SYSTEMIC RISK ANALYTICS

Holistic Visualization and Stress Test App For the Financial System

User Guide

Version 2.0.1 (beta)

RESERVE BANK OF INDIA (RBI)SYSTEMIC RISK ANALYTICS APP

User Guide

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Introduction

Introducing Systemic Risk Analytics: A Holistic Visualization and Stress Test Tool

Systemic Risk Analytics (SRA) is a bespoke financial network analysis and contagion stress testing platform based on the recent developments in the area of modeling financial interconnectedness and systemic risk in financial systems. The manual provides the user instructions for the SRA RBI App developed specifically for the Indian financial system. Professor Sheri Markose, in collaboration with Dr. Simone Giansante and members of the Financial Stability Unit (FSU) of the Reserve Bank of India (RBI), has developed the key conceptual framework to operationalize the data driven model of interconnectedness of the Indian financial system in order to monitor and manage systemic risk within and across multiple financial sectors. Dr. Simone Giansante programmed the software for this in a web-based application in JAVA.

This work was started in August of 2010 and has proceeded in a modular fashion to encompass larger and larger segments of the Indian financial system. Dr, Rabi Mishra, the first Managing Director of the Financial Stability Unit of the RBI was the driving force behind this project. The software that has been developed is bespoke to fit the institutional and regulatory frameworks prevalent in the Indian financial system and the RBI-FSU team, led by Dimple Bhandia, has been meticulous in gathering these details. The work also reflects several high level meetings and discussion sessions involving Deputy Governors of the RBI (Smt.Shyamal Gopinath, Mr.K.C Chakrabarthy, and Dr. Subir Gokarn), Executive Directors and relevant Division Heads. Deputy Governor, Shyamal Gopinath was instrumental in mandating who-to-whom bilateral balance sheet data collection from a large spectrum of financial institutions in the Indian financial system starting with banks. This is a first for a central bank. The high level discussions covered the scope of the online modelling of the large scale granular (bilateral) financial data that was being collected; what are the data gaps and the further mandates needed for this; and finally, on how the set of objectives evolved to guide the software development that can monitor and manage systemic risk in the Indian financial system. Inputs from specialists and heads of electronic financial markets such as the CBLO (Collateralized Borrowing and Lending Obligation) and Repo markets have also been sought.

1.1 Multi-Agent Financial Networks (MAFN) Modeling[1]

Summary of Objectives

This guide covers the technical aspects of the modeling undertaken to date on the first ever large scale collection of bilateral financial data for financial intermediaries (FIs) across multiple sectors in the Indian financial system. The RBI-FSU is first among central banks to mandate collection of bilateral assets and liabilities data from a large sample of bank and non-bank FIs of the Indian financial system. This was initially done on a quarterly basis. The objectives of the modeling framework are as follows:

- To build an ICT (Information and Communication Technology) based platform, which in time has automated access to the electronically collected data base of bilateral financial positions of financial intermediaries (FIs).
- To provide a digital mapping of the Indian financial system with the interconnectedness between financial intermediaries modeled using financial network analysis.
- To provide a holistic visualization of the system with capabilities of 'zooming' to desired levels of granularity in order to monitor the topology of the network structures for their stability and to determine the systemic importance of financial intermediaries.
- To provide systemic risk analytics.

The systemic risk analytics come in two parts. The first, called contagion analysis, monitors the actual pathways based on contractual obligations for the spread of financial contagion in the Indian financial system from the failure of one or several FIs. The channels of financial contagion arising from default of counterparties can take the form of solvency and liquidity impacts. Solvency problems arise when losses of a FI exceed a certain critical threshold of its capital buffers. Liquidity problems follow when a FI's buffer of high quality liquid assets is not sufficient to cover its immediate liabilities and the situation is triggered, in the first instance, from counterparty default of a net lender or the latter withdrawing liquidity for other reasons. Following discussions with regulators and practitioners, the pecking order of short term loans that can be called in by liquidity constrained FIs is programmed in for this stress test exercise. The calling in of short term loans can exacerbate channels of liquidity

[1]This methodology is discussed at length in Markose (2013, 2012) and Markose, Giansante and Shaghaghi (2013). The specific aspects relating to the Indian financial system can be found in Markose, Giansante, Bhandia and Warrior (2013).

contagion. The RBI SRA App has implemented the full contagion analysis when both solvency and liquidity contagion factors operate.

The second part of systemic risk analysis quantifies 3 major issues: (i) Produce a stability based metric, which we call the spectral systemic risk index (S-SRI), that can determine if the networked system has become more or less stable over time, (ii) the extent to which FIs are contributing to the system instability, and (iii) and how are FIs vulnerable to failure in a financial contagion.

The systemic risk model we implement is based on the epidemiology literature that has a long provenance as a causal model of disease spreading and the tipping point it identifies with the maximum eigenvalue of a dynamical model built on interconnections of members of a social network being acknowledged to have produced "the foremost and most valuable ideas that mathematical thinking has brought to epidemic theory" (Heesterbeek and Dietz, 1996). This method, we call the Eigen-pair method, was first adapted in Markose (2012) for modelling the stability of the networked financial system.

Key to the method is the maximum eigenvalue of the so called stability matrix constructed as a network of bilateral net liabilities of FIs relative to Tier 1 capital, and as a fixed point result it can be interpreted as the percentage loss of capital for the financial system as a whole that leads to a tipping point. There is cause for concern when the maximum eigenvalue of this matrix exceeds the capital threshold of losses that the regulator deems to be the upper limit of what can be breached for purposes of capital adequacy. The systemic importance of FIs is given by their rank order in the right eigenvector associated with the maximum eigenvalue. The left eigenvector identifies the rank order of FIs that are vulnerable or exposed. Even if the regulator does not choose to publicly identify and indemnify SIFIs for the threat they pose to others from the negative externality of their inter-connectedness and excessive borrowing/liabilities from counterparties, the eigen-pair method gives the regulator a tool to quantify a Pigou style externalities tax according to the (right) eigen-vector centrality of FIs up to the point where the network system can be stabilized to a desired level.

This document describes the modular and scalable financial network construction that is being undertaken at the RBI-FSU. It is based on the bilateral financial data obtained on a quarterly (and soon to be monthly) basis from about 150 core FIs encoded into groupings from A-J, ranging from banks to the different non-bank FIs such as mutual funds, insurance companies and urban and cooperative banks. The modeling strategy is to first proceed in a modular fashion enlarging the financial network with agents being cumulatively included from the A-J groupings with the proviso that new financial products and markets are to be added on in due course with regulators being vigilant about such developments. When fully completed, there will be a digital map of each FI's activities with all others, both in the non-electronically cleared and in the electronically cleared markets such as the Indian repo and collateralized borrowing and lending (CBLO) markets. The interconnections in the RTGS payment and settlement system will also be mapped. The main product break downs include funded, unfunded (contingent claim/derivatives), short and long term maturity buckets and selected secondary markets such as for certificates of deposits (CDs) and foreign currency convertible bonds. Note, for wider macro-prudential purposes which require the delineation of the transmission channels of financial risk to the real side of the economy, the financial interconnections between FIs also need to be integrated with their linkages with non-financial sector end users such as households, non-financial corporate sector and the public sector. Embedding the FI interconnections of the Indian financial system with the national sectoral flow of funds model and also the global financial flows defines the full scope of the highly granular systemic risk model that integrates the real and financial sides of the economy.[2]

A brief explanation will be given for the granularity of the data collection and the use of computational agent-based modeling of the financial system rather than equation driven econometric or calibrated models. Andrew Haldane of the Bank of England[3]has done much to propagate the Star Trek vision of an ICT based large electronic screen displaying financial data as an interconnected system. The RBI SRA App is one of the first large scale implementations of this computational modeling approach. The motivation behind this data driven causal balance sheet based framework of systemic risk monitoring will be given in the next few sections of the introduction while the technical details of the software outputs will follow in subsequent chapters.

1.1 A Big Financial Data

The 2007 financial crisis highlighted the lack of understanding among economists of the role of interconnectedness of FIs, both nationally and globally, and also the transmission channels between the financial and the real side of the economy. Mainstream macroeconomic models such as Dynamic Stochastic General Equilibrium (DSGE) had, at best, a representative banking sector which does not suffer problems of illiquidity or insolvency let alone pose a threat from domino type failures that became a reality during the 2007 crisis. At worst, these models did not have a financial sector at all.

Pre-2007, the regulatory banking and financial framework was focused on micro-prudential policy of capital requirements based on metrics such as Value at Risk (VAR). This required banks to hold capital to protect themselves from the risks arising from their own investment portfolios. The threat that they pose by their failure to other members of the financial system and to the real side of the economy from leverage fuelled excessive risk taking was not modelled and estimated by regulators. To avert greater losses from the activities of FIs for the rest of society, financial sector bailouts estimated to be the largest to date during the course of the 2007 financial crisis, were borne by tax payers. It is increasingly being recognized, such as with the Dodd Frank Act and the setting up of the Financial Stability Board, that this moral hazard problem

[2]See, Markose (2013) for a fuller discussion on this.

[3]See, Haldane (2009) and his speech at the 2013 January BCBS Workshop. See also, Buchanan (2009).

needs to be addressed. The negative externality that arises from a misalignment between the behavior of financial intermediaries pursuing private objectives and system wide stability is a non-trivial problem for which holistic visualizations of 'big' financial data is part of the solution. In addition, regulatory frameworks can be fraught with perverse incentives and they need to be computationally stressed tested for this prior to implementation and monitored in an ongoing way, Markose (2013).

Research and development of web based visualization of financial data and real time operations relating to financial crisis management has only just started. The fundamental computational methodology for web based visualization of complex data sets is object oriented programming (OOP) and multi-agent modeling. The technological ICT aids of the 'zoom' that can navigate between the coarse grained bird's eye view and the fine grained ones can mitigate the well known befuddling aspects of not being able to see 'the woods for the trees'. The 'probe' can automate and highlight behind the scenes hidden links of each FI in multiple markets.

Agent based computational economics or ACE using the acronym coined by Leigh Tesfatsion (see, Tesfatsion and Judd (2006), Le Baron (2000)) based on object oriented programming (OOP) can produce agents that are both inanimate (eg. repositories of data bases) as well as behavioural agents capable of varying degrees of computational intelligence. These range from fixed rules to fully adaptive agents representing real world entities (such as banks, consumers and regulators) in artificial computer environments which can be replicas of, for instance, the financial system. Unlike conventional programming in which a program entails a lists of tasks or subroutines, in ACE and OOP, each agent which is an instance of a class is capable of interacting with other agents by receiving and sending 'messages', processing data, and producing outputs on the basis of their computational intelligence.

In financial networks, nodes can stand for financial agents such as banks, non-bank intermediaries, the final end users and central banks. The edges or connective links represent directed inflows (in degrees) of liquidity or receivables, and outflows (out degrees) represent obligations to make payments. By data base driven multi-agent financial networks (MAFNs) is meant that disaggregated data at the level of individual FIs with regard to bilateral flows to each of their counterparties will have to be accessed electronically to provide 'as is' quantitative characteristics of FIs based on their contractual obligations.

Integration and automation of financial data bases in a MAFN framework, therefore, aims to transform the data from a document or record view of the world to an object-centric view (see Balakrishnan et. al. 2010), where multiple facts about the same real-world financial entity are accessed to give a composite visualization of their interactions with other such entities in a scalable way.[4]

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[4]See the IBM MIDAS project reports (Balakrishnan et. al., 2010, Hernandez et. al., 2010) on software technologies being developed for large scale firm level financial database driven models for systemic risk analysis.

1.1 B Data Visualization: Holism and Granularity

Figure 1 gives a taster for both granularity and holism, respectively, at the level of each FI in a multi-sectoral network graph for the Indian financial system which incorporates bank holding companies, including foreign banks operating in India and non-bank financial institutions such as mutual funds, insurance companies and urban and cooperative banks. Note, in Figure 1 and Figure 2, the direction of the arrow indicates the net liabilities owed by financial institutions to their creditors (nodes at which the arrow heads end); red nodes denote net borrowers and blue nodes are net lenders. The thickness of the arrows indicates the size of the flows.

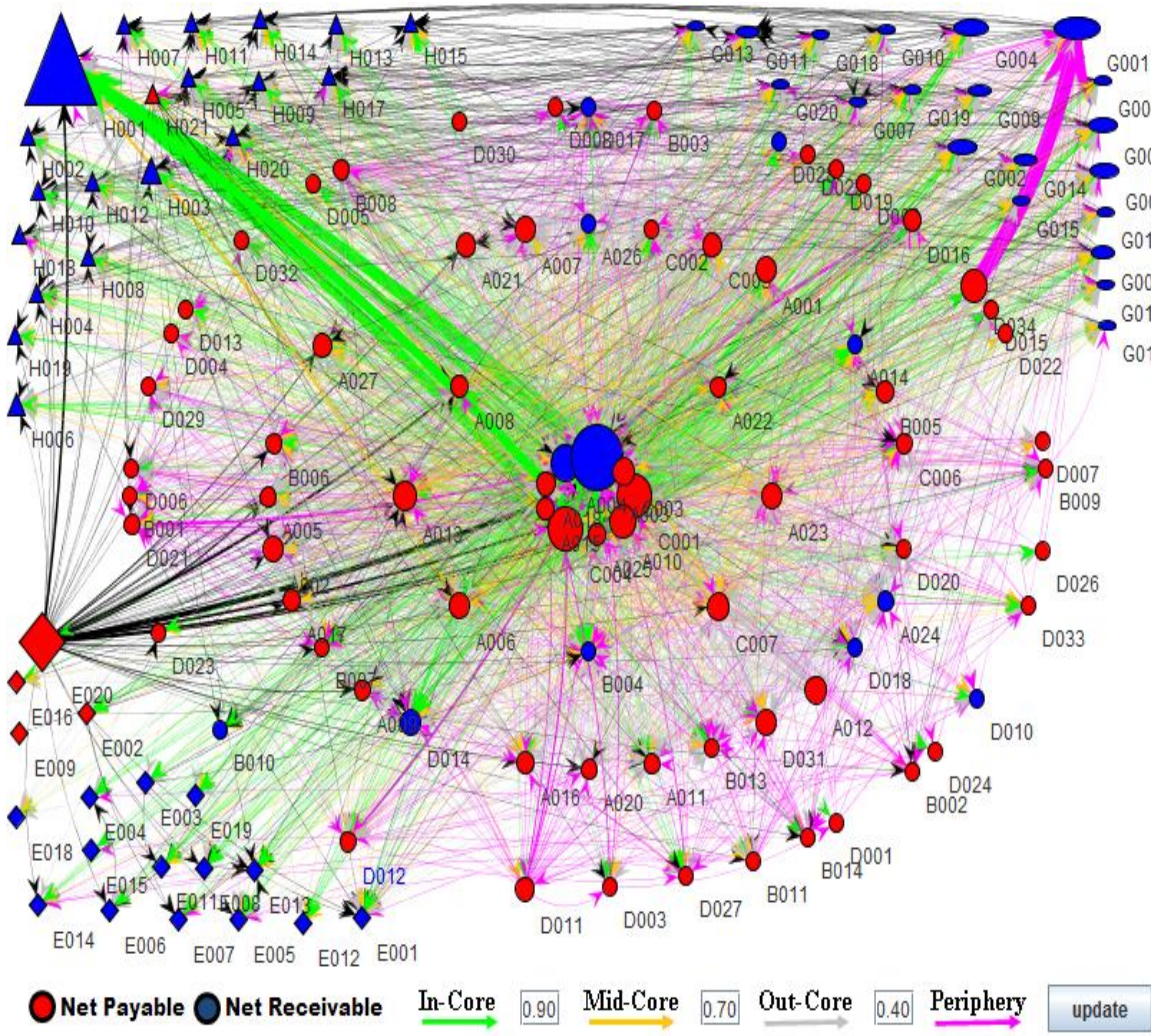


Figure 1 - Granular Multi-Sector Network Map of Indian Financial System (2012 Quarter 4): SRA Graphics

Notes: Tiered central core of Commercial and Public Sector Banks (Circles), Top LHS Insurance Companies (Triangles), Top RHS Mutual Funds (Ellipses), Bottom LHS

Urban and Cooperative Banks, Bottom (Squares), middle RHS Foreign Banks (Code D) with each FI having its own specific encoded ID.

The colour of the arrows Figure 1 relate to where the FI is placed in terms of tiering of the network. FIs are tiered according to the percentage of total in and out links they have relative to the total in and out links. The green arrows start from FIs in the central core of the network; yellow arrows belong to those in the so called mid core; the grey arrows arise from the 'out core' and finally the pink arrows belong to those in the periphery.

The granular holistic network in of the (non electronically cleared) Indian financial system is laid out in the following way. The banks (circles, with codes A- D) are shown in the center of Figure 1with the full tiering structure for this group of FIs given by the concentric circles. The Life Insurance companies (triangles, with codes H) are on the top left hand side (LHS), the Mutual Funds flat elipses on the top right hand side (RHS)) and the Urban and Cooperative banks (diamonds, with codes E) on the bottom LHS.

As blue nodes denote net liquidity providers, Figure 1 reveals the fact that the net liquidity suppliers in the Indian financial system are Life Insurance Companies (top LHS, Triangles, in Figure 1), mutual funds (top RHS, Ellipses in Figure 1) and many of the smaller Urban and Cooperative Banks (bottom RHS, Squares). The majority of bank holding companies are net borrowers. Banks, therefore, pose a threat to the wider system of FIs than just to other banks, while vulnerability of insurance companies and mutual funds can trigger liquidity problems. Thus, focusing only on banking sector interconnections, as the bulk of many financial network studies have done to date, may give the wrong picture of systemic risk. Further, the largest of the Urban and Cooperative banks (bottom LHS in Figure 1) is a net borrower and can pose a threat, especially, to the smaller banks in this class. Finally, a visualization at this level of detail can highlight the case of a foreign bank (D016), which is found to be a very large net borrower from an Indian Mutual Fund (G004), pink arrow on the top RHS of Figure 1. This allows the Deputy Governor in charge to quickly send a query regarding this. Indeed, this holistic network visualization in Figure 1 based on 2012 bilateral balance sheet data, has presaged the trouble that was brewing in the relationship between foreign banks and Indian mutual funds.

In Figure 2, the degree of granularity of all categories of Indian FIs is drastically reduced as they are, respectively, aggregated into single nodes. As will be explained in what follows, SRA provides automated visualization of the data at all levels of granularity.

