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Analysing the systemic risk of Indian banks

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HIGHLIGHTS

- Systemic risk analysis of Indian banks using interbank connectedness has been proposed.
- The connectedness intensifies during a downturn.
- The model helps identify major systemic risk receivers and emitters.

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ABSTRACT

This paper adopts the Tail-Event driven NETwork (TENET) risk model to assess the systemic risk of Indian banks. Building upon the Value at Risk (VaR), Conditional Value at Risk (CoVaR) and a Single Index Model (SIM) in a generalized quantile regression framework, the results suggest that the Indian banks exhibit high interconnectedness during the crisis period. The results also identify the systemically important banks and explain the banking networks.

1. Introduction

The spread of unprecedented risk in the Indian banking system has garnered enormous attention about its riskiness and spillover. The genesis of this crisis is often linked with the mid-2000s investment boom when the Indian government had announced major infrastructure investment plan in power generation, steel, and telecom sectors, majorly financed by banks. Economic Survey (2016–2017) links the banking crisis with the Twin Balance Sheet (hereafter TBS) syndrome that shows the risk spillover from debt-ridden firms to banks. The Asset Quality Review (AQR) conducted by the Reserve Bank of India (hereafter, RBI) further exacerbated the crisis risk, leading to the consolidation and recapitalization of the riskier banks. The banking crisis has recently gained growing consensus among regulators and academia to examine it from the perspectives of risk spillover and systemic risk.

In this study, we aim to measure the strength of interconnectedness among government and privately owned banks to understand the riskiness of the Indian banking system. We adopt the Tail-Event-Driven Networks (TENET) risk given by Härdle et al. (2016). We explore the methodology for two reasons: firstly, it helps to calculate the riskiness of Indian banking system under an ultra high-dimensional set-up which allows incorporating not only the macroeconomic variables but also the balance sheet variables in systemic risk analysis. Secondly, the magnitude of directional connectedness helps us identify the major systemic risk receiver (SRR) and systemic risk emitter (SRE) banks. By taking into account the second week of February 2016 (also known as February Fiasco) as an anecdotal event when the Indian stock market fell by more than 6% on the back of the huge losses reported by Indian banks.

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Table 1
Descriptive statistics of Indian banks.

