too big to fail*" banks.

In the past, YES Bank has been charged for hiding the NPAs.[8] BOB and AXIS are the banks that have underperformed after the AQR of RBI.[9]

[Insert Tables 6–7 here]

The ranking of PRR and PRE, reported in Panel B of Tables 6 and 7, respectively, reveals JPA as the most risk-emitting DDF, while GMR is the highest risk receiver among DDFs. Other PREs are ABAN, SRES, and LANCO, and PRR's ranking includes JPA, ABAN, and JPV at the 5% quantile. This ranking coincides with the RBI's defaulter firms list. A comparative appraisal suggests that the DDFs identified are distressed because of their loan defaults. These should be given priority for resolution under the IBC and Bad Bank scheme.

6. Conclusion and discussion

In systemic risk literature, network models have gained attention due to their ease of implementation and the depiction of the 'too connected to fail' and 'too big to fail' phenomena. This paper explores the above models to identify the systemic risk characteristics of Indian banks in light of recent developments. The Indian banking system offers systemic risk investigation because of the strong interdependence between banks and firms under debt distress. Although the highly regulated banking structure does not provide the scope for systemic risk explosion, recent developments have sought the attention of researchers and academia to examine the Indian banking systemic risk's resilience and whether the connectedness analysis offers some new learnings. The Indian banking system provides this opportunity. This study contributes to the literature from the systemic risk management dimension. And to some extent, the macroprudential rules and regulations as the modeling exercise include a large set of bank and firm-specific variables. As mentioned, the network-based model application helps identify the following banking and firm-level analysis trends.

[8] https://www.livemint.com/Industry/khygxfSSDJDPIY83itUBYN/Yes-Bank-denies-window-dressing-of-corporate-accounts-to-hid.html (accessed on 3rd November 2018).

[9] https://economictimes.indiatimes.com/markets/stocks/news/sbi-icici-bank-axis-bank-bob-bleed/articleshow/50803553.cms (accessed on 3rd November 2018).

First, the high connectedness between banks and distressed firms (deep-in-debt, DDFs) confirms the twin-balance sheet syndrome. The DDFs are strongly connected to government-owned banks, confirming the presence of a large number of government bank's participation in real estate and infrastructure sectors. The possible explanation could be that the consortium of banks financed the mid-2000s investment boom.

Second, the application of network models and the high-dimensional modeling set-up helps reveal the inherent dynamics of the banking sector. It is one of the significant contributions of this study. Third, the other striking finding is the emergence of smaller GOBs in the twin-balance syndrome process than the large GOBs. In this process, the empirical results also account for episodes of the global financial crisis and upheavals in the Indian banking system due to domestic reasons such as demonetization and the promulgation of financial regulations such as insolvency norms and mergers of banks. Lastly, the systemic risk rankings are also commensurate with recent development and policy measures taken by the government, and it matches with the central bank's in-house ranking, which confirms that there is a possibility of drawing similar contours of 'too connected to fail' and 'too big to fail' phenomena using open-source data. The study also allows future researchers to expand the systemic risk literature in this dimension.

Among existing studies, this study is linked to Gulati et al. (2019) and Khan and Ahmad (2022) in seeking the answers to default risk in Indian banks as the network analysis traces the systemic risk possibilities. The present research also extends Verma et al. (2019), who investigated systemic risk measurement by incorporating distressed firms. The findings herein also broaden the scope of investigating the banking sector from default, market competition, and regulatory perspectives. In the future, studies may examine the riskiness of the banking sector using financial market sentiment and bank-level communication efforts from a macroprudential perspective. This study offers new insights into banks' bank-firm dependence structure and systemic risk analysis in emerging markets.

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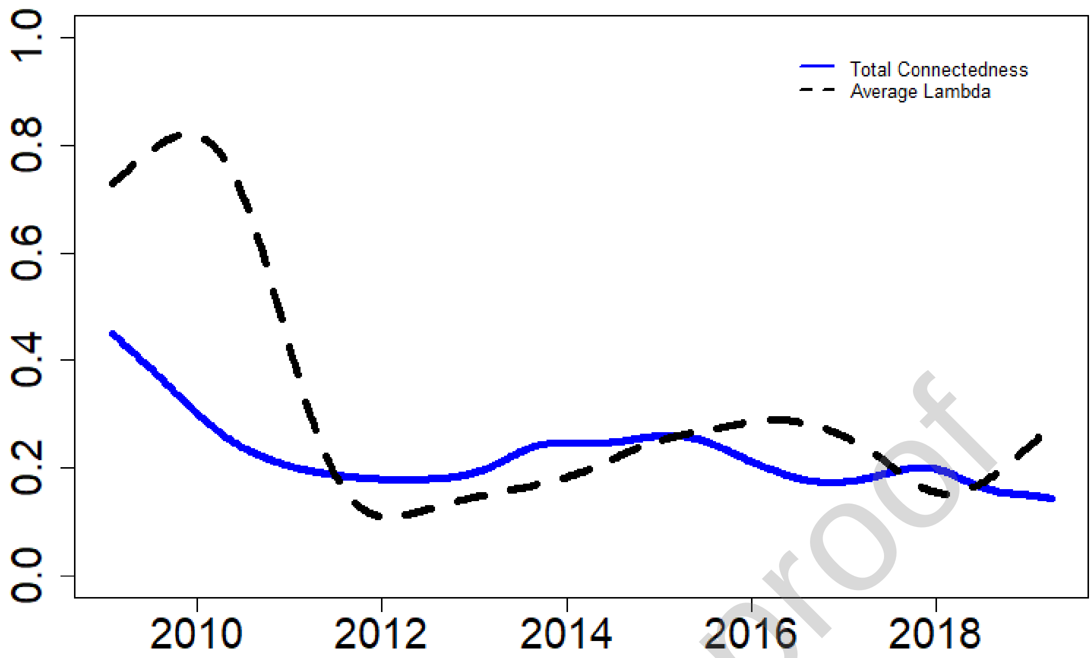
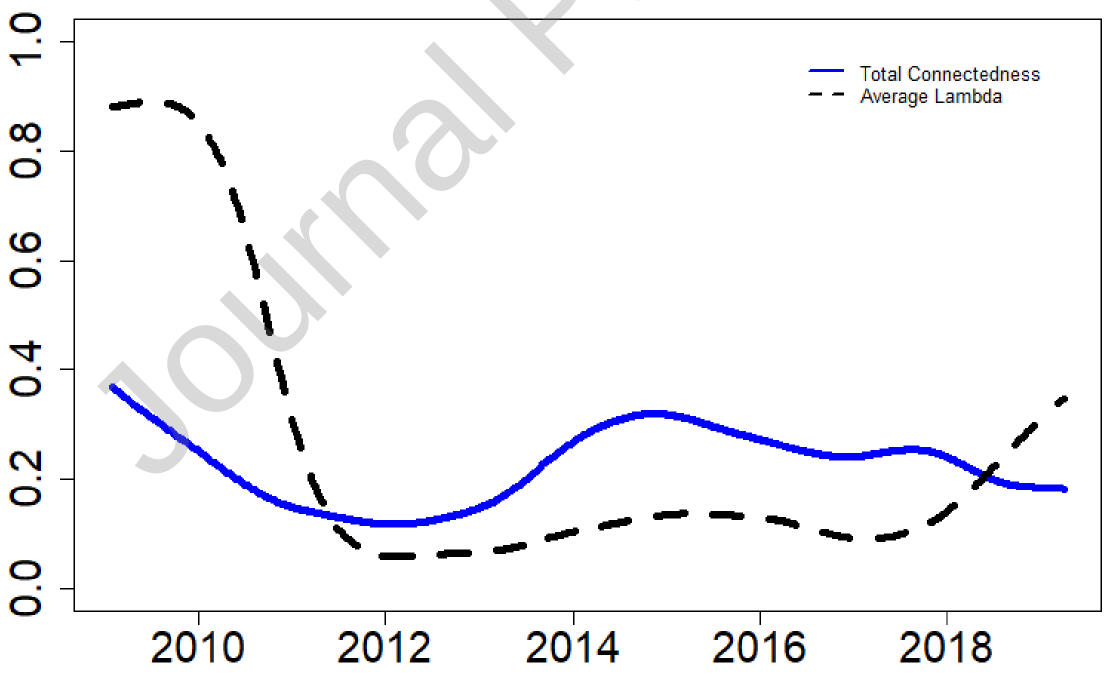
Figure 1: Total connectedness and Lambda
Panel A