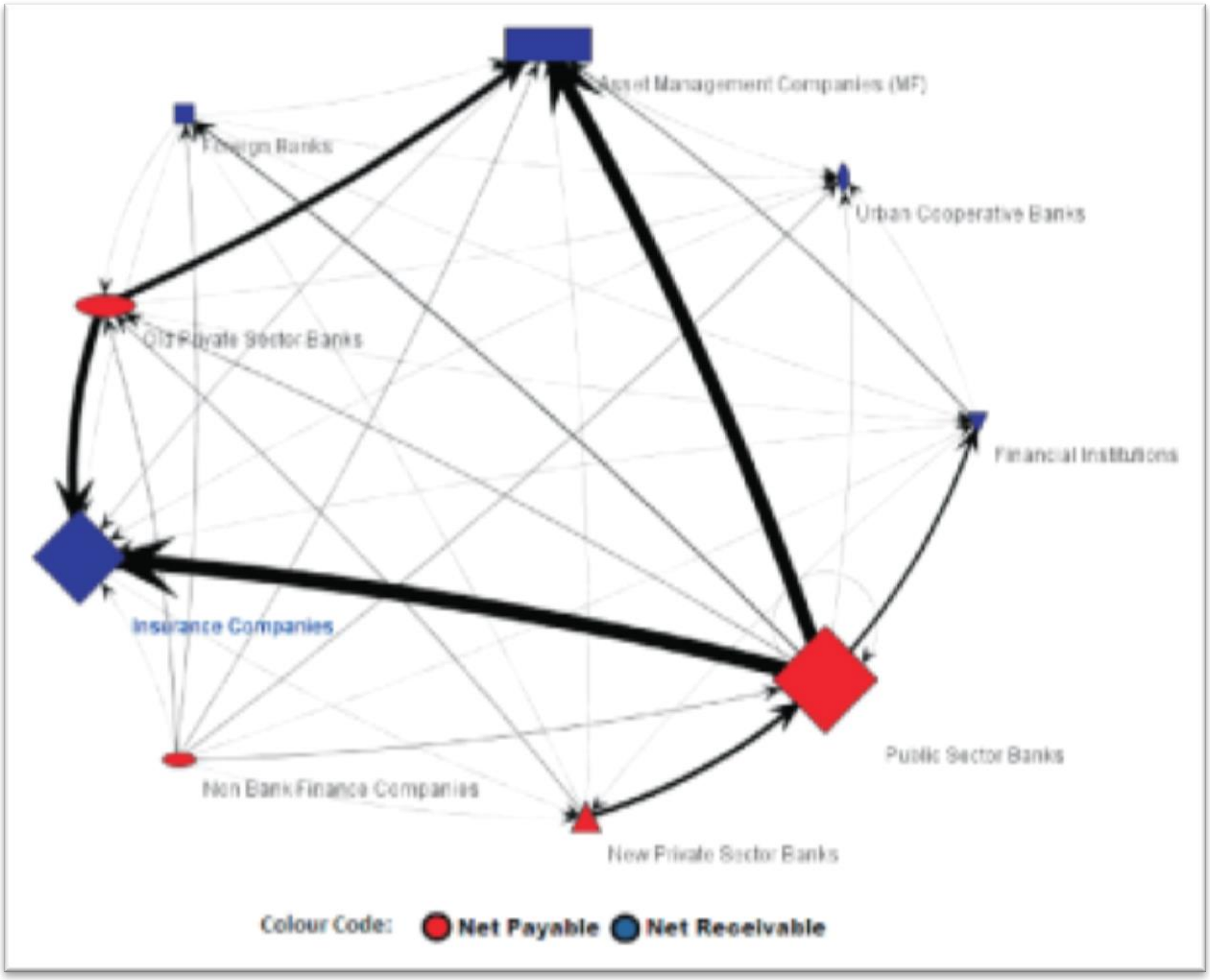
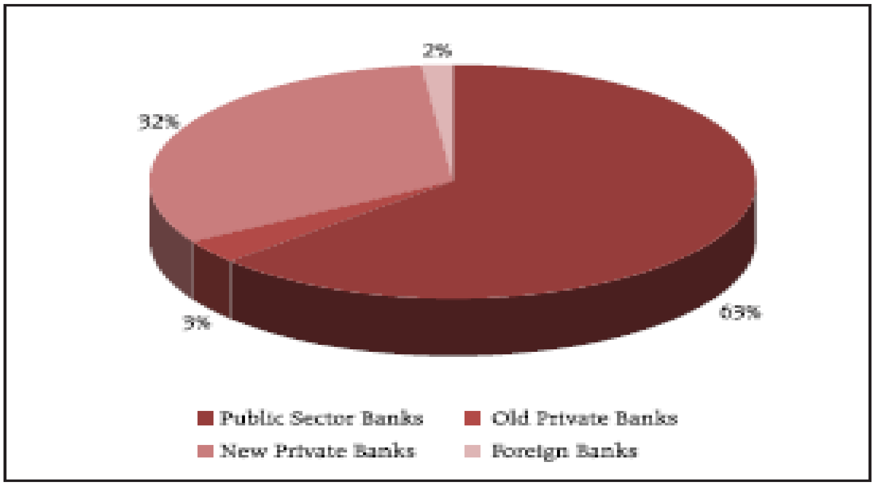


Figure 2 - Respective Indian Financial Sectors Aggregated Into Single Nodes (2012 Quarter 4): SRA Graphics

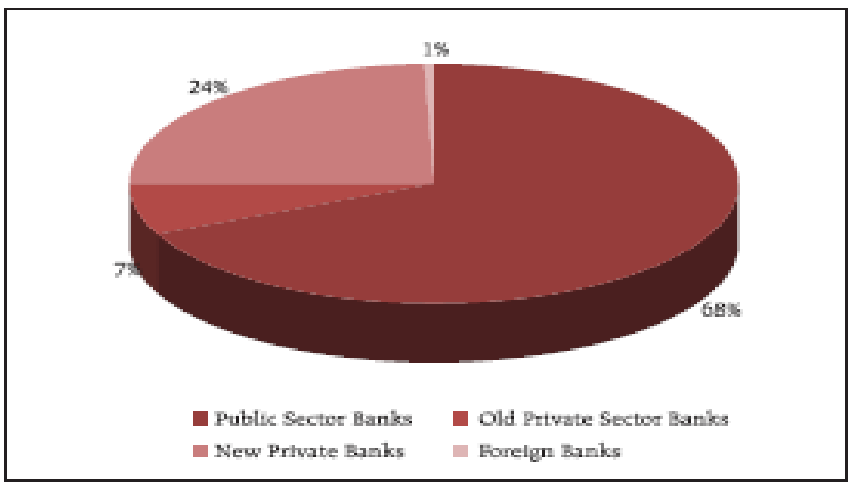
Figure 3 shows how the insurance companies and mutual funds are primarily exposed to public sector banks to the tune of around 68%-69% in 2012. The exposure of insurance companies to new private sector banks is about 32 % while old private sector banks have only a 3% share, which is close to that of foreign banks of 2%. Mutual funds have an exposure to new private sector banks of about 24%, while that to old private sector banks is about 7% and foreign banks is 1%.

Chart 5.19: Insurance companies' investments in different bank groups



Source: RBI staff calculations

Chart 5.20: MFs' investments in different bank groups



Source: RBI staff calculations

Figure 3 - Exposures of Insurance Companies and Mutual Funds to Other FI Groups, Comprising Weighted Flows in Figure 2 (2012 Quarter 4)

In principle, each FI entails a vector of financial activities operating in a multi-layer system of markets for different financial products, each of which has its own network topology, institutional incentives and constraints. This is illustrated in Figure 4.

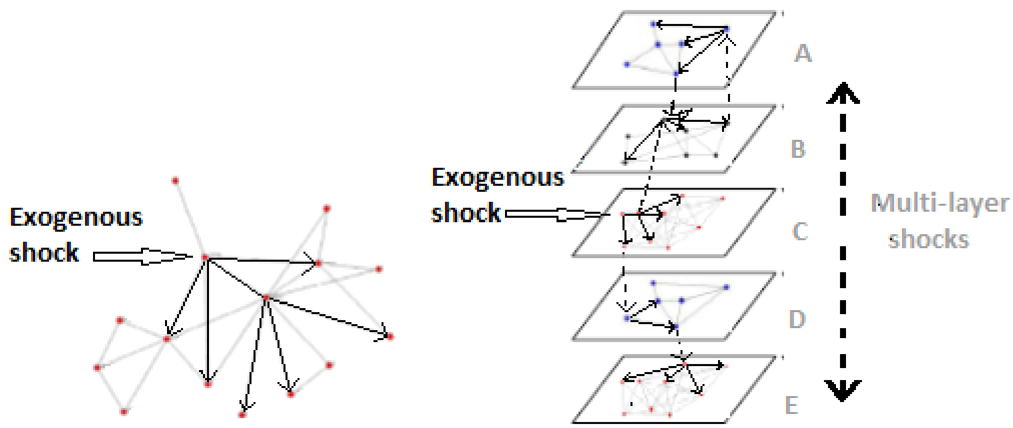


Figure 4 - Single Layer Network (LHS) and Multi-Layer Networks (RHS)

In the multi-layer networks in Figure 4(RHS), the broken vertical lines show the FIs that are common to the different networks for financial products and hence they can become the conduit by which an exogenous shock in one market can be propagated across other markets. Indeed, considerable investment[5] was made in this RBI SRA App (version 2.0.1) software to access and deal with data for different products/markets in a multi-layer network framework, viz. bilateral data from multiple markets can be loaded and dealt with simultaneously. This adds flexibility and versatility for the App so that it is not constrained with depicting only a single layer network format with aggregation of a FI's bilateral positions with counterparties across all products. In the liquidity contagion stress test when loans are called in from counterparties for some categories of assets and not others, a multi-layer network format is essential to keep track of this.

It is now well understood that topology of the network in each market and netting constraints across products[6] have implications for the adequacy of capital and liquidity and hence on the stability of the system. In the exercises done for the Indian financial system this was first observed when bilateral cross product netting was not permitted for different asset categories such as funded and unfunded products. The reduced netting benefits increased the maximum eigenvalue of the single layer financial network obtained without cross netting between the asset categories. This was reported in the presentation given by Sheri Markose in September 2012 at the RBI. Hence, for purposes of regulatory monitoring, the current RBI SRA App permits quarter by quarter snap shots of network visualizations and analytics of bilateral financial flows data both for specific financial products and as a single layer network for flows aggregated across all products or subsets of products. This is important so as not to

[5]Indeed, in 2013 Simone Giansante had to devote considerable amount of his time to revamp the previous edition of the RBI SRA App to fully implement the multi-layer framework in this version.

[6]This is currently being intensively investigated in the context of changing the topology of the OTC derivatives markets reform by using single product CCPs or CCPs for multi-product clearing (see, Duffie and Zhu (2011) and Heath et. al. (2013)).

underestimate instability of the system and of the centrality/systemic importance of FIs in it.

1.2 Why Mandate Bilateral Balance Sheet and Off Balance Sheet Data To Map Financial Interconnectedness?

Two reasons are given here for why the study of financial interconnectedness and systemic risk monitoring and management makes it imperative that financial regulators mandate the collection of bilateral financial data for FIs. The first is that market price based systemic risk measures, though popular as market price data is publicly available, are known not to be able to provide early warning signals. The second reason is that the calibration and estimation, of bilateral financial liabilities and exposures between counterparties from aggregated data across all counterparties for each FI's position across all financial instruments or in product specific markets, is fraught with difficulties that render such exercises of limited use for regulatory purposes in measuring risk for the system as a whole and in particular for identifying systemically important FIs in a quantitative way.[7] These issues will be discussed in turn below.

Market Price-based Systemic Risk Measures: No Early Warning

The lynch pin of pre 2007 risk management was market price based metrics with Value at Risk (VaR) having featured prominently for the determination of capital buffers. Volatility indexes such as the VIX and VFTSE, and credit default swap premia that determine probability of default on underlying reference entities which include financial firms and sovereigns have also been used in recent systemic risk measures.

At a number of forums in September 2012 and April 2013 of the RBI-FSU and the RBI Deputy Governors and Executive Directors, it was identified that market price based systemic risk measures are particularly unsuited to give early warning signals for an impending crisis: by the time market price based systemic risk indexes have spiked, financial markets will already have tanked, Markose (2013). They have been found to suffer from the so called volatility paradox, Borio and Drehmann (2009), which is associated with the cyclicality and regime sensitivity of market risk measured by volatility of asset returns such as that for the stock index which results in the underestimation of systemic risk during asset price booms.

This can be seen in publicly available volatility indexes in that they are extremely low during market booms and are at a local minimum (Figure 5) just before the market crash (at the highest point of the boom in the stock price index) and those who are ignorant of this can be lulled into a false state of complacency when systemic risk is

[7]Some of these issues were raised by Biasis (2012) in their survey on recently proposed systemic risk analytics, especially for the class of Pigovian capital surcharge. They note that the many ad hoc model related assumptions, calibrations and data manipulations, make it questionable whether FIs will or should be made liable for less than robustly derived surcharges. Indeed, Markose (2013) has argued that FIs cannot be held culpable for damage to others from pre-existing macro-economic conditions such as loose monetary conditions or future market conditions that may arise, for example, during deleveraging that are unknowable at the time the financial contracts were entered into with counterparties. FIs can be indemnified only on the basis of systemic risk measures based on legally binding contractual obligations to counterparties.

building up on balance sheets of FIs and households through increased indebtedness. This has been noted by Hyman Minsky (1982) under the rubric of 'paradox of stability' in that the seeds of financial crisis are sown during conditions of market upturns. Enhanced market values for assets of FIs enable increased borrowing. The risk weighting of assets and RWA capital requirements exacerbates this procylicality. These ideas on the procyclicality of leverage are well articulated in Adrian and Shin (2010,2011).

In Figure 6[8], the Sergoviano-Goodhart credit default swap market price based banking stability index (green in Figure 6) spikes are at best contemporaneous with the crisis marked by the publicly available volatility indexes such as VIX or V-FTSE. In the worst case, such market price based systemic risk indexes will show up after the crisis. This is the case of the Contingent Claims analysis (CCA) based distance to distress (DD) systemic risk measure used by Castren and Kovonius (2009) with a high DD signaling low distress. The DD measure "dropped sharply only after (italics added) the crisis had started" (ibid). They claim that the high DDs "in the years 2005-06 were mainly driven by historically low volatility … even though from the market leverage data, it is clear that vulnerabilities were gradually accumulating in the form of rising indebtedness in most sectors" (ibid).

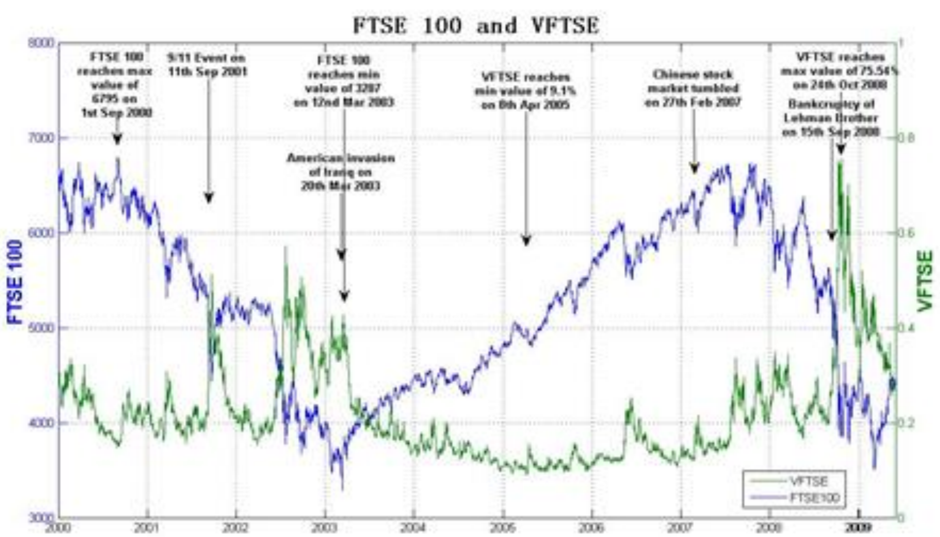


Figure 5 - "Paradox of Stability": Stock Index and Volatility Index.; Paradox of Volatility (Borio and Drehman, 2009; Minsky, 1982).

[8]Figure 5 and Figure 6 were the one which Sheri Markose used in her talk at the 2010 IMF Workshop on *Operationalizing Systemic Risk*and they have been published in Markose (2013).

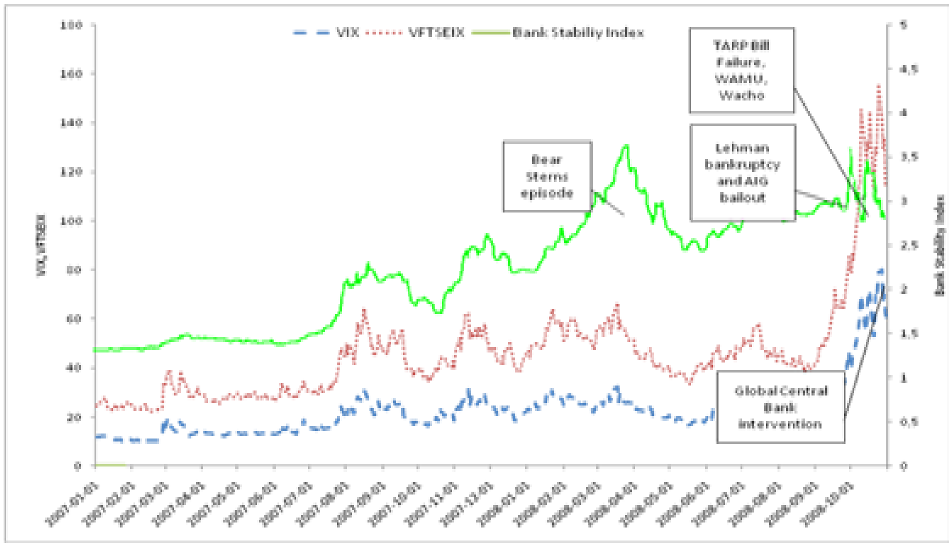


Figure 6 - Banking Stability Index (Segoviano, Goodhart 09/04) vs Market VIX and F-FTSE Indexes

Attempts to produce, for example, systemic risk indexes for the banking sector, from individual metrics for risk management such as VaR or expected shortfall, have relied on incorporating a portfolio of such individual FI risk measures. This has entailed simple weighted averages and in some cases the cross sectional co-movements and dependence structures have also been explicitly modeled. Some of the market-based systemic risk measures that have been proposed are the following (see, Biasis et. al. (2012) and Markose (2013) for a discussion on these): Conditional VaR (CoVaR) Adrian and Brunnermeier (2009); Marginal System Expected Shortfall (MSES) Acharya et al. (2010); Co-risk by Chau-Lan (2010); DIP (Distress Insurance Premium) by Huang et al. (2010); POD (Probability that at least one bank becomes distressed) by Segoviano and Goodhart (2009), Shapley-Value by Tarashev et. al. (2010) and Macro-prudential capital by Gauthier et. al (2009).

Diebold and Yilmaz (2011) developed the Connectedness Index (DY-CI) for banks by applying network topological measures on the econometric decomposition of forecast error variances from a vector auto-regression model for the stock return volatility for the selected banks. While the DY-CI yields good cross-sectional information, the total rolling DY-CI (given in Figure 2 of Diebold and Yilnaz (2011)) shows that it fell in the period around 2006 and remained subdued till close to the 2007 crisis. It is also said "not to provide signals of increasing risk from higher leverage in banks' balance sheets", Saldias (2012).

A recent IMF study by Arsov et. al. (2013) designed the Systemic Financial Stress (SFS) index which records the extreme negative returns at 5 percentile of the (left) tail for the joint distribution of returns of a selected sample of large US and Eurozone FIs. To qualify for inclusion in SFS, in addition to the above, banks also had to experience such negative returns cumulatively for a period of 2 weeks. The IMF SFS index specifies a threshold for extreme stress as one where 25% of FIs suffered such conditions. This index was recorded on a weekly basis for the period from 2002-2011. Ten market based systemic risk indicators (some of them listed above such as Co-VaR, Sergoviano-Goodhart JPoD and DD) were back tested over this period to see if they had any predictive capabilities with respect to the IMF SFS index. The IMF study of Arsov et. al. (2013) acknowledge that the market price based systemic risk measures at best provide *near coincident* and *coincident* signals for crisis and were mostly devoid of early warning capabilities (Figure 4, ibid). Arsov et. al (2013) express the hope that some of their market-price based 'near coincident' indicators will give policy makers what appears to be a few weeks, if that, to "prepare for contingencies (for instance, to release capital buffers that have already been built in advance, and to identify recapitalization needs at a time when the probability of a financial crisis is already very high)." Figure 5 in Arsov et. al. (2013) shows that some indicators provided SFS stress signals round about July 2007, while others took well into 2008 to register stress. Whether such *near coincident* indicators can give sufficient time to prepare for contingencies is doubtful.