Banks	Abbr.	Mean	Max.	Min.	Std. Dev.	Kurtosis	Skewness	Obs.
Government Banks (18)								
Allahabad Bank	ALLA	−0.0003	0.2891	−0.2529	0.0613	2.0796	−0.1030	534
Andhra Bank	ANDB	−0.0008	0.2691	−0.2555	0.0575	2.6483	−0.0853	534
Bank Of Baroda	BOB	0.0024	0.2141	−0.2168	0.0578	1.5482	−0.0404	534
Bank Of Maharashtra	MAHB	−0.0004	0.3450	−0.1551	0.0506	5.1102	0.9561	534
Canara Bank	CNRB	0.0002	0.2593	−0.2009	0.0619	1.7523	0.2259	534
City Union Bank	CUB	0.0047	0.4904	−0.3010	0.0593	13.349	1.2908	534
Corporation Bank	CORP	−0.0005	0.2966	−0.1841	0.0518	3.4480	0.6934	534
Oriental Bank of Commerce	OBC	−0.0009	0.2262	−0.2485	0.0684	0.9536	−0.0653	534
Punjab National Bank	PNB	0.0007	0.2772	−0.2514	0.0575	1.8081	0.1063	534
State Bank of India	SBI	0.0017	0.2766	−0.1978	0.0545	1.9230	0.3272	534
UCO Bank	UCO	0.0009	0.3266	−0.2455	0.0636	2.2695	0.0782	534
Vijaya Bank	VIJB	0.0007	0.3218	−0.2138	0.0573	3.1937	0.4050	534
Syndicate Bank	SYNB	−0.0001	0.2123	−0.2318	0.0606	1.7908	−0.2851	534
Union Bank of India	UBI	0.0004	0.2296	−0.2714	0.0654	1.5135	0.0014	534
IDBI Bank	IDBI	0.0000	0.3586	−0.2500	0.0647	2.7605	0.0596	534
Indian Overseas Bank	IOB	−0.0027	0.2449	−0.2769	0.0597	2.2966	−0.1491	534
Central Bank of India	CBI	0.0001	0.3068	−0.2490	0.0593	3.0750	0.0016	534
Bank of India	BOI	−0.0007	0.2641	−0.2813	0.0671	2.1077	−0.1076	534
Private Banks (13)								
Axis Bank	AXIS	0.0031	0.2303	−0.2397	0.0584	1.1830	−0.2808	534
DCB Bank	DCB	0.0017	0.3696	−0.3613	0.0721	3.5476	−0.1386	534
Dena Bank	DENA	0.0000	0.3076	−0.2435	0.0624	2.4757	0.1205	534
Federal Bank	FEDB	0.0032	0.1695	−0.1911	0.0517	0.6953	0.0421	534
South Indian Bank	SIB	0.0022	0.3231	−0.1799	0.0514	3.9118	0.6358	534
HDFC Bank	HDFC	0.0036	0.1766	−0.1969	0.0416	2.6712	−0.2639	534
ICICI Bank	ICICI	0.0008	0.2566	−0.3272	0.0608	3.3387	−0.3375	534
IndusInd Bank	INDB	0.0061	0.3438	−0.2559	0.0609	3.9474	0.3686	534
Jammu & Kashmir Bank	JKB	0.0002	0.2700	−0.2518	0.0547	3.8846	0.1652	534
Karnataka Bank	KARB	0.0004	0.4410	−0.2781	0.0612	5.4553	0.3595	534
Lakshmi Vilas Bank	LAVB	0.0025	0.1962	−0.2454	0.0521	1.4057	0.1640	534
Yes Bank	YES	0.0045	0.2779	−0.4915	0.0695	6.7093	−0.7017	534
Dhanalaxmi Bank	DHAB	−0.0006	0.2900	−0.3026	0.0706	2.3568	0.4861	534

Notes: The study uses the weekly data of 18 government-owned and 13 privately-owned banks. The banks considered in our study are listed along with their abbreviations and the descriptive statistics for the returns of these banks over the sample period. The sample period: 12 January 2007 to 31 March 2017.

This study is the first one that examines the systemic risk in the Indian context.[1]

The notable studies in the field of systemic risk can be divided into three streams: the first one focuses on factor-based correlations of assets to calculate default probabilities as in Kritzman et al. (2011) and Patro et al. (2013). The second one utilizes tail dependence (Zhou, 2010; Adrian and Brunnermeier, 2016; Acharya et al., 2017) whilst the third stream uses the network models as in Härdle et al. (2016); Wang et al. (2017, 2018a,b) and Demirer et al. (2018). The rest of the paper is organized as follows. In Section 2, we explain the data and TENET model specification. Section 3 discusses the results and application of TENET model. Section 4 concludes.

2. Data and methodology

The study uses the weekly data from 12 January 2007 to 31 March 2017 on 31 Indian Banks, out of which 18 are government-owned banks and 13 are private banks. The banks considered in our study are described in Table 1. The series are retrieved from Thomson DataStream and Reserve Bank of India (RBI). Following Härdle et al. (2016) and Wang et al. (2018a,b), we include the balance sheet variables, which incorporate leverage, size, market to book ratio, debt to maturity, return on assets (ROA). Accounting for liquidity and risk coverage dimension, we consider short-term liquidity spread, immediate period changes in the 90-day treasury bill rate, spread between ten-year and three-month treasury bill rate, credit spread, stock market returns, market volatility, lending rate and weekly equity returns of each sample bank. The sample variables are outlined in online appendix Table (A1).