Note: The below plot shows the total connectedness and average Lambda (λ) values of 34 Indian banks and 21 DDFs at 5% quantile. The rolling window is 52 weeks with a total observation of 631.

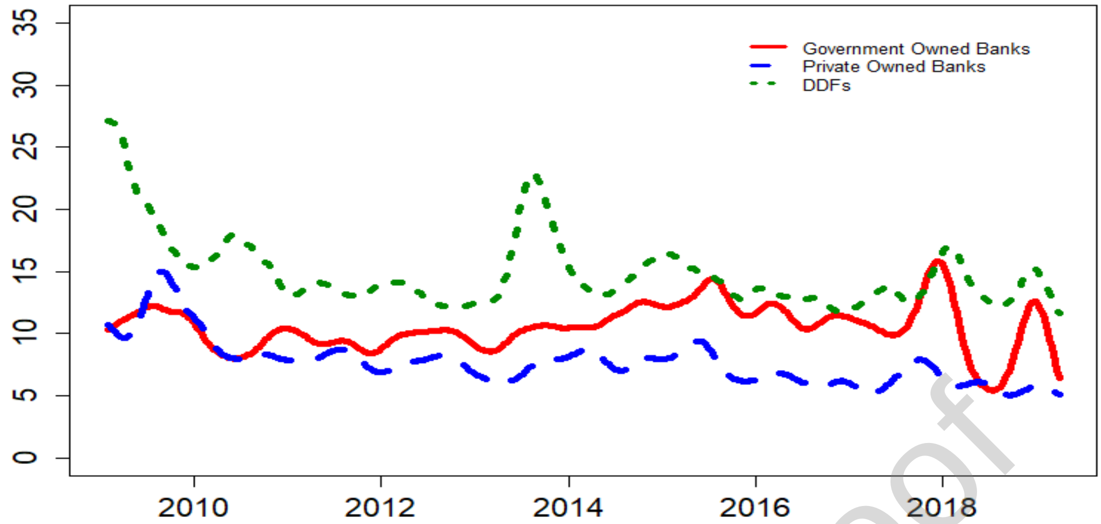
Panel B



Note: The below plot shows the total connectedness and average Lambda (λ) values of 34 Indian banks and 21 DDFs at 1% quantile. The rolling window is 52 weeks with a total observation of 631.

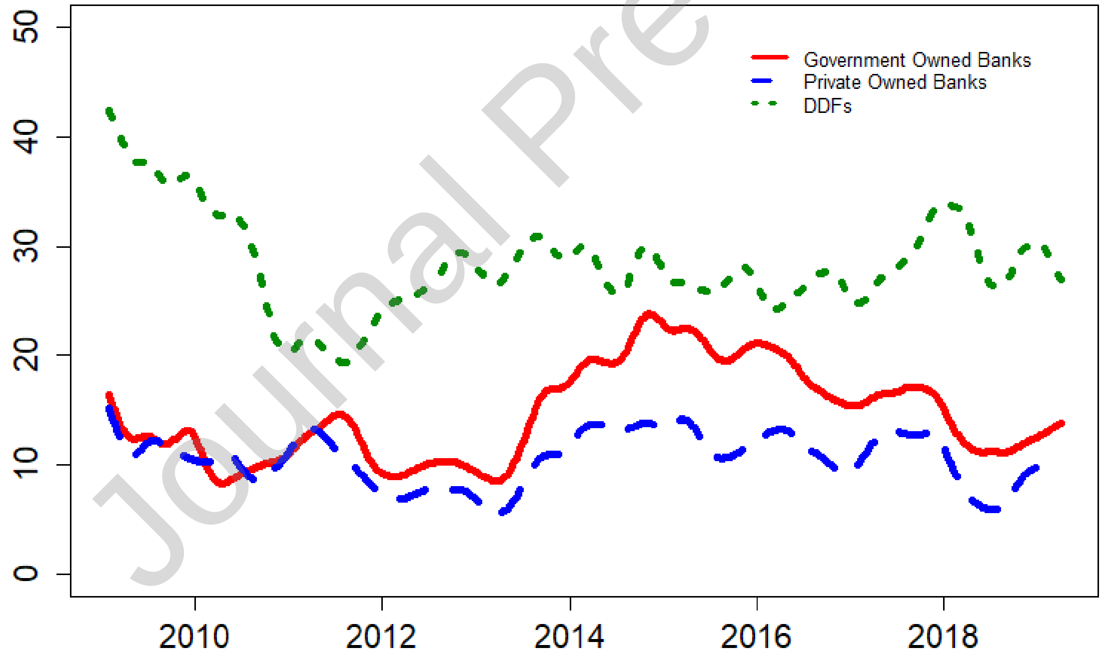
Figure 2: TENET in sample banks and DDFs (Incoming links)

Panel A



Note: Incoming links at 5% quantile for three groups: government owned banks, private owned banks and DDFs. The rolling window size is 52 weeks with a total observation of 631.

