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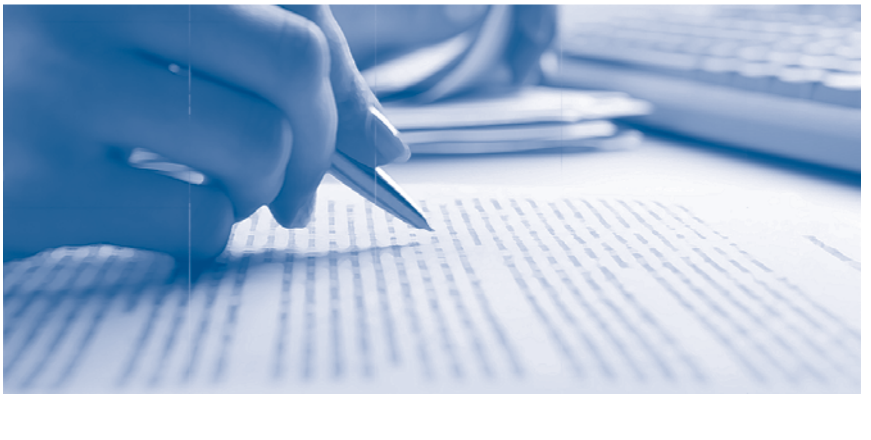

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Contagion Risk within Firm-Bank Bivariate Networks

Rodrigo César de Castro Miranda*

Benjamin Miranda Tabak*†

Abstract

This Working Paper should not be reported as representing the views of the Banco Central do Brasil. The views expressed in the paper are those of the authors and do not necessarily reflect those of the Banco Central do Brasil.

This paper proposes a novel way to model a network of firm-bank and bank-bank interrelationships using a unique dataset for the Brazilian economy. We show that distress originating from firms can be propagated through the interbank network. Furthermore, we present evidence that the distribution of distress can have contagious effects due to correlated exposures. Our modeling approach and empirical results provide useful tools and information for policy makers and contribute to the discussion on assessing systemic risk in an interconnected world.

JEL classification: G01; G15. **Keywords:** complex networks; contagion; bank-firm network; systemic risk; connectivity of financial institutions.

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1 Introduction

In the past decade we have seen the emergence of several stress testing models that can be used to evaluate systemic risk. Čihák (2007) introduces various credit risk stress tests, ranging from general non performing loans shocks to sectoral shocks and mentions the possibility of assessing credit shocks from exposure to large non-bank financial institutions[1].

The recent global financial crisis has shown that the complex network of relationships that is built by financial institutions has to be taken into account when evaluating systemic risk (Markose et al. (2012)). The understanding that interconnections is a crucial aspect has fostered research on the impact of interconnections on systemic risk measures and in the calculation of losses in financial systems due to shocks either to the real economy or to the financial system itself.

This important point has been pointed out by Goodhart (2006), which suggested that current stress testing models were insufficient for financial stability, and that empirical methods that take into account financial linkages between institutions such as Eisenberg and Noe (2001)[2] and Allen and Gale (2001)[2]should be considered.

The global scale of crisis sparked new interest in network models of financial linkages. In IMF (2012) there is a box prepared by Sónia Muñoz and Hiroko Oura which describes the relevance of network models for a better understanding of systemic risk. In spite of this, there are few studies that point to the usage of network theory in stress testing beyond Eisenberg and Noe (2001) and Furfine (2003), which developed interbank clearing algorithms which allows for the assessment of systemic risk through cascading defaults on interbank loans. Nier et al. (2007) examines the effects of idiosyncratic shocks to the banking system and how the spreading of the shock through the network of banks is related to structural properties of the system. Márquez Diez Canedo and Martínez-Jaramillo (2009) and Lopez-Castañon et al. (2012) augment traditional stress tests with network contagion effects. More

[1]There is a variety of stress testing methods and empirical illustrations in Siddique and Hasan (2013), which can be seen as the state of the art in stress testing.

[2]Eisenberg and Noe (2001) and Allen and Gale (2001) in their pioneer works have shown in the early 2000s that interconnections may be an important part of the amplification of contagion in financial markets. These theoretical advances can be seen as stepping stones for the further development of tools for assessing financial stability.

recently Amini et al. (2012) discuss the spread of a macroeconomic shock through a theoretical model of network contagion. Papadimitriou et al. (2013) propose the use of network theory concepts in order to identify institutions that are part of the financial network's core, which enables a supervisor to concentrate efforts.

The cascading defaults model was incorporated into network models of financial networks, such as the DebtRank measure by Battiston et al. (2012), which is a network centrality measure that incorporates the indirect impact of a financial institution. Iori et al. (2006) investigate the interbank market as both stabilizing force and a vehicle for financial contagion. Georg (2011) describes how network topology can impact the cascading defaults.

Although the use of network theory in financial stability starts from purely interbank models, there are other possibilities. Xuqing Huang and Stanley (2013) perform a systemic risk assessment from balance sheet data by building a bipartite network of banks and assets. The interbank market is not modeled in this paper, as it tests systemic risk by applying shocks to the values of assets and then checking for cascading failures among the banks (which can lead to further devaluation of assets and further bank failures).

An important feature of the literature is that it has focused on how banks and financial institutions are linked through a network of liabilities and how shocks to the system can be propagated through the system (Krause and Giansante (2012)). However, so far the literature has not considered that banks can also be linked through a set of common exposures by lending to similar firms (real economy) and this is an additional channel that has to be considered when evaluating risks.

The debate on how public policy regarding the provision of an important public good, financial stability, has been conducted by proposing financial regulation to mitigate the adverse effect that too interconnected banks may have on the financial system and on the real economy (Walter (2012)). On the other hand recent research has shown that interconnections change over time and interconnection is not the only driver of crisis (Minoiu and Reyes (2013); Arnold et al. (2012)). Nonetheless, it is common ground nowadays that interconnection plays an important role in the propagation of crisis.

To the best of our knowledge there are only a very few papers that have considered that banks can be connected through a set of common exposures to firms. Recent research has unveiled the topology of credit networks and bank-firms networks. G. De Masi and Stiglitz (2010); Masi and Gallegati (2012) use network theory to study the network of loans to firms in Italy and Japan, however these papers are not concerned with the propagation of risk, but rather understanding the structure of the underlying network. Fujiwara and Souma (2009) describe the changes in time in the network topology for loans network between banks and large firms in Japan, modeling credit network fragility as eigenvalue problems. Aoyama (2013) presents an extension of DebtRank that incorporate loans to firms and calculates the DebtRank measures in the firms layer. The loan networks formed by banks and firms can be modeled as two-mode networks. Such networks have been investigated in studies in social network analysis such as Scott and Carrington (2011), Borgatti (2009) and Carrington et al. (2005).