We adopt a three-step empirical procedure to perform TENET risk (Härdle et al., 2016) of Indian banks. We first calculate the Value at Risk (VaR) and CoVaR (Conditional Value at Risk) of sample banks at 0.01 and 0.05 quantiles to capture the tail event risk and also to compare the results.[2] We first apply the quantile regression of bank *i* on the macro variables to determine the VaR of a bank *i*:

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

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

where, $B_{i,t}$ and $B_{j,t}$ are the log returns of bank *i* at time *t* and bank *j* at time *t*, respectively. M_{t-1} includes the vector of macroeconomic variables. β_i, $\gamma_{j|i}$ and $\beta_{j|i}$ are the slope parameters. $\beta_{j|i}$ shows the extent of sensitivity of a bank *j* to changes in tail event log return of a bank *i*. CoVaR is obtained by plugging in VaR of bank *i* at level τ estimated in Eq. (3) into the Eq. (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 second step involves the adoption of single index model (SIM) under generalized quantile regression to obtain the systemic risk contribution of each bank conditional on its tail interconnectedness with the relevant banks. The step builds the systemic risk

[1] For stock market performance see (https://www.thehindu.com/business/markets/How-the-stock-markets-fared-in-2016/article16949885.ece) and Bank of Baroda (https://indianexpress.com/article/business/banking-and-finance/rs-3342-crore-loss-bob-reports-biggest-loss-in-banking-history/) accessed on 6th December 2018. For TENET analysis, we have identified February 2016.

[2] CoVaR given by Adrian and Brunnermeier (2016) takes into account the spillover effects and the macroeconomic outlook of the economy.

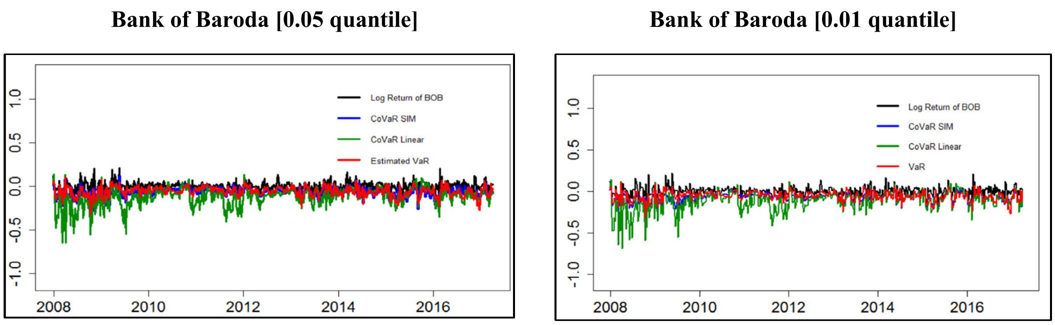

Fig. 1. Riskiness of Bank of Baroda (BOB). Note: This figure shows the log returns of Bank of Baroda (BOB). The conditional risk measures (VaR, CoVaR SIM and CoVaR Linear) of BoB exhibit the clustering effect during 2008–2009, a period marked as global financial crisis period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

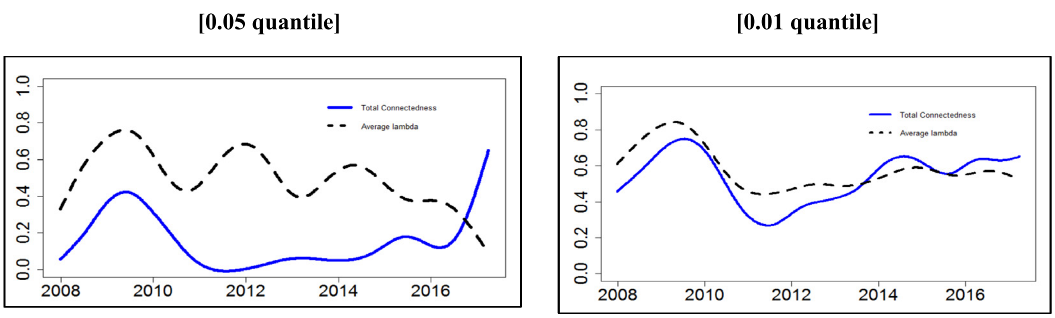

Fig. 2. Total connectedness and Lambda. Note: This figure shows the total connectedness and average Lambda of 31 Indian banks at 0.05 and 0.01 quantiles.