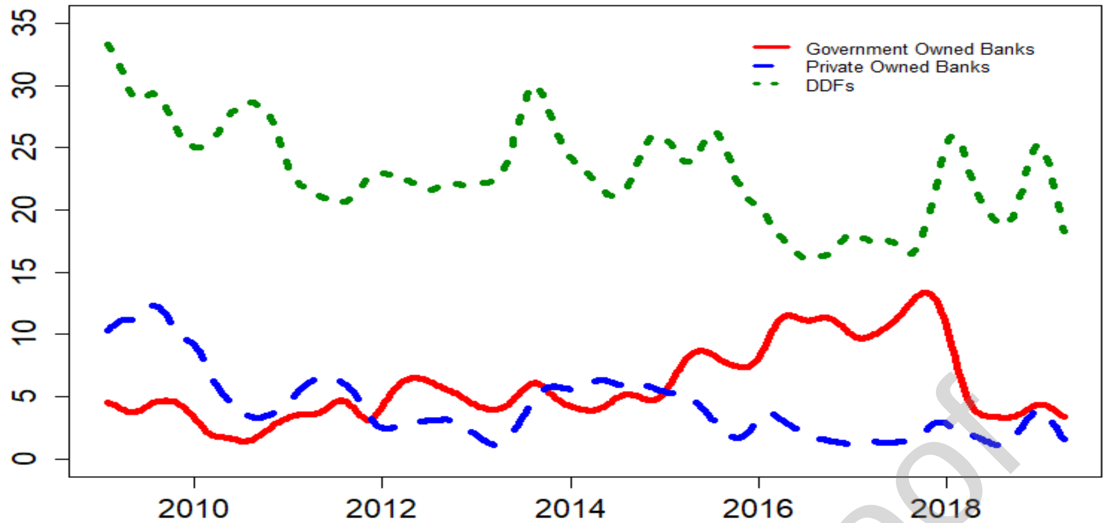
Panel B



Note: Incoming links at 1% quantile for three groups: government owned banks, private owned banks and DDFs. The rolling window size is 52 weeks with a total observation of 631.

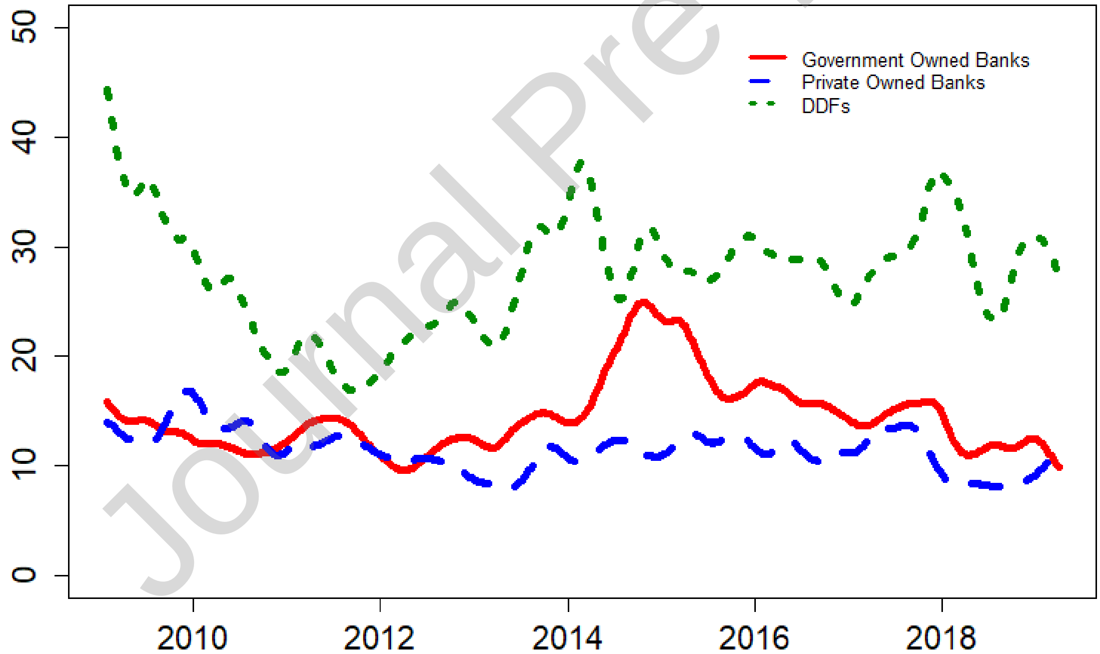
Figure 3: TENET in sample banks and DDFs (Outgoing links)

Panel A:



Note: Incoming links at 5% quantile for three groups: government owned banks, private owned banks and DDFs. The rolling window size is 52 weeks with a total observation of 631.

