NETWORK ANALYSIS

4.30 The previous FSR underscored the importance of developing strong analytical methods that help better identify, monitor and address systemic linkages. To further study the linkages amongst the scheduled commercial banks, an Integrated Communication Technology (ICT) based network model[7] has been developed to assess the degree of connectedness in the system and to analyse the possible domino impacts of bank failures.

Structural aspects of the Indian interbank market

4.31 For the entire analysis, bilateral data as on December 2010[8] has been used. The total gross value of these exposures amounts to around ₹ 6.9 lakh crore. An analysis of the network of net bilateral exposures reveals that, amongst the banking groups, on the aggregate, the public sector and the old private sector banks are the net lenders in the system while the new private sector and foreign banks are the net borrowers (Charts 4.10 to Chart 4.12).

The Indian banking sector– clustered and connected

4.32 The Indian banking system is found to be substantially connected and clustered. Also, as evident from the central circular formation in chart 4.10, most banks have exposures to banks in all banking groups. The system has a total of 1514 *edges (i.e.,* an aggregate of 1514 *in degrees* and *out degrees),* a cluster coefficient of 42 per cent and connectivity of 27 per cent (Box 4.4).

*Contagion Analysis – A stress test scenario*

4.33 The above mentioned network model of bilateral exposures can be used to model the impact of bank failures. The contagion analysis (Box 4.4) works on the basic principle that all net lenders to a failing bank (trigger bank at the centre of the contagion chart) will get affected in the first round

Chart 4.10: Bipartite Representation of Bank Lending in Four Banking Groups
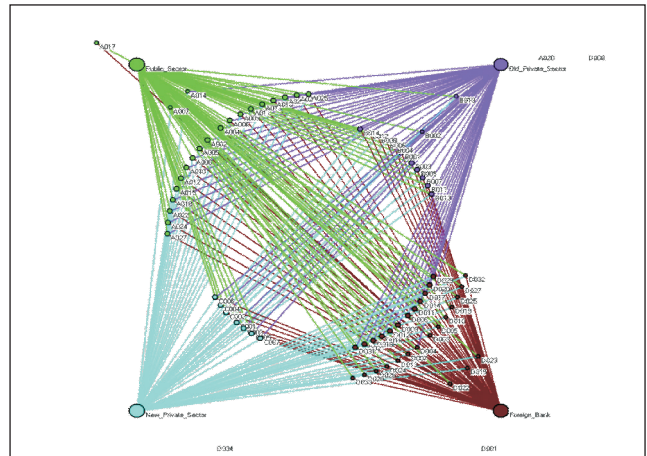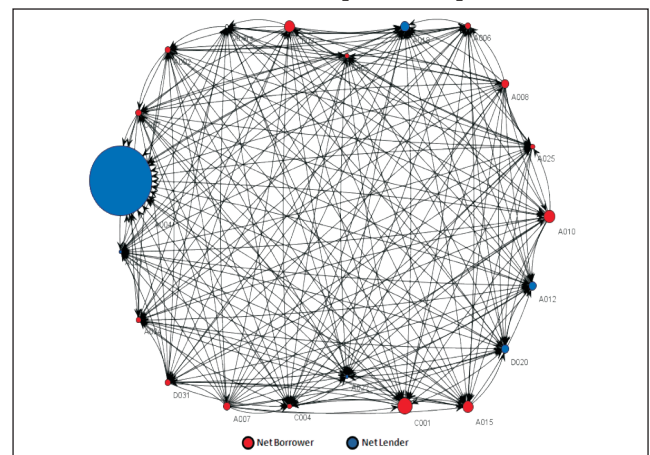

Colour coding: Green (Public Sector Banks); Purple (Old Private Sector Banks) Cyan (New Private Sector Banks); and Brown (Foreign Banks)