These papers are an important step in the right direction in the sense that they provide some insights on the bank-firm relationship and how it generate networks that can used to asses systemic risk. However, since many of these papers do not have information on data on the firm side it is difficult to construct systemic risk measures and to perform stress tests.

Our paper contributes to this debate by focusing on interconnections in the Brazilian banking system. Our contributions are fourfold. First, we build a unique data set that contains information on banks interconnections and on individual loans that were granted to firms with traded shares in the Brazilian economy. Second, we use balance sheet and market data information on firms to study how shocks to specific firms can have adverse effects on the banking system and how such shocks can be further propagated within the banking system. Third, we propose a novel methodology to assess risk using this bivariate firm-bank network, which is partly inspired in the debt-rank methodology proposed by Battiston et al. (2012). Finally, we present some empirical results for the Brazilian economy and show some evidence that if we want to evaluate risks that stem from interconnections we also have to consider the firm-bank relationships, which can be a major source of credit risk in financial systems. Therefore, we show how to stress test the financial system within our approach.

The rest of the paper is structured as follows: section 2 presents the model, 3 presents the empirical experiment and its results, and section 4 concludes the paper and offer suggestions on further work.

2 The model

We are concerned in measuring how defaults in credit market to firms affect the resilience of banks[3] in the interbank market. This is developed as a framework which enables the analysis of distress propagation from the non-interbank assets of the banking system to the interbank market.

We propose to do that by building two networks, a bank-firm[4] two-mode network and a interbank exposures network. We then default some loans[5] in the bank-firm network and check for the propagation effects of these defaults in the banks that form the interbank network.

2.1 Network theory concepts

We are representing the relationships between banks, and between firms and banks by the concept of a network or a graph. A network N is comprised by a set of nodes V, and a set of edges E between these nodes. $|V|$ is the number of nodes and $|E|$ the number of edges. E_i are the edges leaving from or arriving at i. A network is *directed* if the direction of each edge is significant (that is, the edge $i \rightarrow j$ is different from $i \leftarrow j$), otherwise it is an undirected network. For the directed case, I_i is the edges which end in i, and O_i the set of edges which start in i.

A network can have values or other attributes associated with its nodes or edges. For simplicity we will assume that a *weighted network* has values called *weights*

[3]In this paper we will use the terms bank, financial institutions and financial conglomerate interchangeably, meaning institutions that give loans to firms and operate the interbank market. Whenever the financial institutions being analysed are part of a larger conglomerate, the effect of the whole conglomerate will be aggregated.

[4]In this paper we use loans from banks to listed firms for constructing the secondary network, but any a bank-asset network could be used, such as the bank-assets bipartite network use in Xuqing Huang and Stanley (2013).

[5]This could be simply the lowering of asset prices such that exposed banks liquidity buffer suffers a shock.

Concept	Description
Degree	number of edges of a node.
In-degree	number of in-going edges of a node.
Out-degree	number of out-going edges of a node.
Centrality	a measure of how *central* or important a node is in the network.
Clustering coefficient	a measure of the density of connections around a node.
Path	a set of nodes linked by edges.
Loop	a path where the same node appears more than once.

Table 1: Network theory concepts

associated with each edge. Table 1 summarises some basic network concepts.

In the case of an undirected network, a node's degree is equal to its in-degree and its out-degree. A *connected component* is a subgraph of an undirected network, such that there are paths between any two nodes in the component. A *strongly connected component* is an analogous concept, but applied to directed graphs.

Centrality measures are very important in network theory. There are various kinds of centrality measures. For our purposes we are considering *normalized* measures, where each value is divided over the maximum possible value for such measure. This facilitates the comparison of networks of different sizes. For instance *Degree centrality* simply uses the degrees of a node as a measure of importance, that is how connected a node is. It is normalized over all possible connections such that the degree centrality $C_D(i)$ of i is $C_D(i) = \frac{|E_i|}{|V|-1}$.

Betweenness centrality measures how many paths are shortest if they go through a node. Given $\sigma(s,t)$ as the number of shortest (s,t)-paths (paths from s to t), and $\sigma(s,t|v)$ the number of shortest paths from s to t that pass through v ($v \neq s,t$), the betweenness centrality $C_B(v)$ of v is given by $\sum_{s,t \in v} \frac{\sigma(s,t|v)}{\sigma(s,t)}$.

Feedback centrality measures are recursive in nature, that is, a node's centrality is dependent on the centrality of its neighbours. One such measure is the maximum eigenvector centrality which from a adjacency matrix representation of the network extracts its maximum eigenvalue λ_1 and the associated eigenvector $\hat{\mathbf{v}}$ such that the eigenvector centrality $C_E(i)$ of node i is the i^{th} component of the $\hat{\mathbf{v}}$.

In addition to centrality measures, other measure of interest is the *clustering coefficient*. The clustering coefficient $C_C(u)$ for each node u of N is the number of triangles that include u (paths of the form $u \leftarrow v \leftarrow w \leftarrow u$) over all possible triangles, and is given by $C_C(u) = \frac{2T(u)}{|E_i|(|E_i|-1)}$ where $T(u)$ is the number of triangles that include u. The *clustering coefficient* of N, C_N is the average clustering coefficient for N, that is $C_N = \frac{1}{|V|}\sum_{v\in V} C_C(v)$.

The network N is a *Two-mode network* if the set V is divided into two subsets V_{top} and V_{bottom}, $V_{top} \cap V_{bottom} = \emptyset$ such that for all edges in $(u, v) \in E$, $u \in V_{top}$ and $v \in V_{bottom}$, or $u \in V_{bottom}$ and $v \in V_{top}$. That is, all relationships are between nodes that are separated into two classes of node (and hence the name *two-mode*). The network formed by loans from banks to firms is a two-mode network.

Most such measures can be extended to the two-mode case.

The degree centrality for the two-mode case is easily extended by dividing the degree of node u from V_{top} by the size of V_{bottom}. Such approach also works for betweenness centrality. In this paper we adopt a two-mode clustering centrality coefficient taken from Masi and Gallegati (2012). Instead of counting triangles including node u the clustering coefficient $C_{c2}(u)$ is given by the density of cycles of size 4 including u (paths of the form $u \leftarrow i \leftarrow v \leftarrow j \leftarrow u$):

$C_{C2}(u) = \frac{\sum_{m=1}^{|E_u|}\sum_{n=m+1}^{|E_u|} q_u(m,n)}{\sum_{m=1}^{|E_u|}\sum_{n=m+1}^{|E_u|}[a_u(m,n)+q_u(m,n)]}$

where m and n are neighbors of u, $q_u(m, n)$ are the number of commom neighbors between m and n and $a_u(m, n) = (|Em|-\eta_u(m, n))(|En|-\eta_u(m, n))$ with $\eta_u(m, n) = 1 + q_u(m, n) + \theta_{mn}$ and $\theta_{mn} = 1$ if $(m, n) \in E$ or 0 otherwise.