network by applying the directional spill over given by Härdle et al. (2016) as follows:

$$B_{j,t} = f\left(\beta^{\mathrm{T}}_{j|R_j} R_{j,t}\right) + \varepsilon_{j,t} \quad (5)$$

$$\widehat{CoVaR}_{j|\widetilde{R}_j,t,\tau} = \hat{f}\left(\hat{\beta}^{\mathrm{T}}_{j|\widetilde{R}_j} \widetilde{R}_{j,t}\right) \quad (6)$$

$$\hat{D}_{j|\widetilde{R}_j} = \frac{\partial \hat{f}\left(\hat{\beta}^{\mathrm{T}}_{j|R_j} R_{j,t}\right)}{\partial R_{j,t}}\Big|_{R_{j,t}=\widetilde{R}_{j,t}} = \partial \hat{f}\left(\hat{\beta}^{\mathrm{T}}_{j|\widetilde{R}_j} \widetilde{R}_{j,t}\right) \hat{\beta}_{j|\widetilde{R}_j} \quad (7)$$

where $R_{j,t} = \{X_{-jt}, M_{t-1}, S_{j,t-1}\}$ shows the information set which includes k variables. $X_{-jt} = \{X_{1t}, X_{2t}, \ldots, X_{m,t}\}$ are the explanatory variables, which include the returns of all the sample banks except for bank j. m shows the number of banks. $S_{j,t-1}$ is the bank-specific characteristics indicators calculated from their balance sheet. We define the static parameters as $\beta_{j|R_j} = \left\{\beta_{j|-j}, \beta_{j|M}, \beta_{j|S_j}\right\}^{\mathrm{T}}$. For dynamic estimates, a rolling window estimation is used to estimate all coefficients. $\hat{D}_{j|\widetilde{R}_j}$ shows the gradient that measures the marginal effect of covariates evaluated at $R_{j,t} = \widetilde{R}_{j,t}$ and the component-wise expression is $\hat{D}_{j|\widetilde{R}_j} = \left\{\hat{D}_{j|-j}, \hat{D}_{j|M}, \hat{D}_{j|S_j}\right\}^{\mathrm{T}}$. $\hat{D}_{j|-j}$ shows the spillover effects across sample banks. It is noteworthy that the network charts exhibit the partial derivatives of banks j concerning other banks, i.e. $\hat{D}_{j|-j}$ and do not include $\hat{D}_{j|S_j}$ and macroeconomic variables $\hat{D}_{j|M}$.

In the third step, we identify the D-SIBs based on SRR and SRE measures. The SRR for a bank j therefore defined as:

$$SRR_{j,s} = MC_{j,s}\left\{\sum_{i\in k_s^{IN}} (|\widetilde{D}^s_{j|i}|.MC_{i,s})\right\} \quad (8)$$

The SRE for a bank j is defined as

$$SRE_{j,s} = MC_{j,s}\left\{\sum_{i\in k_s^{OUT}} (|\widetilde{D}^s_{i|j}|.MC_{i,s})\right\} \quad (9)$$

where k_s^{IN} and k_s^{OUT} are the set of banks connected with bank j (BOB) by incoming and outgoing networks at window s, respectively. $MC_{i,s}$ represents the market capitalization of bank i at the starting point of window s. $|\widetilde{D}^s_{j|i}|$ and $|\widetilde{D}^s_{i|j}|$ are absolute partial derivatives which represent row (incoming) and column (outgoing) directional connectedness of bank j to i.