Chart 4.11: Net Bilateral Exposures of All Banks[9]
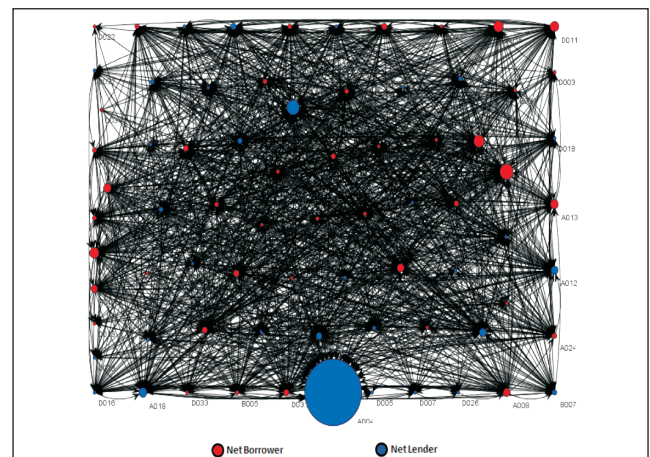
Chart 4.12: Net Bilateral Exposure of Top 20 Banks[10]

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[7] The Network model used in the analysis has been developed by Professor Sheri Markose (University of Essex) and Dr. Simone Giansante (Bath University) in collaboration with the Financial Stability Unit, Reserve Bank of India.

[8] Bilateral data in respect of interbank exposures (both fund based and non fund based) for a sample of 75 scheduled commercial banks.

[9] The size of the node (bank) is rated by the number of in degrees, *i.e.,* net lending.

[10] Top 20 banks are selected based on dominant eigenvalues (Box 4.4).

of contagion. Banks which come under distress[11] from an idiosyncratic event causing the failure of the trigger bank(s) will always have the potential to cause further damage in subsequent rounds of contagion. The contagion eventually ends when the system absorbs all the losses generated (Chart 4.13 and 4.14).

4.34 The impact as the result of failure of top 20 most connected banks, one at a time, and that of the failure of 10 pairs of banks, one pair at a time, are presented in Charts 4.15 to 4.16.

4.35 The above analysis clearly demonstrates the intertwined nature of the banking system in the country and leaves the system vulnerable to domino effects in case of idiosyncratic failure of one or more banks. The impact of such failures, in this model, would depend on how connected the bank is to other banks in the system as also its relationship with other banks (*e.g.* lender or borrower). The above analysis shows that the failure of the most connected bank in the system shaves off nearly 14 per cent of the banking system's core capital. The contagion impact is relatively contained due to regulatory limits on interbank exposures (*e.g.* limits on cross holding of capital amongst banks, limits on call money market exposures and prudential limits on interbank liabilities). The impact could be further aggravated if other entities in the financial system (other banks, NBFCs, Mutual Funds, *etc.*) are brought within the ambit of analysis. In any case, there remains need for continuous monitoring of the interconnectivities in the financial system to identify build up of risks/excesses in the system and to guide policy action to address the same.

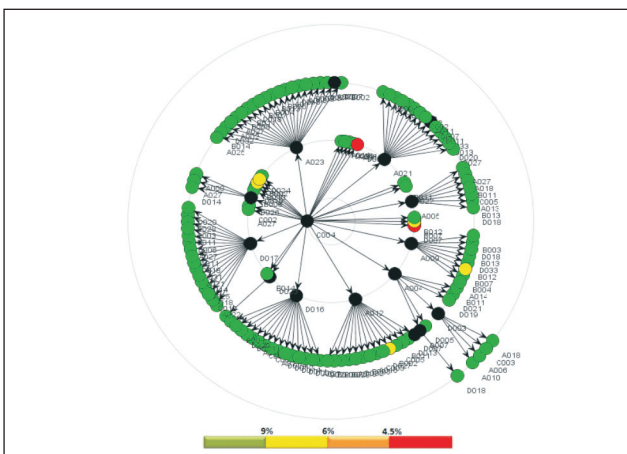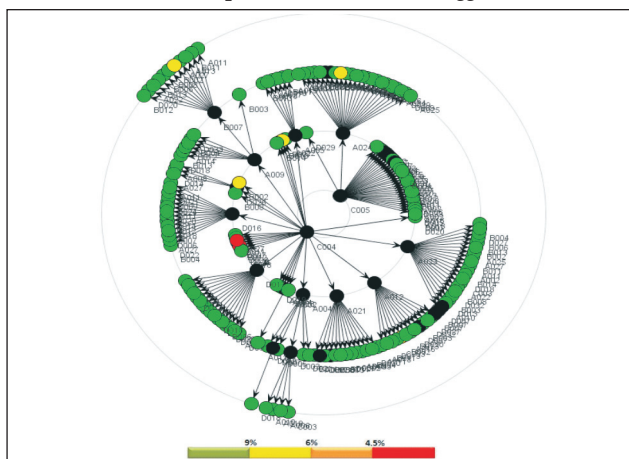
Chart 4.13: Impact of Failure of One Trigger Bank[12]