Finally, it is useful to consider the loss multiplier metric for systemic risk that Castren and Racan (2012) applied to cross border financial flows involving reporting national banking systems. The loss multiplier estimates losses of capital to the system as a whole from the failure of one node in the financial network with its own capital losses taken as the initial point for the multiplier. Again, a systemic risk measure based on the Castren-Racan (2012) loss multiplier as shown in Figure 7(blue lines), unfortunately, peaks well after the crisis has started and the asset side of FIs is considerably weakened. That the loss multiplier is modest during the asset price boom from 2003-2008 and does not shown up till after a major market downturn weakens balance sheets should not be a surprise and *ipso facto* disqualifies it as a useful systemic risk measure if early warning is sought. In contrast, a direct measure of the Markose (2012,2013) maximum eigenvalue, (the green line in Figure 7)of the matrix of liabilities of countries relative to Tier 1 capital of the exposed national banking systems, will capture the growing instability of the network system relative to the distribution of capital buffers well ahead of the actual crisis.

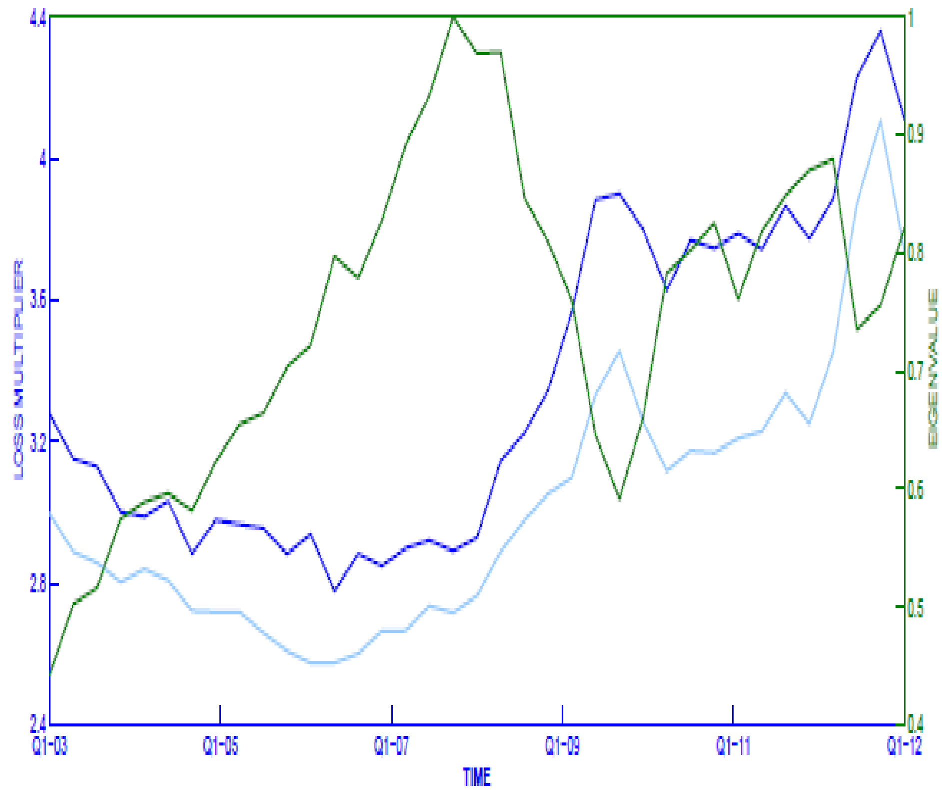


Figure 7 - Castren-Racan Loss Multiplier Systemic Risk Measure (blue) vs. Markose et al (2012, 2013 grenn) Maximum Eigenvalue of Matrix of Net Liabilities Relative to Tier 1 Capital

There is currently a serious problem among economists about accepting the fact that prices in efficient markets are an instantaneous reflection of contemporaneous market conditions and is devoid of information of future market conditions. In addition to the iron clad nature of volatility paradox that renders market risk and credit risk/default risk to be attenuated during asset price booms, attempts to data mine market price data for early warning systemic risk signals is an exercise that has had limited success.

In the light of the above, if risk from growing leverage and indebtedness among FIs has to be evaluated relative to Tier 1 capital buffers of counterparties, then direct access to bilateral balance sheet (and off balance sheet) data of FIs needs to be mandated. A further reason given below on why mandating bilateral financial data is important is that stability of network systems and how they propagate contagion is closely related to the topology of the network. Attempts to calibrate or estimate network of financial obligations from balance sheet data which is aggregated across counterparties have not proven to be robust and hence systemic risk measures based on this will suffer from model risk. In Figure 7, the systemic risk measure directly relating to the stability of the networked system of global banking flows estimated by the maximum eigen-value of the matrix of exposures that national banking system faced relative to their Tier 1 capital gives all the warning that is needed that they are undercapitalized relative to an absolute 6% Tier 1capital threshold (RHS axis ofFigure 7)two years prior to the advent of the financial crisis in 2007.

1.3 Problems with Estimation and Calibration of Network Interconnectedness From Balance Sheet Data For FIs Aggregated Across Counterparties

Since the classic Furfine (2003) stress tests that used financial balance sheet interlinkages to analyse financial contagion from the failure of a 'trigger' FI, a very large body of work using network analysis (see, Upper(2011), Markose (2012) and Yellen (2013) for recent reviews) has developed for systemic risk management. However, post 2007 financial networks models have yielded mixed results and have not provided sufficient understanding of the topology of real world financial systems or how contagion propagates through them. Financial networks have either been assumed to be random with no discernible structures or assumed to be complete networks where every FI is connected to everybody else. A number of analytical and numerically based studies on financial contagion have been confined to random graphs such as Nier et al. (2007) and Gai and Kapadia (2010). These yield interesting qualitative insights but as financial networks are far from random, they have some way to go. The use of the entropy method (see, Upper and Worms (2004) and Boss et al. (2004)) for the construction of the matrix of bilateral obligations of banks which results in a complete network structure for the system as a whole, may greatly vitiate the potential for network instability or contagion.

Network Topology Matters for Stability of Interconnected System

Many have now acknowledged that assumptions that the financial network is a random one or one constructed using a maximum entropy algorithm are misleading (see, Mistrulli, 2011) with regard to the stability of the financial network. In a recent paper by Solorzano-Margain et. al. (2013) based on extensive bilateral data on liabilities and exposures of FIs in the Mexican financial system, financial contagion arising from the unexpected failure of an FI on others is found to be more widespread than from results obtained from calibrated financial network models based on maximum entropy algorithm surveyed in Upper (2011). This has meant that in order to avoid model risk arising from calibration algorithms, structural bilateral balance sheet and off balance sheet data based network models are needed to study systemic risk from financial interconnections. Just as with the use of market price data based systemic risk indexes, wrongly calibrated financial network models can lead to wrong conclusions about impending crisis or systemic risk.

In summary, and as will be briefly illustrated below, it is important to map the actual interconnections between FIs because network topology is a major determinant in how contagion propagates and the system fails. Interventions and stabilization crucially depend on knowing who is linked to whom.

It was as recent as the work by Craig and von Peter (2010) who used bilateral interbank data from German banks to identify that a tiered core–periphery structure persisted in the bilateral flow matrices. This network structure which is sparse is very unlike that in a complete or a random network.[9] The following matrix ***M*** describes the core-periphery structure:

$$M = \begin{bmatrix} CC & CP \\ PC & PP \end{bmatrix}$$

Here, CC stands for the flows among the core banks in the centre of the network, CP for those between core and periphery banks, PC is between periphery and core banks and PP stands for flows between periphery banks. The sparseness of the matrix relates to the fact that PP flows are close to zero and banks in the periphery of the network do not interact with one another.

In keeping with the above discussion on network structures, the different segments of the Indian financial system show different degrees of tiering and sparseness. Figure 8(Top RHS) shows how the unfunded derivatives market network structure for the Indian financial system is the most tiered with a small central core and most remaining banks belonging to the periphery. The funded interbank market, Figure 8(Top LHS) has multiple tiers and a diffused core with more members belonging to the inner tiers than on the periphery. The RTGS is the least tiered with very few FIs in the periphery.

[9]The criticism Craig and von Peter level at extant financial networks literature is worth stating here. They say that popular interbank models (e.g. Allen and Gale (2000), Freixas et al. (2000), and Leitner (2005)) ignore the tiered structure and do not analyze it in any rigorous way : "the notion that banks build yet another layer of intermediation between themselves goes largely unnoticed in the banking literature". The traditional approach to modeling risk sharing in financial institutions as being one of responding to random shocks as noted by Craig and von Peter (2010) goes against the evidence on "the persistence of this tiered structure poses a challenge to interbank theories that build on Diamond and Dybvig (1983). If unexpected liquidity shocks were the basis for interbank activity, should the observed linkages not be as random as the shocks? Should the observed network not change unpredictably every period? If this were the case, it would make little sense for central banks and regulatory authorities to run interbank simulations gauging future contagion risks."

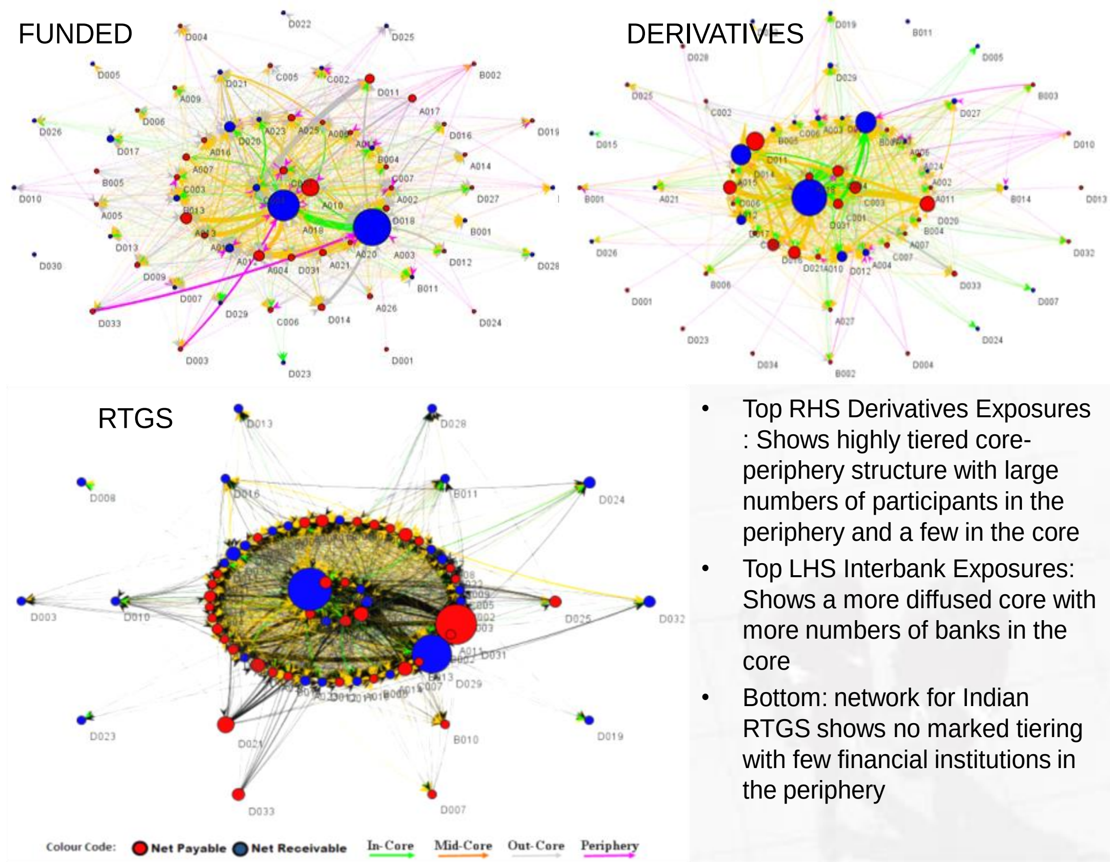


Figure 8 - Tiering Structures in the Different Financial Markets of the Indian Financial System (2012 Quarter 4)

The network structure of the unfunded derivatives markets was first described as being *too interconnected to fail* in the empirically calibrated data based US Credit Default Swap (CDS) market network of Markose et al. (2010). These networks with very sparse adjacency matrices and high clustering of the core financial intermediaries were also found to propagate contagion in a very different way to random networks and complete ones.

Markose et. al (2010, 2012) show how failure of a node, the one placed in the centre of the networks in Figure 9, propagates contagion in a random network structure (right) and that in a core-periphery sparse network (left). The latter depicts what it means to be *too interconnected to fail*. The highly tiered network has a central core of large banks which are densely and directly connected. A large proportion of the members of the central core can collapse when any member in it takes a hit. The contagion stops at this point as the network loses connectivity with the demise of the super-spreaders. But in the spirit of being *too interconnected to fail*, 4 top global banks are brought down, Figure 9 (left). It is of course cold comfort that there are no second order failures spreading to the whole system when the first order shock from the failure of a core bank wipes out the top 4 banks and some 70% of Tier 1 capital of the system. In contrast, the random network with no tiered structure and no bank is too interconnected, suffers as many as 17 (out of the 26) bank failures in a series of cascades which cannot be predicted, Figure 9(right). Thus, as in the context of controlling epidemics, the clustered network allows easier solutions in terms of inoculating the few super-spreaders, while in the random network the whole population has to be inoculated. Haldane(2009)calls such hub banks 'super-spreaders' and he recommends that super-spreaders should have larger buffers. From a perspective of an epidemic, such highly tiered sparse network systems can be viewed as being superior to random graphs in that the bulk of the population on the periphery cause no contagion and can be shielded from contagion from the 'super-spreaders' if the hub buffers are strengthened.

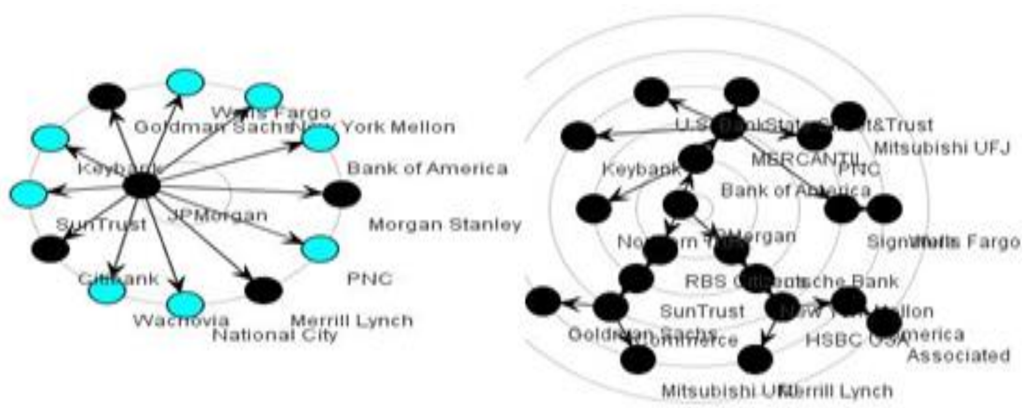


Figure 9 - Instability propagation in Clustered Empirical CDS Network (left) and in Equivalent Random Network (right) NB: Black nodes denote failed banks with successive concentric circles denoting the q-steps of the knock on effects. Source: Markose et al. (2012).

Even having produced network visualizations from bilateral financial data for FIs, the challenge has been to produce metrics to indicate whether the system has become more or less stable and also to identify over time which FIs are contributing to system instability. In this, it is important to move away from the market price based systemic risk measures not just because they are only able to produce coincident or near coincident signals for financial crisis , but because even if they embed probabilistic losses to others from failure of FIs, they do not directly model network stability as a property of dynamical systems. Stability of dynamical systems universally needs to use some eigen-value or spectral analysis. This was first identified by Robert May (1972,1974) as the May-Wigner condition as 'tipping points' for a networked system.

In his study of instability of large networks, May showed that network stability depends on the size of the maximum eigenvalue of an appropriate dynamical characterization of the network system. For a sparse network which has a matrix of bilateral entries given by (standard) normally distributed real numbers, May (1972, 1974) derives a closed form solution for the maximum eigenvalue of the network. The May stability condition is defined in terms of 3 network parameters: ***N***, the number of nodes, ***C***, the probability that any two randomly selected nodes are connected, and σ, the standard deviation of node strength.[10] When the latter statistic is large, it indicates the asymmetry in the number and weights of the out links that some nodes have relative to others. A network is determined to be unstable if its maximum eigenvalue is greater than 1, viz. $\sqrt{NC}\sigma > 1$. May showed that an increase in the number of nodes in a network along with its connectivity that is also accompanied by a growing standard deviation in node strength, contributes to instability. This implies the following trade off, not sufficiently understood by economists in their studies of financial networks: if the size and connectivity of a network grow, unless it is becomes more homogenous in node strength, it will become more unstable. Conversely, large networks such as those for financial derivatives, Markose (2012), which have fat tailed link distribution and a large standard deviation in node strength, need to have very low connectivity, ***C***, to remain stable. Thus, network construction algorithms such as the entropy maximization one by homogenizing cell entries can spuriously reduce network instability (see, Mistrulli (2011), Solorzano-Margain et. al. (2013)).

The Role of Capital Thresholds or Cure Rates in Contagion Models

In the adoption of the May (1972, 1974) framework in epidemiology models and models of internet security as in, respectively, Wang et. al (2003) and Giakkoupis et al (2005), the network stability depends on whether the maximum eigenvalue of an appropriate dynamical characterization of the network system exceeds a common threshold. This threshold is the cure rate in epidemiology or the proportion of buffers that have to be compromised before the contagion can spread.

To date in FSB circles, it has not been sufficiently understood how critical the setting of the capital thresholds are for the detection of stability of the financial network. If the so called 'cure rates' or proportion of buffers are inadvertently set too high, it will appear that the system is stable vis-à-vis contagion. Indeed, in some quarters it has become fashionable to say that direct contagion losses from interconnectedness of balance sheets of FIs are not a significant threat. For example in Brunnemeier et. al (2013) European Systemic Board study of the financial network of a segment of the derivatives market (comprising of CDS on European Sovereign reference entities) was reported to have negligible incidence of direct contagion losses even with the failure of major broker-dealer participants. On closer examination of the capital threshold that was being assumed to being necessary to be breached for insolvency, this was found to be more in keeping with the *entire* financial assets for a FI rather than for the subset of derivatives liabilities being analyzed.

Thus, while it is meaningful to analyze and monitor the stability of any specific financial sector using the eigen-pair method, care must be taken to close off the matrix of financial flows appropriately with a node created to represent flows to and from members of the financial group to those not in the group. Secondly, the capital

[10]Node strength here is a simple measure given by the row sum of the matrix.

thresholds for losses have to be specified carefully. Inadvertent errors can arise from two sources.