Two-mode networks are often analysed by projecting each of their subcomponents into one-mode network. That is, the top-projection of N is the network formed by some nodes $v \in V_{top}$ it set of edges E_top such that an edge $(u, v) \in E_{top}, v \neq u$ if and only if there is at least two edges (u, i) and (v, i) in E and $i \in V_{bottom}$.

2.2 K-shell decomposition

In this paper we shall separate the interbank network using a K-shell decomposition method based on Carmi et al. (2007), that is also used to separate a network into three components.

First, the network nodes are separated into different sets called *k-shells* in the following way:

1 Assign 1 to k.

2 Separate all nodes with degree equal or less than k into the $k-shell$.

3 Remove all those nodes from the network, and add 1 to k.

4 Repeat steps 1 through 3 until there are no nodes left in the network.

The largest such k is k_{max}.

Finally, separate all nodes in the network into three components:

- The *CORE COMPONENT* is made of the nodes in the $k_{max}-shell$, the most connected nodes.
- The *PEER CONNECTED COMPONENT* is the set of nodes, excluding the *CORE* that forms the largest connected component (in the case of directed networks, a *strongly connected component.*
- The *ISOLATED COMPONENT* are all nodes not in the first two.

This technique will be used in the visualization of the networks studied in this paper, and also in some of the stress scenarios that will be tested.

2.3 Dominance

Dominance is a network centrality measure introduced by VanDenBrink and Gilles (2000) which takes into account the weights of each edge. For a loan network we define dominance as the function $\beta(i)$ of i as:

$$\beta(i) = \sum_j \frac{W(i,j)}{\lambda(j)} \tag{1}$$

where $\lambda(j) = \sum_i W(i,j)$ and $W(i,j)$ = value of loans from i to j

In the case of bank-firm loans networks, we can think of dominance in both directions: the dominance of a bank (the bank that lends more) and the dominance of a firm (the firm that borrows more).

2.4 DebtRank

The *DebtRank* measure is a systemic importance metric for financial institutions proposed by Battiston et al. (2012). In this section we give a short overview of *DebtRank*. For a full description see the reference above.

Given a interbank loans network, the *DebtRank* value of a bank is the potential financial impact of its default on the interbank loans network. It is a feedback centrality measure which means that the value of a node's impact depends upon the impact measures of the node's neighbours. It is loosely inspired by PageRank [6], but restricts loops.

Let i and j be two banks, A_{ij} the amount loaned from i to j, $A_i = \sum_j A_{ij}$ the total amount loaned by i, $\nu_i = A_i / \sum_i A_i$ the relative value of i in the interbank loans network, and E_i the capital buffer[7] of i.

We define the direct impact on j from a default by i is $W_{ij} = \min(1, A_{ji}/E_j)$. If $W_{ij} = 1$ then j overcomes its capital buffer and also defaults on its loans. From the individual impact, it follows that the direct impact of given by i on its neighbours is $I_i = \sum_j W_{ij}\nu_j$. However the total impact of a bank's default will be its direct impact on its neighbours, plus the total impact of each of its neighbours:

$$I_i = \sum_j W_{ij}\nu_j + \beta \sum_j W_{ij} I_j \tag{2}$$

This equation has no analytical solution due to the possible existence of loops in the network ($i \to j \to k \to i$), therefore Battiston et al. (2012) devised an algorithm to calculate its value by excluding further impact contributions from banks that was already included in the calculation[8].

[6] Page et al. (1998)

[7] Tier one capital

[8] We refer the reader to Page et al. (1998) for a full explanation.

2.5 The basic framework

Given a set B of banks and a set F of firms that have taken loans from banks in B such that $B \cap F = \emptyset$, and two networks:

- N is the directed interbank loans network. The nodes from N are taken from B, and edges of N are of the form $< i, j, v >$ such that bank i has loaned v to j.
- L is the firm loans network. The nodes from L are taken from the union of F and B and all edges in L are of the form $< b, f, v >$ such that $b \in B$ and $f \in F$ and v is the amount loaned by b to f. The L network is a *two-mode network*, represented by a *bipartite graph.*

We assume that for each bank $b \in B$ we also have the necessary balance sheet information for the calculation of some measure S_b of systemic impact or relevance of b within the N network.

The basic exercise proposed in this paper is to apply the following algorithm:

1. Calculate S_b for each bank $b \in B$.
2. Choose a scenario in which a set $F' \subset F$ will default on its loans[9]from L, and calculate the total loss D_b for each bank $b \in B$ that is a node in L.
3. Apply the loss D_b to the proper balance sheet value of each b in B.
4. Recalculate S_b for each bank $b \in B$ with the updated balance sheet values.
5. Compare the new values of S_b with the original values

From this algorithm we can derive a two-step network-based stress test, which will measure the aggregate impact of simultaneous stress in both the credit and the interbank market.

In this paper we use as the systemic risk measure the *DebtRank* measure which is described in section 2.4, and we apply the losses from loans to firms to the affected bank's tier one capital (which will impact its systemic impact score value). Alternate systemic risk measures can be used, as long as they use some balance sheet value

[9]Or build a network from banks to assets and shock the values of assets, such that this loss of value affects the systemic impact measure S_b.

that is impacted by the losses from the loans to firms. For instance, both Eisenberg and Noe[10] and Furfine[11] measures could be used. Also, the stress buffer that is used could be some other measure, such as an institution's liquid assets.

The main idea of this paper is to verify the network effects due to correlated exposures. Two banks may lend to the same firms, which unexpectedly defaults on both banks. They both end up with a smaller cash flow than was expected, and have less resilience against distress occurring elsewhere (for instance, in the interbank market, or a depositor run). Another key idea is that since the buffer[12] is used to quantify the resilience of each institution (and the system) against distress, and simultaneous depletion of this buffer can lead to higher than expected distress, macro-prudential policy can be established in order to require adequate buffers. In this way the lender of last resort can quantify how much each institution would need from a pool of liquidity, as in a quantitative easing scenario, and optimize the distribution so that the minimum amount of resources are used by targeting the institutions that contribute the most for contagion.[13].

2.6 Defining stress scenarios

One of our aims in this paper is to test how a default by a set of borrowers will affect a set of banks, and how the effect of this simultaneous default decreases the resilience of the whole financial network. That last part is the contagious effect due to the structure of the networks involved and the nature of network-based systemic risk measures.