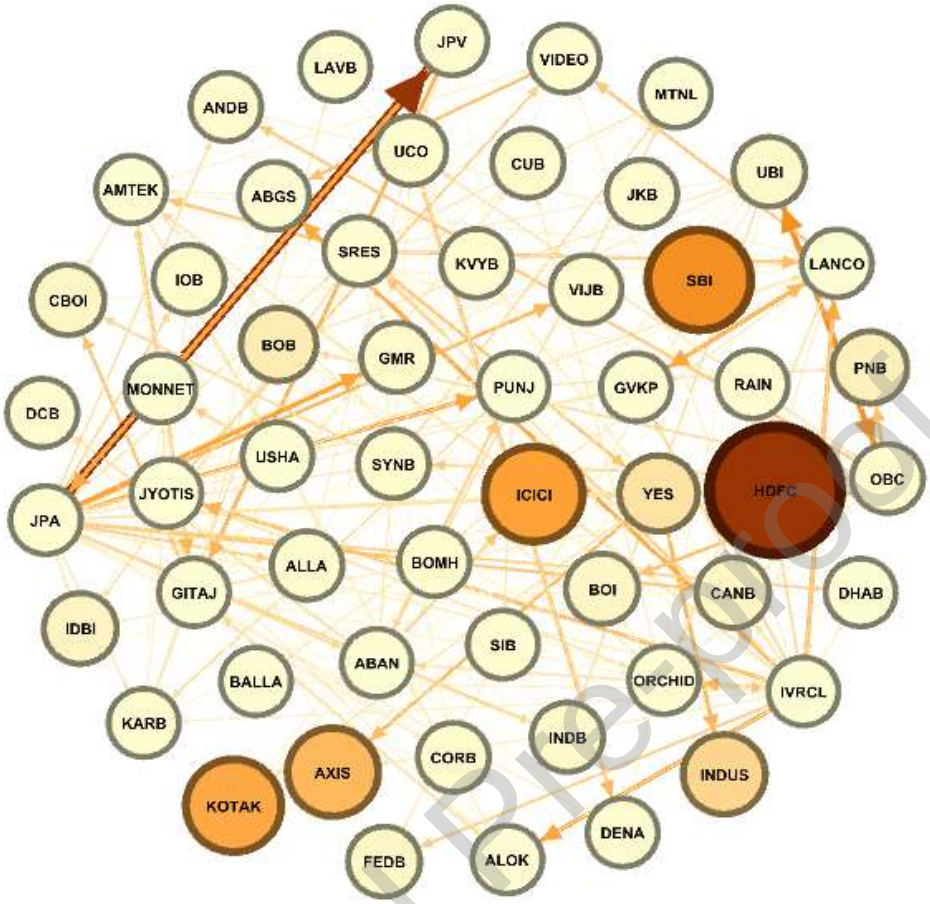
Panel B:



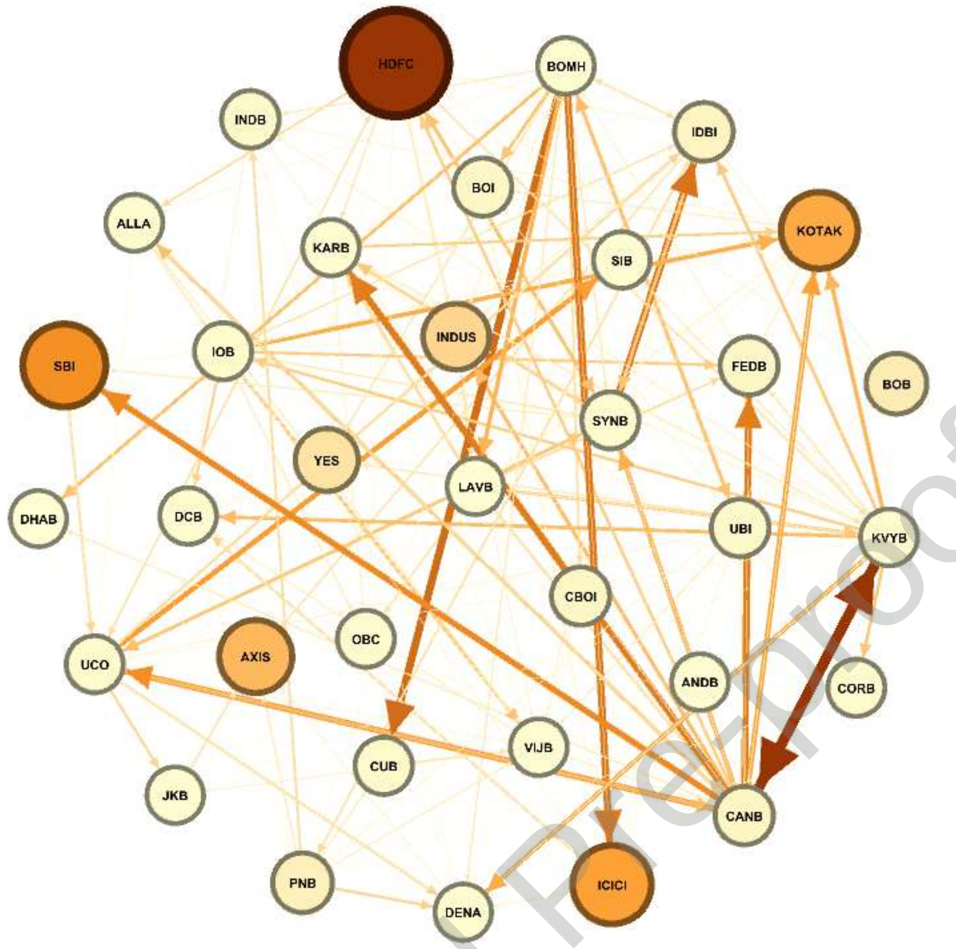
Note: Incoming links at 1% quantile for three groups: government owned banks, private owned banks and DDFs. The rolling window size is 52 weeks with a total observation of 631.

Figure 4: Different networks at 0.05 quantile

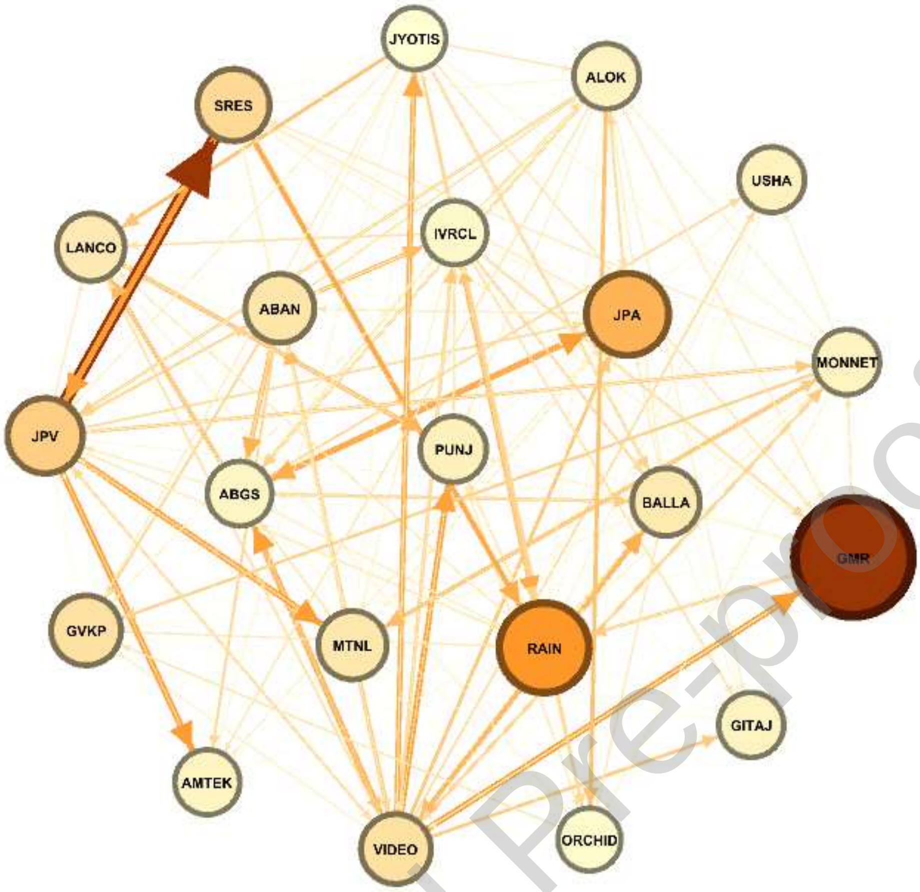
Panel A: Overall connectedness (networks)