Chart 4.14: Impact of Failure of Two Trigger Banks

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[11] For the purpose of the analysis, banks whose ratio of Tier I capital to Risk Weighted Assets falls below 6 per cent are considered to be distressed.
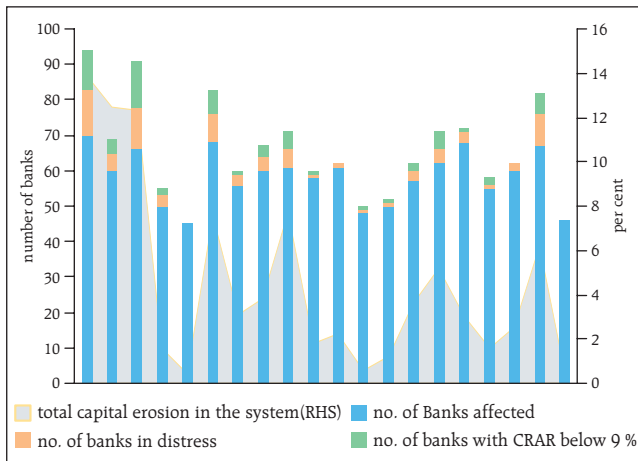[12] Colour code:

Trigger banks: Black

Distressed banks:
(i)   Black: Banks whose core capital ratio falls below 6 per cent
(ii)   Orange: Banks whose total capital adequacy ratio falls below 6 per cent
(iii)   Red: Banks whose total capital adequacy ratio falls below 4.5 per cent
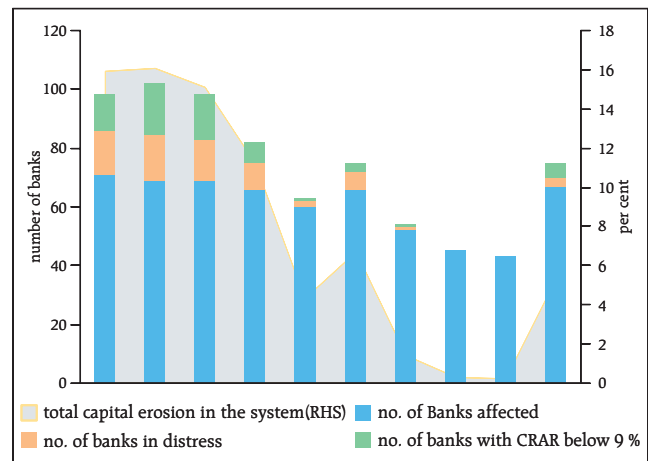
Banks which are affected but not distressed:
(i)   Green: Banks which are affected by the failure of the trigger /distressed banks but whose capital adequacy remains above regulatory requirements
(ii)   Yellow: Banks which are affected by the failure of the trigger /distressed banks and whose capital adequacy falls below 9 per cent but core capital ratio remains above 6 per cent