In order to capture this effect, we must select a subset of firms which will default on their loans. In this paper we use short term loans and maturing loans (maturity less than 90 days, or time-to-maturity less than 30 days). Our reasoning is that those loans are a short-term expected cash-flow, and the time frame is low enough not to give time for a partial recovery of those loans before affecting the lender.

Thus, from the set of available short term and maturing loans, we select a set of firms which will default on all of their loans according to some strategy. For our study,

[10] Eisenberg and Noe (2001).

[11] Furfine (2003).

[12] In this paper, tier one capital.

[13] The authors thanks for João Barata Ribeiro for this insight.

we have chosen two different approaches for selecting defaulting firm scenarios.

The first strategy lies in selecting that will default according to firm characteristics:

- **Highest centrality**: in this scenario the firms that have taken loans from the largest number of banks are selected for defaulting their loans. In this scenario the idea is that as they are more connected, those firms will cause distress directly in a larger number of banks

- **Highest debt**: in this scenario the firms that have the highest debt over assets ratio are selected for defaulting their loans. The idea is that these firms may be more likely to default as they are too indebted already.

The second strategy lies in selecting firms that will default according to bank characteristics in the interbank network. In this case we assign scores to each firm according to a bank statistic so that for the firm f its score will be the sum of the relevant bank statistic of all the banks that have lent to f.

- **Highest centrality**: in this scenario the firms that have taken loans from the banks that are the most connected to other banks in the interbank network are selected for defaulting their loans.

- **Highest dominance**: in this scenario the firms that have taken loans from the banks that are the most dominant in the interbank network are selected for defaulting their loans.

- **Core banks**: in this scenario the firms that have taken loans from the banks that are the core of the interbank network are selected for defaulting their loans. This is a first step in testing how the network structure affects the distribution of distress. Do core banks introduce more distress in the system?

- **Periphery banks**: in this scenario the firms that have taken loans from the banks that are in the periphery of the interbank network are selected for defaulting their loans. This is a second step in testing how the network structure affects the distribution of distress. Do periphery banks introduce more distress in the system?

For each scenario we set up a simple target, which is an increase in total defaults to up to certain percentage of all short term and maturing loans, and provoke default on firms chosen by the scenario. Since we are interested in correlated exposure effects, only firms which have taken loans from more than one bank are selected.

3 Empirical results

3.1 The dataset

Our sample is comprised of:

- Balance sheet data from banks and financial conglomerates.
- All loans to listed firms registered in the Central Bank of Brazil's Credit Risk Bureau System from 2006 through 2012. That is a very rich dataset which includes contract date, duration, amount, type of loan, interest rate and risk classification, among other data. This dataset includes loans from N banks and financial conglomerates and F firms.
- Interbank exposures registered in CETIP[14] as informed to the Central Bank of Brazil's from 2007 through 2012. Only creditor, debtor, financial instrument and amount owed
- Listed firm data from Economatica. This is a very thorough dataset, from which we used mainly the risk measures for each firm such as β and *debt over assets.*

Due to the availability of some of the data, the experiment was done on quarterly data, from March/2007 through June/2012, and in the interbank network only commercial banks and conglomerates or investment banks and conglomerates were included. The *DebtRank* measures were calculated only from September/2008 onward.

3.2 The Brazilian interbank network

The Brazilian interbank network has been the focus of network studies in the past, most notably Bastos e Santos and Cont (2010) and Cajueiro and Tabak (2007). Our

[14] *CETIP* (Organized Over-the-Count Market for Securities and Derivatives) handles the issuance, redemption, interest payments and custody of private fixed-income securities, government securities and state and municipal securities representing debts of the National Treasury.

sample of the Brazilian interbank network consists of monthly exposures between banks of types I and II. For the purposes of this paper, in addition of interbank exposures, we will also use *bank size*, *tier one capital*, and Basel III *Risk-Weighted Assets*. The entire sample consists of 151 banks, although not all banks are present at all dates, as there have been mergers, acquisitions, introduction of new banks and also a few bank failures.

Interbank networks are a important component of systemic risk measures that derive from default cascades. The basic idea is that the exposure portfolios from banks can form a network in which distress can propagate to other banks and financial institutions. The systemic risk measure we use in this paper, *DebtRank*, uses the interbank exposures and tier one capital[15]

The Brazilian interbank market in particular seems highly resilient, as banks have very high levels of capital[16]. In addition, in response to the 2008 crisis the banking system increased its capital, as seen in figure 1, at the same time as interbank exposures were reduced to pre-2008 levels, which is shown in figure 2.

< Place figures 1 and 2 about here >

Banks also deleveraged in response to the crisis[17] in the beginning of 2008, except for Brazilian medium banks which had lower mean leverage at time, and deleveraged more following September, 2008. This is shown on figure 3. The average *DebtRank* measure of the system was also higher on September, 2008, as seen on figure 4, and has since lowered its value.

< Place figures 3 and 4 about here >

The network characterization of the Brazilian interbank market is that of a *scale-free* network, as its degree distribution follows a *power-law*, as described in Bastos e Santos and Cont (2010). Figure 5 shows the degree distribution of the interbank

[15]The choice of tier one capital is aligned with the work done previously in *DebtRank* in Battiston et al. (2012) and other systemic risk measures as in Markose (2012), Furfine (2003) and Mistrulli (2011).

[16]Basel III demand 8% minimum total capital (tier one plus tier two capital) over risk-weighted assets, Brazilian regulatory as of this date demands 11%, and from the Central Bank of Brazil Financial Stability reports, most Brazilian banks have about 14%

[17]We are regarding leverage as related to our systemic risk measure, as the ratio of interbank liabilities over tier one capital.

network for some periods of interest, and figures 6 and 7 show two visualization of the interbank network in June 2012 and its separation into three components[18]: *CORE*, *PEER CONNECTED* and *ISOLATED*.

< Place figures 5, 6, and 7 about here >

3.3 The Firm-Bank Loans Network

The second network in this study is the network formed by loans from banks to listed firms. We chose to use only listed firms because of the availability of data about each firm, such as market value, debt to asset ratio, β, economic sector, and so forth. This data was available in quarterly frequency from *Economatica*.

The network formed is comprised of the full exposures of each bank to each of those listed firms in the given quarter. The whole sample included 118 banks and 351 firms, from March, 2007 to June, 2012. Only loans from banks to firms are considered, and network thus formed is a *two-mode network*. Figure 8 shows the network formed in this way for June 2012.