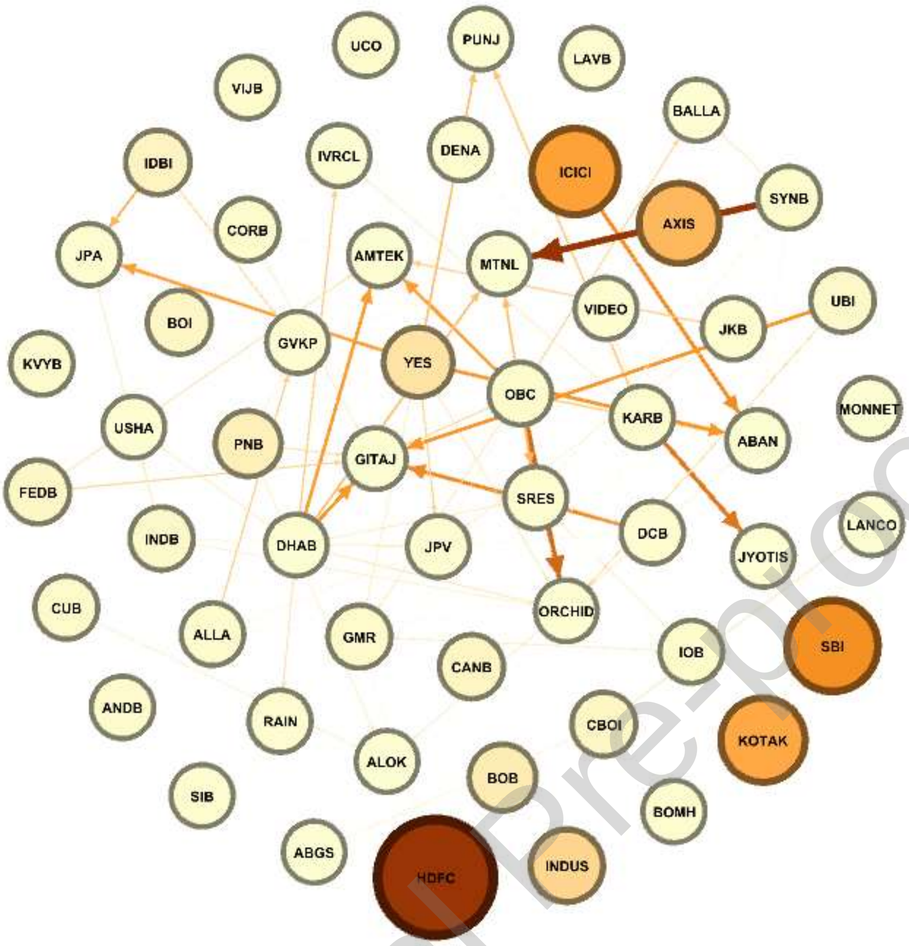
Panel B: Interbank connectedness (networks)



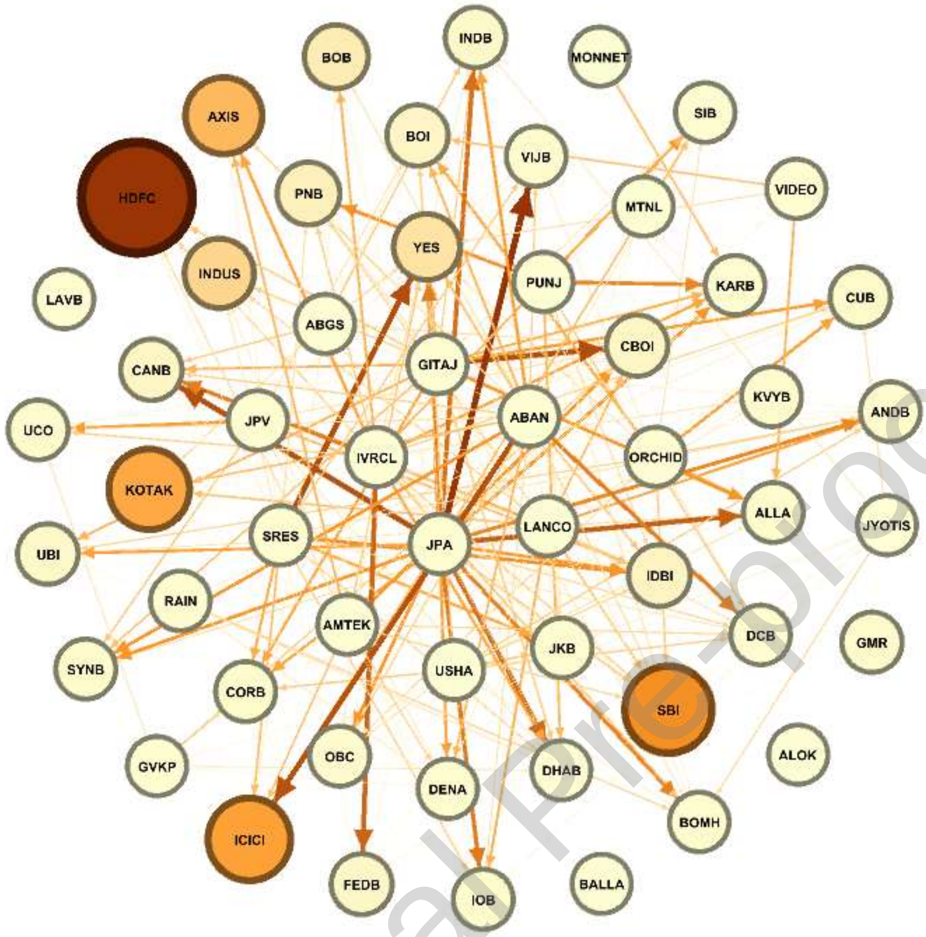
Panel C: Interfirm connectedness (networks)