(i) The well known Basel II criteria for the determination of the on-set of capital inadequacy in a bank from losses of receivables from counterparties can be stated as follows:

$$\frac{Tier\ 1\ Capital - LGD}{RWA} < 0.06 = T_{RWA}. \qquad (1.1)$$

Here LGD is loss given default and the capital loss threshold of in the contagion analysis for bank failure in terms of RWA is denoted as T_{RWA}. In equation (1.1), the Tier 1 capital threshold is assumed to be 6%. However, as the practical aspects of avoiding insolvency requires recapitalization, it is important to see the equivalence of the above Basel rule with permissible LGD set as function of a ratio of Tier 1 capital, denoted as T_C such that T_C xTier 1capital = LGD. Substituting this into (1.1) when the condition in (1.1) is exactly met, we have:

$$T_C \quad = \quad 1 - (T_{RWA}\frac{RWA}{Tier\ 1\ Capital}). \qquad (1.2)$$

In the work done by Markose and Giansante for the Indian financial system which is reported in Markose et. al (2013), it was found that the application of the Basel II capital adequacy criteria in (1.1), given that on average Indian banks hold about 9.4% - 9.8% Tier 1 capital in terms of RWA in all quarters of 2011/2012, implies that a bank have to lose between 36% - 40% of Tier 1 capital (in absolute terms) before they are considered to be in distress.[11]

In the September 2013, the **Macroeconomic Impact Assessment Group for OTC derivatives Reform** (MAGD) Report, that was commissioned by the BCBS and the FSB, cites very low contagion impacts from the failure of G-SIBs, echoing the European Systemic Board conclusions of Brunnemeier et. al (2013). The MAGD Report used the leverage ratio (K/A, where K is Tier 1 Capital and A is total assets) with the proviso that losses from derivatives assets to Tier 1 Capital needs to bring the leverage ratio to below 2.5% to deem the 16 broker dealer G-SIBs and other banks to be in a state of 'crisis' or insolvency in the contagion analysis. Starting with a 6.26% leverage ratio reported to be the average for US G-SIBs for 2012 Q4 using GAAP[12], the 2.5% leverage ratio 'crisis' threshold implies that US G-SIBs can lose up to

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[11]For this, note $\frac{RWA}{Tier\ 1\ Capital}$ in (1.2), viz the reciprocal of the Tier1 Capital to RWA ratio for the Indian banks is about 10.63 to 10.20. Substituting these numbers into (1.2), this gives the permissible LGD to Tier 1 Capital ratio, T_C, to be between 36% - 40%.

[12]Recently, the US Federal Reserve Bank made the announcement that the minimum Basel III leverage ratio would be 6% for 8 US G-SIB banks. The average leverage ratios for 2012 2nd quarter for US G-SIBs are given below to be 6.26% under GAAP and 4.30% under IFRS, http://www.fdic.gov/about/learn/board/hoenig/capitalizationratios.pdf.

61%[13] of their Tier 1 capital on average before they are declared in a state of crisis. If on the other hand, the IFRS leverage ratio is used, assets in the denominator are calculated on the basis of less generous netting especially for derivatives assets, as the average IFRS leverage ratio for US G-SIBs is 4.30% then the 2.5% leverage ratio crisis threshold implies that losing about 42% of Tier 1 capital on average is permissible.

Thus, using the leverage ratio of 2.5% as a threshold for contagion from insolvency in the MAGD Report stress test platform implies very large permissible loss given default as a percentage of Tier 1 capital for US G-SIBs. It is unrealistic to assume that banks can survive with losses of 35% and upwards of Tier 1 capital.[14]

(ii) Secondly, when only a subset of total liabilities of a FI is being considered, even if there is a 100% default on this subset of a FI's liabilities, this may remain less than upwards of 30% of total Tier 1 capital held by its counterparties (using the Tier 1 capital to RWA criteria or the leverage ratio criteria of the MAGD Report). It will, therefore, appear that no problems of direct contagion can arise from this segment of financial markets. This is, ofcourse, the wrong conclusion as losses on a subset of a FI's total liabilities must be offset against the pro rata Tier 1 capital that the exposed counterparty holds against this category of assets. In other words, such generous contagion capital loss thresholds (viz. involving all of Tier 1 captial ratio) when applied to financial networks representing *subsets* of total assets of a FI will only confound the problem of inappropriateness of the thresholds being used in many recent network based contagion analyses.

In summary, all financial contagion modelers of financial networks have to specify an appropriate threshold at which bank/nodes are declared 'dead', insolvent or in crisis. The discussion above highlights that there are some important clarifications needed here. It is crucial for the modeler/regulator to understand what such thresholds involving ratios of assets as in the leverage ratios or in the case of risk weighted assets imply in terms of permissible loss of Tier 1 capital in absolute terms.

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[13]Here simply use the formula for numerator and denominator of the leverage ratio adjusted for losses given in equation (3) page 25 MAGD report. In the GAAP case the implied LGD (loss given default) for the leverage ratio to fall to 2.5 % is given by [(642.799- LGD)/(10219-LGD)] = .025 where average Tier 1 capital is $642.77 bn and $10219bn is the average asset size for the 6 US G-SIBs using GAAP, reported in FDIC weblink given in footnote 10. This implies LGD to equal $397.2307 bns which is 61% of average Tier 1 capital of $642.77 bn in the GAAP case. When IFRS average leverage ratio for 2012 Q2 data is used with average assets given as $14693 bn, implied LGD is given by [(631.799- LGD)/(14693-LGD)] = .025. The LGD works out to be $271.255 which implies a 42.9% of the average Tier 1 capital of $631.799 for the US G-SIBs under IFRS accounting rules.

[14]Sheri Markose, who was an academic advisor to the MAGD Report, was able to draw on her experience with the Basel RWA thresholds in the contagion analysis of the Indian financial system. She pointed out that the absence of contagion in the MAGD stress tests was in part an artifact of a very generous absolute capital failure threshold.

Further, as some banks can use the standard approach to risk weighting and others an internal ratings based approach (IRB), for purposes of transparacny it is recommended that equation (1.2) is used to convert what their actual Tier 1 capital to risk weighted assets ratio implies in terms of the absolute Tier 1 capital threshold (denoted by T_c) that will determine they are in distress. As the maximum eigenvalue and the tipping point thereof for the financial network is stipulated in relation to an absolute Tier 1 capital loss threshold, the conversion into absolute capital loss threshold is essential. This will also help national and global regulatory authorities not to be misled about the stability of their financial systems because of very generous absolute capital loss thresholds implied in the Tier 1capital ratio to risk weighted assets ratio. In view of this, the Markose-Giansante eigen-pair framework recommends the use of a simple Tier 1 absolute capital threshold of in the range of between 25% - 30% that the regulator thinks is appropriate for a financial network for total liabilities of FIs and for any subset thereof a pro rata reduction in the loss threshold is needed.

1.4 Evidence: Does Any of this Work ?

We will give two important pieces of evidence that indicate that the eigen-pair method based systemic risk metrics give early warning. The first demonstration came within 18 months into the RBI project (see, Markose et. al. (2013), circulated at the Fianancial Stability Unit and presented at the RBI workshop on the same).

The following Table 1 tracks the eigenvector centrality (the pink section of Table1) which gives the rank order of banks in terms of their systemic risk importance, viz. their capacity to bring about loss of capital in their system from the financial contagion ensuing from their failure, in the absence of regulatory interventions. Sudden changes in rank order of the centrality metrics at the top end should be taken seriously. In 2012 when the eigenvector centralities for top 25 Indian banks was tabulated for the 4 quarters, it was found that the bank C001, which was ranked substantially lower down had in a matter of 6-8 months become the most systemically important bank in India From being a mid Tier bank it had jumped to be in the central Tier (shown in yellow and green section of Table 1) . This sudden elevation in terms of systemic importance of C001 is comparable to that of HBOS and Northern Rock in the UK. C001 was winning Bank of the Year Awards as it was increasing market share. An increase in the eigenvector centrality of the bank which occupies the most central position in the financial network, as explained in detail in Chapter 5 p. 55 of this handbook and also in Markose (2012), occurs as the both the number of its net lender counterparties and the liabilities of this bank increase relative to Tier 1 capital of the banks exposed to it. In other word, this bank is borrowing aggressively in the inter-bank market. Further, the upper bound of the maximum eigen value, the systemic stability metric, is impacted on in an upward direction by increases in the row sum of the bank ranked 1 in terms of eigenvector centrality, viz weighted sum of liabilities relative to capital of the net lenders of the most systemically important bank. The higher resultant maximum eigenvalue of the financial system also signals that the system can now lose a larger percentage of capital of the whole system, if this most systemically important bank is to fail. As the activities of C001 was found to almost double the systemic risk of the

Indian banking system,[15] action was taken by the Deputy Governor in charge of Financial Stability Unit.

Funded Sector (Q1-Q4 2011) Top 25 Banks Systemic Importance Measures : Net Liabilities , Eigen vector Centrality, Tiering

Banks	Net Position (Rs Crores;+Liabilities, - Assets)				Eigen Vector Centrality (right)				Tiering			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
C001	15553.050	19590.740	25559.910	24684.990	0.234	0.505	0.501	0.481	0.817	0.856	1.000	1.000
A010	15972.150	15075.100	17556.550	15059.150	0.471	0.401	0.549	0.401	0.859	0.855	0.957	0.800
C004	-4684.150	-1055.790	5005.490	4819.860	0.148	0.214	0.165	0.525	0.875	0.912	0.984	0.900
A015	10259.590	9565.660	-1.170	-6506.250	0.448	0.566	0.166	0.254	0.901	0.882	0.965	0.871
C007	2052.650	5056.800	7626.780	9406.210	0.095	0.105	0.159	0.221	0.704	0.662	0.651	0.686
A013	6226.400	7769.360	9647.920	9565.900	0.099	0.190	0.205	0.199	0.690	0.750	0.841	0.700
A008	9551.610	5785.090	5490.550	7656.960	0.515	0.167	0.095	0.199	0.761	0.765	0.778	0.745
A001	4155.950	4845.250	5726.500	5525.170	0.115	0.159	0.517	0.192	0.704	0.691	0.778	0.671
A027	972.490	4777.180	7586.210	6146.000	0.115	0.140	0.265	0.176	0.646	0.721	0.651	0.629
A023	2257.580	2162.780	1511.650	-2515.810	0.156	0.118	0.121	0.176	0.704	0.676	0.762	0.686
A016	2946.890	2644.700	1544.860	6007.520	0.051	0.065	0.041	0.166	0.555	0.559	0.778	0.500
A002	4276.650	4965.250	5542.560	5016.420	0.125	0.156	0.205	0.155	0.606	0.662	0.746	0.657
A018	-44152.990	-45066.050	-20927.550	-18875.800	0.066	0.108	0.066	0.147	1.000	1.000	0.952	0.886
C006	1855.640	2929.740	7127.050	5527.860	0.075	0.065	0.126	0.154	0.425	0.529	0.480	0.471
A012	557.970	2274.000	2776.180	5791.040	0.062	0.072	0.155	0.122	0.775	0.809	0.810	0.745
D018	-2904.000	-5154.980	-4452.480	-950.260	0.021	0.105	0.000	0.115	0.620	0.652	0.667	0.645
C005	2254.170	5541.980	5569.750	5954.640	0.066	0.152	0.152	0.105	0.690	0.706	0.746	0.645
A011	-1795.610	-96.050	1995.760	1654.750	0.042	0.057	0.062	0.094	0.676	0.755	0.778	0.771
A017	5144.420	5227.980	6785.620	5566.400	0.109	0.157	0.255	0.094	0.555	0.652	0.605	0.700
A024	7856.120	2590.120	6856.660	440.770	0.207	0.099	0.157	0.092	0.718	0.750	0.857	0.714
A006	9405.200	5946.670	9525.720	-2500.260	0.251	0.510	0.222	0.092	0.851	0.855	0.952	0.886
C003	457.910	5865.500	4865.570	5850.250	0.074	0.069	0.091	0.069	0.845	0.855	0.968	0.871
B005	1682.770	2059.080	2587.580	2971.870	0.049	0.059	0.065	0.066	0.408	0.456	0.508	0.500
A022	1970.450	2798.480	2621.420	2911.610	0.052	0.102	0.062	0.064	0.485	0.559	0.605	0.514
A020	2575.870	2019.740	2721.100	5191.910	0.055	0.065	0.090	0.080	0.521	0.485	0.619	0.586

Table 1 : Evidence Over 2011 Q1-Q4 period that a Tier 2 Bank C001 jumps to the Most Systemically Important Bank (Highest Eigen-vector Central)

The eigen-pair method being implemented at the RBI, was applied to the only publicly available bilateral available data based on the BIS Consolidated Banking Statistics. While the case of Greece is marked by the negative capital that the country's big banks suffered since 2011 Q2 (leading to a break in data at this point in Figure 10), what is interesting is how the eigen-pair methods yields results for the rank order of the vulnerable countries in the periphery of the Eurozone (Portugal, Ireland, Italy, Greece and Spain). What is remarkable is that the recent vulnerability of the Portugese banking system that can clearly be seen in late 2013 using the vulnerability index based on the Markose et. al. left eigenvector centrality metric. This eventually culminated in the collapse of the major Portugese Banco Espirito Santo in August 2014, sparking fears of a second round

[15] C001 was already on the radar of the authorities in 2011, as noted by Deputy Governor Shyamala Gopinath. The SRA tool of the RBI provides the quantitative evidence of the nature of the systemic risk posed by C001.

of banking contagion in the Eurozone. The status of Portugal can be seen in Figure 10 where by the end of 2013 Q4, Portugal becomes the most vulnerable banking system in the Eurozone. This was not anticipated by other methods of analysis such as those given by the IMF. [16]The top rank occupied in the left eigenvecor by Portugal, makes it the most vulnerable banking system in the periphery of the Eurozone. This arises because big Portugese banks have the largest net exposures to other banks relative to their own capital buffers.

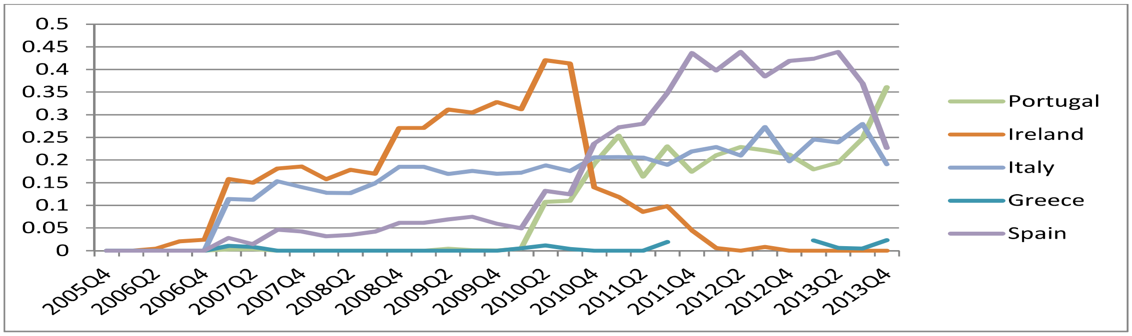

Figure 10- Systemic Importance of Debtor Eurozone Countries given by the (rank order of) Right Eigenvector (Top Panel and Vunerability of the PIIGS Banking Systems given by Left Eigenvector (Bottom Panel)

1.5 Concluding Remarks and Future Work

The need for regulators to mandate actual bilateral data on contractual obligations of FIs has been emphasized as calibrations and probabilistic measures based on market price data add layer upon layer of assumptions that contribute to model risk that detract from assessing the stability of the networked financial system and the assignment of systemic risk measures to FIs. The eigen-pair method recommended in the SRA App has the advantage that it is based only on extant bilateral contractual financial obligations of FIs and their Tier 1 capital and the network topology that is implied by the certified bilateral data submissions.

Given the relative simplicity in the determination of the above systemic risk metrics for the financial network representing the appropriate dynamical system for the demise of FIs from failing counterparties, the eigen-pair method was applied on the bilateral financial data for the Indian interbank market on a quarterly basis from mid-2010 to end of 2011. These results were presented in April/September 2012 at the RBI and have been reported in Markose et. al (2013). Remarkably, a situation reminiscent of the aggressive borrowing on the interbank, short term money markets, done by UK banks that demised in the 2007 crisis was observed. From mid-2011, an Indian bank that was ranked number 5 or 6 in terms of eigenvector centrality in mid-2010 was seen to have

16 The Financial Times report on 10 August 2014 stated: In contrast with Ireland and Spain, banks were not seen as Portugal's central vulnerability when it agreed to a €78bn bailout by the EU and the International Monetary Fund in 2011. In a progress report on the rescue in January, the IMF said "the financial sector remains stable" thanks to capital increases in the previous two years, while "adequate provisioning levels are being safeguarded through periodical impairment reviews". http://www.ft.com/cms/s/0/2965c812-1e29-11e4-bb68-00144feabdc0.html#axzz3Flz9KbKZ

catapulted to the being the bank with the highest eigen-vector centrality within a few quarters. A combination of increased connectivity of the FI and its large liabilities relative to the distribution of capital in the system accounts for its dominant eigen-vector central position. Clearly, what is rational/profitable for this bank that enabled it to increase its loan market share can lead to an adverse loss of stability for the interbank system. System wide capital losses from a Furfine type stress test, with this bank as the trigger, jumped to 29.4% from more modest levels of 6%-14% in previous quarters when other banks were dominant in terms of eigen-vector centrality. This real world exercise shows that it is not sensible to have a priori lists for SIFIs in macro-prudential policy and sudden jumps in eigen-vector centrality of a bank should give cause for concern.

The results for how a Pigou tax based on the eigen-vector centrality of Indian FIs was also reported in Markose et. al (2013). Each FI is taxed according to its right eigenvector centrality in order for the FI to internalize the costs that they inflict on others by their failure and to mitigate their contribution to network instability as given by the maximum eigenvalue. The progressive nature of the tax justifies the moniker 'super-spreader' tax. The rationale behind the application of the right eigenvector centrality of a node as the basis of the Pigou tax is to enable a FI to provide a buffer proportional to its own capacity to propagate contagion.

As the spectral methods for stability analysis permit generalizations across different matrices or multi-layer representations of multi-products in the financial system (see Markose and Rais Shaghaghi, 2014), it is envisaged that the solvency and liquidity contagion analysis can be integrated within amore convenient systemic risk stability metric. Currently, the RBI SRA App can conduct a Furfine style contagion stress test where both solvency and liquidity factors play a role. For this considerable work has been done in identifying the high quality liquid assets (HQLA) in the Indian financial system and also identified contagion channels from liquidity factors. However, a lot more work remains to be done on developing regulatory ratios for HQLA that are similar to regulatory ratios regarding Tier 1 capital that aim at enhancing solvency.

While some preliminary analysis has been done for the electronically cleared financial markets such as the REPO and CBLO, once data collection for this has been done, activities of FIs in these markets will be integrated into the multi-sectorial framework. The same goes for the granular network models for Indian FIs with the global financial markets.

Finally, the multi-layer framework of networks for the Indian financial system has to be embedded into the sector flow of funds for the Indian economy. Following the Castren-Racan (2012) ECB work, the software for this has already been developed and tried out by Markose and Giansante on the BIS consolidated global banking flows which since 2010 give the non-bank real side sectorial break downs for 10 Eurozone countries. However, much work remains for adapting this for the integration of the much more granular network depiction of the Indian financial system with the Indian sectorial flow of funds.