< Place figure 8 about here >

Comparing to the study by G. De Masi and Stiglitz (2010) about italian firms, our data set is much smaller, 118 versus 50 banks, and 351 versus 39194 firms. However some parallels may be drawn. As in G. De Masi and Stiglitz (2010), the degree distributions of both banks and firms are heavy-tailed power-law distributions, as shown on figure 9. In addition, we calculated the bipartite density CC^2 as in G. De Masi and Stiglitz (2010), and show the distribution in figure 10. Although the density distribution of banks follow a power law, unlike in G. De Masi and Stiglitz (2010) we find no clear relation between cluster density and bank degree. The dominance distribution of both banks and firms also follows a power law as shown on figure 11.

< Place figures 9, 10 and 11 about here >

In figures 12 and 13 we show the average degree of banks by bank size, and the average market value of firms that took loans from each category of bank sizes. We find that larger banks are the banks with the highest average degree, as in G. De Masi

[18]As described in section 2.2.

and Stiglitz (2010), however the average market value of firms that borrowed from small and medium banks tends to be higher. That results from smaller firms taking loans from the larger banks, which also have a much higher degree.

< Place figures 12 and 13 about here >

Overall we find that in our sample the loan-to-firms network is dominated by large banks. The banks-projection of the loan-to-firm for June, 2012 is shown in figures 14 and 15, with banks colored according to their position in the interbank network for the same date. Usually the banks that are in the core of the interbank network are also in the core of the loan-network projection.

< Place figures 14 and 15 about here >

3.4 Results

We simulate a shock to the interbank network by simulating defaults from a subset of firms selected according to a scenario, and then apply the simulated losses to the banks and recalculate the interbank systemic risk measure.

In this way we can visualize the multi-network formed from both the interbank network and the loans-to-firms network with the interbank network at the top and the firms at the bottom, as shown on figure 16 which represents the multi-network for June 2012.

< Place figure 16 about here >

The target for the shock is an increase in defaults in short-term and maturing loans for each date to 15% (which for our sample represents from 0.8% to 3.0% of all loans to listed firms). Only firms that took loans from more than one bank are considered for the simulation of defaults.

After applying the algorithm described in section 2.5 to our sample we find that there is a dispersion effect of distress, in which the increase in financial fragility caused by the loss of loans is not restricted to the directly affected banks. We also find that the mean individual systemic impact score increases more than the total capital loss of the system. We believe that both effects are related to the recursive nature of the *DebtRank* measure, which takes into account both direct and indirect impact in the case of cascading defaults.

Visual representations of the effects of each scenario are shown on figures 17, 18, 19, 20, 21, and 22. Given the initial state (as in figure 16), the shock is propagated from the simulated defaults in firms (at the bottom of the graph, defaulting firms colored red) toward the interbank network (at the top of the graph). Banks directly affected[19] are colored red, and banks indirectly affected[20] are colored yellow.

< Place figures 17, 18, 19, 20, 21, and 22 about here >

Tables 2, 3, 4, 5, 6 and 7 show the dispersion effect of the defaults in the loans to firms. Basically, what happens is that the banks that are directly affected are in the direct or indirect exposure path of many other banks, and therefore if their individual impact measure grows, the impact of every bank that have them in its exposure path will also grow. In this way there is a growth in the total fragility of the system. The number of banks affected range from 60 to 80% of the banks in the interbank network sample. Also, in our sample, the type of scenario chosen has not changed significantly the total number of banks affected.

< Place tables 2, 3, 4, 5, 6 and 7 about here >

Tables8, 9, 10, 11, 12 and 13 show how the loss of tier one capital relates to the increase in the systemic impact score. In nearly all cases the mean *DebtRank*[21] of directly affected banks increases more than the loss of capital of the system, and in all cases the score of indirectly affected banks increases more than the loss of capital of the system. The cases in which the directly affected banks' impact score increased less than the system's capital loss seem to be all after December 2011, but it is not yet clear why.

< Place tables 8, 9, 10, 11, 12 and 13 about here >

What we see in these results is the effects of the correlated risk exposure. If the simulated defaulting firms took loans only from a single bank, those firms' defaults

[19] Banks directly affected are those taking losses to their capital buffers from the simulated defaults.

[20] Banks indirectly affected had their systemic risk measure increased in spite of not suffering a loss to capital.

[21] In our exercise, the *DebtRank* score of a bank is a measure of the potential systemic impact of that banks's default in the interbank network.

would not impact the bank's systemic impact measure[22]. However, most firms have taken loans from more than one bank, which spreads the distress throughout the network. In addition, it is very likely that any given firm has also taken at least a single loan from a bank in the core of the interbank network, which makes these correlated exposures even more contagious.

This exercise shows that a very small shock can suffer a multiplicative effect as the correlated exposures do not seem to be normally distributed. The measure of connectivity of firms in the bank-firm network follows a power law, which means that the distribution of correlated risk seem to be heavy-tailed.

4 Conclusion and further work

In this paper we present an exercise that shows that risk stemming from the bank-firm network can propagate to the interbank market and can have a multiplicative effect that increases even the impacts of banks that were not directly affected by the original shocks. This result is possible only under the assumption that the variable impacted by firms defaulting in their loans is relevant to the calculus of systemic risk in the interbank market.

Also, we show that even if few institutions are directly affected by the default on their loans to firms, the fact that they are part of a interbank network can increase the potential financial impact of the distress in a larger number of banks. These results also relies on an assumption: basically that systemic impact is recursive, that is the total impact of an bank depends also on the impact of other banks.

Finally, those impacts are not normally distributed. If they originate in a network whose distribution of connectivity follows a power law, and are spread to another network whose connectivity also follows a power law, the actual systemic impact may have an unexpected distribution across the financial system.

Our main contribution is that in addition of being part of a very small set of papers that investigate networks of loans from banks to firms, to our knowledge, this is the first paper that attempts to integrate the potential effect of defaults on loans to the

[22]That is because the simulated losses are subtracted from the bank's capital, but the calculus of the bank's *DebtRank* score already implies that its capital is zero for the impact calculation.

real sector in calculations of systemic impact in the interbank market using complex network theory models.

Further work would integrate other effect such as liquidity shortages, which can affect both the interbank market and the loans to firms, and indirect contagion effects. We also believe that properly modeling the statistical dynamics and simulation methods would be great contributions.