3. Results

Fig. 1 shows the estimated VaR (red line) and CoVaR of BOB estimated by applying linear and SIM models (green and blue lines). The two measures (VaRs and CoVaRs) at 0.01 and 0.05 quantiles exhibit high variations during 2008–2009, a period marked as a global financial crisis (GFC, 2008). We observe a similar trend from the plot of total connectedness index and averaged (λ) values (dashed line) which are a penalization parameter (see Fig. 2). We then analyse the connectedness of Indian banks with incoming and outgoing links at 0.05 and 0.01 quantiles shown in Fig. 2 in panels A & B.[3] We divide our sample into two groups: government-owned banks (GOBs) and private-owned banks (POBs). The results indicate that the GOBs appear to be more sensitive during crisis and slowdown phases as compared to POBs. The figures also capture the major crisis events such as the GFC and the periods of the subdued performance of Indian banks as reported by the Financial Stability Report (FSR, December 2015) of RBI. The FSR (2015) revealed the issues of reforms and recapitalization of Indian banks and balance sheet slowdown.[4] The steep rise in the incoming and outgoing links of both the groups exhibit the strong connection, suggesting the possible impact of the post-TBS crisis and the enactment of Insolvency and Bankruptcy Code (IBC, 2016) (see Fig. 3).

3 The detailed results are available upon request.

4 See for details: https://rbi.org.in/Scripts/FsReports.aspx (accessed on 22 April 2018).

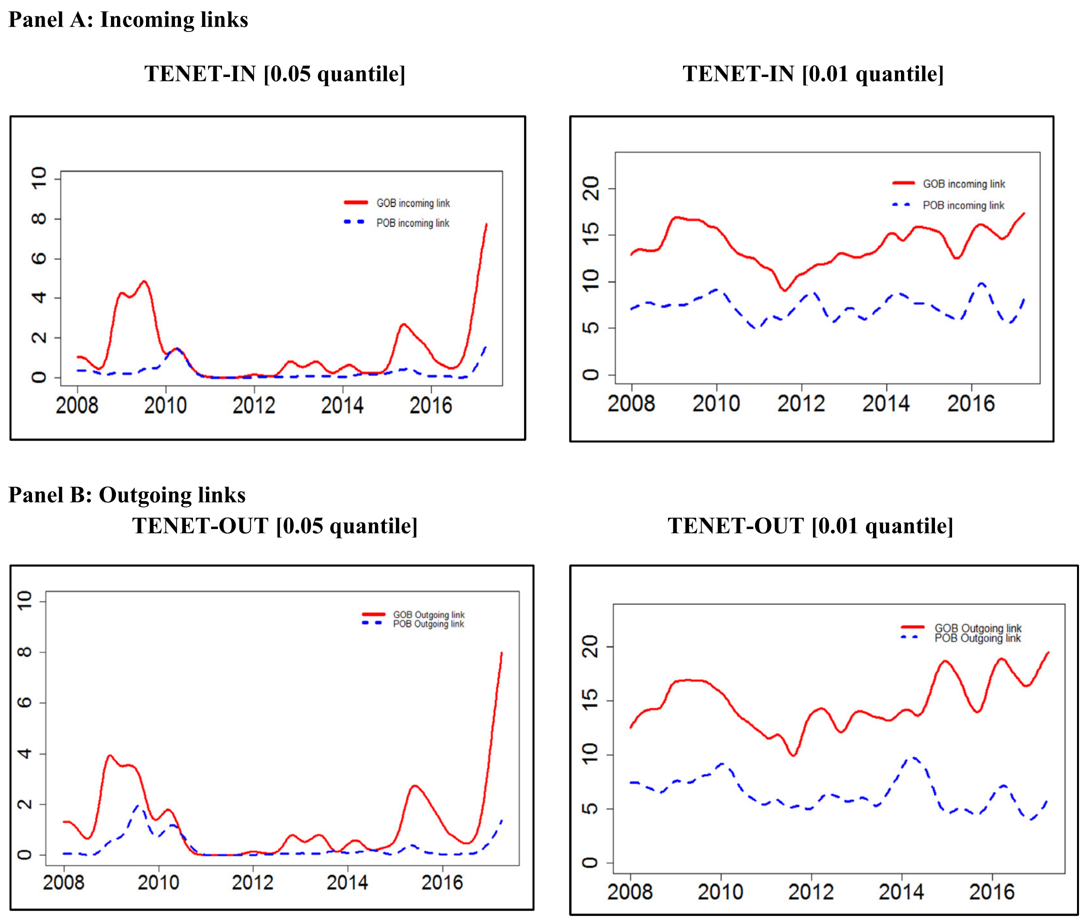

Fig. 3. TENET in Indian Banking Sector (Incoming and Outgoing links). Note: GOB included 18 banks and POB included 13 banks.