Summary of SRA Features

The main features of SRA are:

1. Fully integrated network application for digital mapping of financial systems.
2. An intuitive two-step procedure for data import from Comma-Separated Value files (CSV).
3. The SRA database integration allows automated data access.
4. A statistical package that provides a wide range of information regarding balance sheets of FIs, network characteristics of markets, and the identification of *Systemically Important Financial Institutions* (SIFIs).
5. A financial contagion package with state-of-the-art contagion algorithms for failure from solvency and liquidity shocks.
6. A holistic network visualization package that graphically displays topology of networks as well as contagion maps.
7. An innovative macro-prudential regulation package based on the *eigen-pair analysis* that provides metrics for the stability of networks and also the systemic importance of FIs.
8. A method for stabilization of networks based on the eigen-pair approach which determines the tax to be levied on SIFIs for their contribution to the systemic risk of the financial network.This can be a notional exercise for the regulator to quantify the negative externality posed by a highly eigenvector central FI.
9. The facility to export all the outcomes either in excels files or as pictures which have been produced by the SRA visualization package.
10. SRA software architecture builds in a multi-layer network framework to access and deal with data for different products/markets, viz. bilateral data from multiple markets can be loaded and dealt with simultaneously.

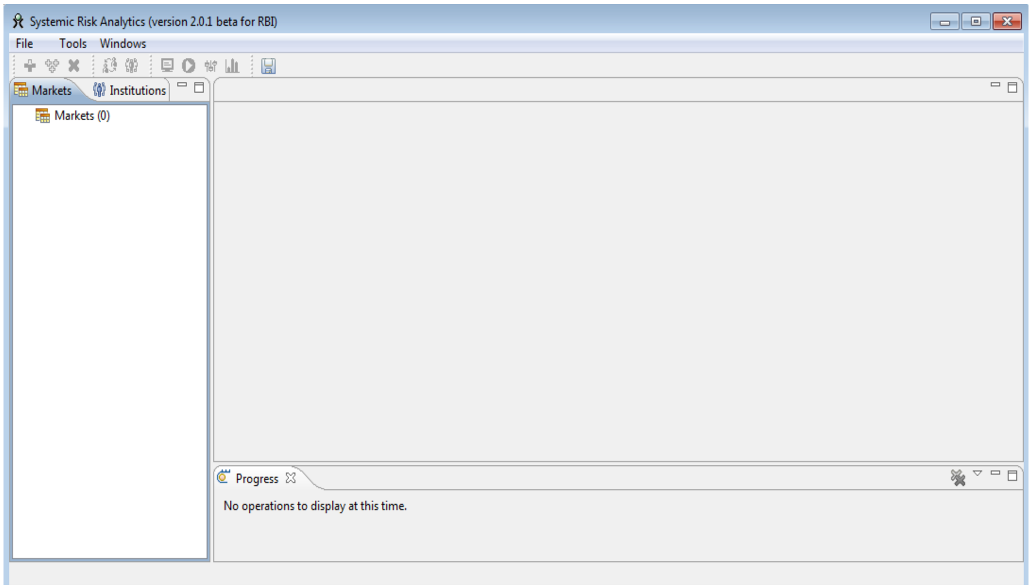

Figure 10 - The SRA application environment and main components.

The main panels in SRA are shown in Figure 10. Starting from the top left of the window, we have

- The TOP main menu with icons toolbar for a direct access of the different operations.
- The LEFT explorer panel that lists all objects, markets and institutions, which are the list of the *markets* and the *institutions*.Note institutions are the participating financial institutions in a financial market.
- The MAIN CENTRAL panel displays all the main outputs of the application, in particular for the individual objects.
- The BOTTOM panel gives a *progress bars* for ongoing operations as well as summaries of the generated outputs.

The External Libraries

SRA makes use of the following third-party libraries for both graphical and computational tasks:

- The Eclipse Rich Client Platform that constitutes the skeleton and visual panels of the entire application (http://wiki.eclipse.org/index.php/Rich_Client_Platform).

- Colt libraries for high performance scientific and technical computing in Java (http://acs.lbl.gov/software/colt/).

- JFreeChart library for professional quality charts (http://www.jfree.org/jfreechart/).

- The Java Universal Network/Graph Framework library for modeling, analyzing and visualization of data as graph of network (http://jung.sourceforge.net/).

- MySQL connector/J for the JDBC drivers for MySQL in JAVA (http://dev.mysql.com/downloads/connector/j/).

Chapter 2

Data Import

Import financial data in SRA manually or via an automated database connection

Getting started on SRA requires, as first step, knowledge on how to prepare your financial data in order to import them into SRA. This chapter provides a basic two-step manual import facility based on standard comma-separated value input files as well as a more sophisticated database connectivity for large scale financial data.

ICON KEY
Import Market
Import Institutions

Manual Import

The manual import is a basic two-step approach consisting of two main csv data files to be loaded into SRA: *market data* and*institutions data* files.

Market Data

The market data file must be constructed as a $(N+1)\times(N+1)$ matrix where N represents the number of institutions participating in the market. The first column and row are dedicated to row and columns headers, respectively.

Note

SRA interprets market matrices as LIABILITY FLOWS from the row institutions (guarantors/borrowers) to the column institutions (guarantees/lenders).

In financial networks nodes stand for financial entities such as banks, other FIs, and their non-financial customers or end users. The edges or connective links represent contractual flows between two financial entities. Let i and j be two institutions. When a direct link originates with i and ends with j, viz. an out degree for i, it represents financial outflows or payables for which i is the guarantor. A link from j to i yields an in degree for i and represents cash inflows or financial receivables for i from$j$.

Figure 11 shows an example of the csv file loaded in Microsoft Excel. Names of institutions MUST be in the same sequence in the row and column headers.

	A	B	C	D	E	F	G	H	I	J
1		A001	A002	A003	A004	A005	A006	A007	A008	A009
2	A001	0	0	0	0	0	0	0	0	0
3	A002	23	0	0	110	0	0	0	0	0
4	A003	0	100	0	852	0	0	0	0	0
5	A004	0	0	0	0	100	0	0	0	0
6	A005	22	30	0	0	0	0	0	200	0
7	A006	0	0	0	0	0	0	0	0	0
8	A007	0	0	0	0	0	0	0	0	0
9	A008	0	0	0	0	0	0	0	0	0
10	A009	0	0	0	0	0	0	0	0	0

Figure 11 – Market data csv input file for GROSS bilateral obligations. Institutions name are labeled A001 to A009.

Important

All entries in the csv files must be non-negative and represent GROSS values. No cells should be empty or have values (delete filled) filled outside the perimeter of the matrix.

Once the file is ready, it can be easily imported by selecting the *Markets* tab in the explorer panel (See Figure 10) and then clicking the button as displayed in Figure 12. A pop-up window will allow the user to browse for market data csv files. Each market data file is market and time specific. For example, the user can upload csv files for the same market for different dates or different markets at the same date. The markets will then be listed in the Markets list. SRA allows you to load as many markets as you want, as long as they are consistent with the same list of institutions.

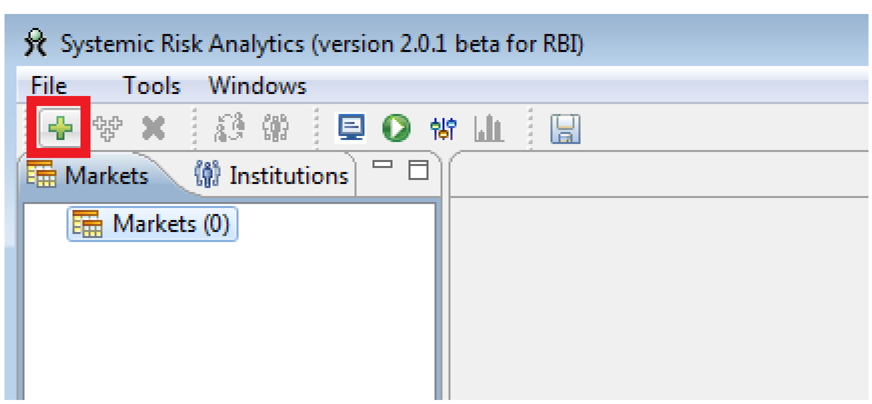

Figure 12 – The TOP LEFT hand side of the main toolbar.

Institutions data

The institution data must be constructed as a $(N+1) \times Z$ matrix where N represents the number of institutions participating in the market and Z the characteristics of each institution. The first row is dedicated to columns headers. In the current version of the SRA app, the 2.0.1 beta, the required institutions column variables are the following:

A. Name

B. Total Assets

C. Total Borrowing

D. Liquidity Buffer

E. Capital Buffer

F. Risk Weighted Assets

G. Min Capital/RWA

H. Group Id

I. Group Name

	A	B	C	D	E	F	G	H	I	J
1	Banks	Total assets	Total borrowing	Liquidity Buffer	Capital Buffer	RWA	Min Cap/RWA	Group Id	Group name	
2	A001	190563.21	17587	4028.5568	10971.2609	125385.5962	0.06	-1	Public Sector Bank	
3	A002	134975.77	4814	3609.7295	7658.8882	95022.774	0.06	-1	Public Sector Bank	
4	A003	348050.95	25475	9550.1435	26719.138	286441.9235	0.06	-1	Public Sector Bank	
5	A004	312980.9	15950	7830.0121	20245.5043	265082.2086	0.06	-1	Public Sector Bank	
6	A005	119989.66	3309	3242.5466	4142.272146	69037.8691	0.06	-1	Public Sector Bank	
7	A006	361112.31	39172	6426.7031	21783.0945	223098.6156	0.06	-1	Public Sector Bank	
8	A007	246488.22	13059	6098.94	11464.62	163318.8928	0.06	-1	Public Sector Bank	
9	A008	171540.59	9405	4989.4597	8963.9712	111035.9484	0.06	-1	Public Sector Bank	
10	A009	97193.5	4426	2190.6651	4322.4703	56769.5902	0.06	-1	Public Sector Bank	

Figure 13 - Institutions data csv input file. Institutions name are labeled A001 to A009.

Note

If data for the column variables is not available, viz they are not used for the analysis. The default value should be 1

The interpretation of the first six variables is straightforward. The "Min Cap/RWA" represents the minimum regulatory requirement of capital buffer over risk-weighted assets for the selected institution to be solvent (in the example in Figure 13 we define a 6% threshold). A detailed explanation for the use of the above variables will be given in the following Chapters. The last two variables define grouping characteristics (non-negative id and the name of the group respectively) of each institution, for example the type (bank, insurance company, etc.). In column H institutions with a unique group id (using numbers from 0 onwards) will be grouped together in the network analysis. Group Id "-1"is used ifno grouping is required.

Important

The order of the institutions in the Institutions data csv list MUST be identical to the one in the market data file

To import the institution data file, click the button (in Figure 12) to access browser.

Chapter

3

Network Analysis

Network Analysis

This Chapter introduces the statistical properties of the networks that are loaded into SRA according to the instructions in Chapter 2. This facility allows the user to assess the main network and nodes statistics as well as a simple way of personalizing the graphical visualization of the network.

ICON KEY
Inspect Institution
Inspect Market
Network Plot

Objects Inspector

The list of objects loaded in SRA is displayed in the package explorer (LEFT panel in Figure 10). The user can inspect any object by double-clicking on a selected item. A new view window will be shown in the main central panel with the individual properties of either the institution (represented by the icon) or the market selected (represented by the icon).

Market Properties

The *Inspect Market* view provides a detailed probe of the structure of the market. It is made up of two main sections: Details and Data Statistics.

Important

The *Inspect Market* is only available when a market object is selected from the explorer panel.

Market Headlines

Market headline provides a general overview of the macro information of the market, such as number of participants, total gross and net liabilities, etc.

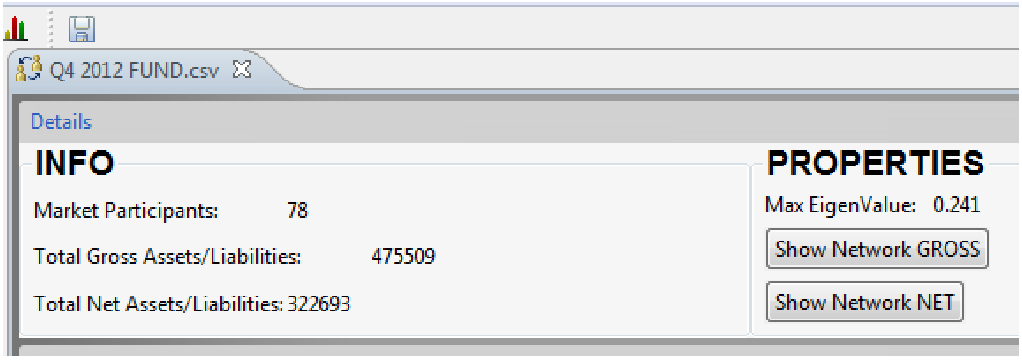

Figure 14 - Market Headlines

Data Statistics

Data Statisticscontainstwo main tables: Market Data Statistics, Node Statistics and Network Statistics.

Data Statistics

Raw Data | Network Statistics

Name	Type	Tot Payables	Tot Receivables	Liquidity	T1 Cap	RWA	T1 Ratio
A001	Public Sector Bank	12133 (2.55%)	6093 (0.0%)	4028	10971	125385	8.75%
A002	Public Sector Bank	10660 (2.24%)	2558 (0.0%)	3609	7658	95022	8.06%
A003	Public Sector Bank	28524 (6.0%)	77664 (0.0%)	9550	26719	286441	9.33%
A004	Public Sector Bank	21657 (4.55%)	76792 (0.0%)	7830	20245	265082	7.64%
A005	Public Sector Bank	3580 (0.75%)	3417 (0.0%)	3242	4142	69037	6.0%
A006	Public Sector Bank	17150 (3.61%)	19153 (0.0%)	6426	21783	223098	9.76%
A007	Public Sector Bank	9793 (2.06%)	2270 (0.0%)	6098	11464	163318	7.02%
A008	Public Sector Bank	13920 (2.93%)	1545 (0.0%)	4989	8963	111035	8.07%
A009	Public Sector Bank	2416 (0.51%)	1537 (0.0%)	2190	4322	56769	7.61%

Figure 15 - Market Data Statistics

Market Data Statistics

Market Data Statistics shows statistics of the market data loaded as input file (see Chapter 2), such as institution type, tot payables and receivables (both in absolute and % values giving market share of total payables and receivables respectively), amount of liquid assets, core Tier 1 Capital (T1) and risk weighted assets (RWA) along with the T1 ratio calculated as the ratio between T1 capital and RWA.

Data Statistics

Raw Data | Network Statistics

Name	Type	K in	K out	Conn in	Conn out	CC	SP	BTW	unw EVC
A001	Public Sector Bank	18	24	23.08%	30.77%	54.53...	1.7	68.8	0.113
A002	Public Sector Bank	10	34	12.82%	43.59%	51.84...	1.46	97.71	0.229
A003	Public Sector Bank	50	12	64.1%	15.38%	37.31...	2.1	360.57	0.029
A004	Public Sector Bank	54	10	69.23%	12.82%	35.37...	2.42	137.03	0.013
A005	Public Sector Bank	15	25	19.23%	32.05%	60.13...	1.58	47.62	0.154
A006	Public Sector Bank	26	30	33.33%	38.46%	41.88...	1.57	206.13	0.103
A007	Public Sector Bank	12	36	15.38%	46.15%	52.26...	1.43	78.85	0.199
A008	Public Sector Bank	9	39	11.54%	50.0%	50.0%	1.38	76.33	0.236
A009	Public Sector Bank	14	24	17.95%	30.77%	62.28...	1.59	45.74	0.142

Figure 16 - Node Statistics

Node Statistics

Key to the network topology is the bilateral relations between agents and is given by the adjacency matrix $\boldsymbol{A} = (a_{ij})^I$ where *I*is the indicator function with $a_{ij} = 1$ if a directed link from i to j exists, 0 otherwise. We can define here the GROSS liability matrix $\boldsymbol{X}$ such that x_{ij} represents the flow of gross obligations from i to *j*. The total gross payables fornode*i* is the sum over j columns (or counterparties), $G_i = \sum_j x_{ij}$ while the total gross receivables for i is the sum over i rows $B_i = \sum_i x_{ij}$. We also define the NET liability matrix $\boldsymbol{M}$ with entries $m_{ij} = (x_{ij} - x_{ji})$ representing the bilateral net payables of i vis-á-vis *j*. Note the matrix M is skew symmetric with entries $m_{ij} = -m_{ji}$. To analyse the dynamics of the cascade of failure of the i^{th} FI on the j^{th} one, the matrix that is relevant will only contain the positive elements of the M matrix, named $\mathbf{M}^{+}$.

Node Statistics in SRA provides node statistics of the participant of the GROSS network$\boldsymbol{X}$, such as:

- **k in** and **out**: in and out degree for each Institution

$$k_j^{in} = \sum_i a_{ij}; \qquad k_i^{out} = \sum_j a_{ij} \quad (3.1)$$

- **Conn in** and **out**: individual in and out connectivity, calculated as follows

$$Conn_i^{in/out} = \frac{k_i^{in/out}}{N-1} \qquad (3.2)$$

- **CC**: individual cluster coefficient according to the equation 3.3.

$$CC_i = \frac{E_i}{k_i(k_i-1)}. \qquad (3.3)$$

  $E_i$denotes the actual number of links between agent *i*'s k_i neighbors, viz. those of *i*'s $k_i$neighbors who are also neighbors.

- **SP**: average shortest path of the selected node vis-a-visits neighbors.

- **Unw EVC**: unweighted eigen vector centralitycalculated as the eigen vector of the largest eigen value of the adjacency matrix A.

Network Statistics

Network Statistics provides main network properties of the market that are listed below:

- **K in** and **out**: number of in-degrees and out-degrees of the network, which represents the amount of bilateral assets and liabilities respectively;

- **Conn in** and **out**: connectivity of the network for in and out degrees respectively calculated as follows:

$$Conn_i^{in/out} = \frac{\sum_i k_i^{in/out}}{N(N-1)} \qquad (3.4)$$

- **CC**: cluster coefficient of the network, calculated as follows:

$$CC = \frac{\sum_i CC_i}{N} \qquad (3.5)$$

Network Visualizer

The network visualizer can be accessed from the main menu "Networks Plot". It provides the facility to visualize both GROSS (***X*** matrix) and NET (***M***[+]) networks.

Circle Layout

SRA employs a basic **Circle layout**, where nodes are placed in circle fashion, as described inFigure 17.

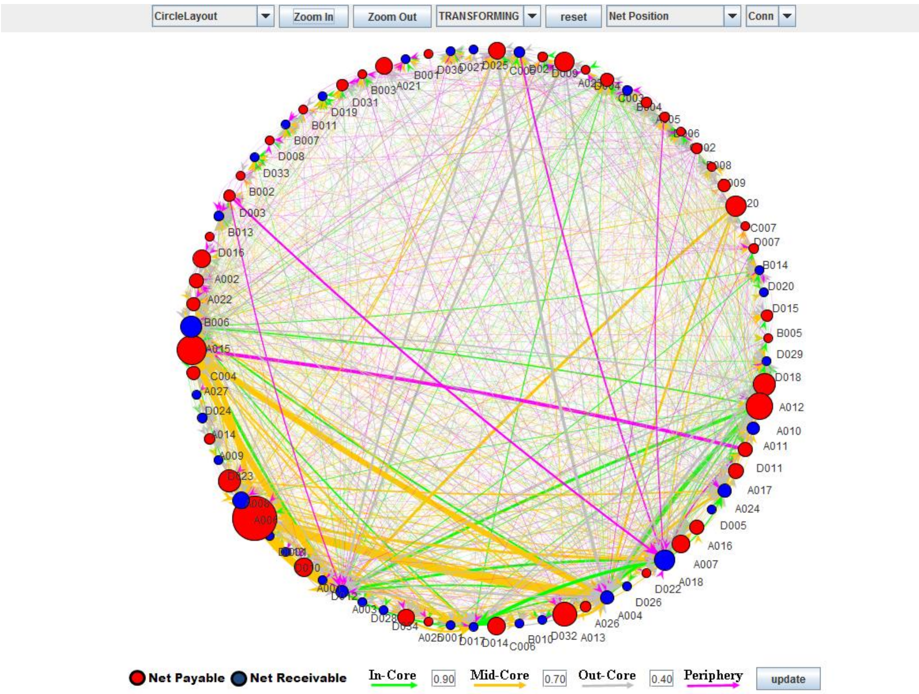

Figure 17 - Circle layout

Tiering layout

A dedicated network layout called **Tiering layout**, has been specifically designed to capture tiering structures in the financial network as shown inFigure 18.