Panel D: Pairwise Connectedness (network) from banks to DDFs


UCO
PUNJ
LAVB
VIJB
BALLA
IDBI
IVRCL
DENA
ICICI
SYNB
AXIS
CORB
JPA
AMTEK
MTNL
UBI
BOI
GVKP
VIDEO
JKB
KVYB
YES
OBC
MONNET
USHA
PNB
KARB
ABAN
GITAJ
FEDB
SRES
LANCO
INDB
DHAB
JPV
DCB
JYOTIS
CUB
ALLA
ORCHID
GMR
IOB
SBI
CANB
ANDB
RAIN
CBOI
KOTAK
ALOK
SIB
BOB
BOMH
ABGS
HDFC
INDUS

Panel E: Pairwise Connectedness (network) from DDFs to banks



Note: The size of the node shows the strongest connectedness. Larger the size of the node, highest is the value of pairwise connectedness among sample banks and DDFs. The dark yellow colour shows the strongest pairwise connection followed by yellow (moderate) and faded yellow as the weakest. Similarly, the colour scheme of the edge is as follows: yellow colour (strongest) followed by faded yellow (weakest). The rolling window estimation has a size of 100 weeks.

Graphical abstract

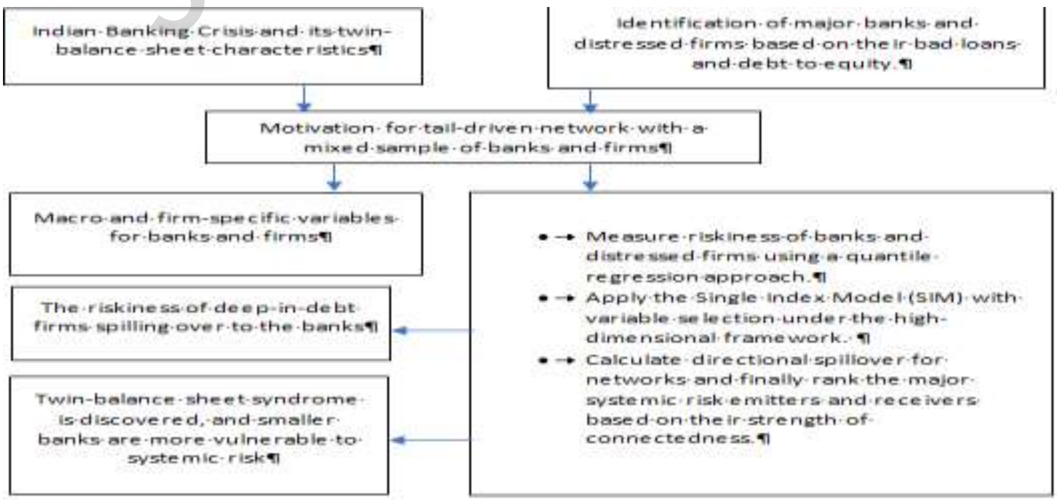


Table 1: Descriptive statistics of banks

Banks	Abbr.	Mean	Min	Max.	Std. Dev.	Kurtosis	Skewness	Count
Government Banks (19)								
Allahabad Bank	ALLA	-0.0549	-25.2894	28.9085	6.1694	1.8321	-0.0587	631
Andhra Bank	ANDB	-0.1619	-25.5458	26.9068	5.7430	2.4292	0.0122	631
Bank Of Baroda	BOB	0.1752	-21.6827	25.6891	5.7737	1.9028	0.0630	631
Bank Of Maharashtra	BOMH	-0.1652	-21.6379	34.4968	5.0194	5.0884	0.7793	631
Canara Bank	CANB	0.0566	-20.9384	28.9362	6.2402	2.1351	0.2989	631
City Union Bank	CUB	0.4767	-30.0951	49.0370	5.6179	14.1758	1.2693	631
Corporation Bank	CORB	-0.1022	-18.4117	29.6590	5.1953	3.2745	0.7375	631
Oriental Bank of Commerce	OBC	-0.0855	-24.8461	22.6218	6.7186	0.9381	-0.0301	631
Punjab National Bank	PNB	0.0149	-25.1382	41.7327	6.0489	4.7358	0.4199	631
State Bank of India	SBI	0.1850	-19.7759	27.6583	5.3262	2.4788	0.4633	631
UCO Bank	UCO	-0.0220	-24.5467	32.6623	6.1700	2.2385	0.1387	631
Vijaya Bank	VIJB	0.0098	-21.3754	32.1766	5.6903	3.2156	0.4377	631
Syndicate Bank	SYNB	-0.0719	-23.1753	21.2349	6.1390	1.4449	-0.2354	631
Union Bank of India	UBI	-0.0058	-27.1373	33.3144	6.6081	2.0749	0.1958	631
IDBI Bank	IDBI	-0.0981	-25.0013	35.8634	6.3954	2.8279	0.1335	631
Indian Overseas Bank	IOB	-0.3140	-27.6874	24.4923	5.7405	2.4358	-0.1039	631
Central Bank of India	CBOI	-0.1728	-25.7158	30.6803	6.2022	3.2279	-0.0955	631
Bank of India	BOI	-0.0654	-28.1336	29.5422	6.7743	2.2329	0.0642	631
Indian Bank	INDB	0.1553	-31.1273	26.0823	6.5662	2.2345	0.2387	631
Private Banks (15)								
Axis Bank	AXIS	0.3279	-23.9728	23.0258	5.5368	1.4827	-0.2995	631
DCB Bank	DCB	0.1765	-36.1325	36.9588	6.7900	4.0683	-0.1687	631
Dena Bank	DENA	-0.1565	-24.3488	30.7640	6.1230	2.3802	0.0995	631
Federal Bank	FEDB	0.2730	-19.1146	16.9460	5.0211	0.7675	0.0606	631
South Indian Bank	SIB	0.1320	-21.7606	32.3109	5.2130	3.6196	0.4022	631
HDFC Bank	HDFC	0.3951	-19.6888	17.6650	3.8763	3.3592	-0.2667	631
ICICI Bank	ICICI	0.1406	-32.7172	25.6620	5.8060	3.6305	-0.3050	631
IndusInd Bank	INDB	0.1553	-31.1273	26.0823	6.5662	2.2345	0.2387	631
Jammu & Kashmir Bank	JKB	-0.0261	-25.1814	27.0031	5.4155	3.6303	0.2004	631
Karnataka Bank	KARB	0.0037	-27.8069	44.0991	5.8598	5.6546	0.3264	631
Lakshmi Vilas Bank	LAVB	0.0825	-24.5433	19.6216	5.2530	1.4915	0.1527	631
Yes Bank	YES	0.3509	-49.1503	27.7870	7.1112	6.1979	-0.7769	631
Dhanalaxmi Bank	DHAB	-0.1435	-30.2558	42.2463	6.9705	4.1785	0.8076	631
Kotak Mahindra Bank	KOTAK	0.3960	-36.9158	24.1269	5.5233	5.9844	-0.6285	631
Karur Vysya Bank	KVYB	0.1616	-21.7627	18.4000	4.0879	3.1986	0.4154	631