Fig. 4 shows the bank level interconnectedness using networks: $DC^s_{j|i} = |\hat{D}^s_{j|i}|$. The node shows the size of the bank represented by market capitalization and edge shows the strength of pairwise connections. We find that at 0.05 quantile, OBC appears to be strongly connected to UBI and ALLA. And at 0.01 quantile, two pairs (ALLA to ANDB) and (OBC to UBI) exhibit a strong interdependence. Overall, we find that OBC appears to be common at both quantiles exhibiting the strong interbank connectedness. It may need further investigation at the micro level. Moreover, mid-size banks seem to have strong bilateral connections than the large banks. GOBs exhibit directional connectedness with POBs. For instance, HDFC, ICICI, AXIS, FEDB and YES banks exhibit limited interdependence except for DCB. We also rank the banks based on the magnitude of outgoing (To) and incoming (From) links shown in online appendix tables (A2 & A3). We find that the most connected bank with the incoming link is UBI followed by IOB and OBC. The most connected bank with the outgoing link is OBC followed by UBI and DCB. These results suggest that the most risk emitting bank seems to be OBC followed by ALLA.

Tables 2 and 3 show the ranking of the top 10 calculated SRRs and SREs at 0.05 and 0.01 quantiles, respectively. At 0.05 quantile, top three SRRs and SREs are SBI, HDFC & CNRB and PNB, YES & AXIS, respectively. At 0.01 quantile, top three SRR and SRE are the same: HDFC, ICICI, and AXIS. The striking finding is that the rankings confirm the RBI's classification of D-SIBs. Since August 2015, RBI has been publishing the list of D-SIBs as part of its Financial Stability Report. As of April 2016, the D-SIBs included SBI, ICICI and HDFC banks.[5] Out of these three, two banks (SBI and HDFC) appeared in our list of SRR rankings. Similarly, at 0.01 quantile, we find HDFC and ICICI as the major SRE banks. Interestingly, smaller banks seem to be riskier than what is often not perceived. The lending pattern of these banks may also provide a deep insight into the riskiness of YES, AXIS, BOB and PNB.

4. Conclusion

We assess the systemic risk of the crisis-ridden Indian banking sector using a novel methodology, which reveals the different facets of inter-bank connectedness. The TENET model helps identify the major risk receiving and emitting banks. We also identify the D-SIBs which agree with the rankings of RBI. We finally recommend the formal adoption of TENET model in systemic risk analysis.