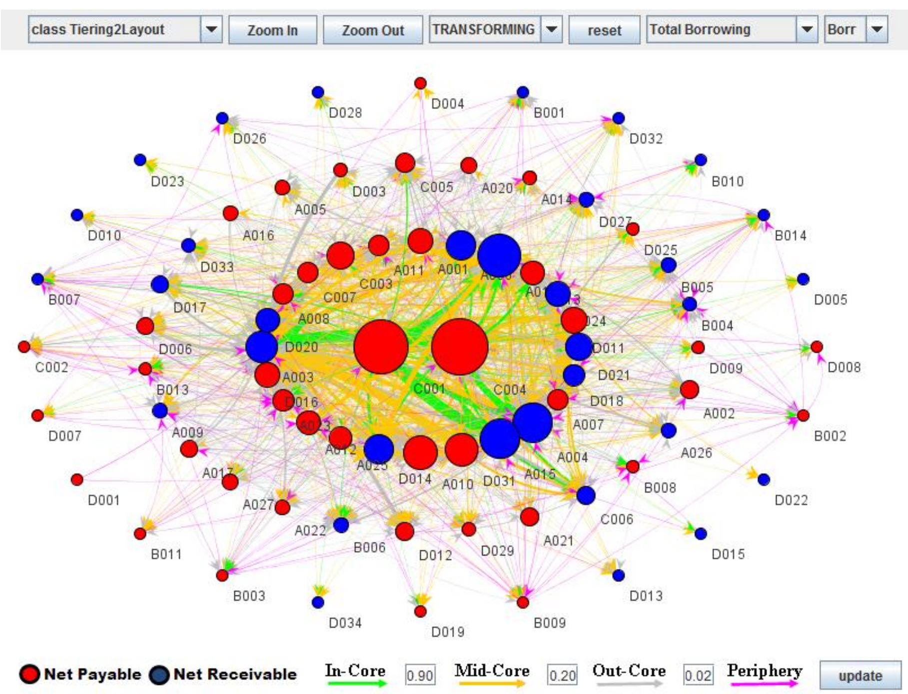

Figure 18 – Tiering layout of interbank market in Inda

The layout takes the range of connectivity of all nodes as a ratio of each node's in and out links divided by that of the most connected node. Nodes that are ranked in the top 10 percentile of this ratio constitute the inner core. This is followed by a mid-core between 90 and 70 percentile and a 3rd tier between 40 and 70 percentile. Those with connectivity ratio less than 40% arecategorized as the periphery. Nodes in the periphery are typically not connected to one another. The percentiles can also be personalized with custom ranges to be specified in the bottom area of the plot. The button UPDATE will refresh the plot with the customized percentiles.

Tiering Group Layout

In this facility the group id plays a role. The institutions with id "-1" automatically occupy the center tiering structure while non "-1" institutions will appear on the top with different shaped icons as inFigure 19.

.

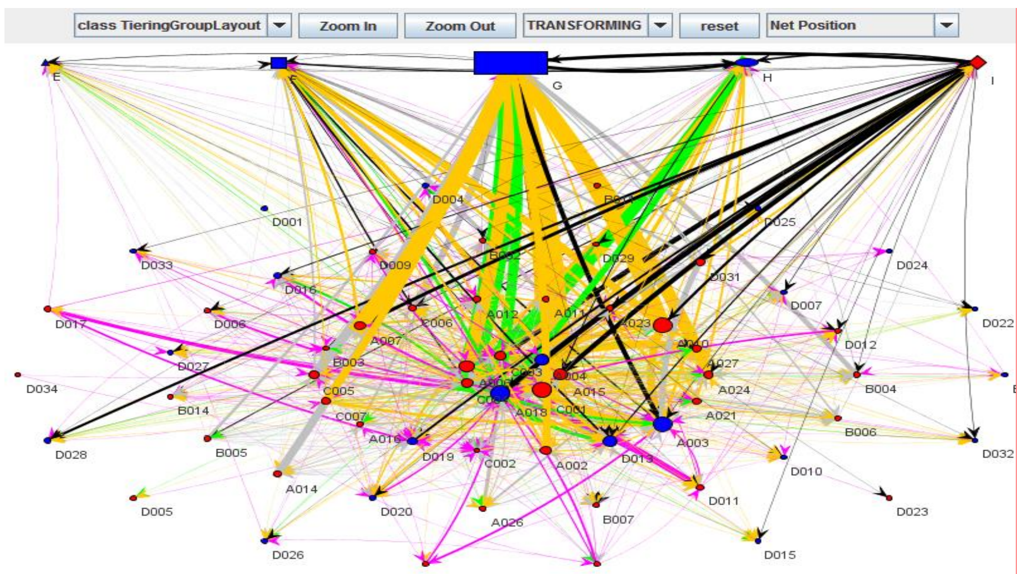

Figure 19 - Group tiering layout

InFigure 19, banks are given central status (because they were assigned id "-1") while non banks appears in an aggregated form on the top (top central group is Insurance Companies (G node), Mutual Funds (F node), etc…).

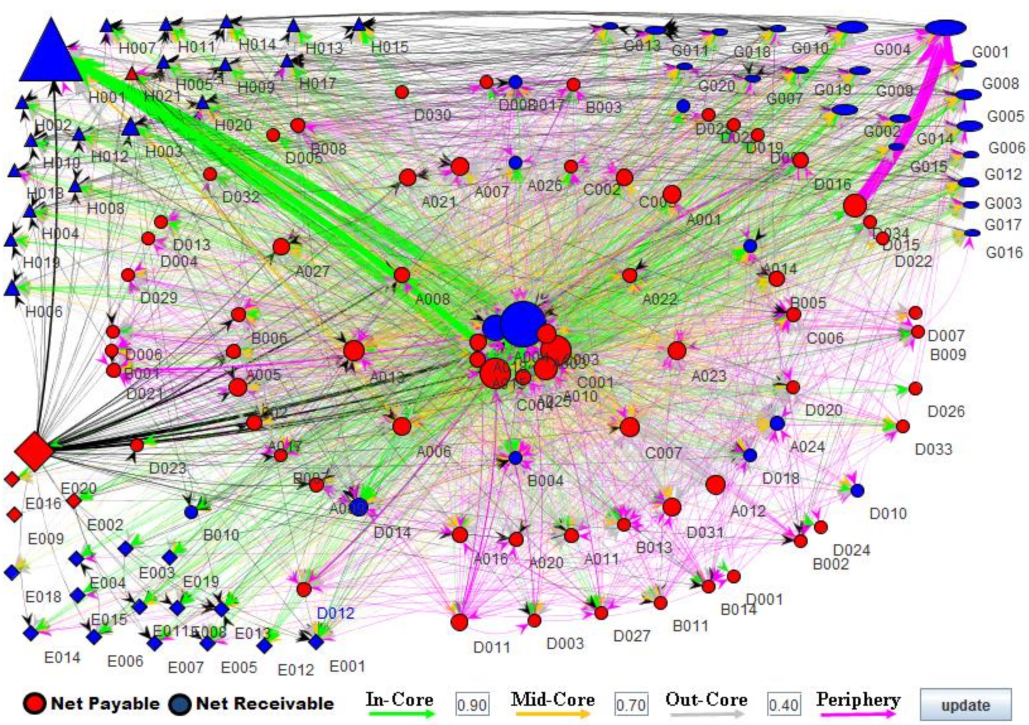

Figure 20 - individual grouping

Figure 20can be achieved by using the tiering layout and the user can manually pick and move as in this case the non bank institutions to location of their choice. For example top left are triangles are (H nodes) Insurance companies, all net lenders except H21; Bottom left Diamonds areUrban and Cooperative Banks.

> **Important**
>
> Only institutions with a specified group id ≠ -1 can be placed on top. The remaining institutions with group id = -1 will be kept in the center tiering layout.

Personalizing network plot

The links from a node are out-degrees and depict borrowing. The links are weighted and the thicker the links, the larger the size of their obligations. The links are colour coded in the tiered layout,Figure 18. Nodes are colour coder red if they have net payables and blue if they have net receivables as in Figure 18. For example, the yellow links show where the second tier (mid core) banks are borrowing from.

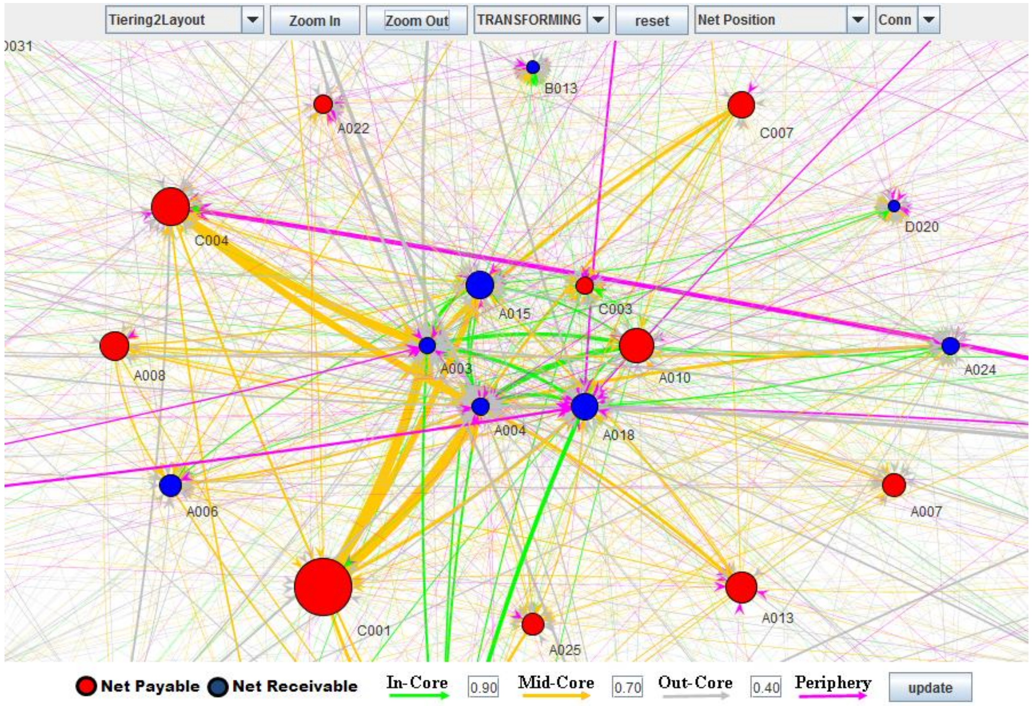

Figure 21 - Networ plot zoom-in functionality

Basic functionalities are

- Zoom-in and zoom-out (that is also available by using the mouse scroll wheel),
- Transforming and picking to move the whole network or a single node respectively and
- Reset button to reset the layout to the default state are placed at the top of the plot.
- Node sizecan be determined by criteria given by drop-down menu (according to total borrowing, capital, net positions, etc. of each node)

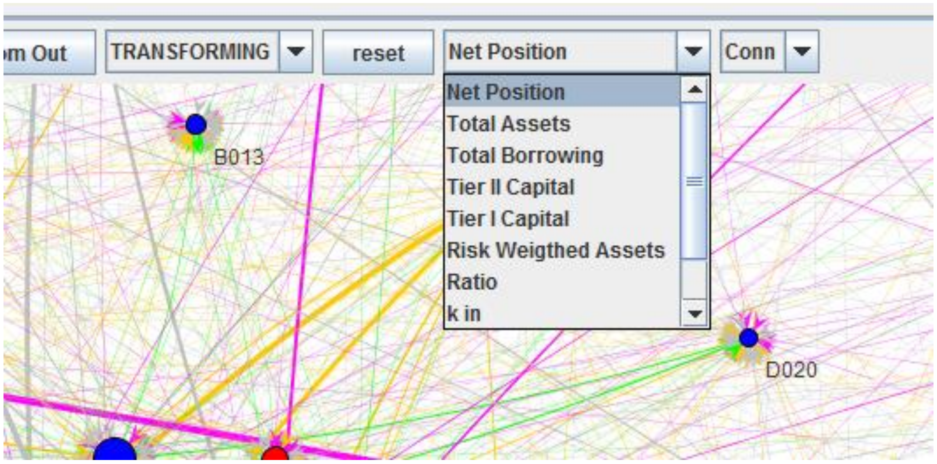

Figure 22 - Network Plot Drop Down Menu of Node Size

- Non-default tiering criteria. By default, the total connectivity is used. However, the user can personalize it by selecting a different criterion, such only in or out degree, EVC and so on.

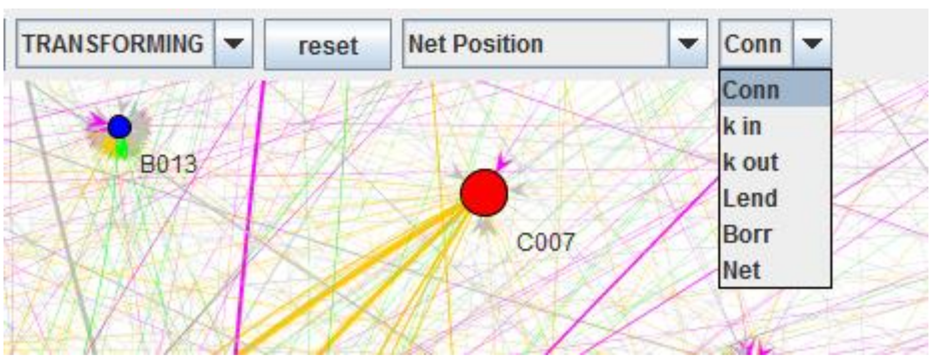

Figure 23 - Network Plot Drop Down Menu of Tiering Criteri

Chapter

4

Contagion Stress Test

Contagion Algorithms and Stress Test Analysis of Financial Networks

Contagion analysisis an important and well established procedure to assess systemic risk in financial markets. SRA employs a sophisticated contagion algorithm implementing solvency and liquidity constraints andprovides a detailed analysis of loss propagationamong financial institutions interconnected by balance sheet and off balance sheet linkages.

ICON KEY
Run contagion
Contagion results
Inspect contagion

Introduction

Due to a FI's balance sheet and off balance sheet inter-linkages with those of other FIs, FIs suffer the following type of risks :

(i) Counterparty risk arises when financial counterparties fail and default on obligations. Failure ofcounterparty can affect both liquidity and solvency of a financial entity. The failure of debtors to repay can threaten the solvency of lenders while failure of lenders or holders of contingent claims can mean that their counterparties are short of funds to make their own payments.

(ii) Direct credit risk of credit instruments occurs when the issuer defaults. This may be aggravated as counterparty risk when solvency of guarantoris correlated with the credit risk of the underlying credit instruments.

(iii) Credit risk of non –financial debtors arising from their default, and

(iv) Market and funding liquidity risk.

Finally,

(v) there is market risk on the valuation of balance sheet securities.

Market liquidity risk refers to the loss of value of assets sold under conditions of fire sales. Funding liquidity risk, in addition to failure of lenders in the system ((i) above), can arise when (a) lenders do not roll over loans in repo, (b) prime brokers pull the plug, (c) in secured or collateral based loans, collateral loses value , and (d) the repo rate/haircut increases. Finally, the close link between liquidity and solvency arises from the fact that factors (i- v above) that cause asset quality deterioration will also reduce the quantity of liquid funds that the financial institution can raise.

SRA models the credit and counterparty risk from failure of debtors or derivatives sellers on net liabilities between FIs. Liquidity shocks are however modeled in gross flow terms as the bankruptcy laws implies that counterparties of failed FIs continue to fulfill their obligations in gross values.

The criterion of bank failure as a result of illiquidity is harder to identify than in the case of solvency. Unlike the Tier 1 capital which is a clear cut benchmark against which solvency criteria can be defined, a FI's available high quality liquid funds are harder to identify. In what follows, RBI regulators specify the instruments that can be called in when there is a liquidity shortfall. Market liquidity risk requires additional modeling of the market price impact functions in relevant secondary markets from fire sales of assets. The algorithm developed for SRA combines both solvency and liquidity channels. The mathematics underpinning the algorithm is given in the next section.

Contagion view in SRA

By clicking on the contagion button a pop-up window shows the options the user can choose.

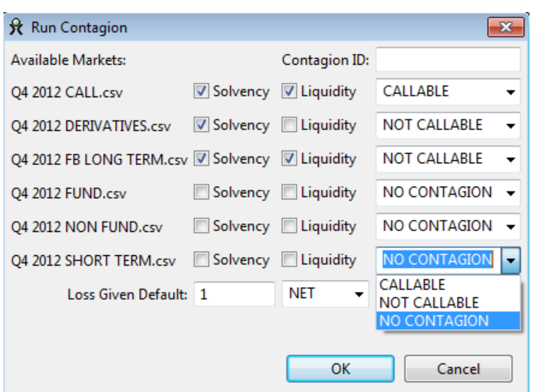

Figure 24 - pop-up window for contagion options

First of all, a name has to be specified to refer to that contagion run, for example "run 1" of "banks only solvency". Second, the user is free to choose solvency only, liquidity only or both solvency and liquidity contagion runs by ticking in the drop-down menu. Features can be attributed to each market loaded in SRA, such as:

- **SOLVENCY**: by ticking this option for the selected market(s) solvency contagion analysis will be conducted as described in equations (4.2) and (4.3) below.

- **LIQUIDITY**: by ticking this option, the market(s) that will be included for the propagation of liquidity shocks have to be selected. In this case, additional information must be provided, such as:
    - **CALLABLE**: assets in this market can be called in in case of liquidity shortage according to equations 4.5 in the secondary liquidation.
    - **NOT CALLABLE**: assetsto be considered in primary liquidation only.
    - **NO CONTAGION**:specify nodes in the bilateral matrix that are assumed not to fail.

Figure 248provides an example of the contagion set up explained above.

Contagion Visualization

Multi-run Contagion Results

Once the contagion algorithm is run, the results are presented in a ***contagion view***. The contagion results table reports, for each trigger, aggregated losses in terms of capital (for solvency shocks) and liquidity (for liquidity shocks). These are presented in both absolute and percentage values of total capital and liquidity respectively.

Trigger	Solvency Losses	% of Capital	Liquidity Losses	% of Reserves	TOT Domino L...	Global Losses	Num DBS	Num DBL	Num DB
A001	14093	3.89%	8699.0	2.05%	22792	23037	1	0	1
A002	12882	3.12%	5381.0	1.27%	18263	18463	1	0	1
A003	89147	53.05%	221398.5	52.16%	310546	326942	15	5	20
A004	49535	37.13%	167796.45	39.53%	217331	223800	6	4	10
A005	3043	1.1%	3417.0	0.8%	6460	6460	0	0	0
A006	13634	5.6%	19149.0	4.51%	32783	32783	0	0	0
A007	13523	3.25%	5508.0	1.3%	19031	19033	1	0	1
A008	16107	3.56%	4712.0	1.11%	20819	21023	1	0	1
A009	8023	2.54%	6873.0	1.62%	14896	14896	2	0	2

Figure 25– Multi-run Contagion Table (Result for all FIs as 'Triggers' is given)

Number of defaulted banks at the end of each contagion event is presented (column **DB**) as well as a description of those whom finally fail due to solvency losses (**DBS**) and liquidity shortfalls (**BDL**).