Chart 4.15: Impact of the Failure of Top 20 Banks
(One at a time)

| total capital erosion in the system(RHS) | no. of Banks affected |
| no. of banks in distress | no. of banks with CRAR below 9 % |

Chart 4.16: Impact of the Failure of Ten Pairs of Trigger Banks
(One pair at a time)

| total capital erosion in the system(RHS) | no. of Banks affected |
| no. of banks in distress | no. of banks with CRAR below 9 % |

Box 4.4: Network Analysis of the Indian Interbank Market – Analytics and Methodology

At the core of the analysis is matrix algebra, wherein the links or the relationships in the form of lending and borrowing, which exists between N banks are viewed in an N x N matrix. In a system of linkages modelled by undirected graphs, these relationships produce a symmetric matrix, as a link between two banks will produce the same outcome whichever of the two banks initiated it. In contrast, directed graphs are useful to study relative asymmetries and imbalances in link formation and their weights. For the network analysis, directed graphs have been used, as we aim to model banks as having complete discretion over the initiation of any link that they may choose to form.

Key to the network topology is the bilateral relations between banks which is represented by an adjacency matrix. The adjacency matrix becomes the gross flow matrix X such that x_{ij} represents the flow of gross financial obligations from the borrower i to the lender j. A bilaterally netted matrix M with entries $(x_{ij} - x_{ji})$ is then derived from the matrix X. The matrix M, which is skew symmetric to the matrix X, gives the netted position between banks i and j. For the contagion analysis, the matrix M representing the net payables and receivables of all the banks in the network topology, is the critical feature. The number of links or directions representing net receivables for a bank (node) from others is referred to as *in degrees* and the number of links or directions representing net payable as *out degrees*.

Connectivity statistics

Statistical analysis is subsequently carried out on the aforesaid matrix to determine the level of interconnectedness and activity that exists in the system. Some of these tools that are used are as follows.

(a) **Connectivity**: This is a statistic that measures the extent of links between the nodes relative to all possible links in a complete graph. For a directed graph, denoting the total number of out degrees to equal $K = \sum_{i=1}^{N} k_i$ and N as the total number of nodes, connectivity of a network is given as $\frac{K}{N(N-1)}$.

(b) **Cluster Coefficient**: Clustering in networks measures how interconnected each node is. Specifically, there should be an increased probability that two of a node's neighbours (banks' counterparties in case of the financial network) are also neighbours to each other. A high clustering coefficient for the network corresponds with high interconnectedness prevailing in the system.

(c) **Average Path Length**: This is used to measure the distance that exists between any two nodes in the network.

(d) **Shortest Path Length**: This gives the average number of directed links between a node and each of the other nodes in the network. Those nodes with the shortest path can be identified as hubs in the system.

(e) **In-betweeness centrality**: This statistic reports how shortest path lengths pass through a particular node.

(f) **Eigenvector measure of centrality**: Eigenvector centrality is a measure of the importance of a node (bank) in a network. It describes how connected a node's neighbours are and attempts to capture more than just the number of *out degrees* or direct 'neighbours' a node has. Hence, if two nodes have the same number of neighbours, then the one that is likely to have a higher eigenvector centrality is the node whose neighbours have the larger number of neighbours. This measure of centrality assigns relative scores to all nodes in the network based on the above principle. In general, for an N x N matrix there will be N different eigenvalues ě for which an eigenvector solution exists. For the centrality measure, we take the dominant eigenvalue and the associated eigenvector. The ith component of this eigenvector then gives the centrality score of the ith bank in the network.

Contagion analysis

The contagion analysis is basically a stress test where the gross loss to the banking system owing to a domino effect of one or more bank failing is ascertained. We follow the round by round or sequential algorithm for simulating contagion that is now well known from Furfine (2003). Starting with a trigger bank i that fails at time 0, we denote the set of banks that go into distress at each round or iteration by D^q, q= 1,2, …For this analysis, a bank is considered to be in distress when its core CRAR goes below 6 per cent.

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