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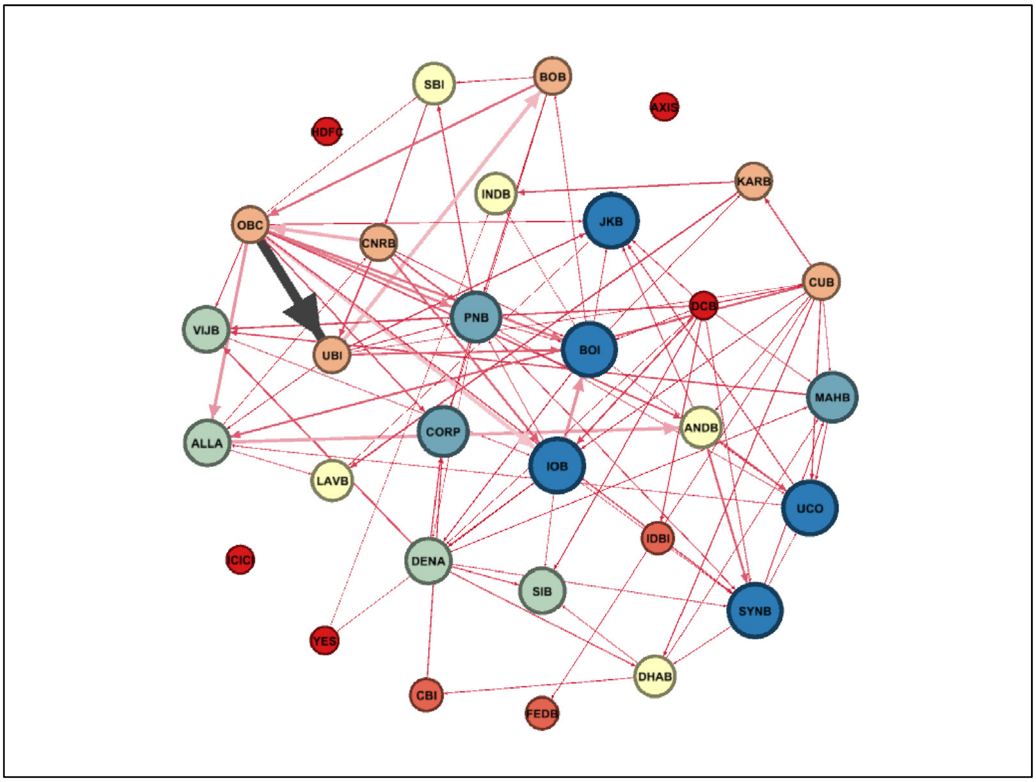
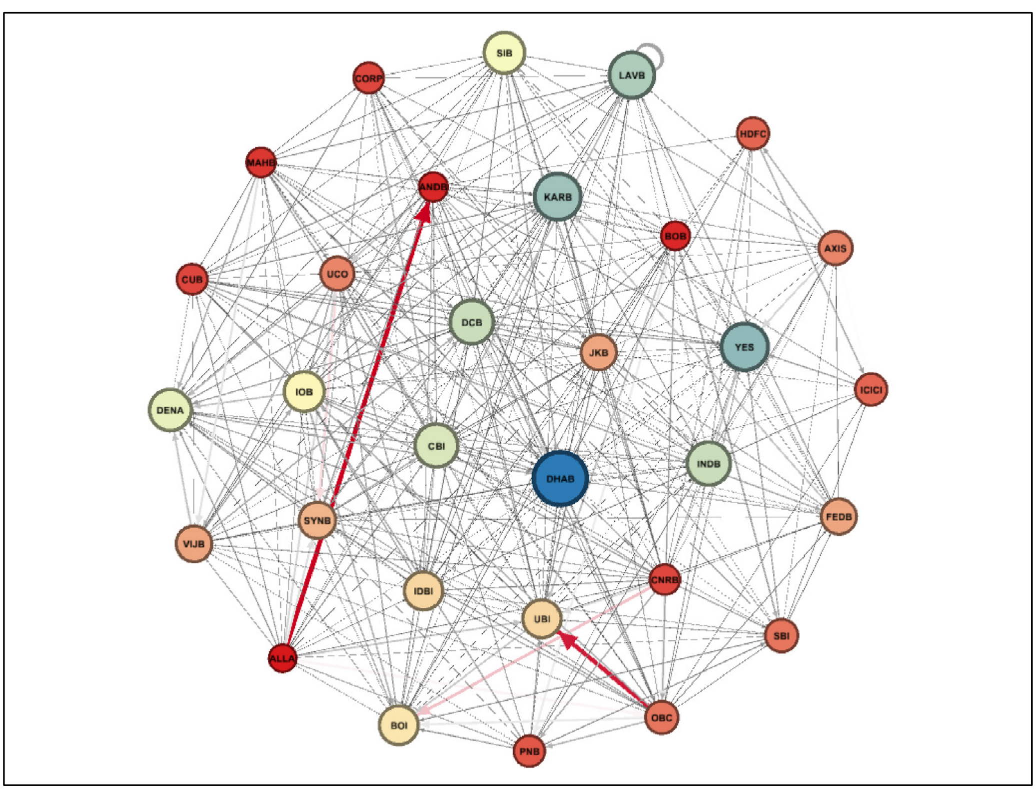
5 For more details, https://rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=41556 (accessed on 24 April 2018).