Inspecting an individual contagion event

By clicking on one of the rows in the contagion view table the user can inspect that specific event. An individual contagion view provides additional information about that event. In particular, a contagion plot describes the sequence of failures of direct and indirect counterparties of the trigger FI.

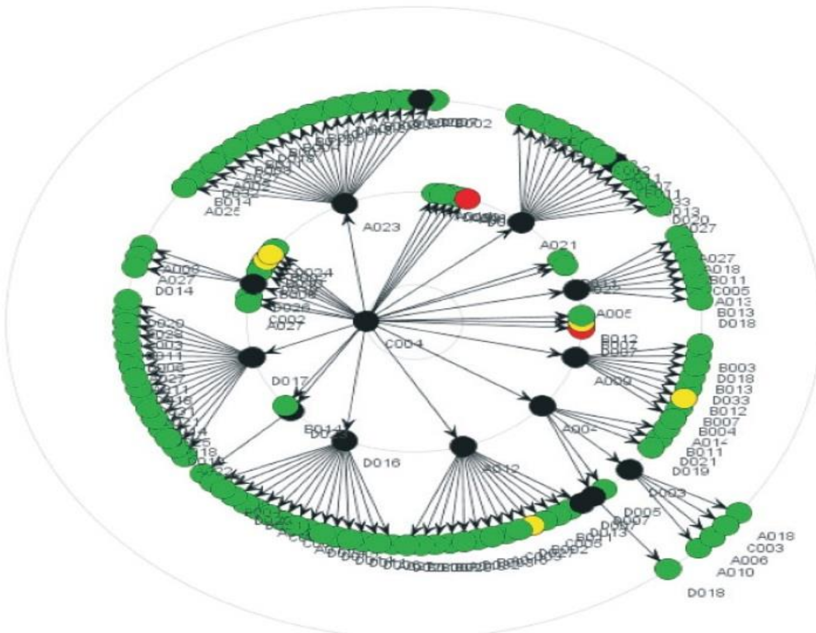

Figure 26 - Contagion plot with both solvency and liquidity shocks

The contagion propagation from failure of a 'trigger' institution (center most black node in Figure 26) is displayed in terms of direct failures (black nodes) placed on the first concentric circle, the second order failures are on the circles beyond. The concentric circles denote the sequence of failure specified in the next Section. The contagion halts when no further bank failures follow. The color coding in Figure 26shows the fragility of institutions approachingthe defaulting threshold. The light green nodes represents healthy institutions, those that are yellow are more fragile and close to default while the black nodes have failed. The red nodes specify the institutions that fail because of liquidity problems.Below red triangle is given instead of red circle.

Simultaneous multiple viewing of contagion plots

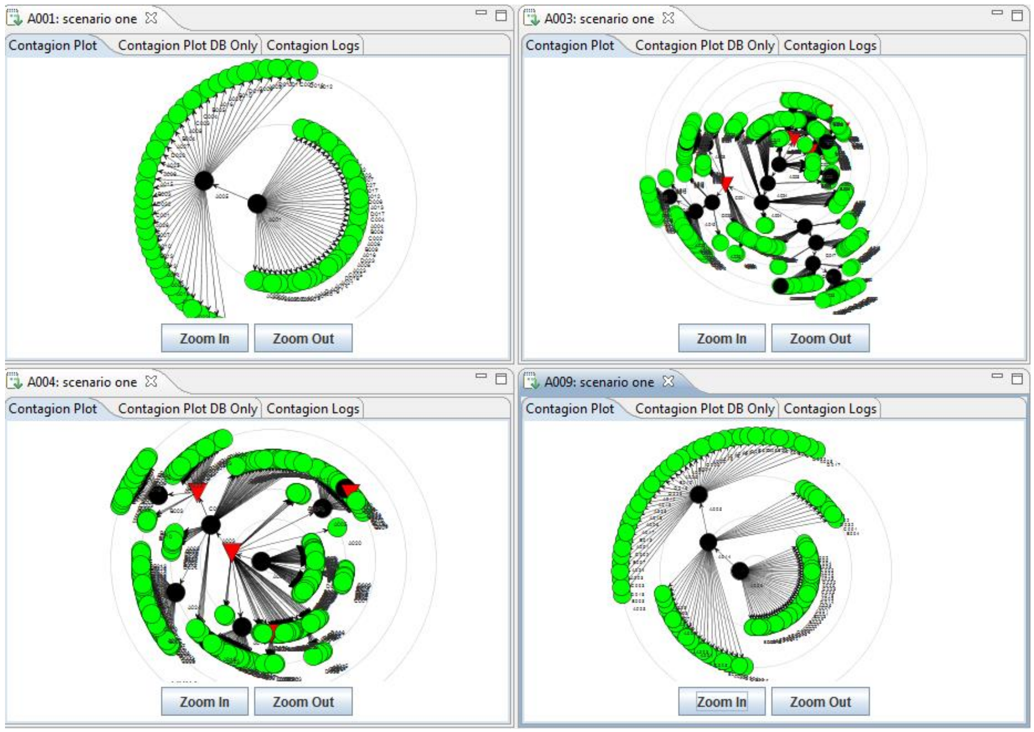

Figure 27 - Simultaneous multiple viewing of contagion plots for different Trigger FIs.

Contagion algorithm

The algorithm starts at q=0 and the trigger bank that fails is denoted by h.

Assume at iteration q, the set of banks that have demised is denoted by $\boldsymbol{D}_q$.

Thus, h $\in \boldsymbol{D}_q$are the FIs that have failed at q.

The set of financial institutions (FIs) that fail at q+1 will be denoted by $\boldsymbol{D}_{q+1}$.Note that banks that fail at q+1 are those that fail from direct solvency shocks $\boldsymbol{S}_{q+1}$ and those that fail from liquidity shocks $\boldsymbol{L}_{q+1}^{T}$.

$$\boldsymbol{D}_{q+1} = \boldsymbol{D}_q \cup \boldsymbol{S}_{q+1} \cup \boldsymbol{L}_{q+1}^{T}. \qquad (4.1)$$

As primary and secondary liquidation can occur in the course of a liquidity contagion event, the superscript T in $\boldsymbol{L}_{q+1}^{T}$ specifies the end of secondary liquidations.

Note

Note the set $\cup_q \ D_q$ the set of all FIs that have demised at all q including q. Note, in what follows, the subscript s denotes the set of all markets/products. Of the full set of products only a subset s is considered to be callable in the course of a liquidity shockas specified in the drop-down menu inFigure 24.

Solvency shocks

Non-failed FIs at q will be considered to fail at q+1 if the followingsolvency based failure condition holds. For a given FI,the unit value for the indicator function f_i signals failure:

$$f_{i\#}(w_i) = 1 \quad \text{if} \quad w_i = \left(\sum_s \sum_{h \epsilon D_q} \frac{Capital_i - m_{hi}^{s+}}{RWA_i} - \rho \right) > 0 \qquad (4.2)$$

Here, $i^{\#}$ denotes those non-failed counterparties (viz. $i^* \notin \cup_q \ D_q$) who fail at q+1 from the above solvency condition. Note, m_{hi}^{s+} is the netted liabilities between h and i for the s^{th} financial sector/product. Thus, the condition in (4.2) states that the ratio of its Capital less net liabilities of failed counterparties of i at q with RWA of *i* exceeds certain ρ threshold.

We define a new set of failed FIs who demise from the solvency condition (4.2)

$$\boldsymbol{S_{q+1}} = (i^{\#} | \, (4.2) \text{ holds}) \ . \qquad (4.3)$$

Note those $i^{\#} \epsilon \boldsymbol{S_{q+1}}$ having failed in the q to q+1 cycle are only unwound at the end of q+1. Note in what follows the superscript # denotes failed FIs and superscript * denotes those that have survived.

Liquidity shocks

Failed FIs at q impart liquidity shocks in the following way:

- **Primary Liquidity Shock**: In a primary liquidity shock, all the failed banks h withdraw all loans to counterparties from all sectors. This will also been called the final 'winding up' which occurs only once at q for banks that failed at q, i.e. $h \in D_q$.

- **Secondary Liquidity Shock**: A secondary liquidity shock applies to loans callable only from the subset s of loans and these are done by financial institutions who survive the direct liquidity shock by calling in loans from other banks that have survived beyond q but exclude $i^{\#}$from eq. 4.2, 4.3. We impose the condition that for loans called in between surviving FIs, only net lenders can do so. Surviving net lender is limited to call in loans only once from the same counterparty.

In a liquidity contagion, the criteria that is first checked is which FIs need to call in loans at initial point τ=0 and this is defined in (4.4). Here, the indicator function denotes failure of i^{*c}who fails despite calling in loans at τ=0in the face of failure of lenders at q.LB_i is the liquidity buffer of i^*.

$f_{i\#}^{c\tau=0}(w_i*) = 1$
if $w_i^* = \sum_s \sum_{j\# \in \boldsymbol{D}_q} X^s_{i*j\#} \;-\; (LB_{i*} + \sum_{S*} \sum_{x*} Call^{S*}_{x*i*\notin \cup_q D_q \,\cup\, S_{q+1}}) > 0$ (4.4)

A superscript c denotes variables pertaining to those FIs who need to call in funds. This depends on whether their initial liquidity buffers (LB) are breached. Such FIs that call in loans are denoted by $i*^c$. Here $i*^{\tau=0}$are the initial non failed FIs from (4.2) and (4.3), $i^* \notin \cup_q \; D_q \; \cup \; S_{q+1}$.

The terms $\sum_s \sum_{j\# \in \boldsymbol{D}_q} X^s_{i*j\#}$denotes the loans called in by $j^{\#}$ who are lenders to i^* and who have demised at q. The term, $\sum_{S*} \sum_{x*} Call^{S*}_{x*i*\notin \cup_q D_q \,\cup\, S_{q+1}}$in the brackets in (4.4), contains the value of loans called in by i^* from counterparties x^* who have survived and to whom i^* is a net lender.

Note

The contagion from the liquidation process entails a sequence of subroutines within the (q, q+1) interval with the subroutines for secondary liquidation denoted by $\boldsymbol{\tau}$, τ=0, 1,2, …. , T.

The general condition for failure from liquidity contagion at$\boldsymbol{\tau \geq 1}$ is given by:

$f_{i\#}^{c\tau}(w_{i*}) = 1$ if:

$$w_i^* = \left(\left(\sum_s \sum_{h\# \in D_q} X^s_{i*j\#} + \sum_{S*} \sum_{j*c \in \boldsymbol{L}^{c\tau-1}_{q+1}} X^{S*}_{i*j*c}\right) - \left(LB_{i*} + \sum_{S*} \sum_{x*} Call^{S*}_{x*i*\notin \boldsymbol{L}^{\tau-1}_{q+1} \cup_q D_q}\right)\right) > 0 \quad (4.5)$$

$i^{\#c\tau}$ are those who fail due to condition in (4.5) at τ. The term $\sum_{S*} \sum_{x*} Call^{S*}_{x*i* \notin \boldsymbol{L}^{\tau-1}_{q+1} \cup_q D_q}$in (4.5) gives the amounts that i^{*c} succeeds in calling in from counterparties to which it is a net lender. On the other hand, the term

$\sum_{S*} \sum_{j*c \in L_{q+1}^{c\tau-1}} X_{i*j*c}^{S*}$ in (4.5) with j^{*c} refers to surviving banks at τ-1 who are net lenders to i^{*c} who need to call in loans.

At each $\tau \geq 0$, we have new sets of FIs that fail due to the criterion in (4.5) and this is defined by

$$\boldsymbol{L_{q+1}^{T}} = (\text{ i}\#^{c\tau} \mid (4.5) \text{ holds }) \text{ with } \boldsymbol{L_{q+1}^{\tau=0}} = \emptyset \text{ .} \qquad (4.6)$$

The final subroutine T marks the point at which no further FI fails due to secondary liquidity contagion and it defines the set $\boldsymbol{L_{q+1}^{T}}$ which contains all FIs that fail due to the secondary shocks from $\tau > 0$ that arise from certain loans being called in by distressed FIs. We denote by $\boldsymbol{L_{q+1}^{c\tau}}$ the set of those non-failed FIs that call in loans at τ.

To summarize, in a liquidity contagion, the calling in of loans by surviving banks may trigger further failure by the condition in (4.5) and note, we follow the criteria that surviving banks can only call in net amounts for which they are net lenders and they can do this only once with respect to a counterparty.

This process terminates at the point τ= T when no more FIs fail from condition (4.5). Thus: $\boldsymbol{L_{q+1}^{T}}$, $i^{\#T} = 0$ no further FIs fail from condition (4.5).

Important

Analogous to the Furfine algorithm that holds only for contagion from the solvency condition in (4.1) , the algorithm that combines failures of FIs from solvency and liquidity shocks update the set of number of failed banks at q+1 to be

$$\boldsymbol{D_{q+1}} = \boldsymbol{D_q} \cup \boldsymbol{S_{q+1}} \cup \boldsymbol{L_{q+1}^{T}}.$$

The diagram inFigure 28graphically describes the routines of the contagion algorithm according to the analytical description presented above.

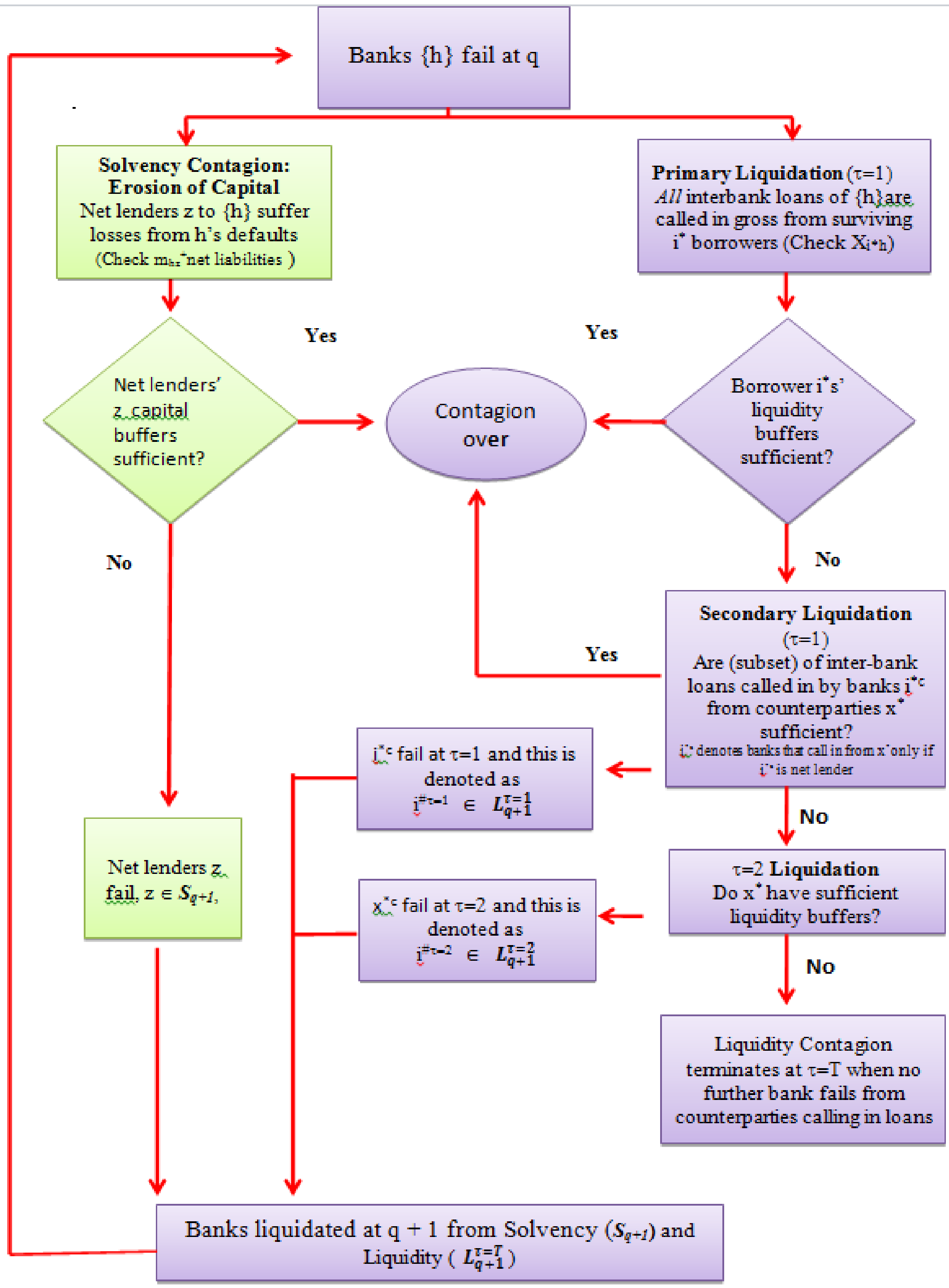

Figure 28- Contagion diagram

Chapter

5

Stability Analysis

Metrics for Financial Network Stability and Identifications of SIFIs.

In the design of macro prudential policy for monitoring and managing systemic risk, it is important to know whether the financial network is becoming more or less stable relative to the capital in the system and also who are most instrumental in causing the instability. This Chapter discusses the implementation of the eigen-pair approach first proposed in Markose (2012) into SRA. The methodology simultaneously derives two metrics, one for the stability of the financial network and the other for the systemic importance of FIs in the network. The need to design a Pigou tax to control systemic risk from SIFIs and to have them internalize this cost has come to the forefront after extensive tax payer bail outs in the aftermath of the 2007 financial crisis.

Introduction

The exclusive focus in Basel I and II on managing risk and stress tests relating to how a bank's activities affect its individual chances of failure, with no consideration as to how individual-level choices affect system wide tail risks, is now acknowledged to have been flawed, Haldane (2009.a). Macro-prudential policy (Carauna, 2010, Clement,2010) is concerned with monitoring and managing systemic risks that arise from monetary and financial sector activities that have negative externalities that can spread cross-sectionally, or build up over time as in asset bubbles. These have spillovers into the real side of the economy.

Operationalizing systemic risk monitoring and management of FIs, at a minimum, needs to address the following: Is there a metric that can identify if financial intermediation is growing more unstable relative to Tier 1 capital in the system? Which FIs contribute to this instability and how does the failure of a FI result in domino losses in the ensuing financial contagion? How can a Pigou tax be shown to mitigate a FI's negative externality? Indeed, the efficacy of a systemic risk framework lies in whether it can help detect potential threats reminiscent of the AIG or Northern Rock debacle, viz. a combination of excessive buildup of liabilities with growing interconnectedness with counterparties. These FIs in pursuit of privately rational objectives of increasing market share and short term profits by aggressively borrowing in the interbank market and taking on large derivatives liabilities positions, respectively, became potential threats to the system.

Steps are now underway to design 'bail in' arrangements at the time of failure of FIs as part of resolution procedures (see, Heurtas, 2011, Dewatriport and Freixas, 2010, FSB November 2012 Report on Resolution of SIFIs) and those that are paid for by FIs before failure to alleviate unacceptable socialization of losses from them. SRA implements the eigen-pair methodology in which the instability of the financial network is measured in terms of the maximum eigenvalue of a specially constructed matrix of financial obligation relative to tier 1 capital. There is cause for concern for the regulator if the maximum eigenvalue of this matrix is greater that a common threshold of Tier 1 capital that determines the insolvency of FIs. The corresponding eigenvector centrality of the FIs in this matrix determines the rank order of the FIs contributing to the instability of the network.