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A Figures

A.1 Interbank network

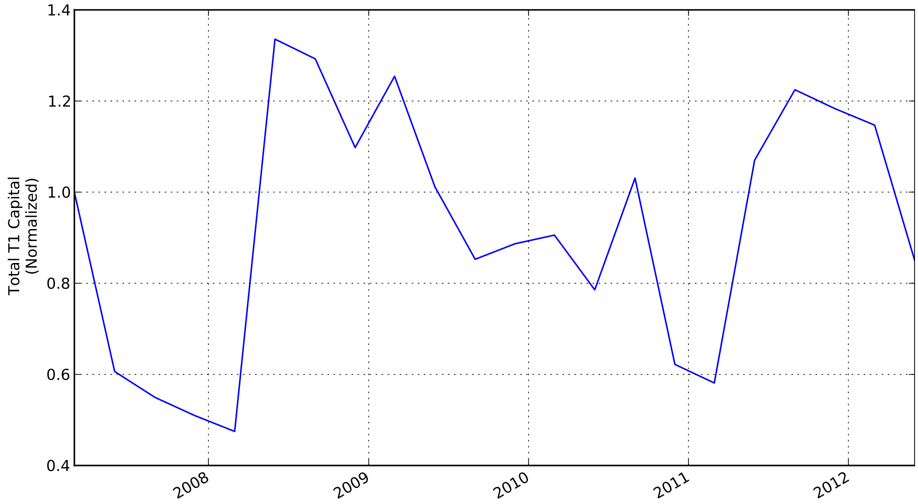

Figure 1: Total Tier 1 Capital – Normalized to March/2007

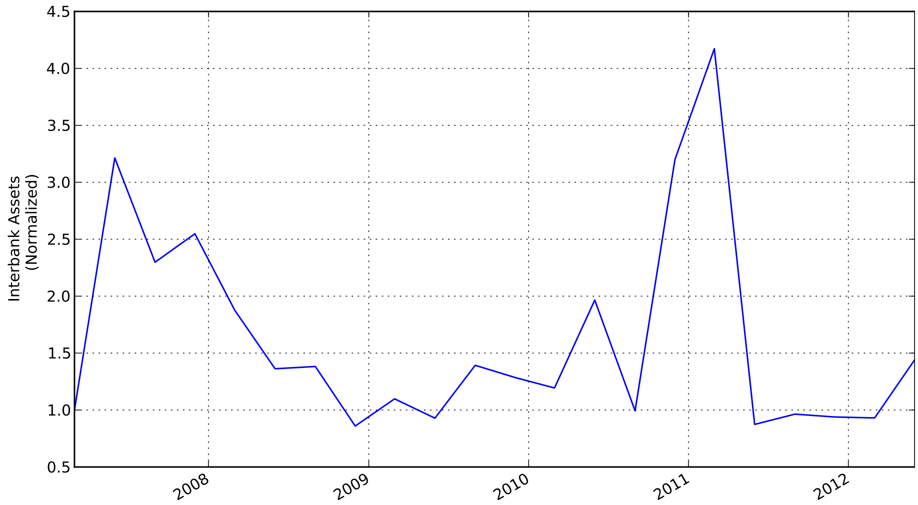

Figure 2: Total Interbank assets – Normalized to March/2007

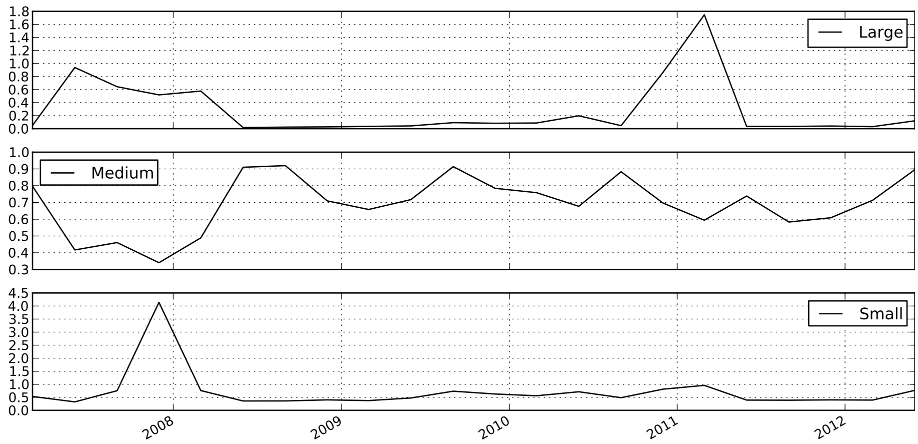

Figure 3: Average interbank leverage by Bank Size ($\frac{IntebankLiabilities}{TierOneCapital}$)