Note: The study uses weekly data of 19 government owned and 15 privately owned banks. The sample period is March 2, 2007, to March 31, 2019. This tables lists the banks considered in the study with their abbreviations and the descriptive statistics of their returns over the sample period.

Table 2: Descriptive statistics of Deep in Debt Firms (DDFs)

Firms	Abbr.	Mean	Min.	Max.	Std. Dev.	Kurtosis	Skewness	Obs.
Lanco Infratech	LANCO	-0.6454	-52.4524	58.7464	10.2734	5.1530	0.3842	631
Alok Industries	ALOK	-0.3888	-34.4329	36.7725	8.3034	2.9927	0.4399	631
Gitanjali Gems Limited	GITAJ	-0.8599	-76.2418	42.6574	9.7978	8.6077	-0.8657	631
GVK Power & Infrastructure	GVK	-0.2298	-41.3465	50.5144	8.1958	4.6363	0.5780	631
Jaiprakash Associates	JPA	-0.4194	-42.2683	40.1510	9.2637	2.0621	0.0085	631
Jaiprakash Power Ventures	JPV	-0.4439	-26.8108	44.1833	8.4234	3.9635	0.8050	631
MTNL	MTNL	-0.3880	-28.9671	44.8845	6.8654	5.2498	0.7894	631
IVRCL	IVRCL	-0.8407	-57.2773	49.0155	9.6395	4.5178	0.2305	631
Shree Renuka Sugars	SRES	-0.0503	-45.9290	44.7217	7.8832	4.9100	0.0989	631
Punj Lloyd Limited	PUNJ	-0.6927	-47.8036	32.2114	8.1154	2.9296	-0.3860	631
Videocon Industries	VIDEO	-0.8017	-74.4295	30.4116	7.6419	16.6816	-1.3980	631
Orchid Chemicals & Pharma	ORCHID	-0.6107	-57.8140	33.6136	8.5525	5.1319	-0.3597	631
ABG Shipyard Limited	ABGS	-0.8279	-39.3344	36.2735	8.3834	3.8370	0.2525	631
Ballarpur Industries	BALLA	-0.3214	-25.4441	44.6838	6.2969	5.9004	0.9074	631
Usha Martin Limited	USHA	0.0060	-48.1808	33.8190	8.2355	3.9873	0.1463	631
Aban Offshore Limited	ABAN	-0.5530	-45.0558	31.7338	8.1428	3.5958	0.0051	631
Rain Industries Limited	RAIN	0.1877	-22.9141	34.4994	7.4688	2.2041	0.5540	631
GMR Infrastructure	GMR	-0.1009	-33.5055	39.6786	7.0860	3.3096	0.3326	631
Amtek Group	AMTEK	-0.7841	-84.7298	35.8655	8.6580	17.3455	-1.5568	631
Monet Ispat Limited	MONNET	-0.5124	-73.4008	43.3620	8.5619	15.3010	-1.1574	631
Jyoti Structures Limited	JYOTIS	-0.7093	-42.3233	37.1509	9.0287	2.5422	0.2919	631

Note: The study uses weekly data of 21 deep-in-debt firms. The sample period is March 2, 2007, to March 31, 2019. This tables lists the DDFs considered in the study with their abbreviations and the descriptive statistics of their returns over the sample period.

Table 3: Total directional connectedness (to)

Panel A: Banks

Rank	Banks	To All	Rank of MC (Value)
1	OBC	789.30	21 (71362315)
2	YES	566.02	7(549908741)
3	UBI	445.30	15(114995803)
4	SYNB	363.36	20(73019489)
5	KARB	301.08	31(30567942)
6	UCO	271.05	22(63732704)
7	DCB	242.70	27(43109893)
8	DHAB	213.29	34(4999061)
9	ALLA	208.55	24(60379030)
10	DENA	172.69	32(29794082)

Panel B: DDFs

Rank	Firms	To All	Rank of MC (Value)
1	JPA	1570.31	3(34346293)
2	IVRCL	1351.99	19(3762847)
3	ABAN	920.48	8(12131083)
4	GITAJ	872.24	16(5753138)

5	LANCO	863.11	10(10104661)
6	SRES	787.61	5(17634908)
7	AMTEK	714.88	17(5520409)
8	USHA	628.18	13(6750030)
9	ORCHID	601.79	20(2395711)
10	JYOTIS	564.83	21(1192757)

Note: Top 10 banks (Panel A) and DDFs (Panel B) ranked according to outgoing links calculated by the sum of absolute value of the partial derivatives. The rank of market capitalization (MC) is also shown. The estimation quantile level is 5%, window size 52 weeks and total observations are 631.