Eigen Pair Analysis

The causal direction of the contagion and hence systemic risk of a FI, follows from the 'trigger' FI, *i*, owing its counterparty j more than what j owes *i*, relative to *j*'s Tier1 capital. This is denoted by the positive entries $(xij - xji)^+ / C_{j0}$ in matrix (5.1) for those pairs of FIs which have a direct financial links. Here, C_{j0} is *j*'s initial capital. Hence, the matrix Θ that is crucial for the contagion analysis will have elements given as follows:

$$\Theta = \begin{bmatrix} 0 & \frac{(x_{12}-x_{21})^+}{C_{20}} & \frac{(x_{13}-x_{31})^+}{C_{30}} & 0 & .... & 0 \\ 0 & 0 & \frac{(x_{23}-x_{32})^+}{C_{30}} & .... & .... & \frac{(x_{3N}-x_{N3})^+}{C_{N0}} \\ . & . & 0 & .... & .... & . \\ \frac{(x_{i1}-x_{1i})}{C_{10}} & . & ... & 0 & ... & \frac{(x_{iN}-x_{Ni})}{C_{N0}} \\ . & . & ... & ... & 0 & . \\ \frac{(x_{N1}-x_{1N})^+}{C_{10}} & . & ... & \frac{(x_{Nj}-x_{jN})^+}{C_{j0}} & ... & 0 \end{bmatrix} \quad (5.1)$$

Failure of a FI is usually determined by the criteria that losses exceed a predetermined buffer ratio, ρ, of Tier 1 capital. In the epidemiology literature, Wang et. al. (2003), ρ is the common cure rate and (1 - ρ) is the rate of not surviving in the worst case scenario. The dynamics relating to the probability of failure of each ith FI at a given time step q+1 denoted by u_{iq+1}, given j counterparties of *i* have failed at the previous time step q. This is determined by:

(i) i's own survival probability given by the capital C_{iq} it has remaining at q relative to initial capital C_{i0} .
(ii) The sum of 'infection rates' defined by the sum of net liabilities of its j failed counterparties relative to its own capital is given by the term $\sum_j \frac{(x_{ji}-x_{ij})^+}{C_{i0}}$.

Note

The 'infection rate' or how counterparties impact on an FI is pair wise heterogeneous.

RWA loss vs Absolute Capital Loss

The criteria of failure of a bank in the contagion analysis is based on the Basel rule that

$$(Tier\ 1\ Capital - Loss)/\ RWA\ <\ 0.06\ =\ T_{RWA}$$

Here the threshold for bank failure in terms of RWA is denoted as T_{RWA}. However, as the practical aspects of insolvency requires recapitalization, it is important to see the equivalence of the above Basel rule with anabsolute Tier 1 capital threshold criteria (T_c) for failure, which is given below for the case where the 6% T_{RWA} constraint holds:

$$T_c \quad = \quad 1\ -\ T_{RWA} \frac{RWA}{Tier\ 1\ Capital}.$$

The dynamical system

The dynamics characterizing transmission of 'infection' in a financial network system can be given by

$$u_{iq+1} = (1 - \rho)\ u_{iq} + \sum_j \frac{(x_{ji}-x_{ij})^+}{C_{i0}}\ u^1_{jq}. \qquad (5.2)$$

Here, we have a FI's own metric of failure at q which is given by $u_{iq} = (1 - C_{iq}/C_{i0})$, where C_{iq}/C_{i0} is the ratio of i's capital at q and capital at initial date. The second term in (5.2) involves the losses from counterparties, j, that fail at q and these are denoted by the indicator function u^1_{jq}which is set equal to 1 if counterparty j fails. The sum of 'infection rates' is defined by the sum of net liabilities of its j failed counterparties relative to its own capital is given by the term $\sum_j \frac{(x_{ji}-x_{ij})^+}{C_{i0}}$. In matrix notation, (5.2) yields to

$$\mathbf{U}_{q+1} = [(1 - \rho)\mathbf{I}\ + \mathbf{\Theta}\ ]\mathbf{U}_q = \mathbf{QU}_q\ . \qquad (5.3)$$

Here, $\boldsymbol{\Theta}'$ is the transpose of the matrix in (5.1) with each element $\Theta_{ij}' = \Theta_{ji}$ and $\mathbf{I}$ is the identity matrix.

Eigen Vector Centrality

The network centrality measure that has been found by us to correlate best with the capacity of a FI to cause the largest contagion losses on others in the Furfine (2003) type stress test is its right eigenvector centrality statistic obtained for matrix $\boldsymbol{\Theta}$ in (5.1). The algorithm that determines it assigns relative centrality scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Denoting $\tilde{v}_i$ as the right eigenvector centrality for the ith node for matrix $\boldsymbol{\Theta}$, the centrality score is proportional to the sum of the centrality scores of all nodes to which it is connected (i.e., k_i neighbours). Hence,

$$\tilde{v}_i = \frac{1}{\lambda} \sum_j \theta_{ij} \tilde{v}_j . \quad (5.4)$$

For the centrality measure in (5.4), the largest eigenvalue, λ_{max}, and its associated eigenvector are taken. The i^{th} component of this eigenvector then gives the centrality score of the i^{th} node in the network. Using vector notation, the eigenvalue equation for the matrix in (5.1) for the eigen-pair (λ_{max}, $\widetilde{\boldsymbol{v_1}}$) is given as:

$$\boldsymbol{\Theta}\widetilde{\boldsymbol{v_1}} = \lambda_{max} \widetilde{\boldsymbol{v_1}} . \quad (5.5a)$$

Note that for a non-negative matrix $\boldsymbol{\Theta}$ in (5.1) with real entries, λ_{max} is a real positive number and the right eigenvector $\widetilde{\boldsymbol{v_1}}$ associated with the largest eigenvalue has non-negative components by the Perron-Frobenius theorem (see Meyer, 2000, Chapter 8).Positive values for the centralities of all nodes of matrix $\boldsymbol{\Theta}$ in (5.1) are guaranteed by Perron-Frobenius theorem only if $\boldsymbol{\Theta}$ in (5.2) is irreducible.[17]For matrix $\boldsymbol{\Theta}$, clearly, given equation (5.5a), those nodes in the periphery with no out-degrees will have zero eigenvector centrality.

Finally, from the perspective of the measure of systemic risk, the so called right eigenvector of $\boldsymbol{\Theta}$matrix given above in (5.5a), as will be discussed, is what matters. A FI's systemic risk index will be based on this. It measures the impact of an FI's total liabilities relative to the respective capital of each of its counterparties given by the row sums of matrix $\boldsymbol{\Theta}$ in (5.1) on the stability of the system characterized

[17] The condition of the Perron-Frobenius theorem that guarantees a positive eigenvector corresponding to the maximum eigenvalue for the non-negative matrix $\boldsymbol{\Theta}$ is that the directed graph it represents should be irreducible.That is, for any randomly selected pairs of nodes (*i,j*) there is a path between them, viz. $\boldsymbol{\Theta}$ is strongly connected, Meyer (2000).

by the maximum eigenvalue. The so-called dual left eigenvector, on the other hand, gives the impact of the exposures of each FI to others and hence can be seen to yield vulnerability indices. The left eigenvector of Θ, denoted by $\mathbf{v_1}$ is defined as

$$\boldsymbol{v}_1\Theta = \boldsymbol{\Theta}' \boldsymbol{v}_1 = \lambda_{max} \boldsymbol{v}_1. \qquad (5.5b)$$

Note

The left and right eigenvectors using the respective eigen value equations in (5.5a) and (5.5b) yield the same maximum eigenvalue for the matrix $\boldsymbol{\Theta}$ in (5.1).

System stability

The system stability of (5.3) will be evaluated on the basis of the power iteration of the matrix $\mathbf{Q}=[(1-\rho)\mathbf{I}+\boldsymbol{\Theta}']$. From (5.3), U_q takes the form:

$$\mathbf{U}_q = \mathbf{Q}^q \, \mathbf{U}_0. \qquad (5.6)$$

Markose (2012) shows how the stability of the system in (5.6) as q tends to infinity, requires that the maximum eigen-value, λ_{max}, is less than the common threshold on capital, ρ.

$$\lambda_{max}(\Theta') < \rho\ . \qquad (5.7)$$

If this condition is violated, any initial perturbation/negative shock, in the absence of outside interventions, can propagate through the networked system as a whole and cause system failure.

What is important to note, as discussed in Markose (2012), is how the power iteration algorithm yields a simple relationship between the upper bound of λ_{max} and the maximum row (column) sum[18] of the matrix $\boldsymbol{\Theta}'$ ($\boldsymbol{\Theta}$ in (5.1)).

Hence, FIs with high connectivity to a large number of counterparties and also have large liabilities relative to capital of their respective counterparties contribute

[18] Denoting the row sum of the i^{th} row of Θ' by $S_i = \sum_j \theta_{ji}$, $\lambda_{max} \leq max S_i$.

to the high row sum values for matrix $\boldsymbol{\Theta}$ and the largest of these constitutes the upper bound of λ_{max}.

Pigou Tax

The aim of the super-spreader tax is to have FIs with high right eigenvector centrality parameters to internalize the costs that they can inflict on others by their failure and to mitigate their impact on the system by reducing their contribution to network instability as given by λ_{max}. As discussed, critical to the von-Mises power iteration algorithm for the calculation of λ_{max} are the row sums S_i of the ith row in Θ':

$$S_i = \sum_j \theta_{ji} = \frac{1}{C_i} \sum_j (x_{ji} - x_{ij})^+. \qquad (5.8)$$

A new row sum $S_i^{\#}$ is created for each node so that a super-spreader tax denoted by $\tau(\tilde{v}_i)$ is applied on the ith node in proportion to its right eigenvector centrality $\tilde{v}_i$ that is a measure of its systemic risk:[19]

$$S_i^{\#} = \sum_j \theta_{ji}\# = \sum_j [\frac{1}{C_i}(x_{ji} - x_{ij})^+ - \tau(\tilde{v}_i)]. \qquad (5.9)$$

Note the elements in the square bracket in (5.9) are restricted to be non-negative with negative numbers set equal to zero. The rationale behind this application of the right eigenvector centrality of a node as the basis of the super-spreader tax is to enable a node to provide a buffer proportional to its own capacity to propagate contagion. Note that the funds that will be escrowed here using $\tau(\tilde{v}_i)$ is not calibrated to mitigate failure of FI *i* due to its exposures to *j* counterparties, but it is in keeping with its own spreading powers.

Thus,

$$S_i^{\#} < S_i \quad \text{for} \quad \tau(\tilde{v}_i) > 0. \qquad (5.10)$$

We will consider two formulations of the super-spreader tax:

$$\tau(\tilde{v}_i) = \alpha \tilde{v}_i, \quad 0 < \alpha \leq 1 \ \ or\ \alpha > 1, \qquad (5.11a)$$

$$\text{and } \tau(\tilde{v}_i) = \alpha \tilde{v}_i^2, \quad 0 < \alpha \leq 1 \ \ or\ \alpha > 1. \qquad (5.11b)$$

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19 Clearly, it is possible to apply the capital surcharge $\tau(\tilde{v}_i)$ in denominator of (5.9), $S_i^{\#} = \sum_j \theta_{ji}\# = \frac{1}{(1+\tau((\tilde{v}_i))C_i} \sum_j (x_{ji} - x_{ij})^+$.This was, in fact, tried out in an earlier draft of the paper.But following the principle of 'greedy' algorithms as in the EIG algorithm of Giakkoupis et. al. (2005) that seeks the largest possible reductions of the maximum eigenvalue of the system, the current proposal in (5.9) was found to be more effective.Note, the algorithm applied $\tau(\tilde{v}_i)$ in equation (15) was constrained to retain a non-negative matrix for $\Theta'^{\#}(\alpha)$.

In (5.11a), the super-spreader tax $\tau(\tilde{v}_i)$ is a linear function of a FI's eigenvector centrality while the super-spreader tax is set proportionate to $\tilde{v}_i^2$rather than to $\tilde{v}_i$ in (5.11b). The advantage of this is that $\tilde{v}_i^2$is a naturally normalized variable with $\sum_i \tilde{v}_i^2 = 1$. Further, with the super-spreader tax being a function of $\tilde{v}_i^2$rather than $\tilde{v}_i$, this will penalize nodes with higher eigenvector centrality more than others. This is useful when the dominant eigenvector central node is distinctly more dominant than others and hence the progressivity of the tax rate becomes more apparent with the application of $\tilde{v}_i^2$ than $\tilde{v}_i$. In contrast, when several nodes are equally dominant, the use of $\tau(\tilde{v}_i) = \alpha\tilde{v}_i$is more appropriate. Finally, as $0 \leq \tau(\tilde{v}_i) < 1$, equation (17.a) can extract more tax across the population with non-zero centrality measures than a tax rate using $\tilde{v}_i^2$ and hence also deliver faster rates of decline of the $\lambda_{max}$of the system.

The network stabilization algorithm will be called the EIG algorithm in keeping with Giakkoupis et. al.(2005). The new matrix associated with $S_i^{\#}(\alpha)$ will be denoted as $\Theta'^{\#}(\alpha)$. The alpha parameter when set at 0 obtains the λ_{max} associated with the untaxed initial matrix Θ'. When α=1, each node is exactly penalized by $\tilde{v}$ or$\tilde{v}_i^2$ that yields the λ_{max} for $\Theta'^{\#}(\alpha=1)$. Considering, $1>\alpha>0$,there is a monotonic reduction in the λ_{max} associated with the matrices $\{\Theta'^{\#}(\alpha)\}$ corresponding to the monotonic reduction in row sums $S_i^{\#}(\alpha > 1) < S_i^{\#}(\alpha = 1) < \ldots < S_i^{\#}(\alpha = 0.75) < \ldots < S_i^{\#}(\alpha = 0.5) < \ldots < S_i(\alpha = 0)$. The case of $\alpha>1$ may apply when the initial matrix Θ' needs a more aggressive application of the tax to stabilize the matrix to the point where $S_i^{\#}(\alpha > 1)$ for all i such that $\lambda_{max}<\rho$ for $\Theta'^{\#}(\alpha>1)$. Clearly, if $\alpha>1$ is needed to stabilize the system, the sustainability of such a market for risk sharing is in question. In fact, full stabilization to levels of $\lambda_{max}(\Theta'^{\#}) \approx \rho$ may not be technically possible and/or economically feasible. However, what the eigen-pair method of estimating and managing systemic risk in an interconnected financial network based on bilateral on- and off-balance sheet data provides is a clear cut mathematical benchmark for whether the system has become more or less unstable and who within it contributes most to this.

Stability Analysis in SRA

ICON KEY

- Market
- Markets
- Stability Analysis

Stability analysis view can be activated by selecting on a specific market listed in the left explorer panel Markets. Once a market is selected, the stability analysis action will be available on the toolbar by pressing the button. The user has to specify the value of the Tier 1 capital threshold ρ *vis-à-vis* which the $\lambda_{max}(\Theta)$is compared to determine stability of the market.

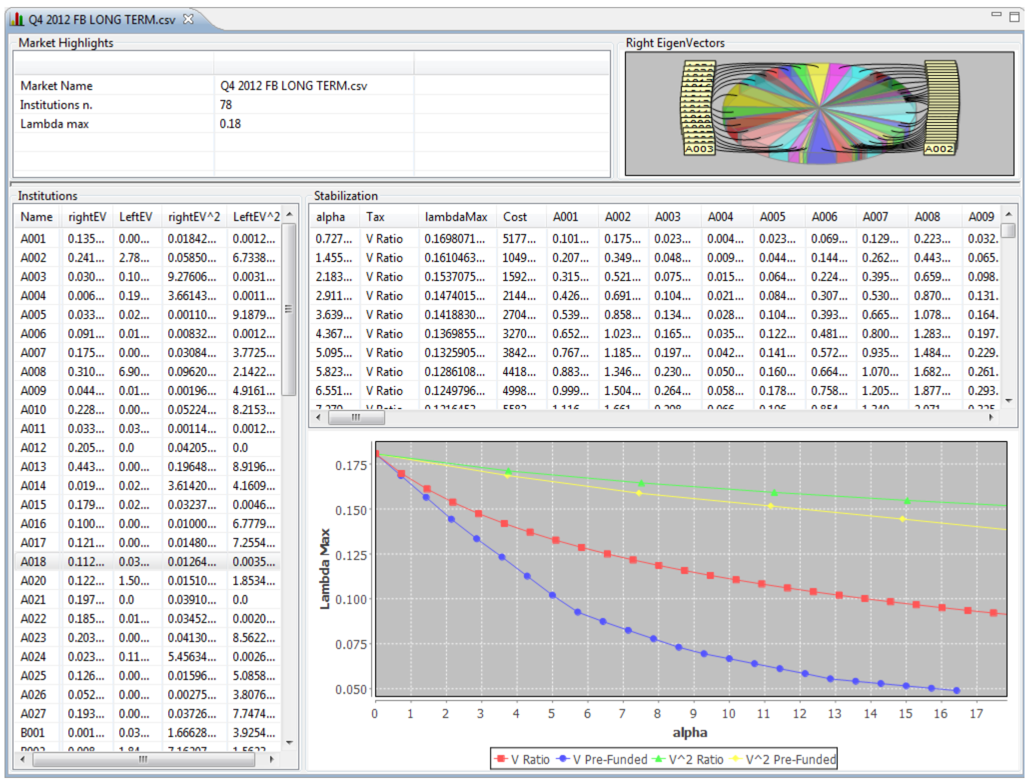

Figure 29 - Stability Analysis View

Figure 29 shows the Stability analysis view in SRA once the stabilization is completed.[20]

The stabilization algorithm implemented in SRA tries to reduce $\lambda_{max}(\Theta)$ below the selected ρ by taxing the individual entries of the matrix Θ according to right eigen vector centrality $\tilde{v}_i$ of each node. We recall $\theta_{ij} = \frac{1}{c_j}(x_{ij} - x_{ji})^+$as the entries of the matrix Θ. Two basic tax regimes are implemented:

1. **Pre-Funded** tax which applies a tax $\tau(\tilde{v}_i\ )$ to the numerator according to eq. (5.2)

[20]For very unstable markets, the stabilization process may require many seconds to complete. In that event, a progress bar showing the status of the stabilization will appear.

2. **Ratio** tax which applies a tax $\tau(\tilde{v}_i\ )$ to the denominator (see footnote 5).

The stabilization can also adopt a less severe tax procedure based on $\tilde{v}_i^2$ instead of $\tilde{v}_i$.

The results are organized in several components presented in Figure 29:

- **Market Highlights Table** (TOP LEFT of the view) highlighting the name of the market, number of active institutions and the $\lambda_{max}(\Theta)$.
- **Institutions Table** (CENTRE LEFT) listing the right and left eigenvectors ($\tilde{v}$ and v respectively) as well as the eigenvectors square.
- **Right Eigen Vectors Bar Plot** (TOP RIGHT)graphically shows the distribution of the vector $\tilde{v}$.
- **Stabilization Table** (CENTRE RIGHT) shows the stabilization results with different values of αs according to the progression tax $\tau(\tilde{v}_i\ ) = \alpha\tilde{v}_i$, including the cost of taxation and the individual contribution of the nodes.
- **Stabilization plot** (BOTTOM RIGHT) visualizes the decline of $\lambda_{max}(\Theta)$ under different tax regimes to find the appropriate α that stabilizes the system.

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