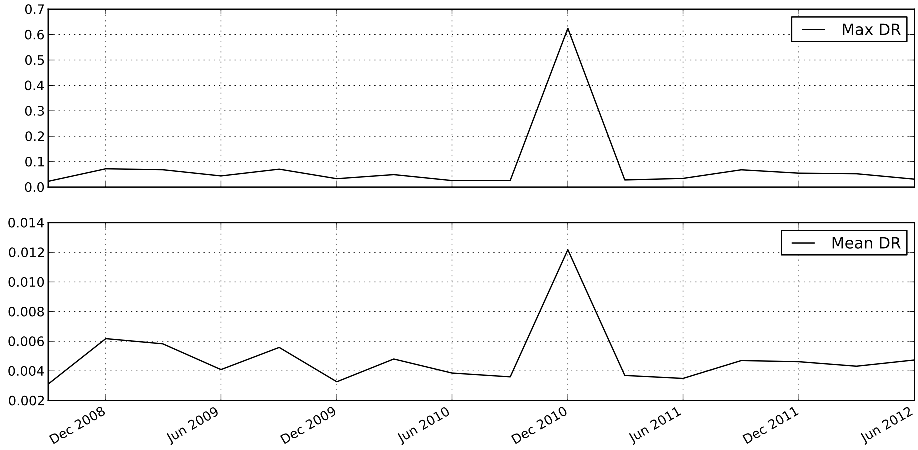

Figure 4: Average *DebtRank*

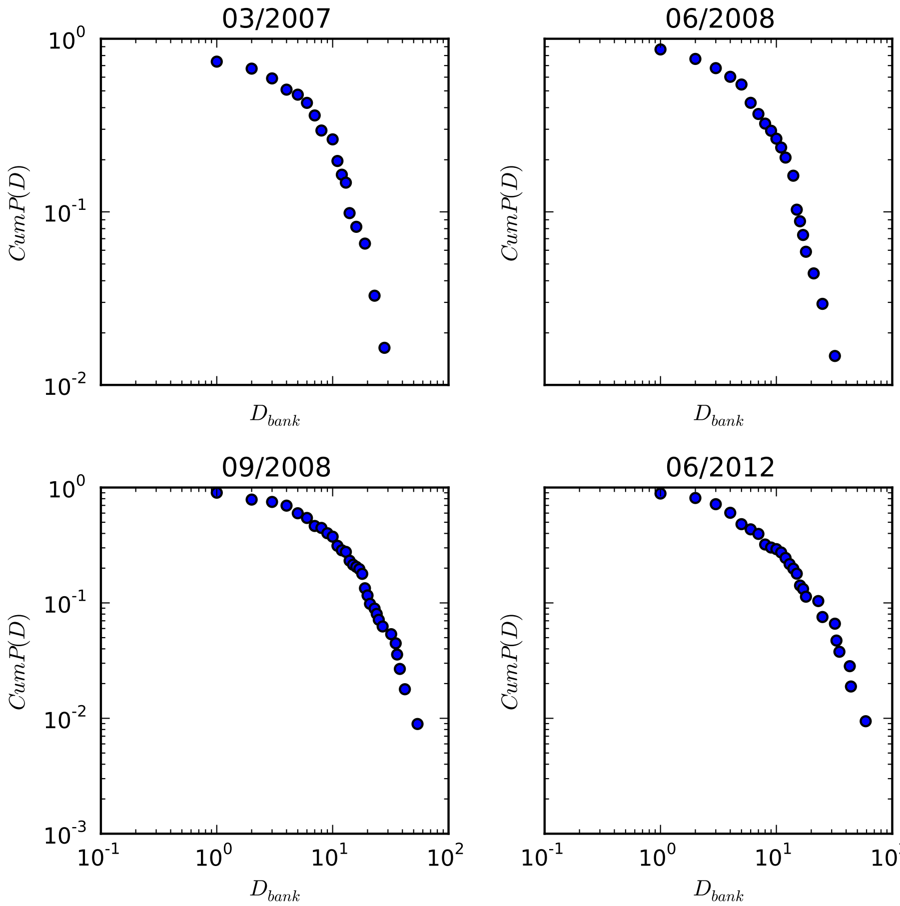

Figure 5: Interbank network degree probability distribution

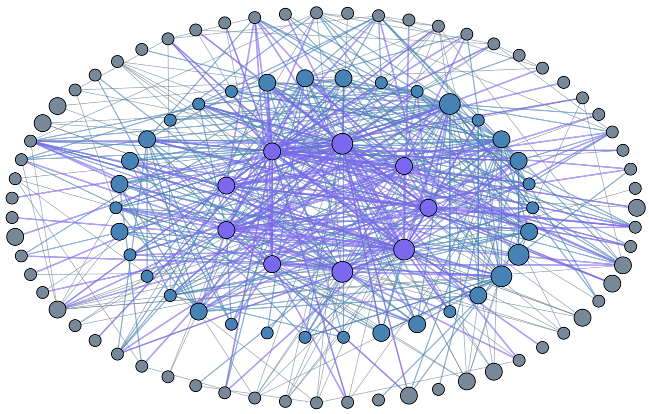

Figure 6: Interbank Sample Network – June/2012 – *Core Banks* purple, *Peer Component* Banks blue, *Isolated Component Banks* gray

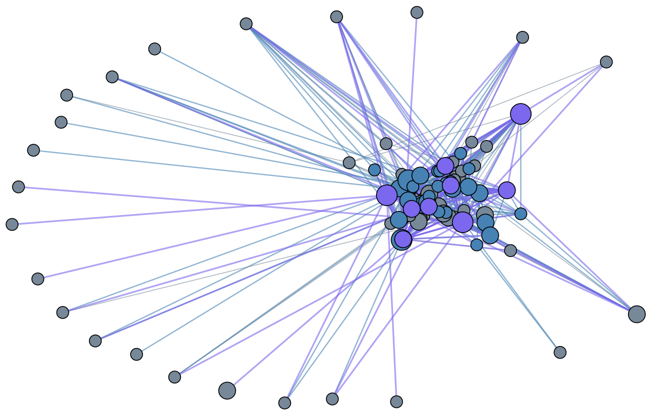

Figure 7: Interbank Sample Network – June/2012 – Force-Based layout – *Core Banks* purple, *Peer Component Banks* Blue, *Isolated Component Banks* gray

A.2 The Bank-Firm Loans network

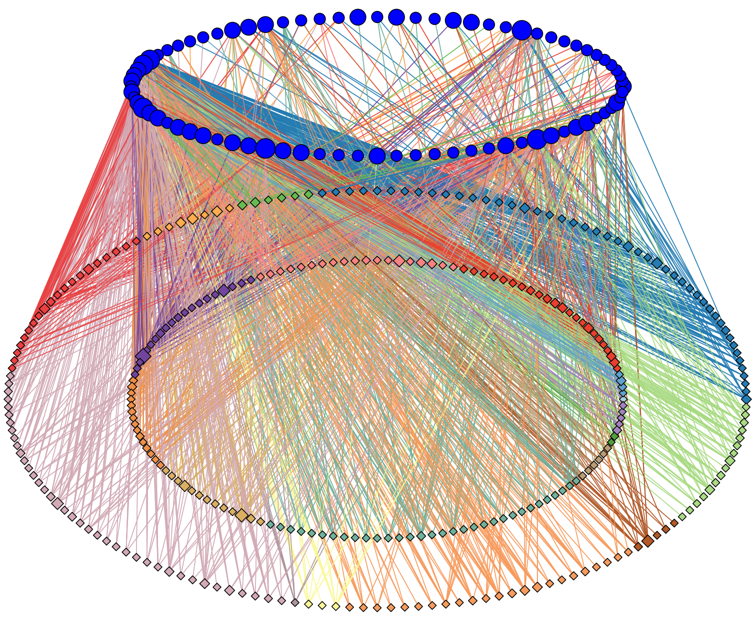

Figure 8: Bank-Firms loan network – June/2012 – firms colored by economic sector, edges representing loans are colored by the economic sector of firm taking loan