Table 4: Total directional connectedness (from)

Panel A: Banks

Rank	Banks	From All	Rank of MC (Value)
1	YES	399.05	7 (549908741)
2	BOI	371.18	13 (162023633)
3	UBI	370.84	15 (114995803)
4	PNB	354.64	9 (291173259)
5	DENA	354.28	32 (29794082)
6	OBC	352.75	21 (71362315)
7	INDB	336.32	16 (109074234)
8	ALLA	335.90	24 (60379030)
9	SYNB	335.83	20 (73019489)
10	UCO	334.64	22 (63732704)

Panel B: DDFs

Rank	Firms	From All	Rank of MC (Value)
1	GITAJ	611.14	16 (5753138)
2	LANCO	483.92	10 (10104661)
3	GVKP	434.99	6 (13912844)
4	JPA	434.77	3 (34346293)
5	ABAN	431.02	8 (12131083)
6	JPV	430.55	4 (22665976)
7	ORCHID	427.28	20 (2395711)
8	AMTEK	419.93	17 (5520409)
9	IVRCL	418.35	19 (3762847)
10	ABGS	370.01	18 (4972477)

Note: Top 10 banks (Panel A) and DDFs (Panel B) ranked according to incoming links calculated by the sum of absolute value of the partial derivatives. The rank of market capitalization (MC) is also shown. The estimation quantile level is 5%, window size 52 weeks and total observations are 631.

Table 5: Total pairwise directional connectedness

Panel A: Between Banks				Panel B: Between DDFs			
Rank	**From**	**To**	**Connect**	**Rank**	**From**	**To**	**Connect**
1	UBI	OBC	98.55	1	JPA	JPV	163.48
2	OBC	UBI	97.80	2	JPA	GMR	82.73
3	YES	INDUS	71.72	3	JPA	PUNJ	81.81
4	UCO	DENA	68.69	4	IVRCL	ALOK	81.77
5	YES	AXIS	66.55	5	LANCO	GVKP	81.50
6	OBC	PNB	63.91	6	IVRCL	LANCO	79.75
7	OBC	BOI	63.82	7	JPV	JPA	79.74
8	OBC	ANDB	58.07	8	IVRCL	ABGS	79.02
9	OBC	SYNB	55.97	9	IVRCL	JYOTIS	72.43
10	SYNB	CBOI	48.62	10	AMTEK	GITAJ	71.97

Panel C: Banks to DDFs				Panel D: DDFs to Banks			
Rank	**From**	**To**	**Connect**	**Rank**	**From**	**To**	**Connect**
1	SYNB	MTNL	43.15	1	JPA	VIJB	69.67
2	OBC	ORCHID	32.85	2	GITAJ	CBOI	61.02
3	KARB	JYOTIS	30.22	3	SRES	YES	60.85
4	DCB	GITAJ	26.86	4	JPA	CANB	60.39
5	ICICI	ABAN	26.30	5	ABAN	ICICI	60.03
6	YES	ABAN	24.84	6	JPA	ALLA	54.66
7	UBI	GITAJ	24.67	7	IVRCL	FEDB	53.61
8	DHAB	GITAJ	24.13	8	JPA	DHAB	51.28
9	DHAB	AMTEK	23.61	9	JPA	INDB	49.99
10	OBC	AMTEK	23.34	10	JPA	IOB	46.77

Note: This table lists the most connected pairs in the respective category. The ranks are decided based on the absolute value of partial derivatives. ("To plus From") estimated at the quantile of 5%. Panel A lists the top 10 pairwise directional spillover from one bank to another while Panel B does the same for DDFs. Panel C and Panel D list the top 10 connections from banks to DDFs and from DDFs to banks respectively. The window size is 52 weeks and total observations are 631.

Table 6: The top 10 Systemic Risk Emitter (SRE) and Prime Risk Emitter (PRE)

Panel A: Banks

Rank	Banks	SRE Values	Rank of MC (Value)
1	YES	2.5E+20	7 (549908740)
2	ICICI	9.3E+19	3 (1837710409)
3	AXIS	6.9E+19	5 (1374162823)
4	KOTAK	4.7E+19	4 (1682493460)
5	BOB	3.5E+19	8 (363119608)
6	SBI	1.5E+19	2 (2186778532)
7	OBC	1.0E+19	21 (71362315)
8	UBI	1.0E+19	15 (114995803)
9	INDUS	1.0E+19	6 (809697385)
10	CANB	9.7E+18	11 (174345197)

Panel B: DDFs

Rank	Firms	SRE Values	Rank of MC (Value)
1	JPA	8.02E+18	3 (34346292)
2	ABAN	3.64E+18	8 (12131083)
3	SRES	3.29E+18	5 (17634907)
4	LANCO	1.71E+18	10 (10104661)
5	AMTEK	1.32E+18	17 (5520409)
6	RAIN	1.18E+18	2 (46782320)
7	GITAJ	1.17E+18	16 (5753137)
8	IVRCL	9.84E+17	19 (3762847)
9	GMR	7.69E+17	1 (92041237)
10	JPV	7.53E+17	4 (22665976)

Note: The table provides the ranking of top 10 SREs and PREs among sample banks and DDFs. The rank of market capitalization (MC) is also shown.

Table 7: The top 10 Systemic Risk Receivers (SRRs) and Prime Risk Receivers (PRRs)

Panel A: Banks

Rank	Banks	SRR Values	Rank of MC (Value)
1	HDFC	1.87E+20	1 (4035547105)
2	AXIS	8.35E+19	5 (1374162823)
3	ICICI	5.75E+19	3 (1837710409)
4	KOTAK	5.72E+19	4 (1682493460)
5	YES	4.88E+19	7 (549908740)
6	SBI	4.56E+19	2 (2186778532)
7	INDUS	3.56E+19	6 (809697385)
8	PNB	2.15E+19	9 (291173259)
9	BOB	1.65E+19	8 (363119608)
10	BOI	1.02E+19	13 (162023633)

Panel B: DDFs

Rank	Firms	SRR Values	Rank of MC (Value)
1	GMR	3.5E+18	1 (92041237)
2	JPA	1.19E+18	3 (34346292)
3	ABAN	9.44E+17	8 (12131083)
4	JPV	4.54E+17	4 (22665976)
5	GVKP	4.29E+17	6 (13912843)
6	RAIN	4.12E+17	2 (46782320)
7	SRES	3.29E+17	5 (17634907)
8	LANCO	2.26E+17	10 (10104661)
9	GITAJ	2.23E+17	16 (5753137)
10	PUNJ	1.76E+17	12 (7356105)

Note: The table provides the ranking of top 10 SRRs and PRRs among sample banks and DDFs. The rank of market capitalization (MC) is also shown.

CRediT authorship contribution statement

All authors have equally contributed to this paper

Declaration of competing interest

None.

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Highlights

- Examines the twin-balance sheet syndrome for the Indian banking sector upheaval.
- The tail-driven network model explains the high interconnectedness during the banking sector shock.
- The systemic risk and financial vulnerabilities are analyzed and discussed.