Quantile 0.05



Quantile 0.01

Fig. 4. The tail-event driven network (TENET) of Indian banks. Note: To exhibit the interbank connectedness, we identify the anecdotal event date as 12 February 2016 when the stock market received the major jolt on the back of huge losses reported by major banks.

Table 2
Systemic Risk Receiver (SRR).

Panel A: 0.05 Quantile				Panel B: 0.01 Quantile			
Rank	Banks	SRR	Rank of MC (Value)	Rank	Banks	SRR	Rank of MC (Value)
1	SBI	1.73E+16	2 (2339426203)	1	HDFC	7.64E+17	1 (3696600324)
2	HDFC	1.51E+16	1 (3696600324)	2	ICICI	7.06E+17	3 (1612506230)
3	CNRB	5.83E+15	10 (180829596)	3	AXIS	5.87E+17	4 (1175483722)
4	BOB	3.99E+15	7 (398504402)	4	SBI	4.63E+17	2 (2339426203)
5	INDB	3.46E+15	5 (852451627)	5	YES	2.50E+17	6 (706069431)
6	PNB	2.65E+15	8 (318982442)	6	INDB	2.38E+17	5 (852451627)
7	AXIS	1.22E+15	4 (1175483722)	7	BOB	1.45E+17	7 (398504402)
8	BOI	1.12E+15	13 (146866293)	8	PNB	5.83E+16	8 (318982442)
9	UBI	9.87E+14	14 (107172070)	9	CNRB	4.20E+16	10 (180829596)
10	IOB	7.94E+14	17 (65418526)	10	BOI	3.17E+16	13 (146866293)

Notes: This table provides the ranking of the top 10 Systemic Risk Receiver (SRR) banks. The size is decided by the magnitude of market capitalization. The list of top 10 Indian banks based on the index of Systemic Risk Receiver (SRR) at 0.05 quantile (Panel A) and 0.01 quantile (Panel B).

Table 3
Systemic Risk Emitter (SRE).

Panel A: 0.05 Quantile				Panel B: 0.01 Quantile			
Rank	Banks	SRE	Rank of MC (Value)	Rank	Banks	SRE	Rank of MC (Value)
1	PNB	1.18E+16	8 (318982442)	1	HDFC	7.59E+17	1 (3696600324)
2	YES	8.94E+15	6 (706069431)	2	ICICI	7.44E+17	3 (1612506230)
3	AXIS	8.85E+15	4 (1175483722)	3	AXIS	5.47E+17	4 (1175483722)
4	BOB	7.94E+15	7 (398504402)	4	SBI	3.40E+17	2 (2339426203)
5	SBI	5.53E+15	2 (2339426203)	5	YES	3.25E+17	6 (706069431)
6	UBI	2.90E+15	14 (107172070)	6	INDB	1.82E+17	5 (852451627)
7	OBC	2.54E+15	22 (48758103)	7	BOB	1.26E+17	7 (398504402)
8	ICICI	2.25E+15	3 (1612506230)	8	PNB	1.04E+17	8 (318982442)
9	BOI	2.04E+15	13 (146866293)	9	CNRB	5.77E+16	10 (180829596)
10	CNRB	1.59E+15	10 (180829596)	10	CBI	4.65E+16	9 (200964362)

This table provides the ranking of the top 10 Systemic Risk Emitter (SRE) banks. The size is decided by the magnitude of market capitalization. The list of top 10 Indian banks based on the index of SRE at 0.05 quantile (Panel A) and 0.01 quantile (Panel B).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2019.01.003.

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