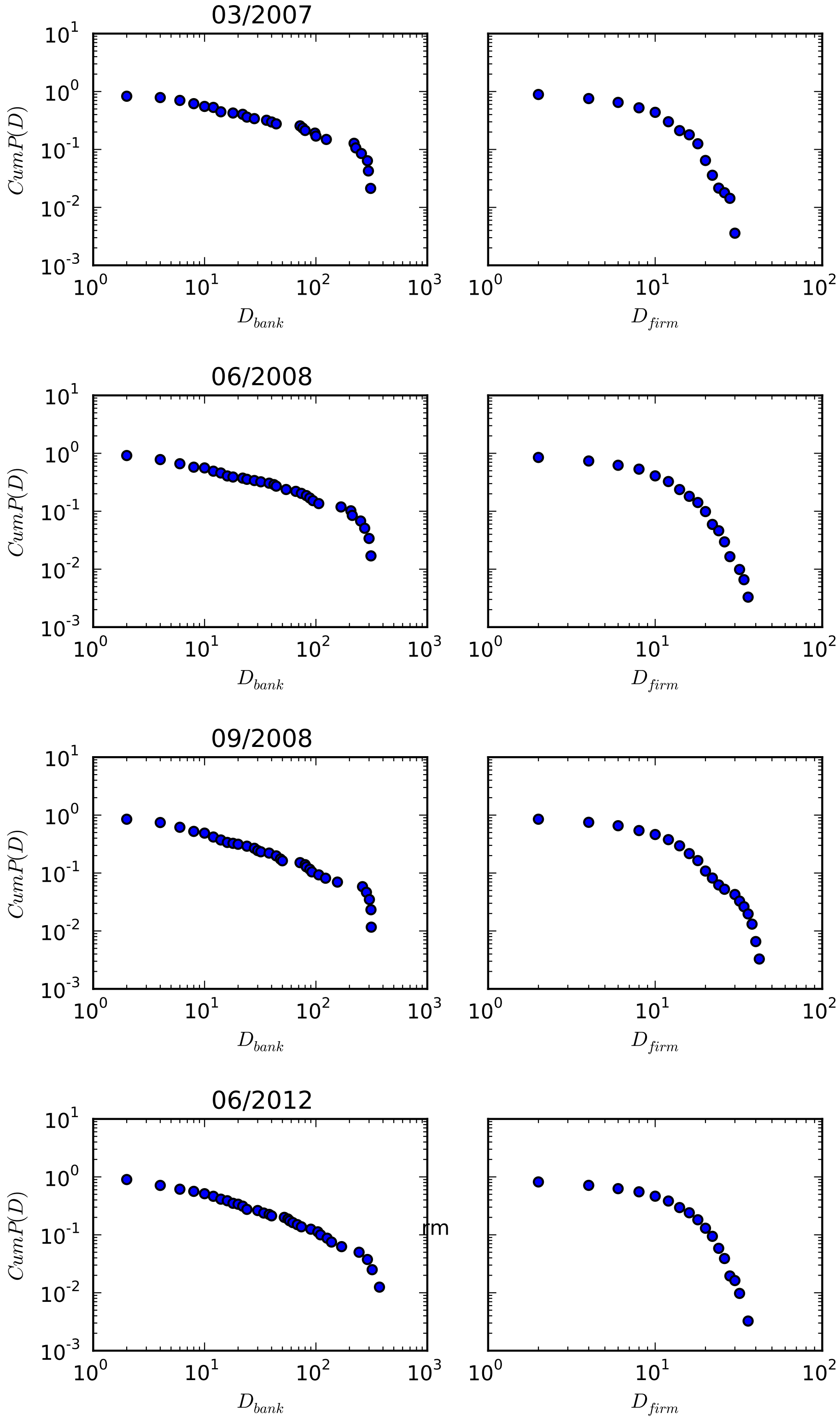

Figure 9: Bank-Firms loan network - Degree distributions D_{bank} and D_{firm}

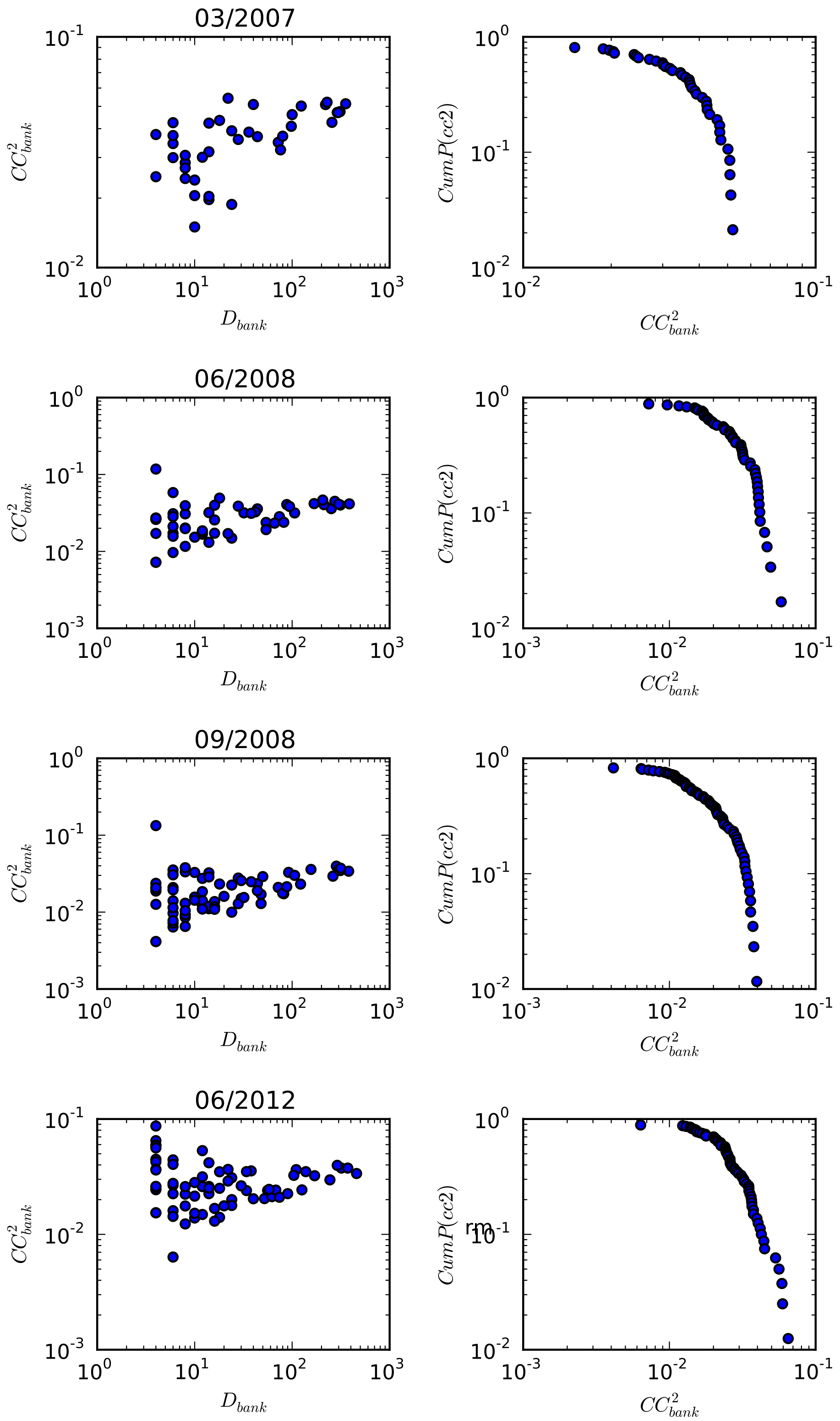

Figure 10: Bank-Firms loan network - Density versus Degree ($CC^2_{bank} x D_{bank}$) and Density distributions for CC^2_{bank}

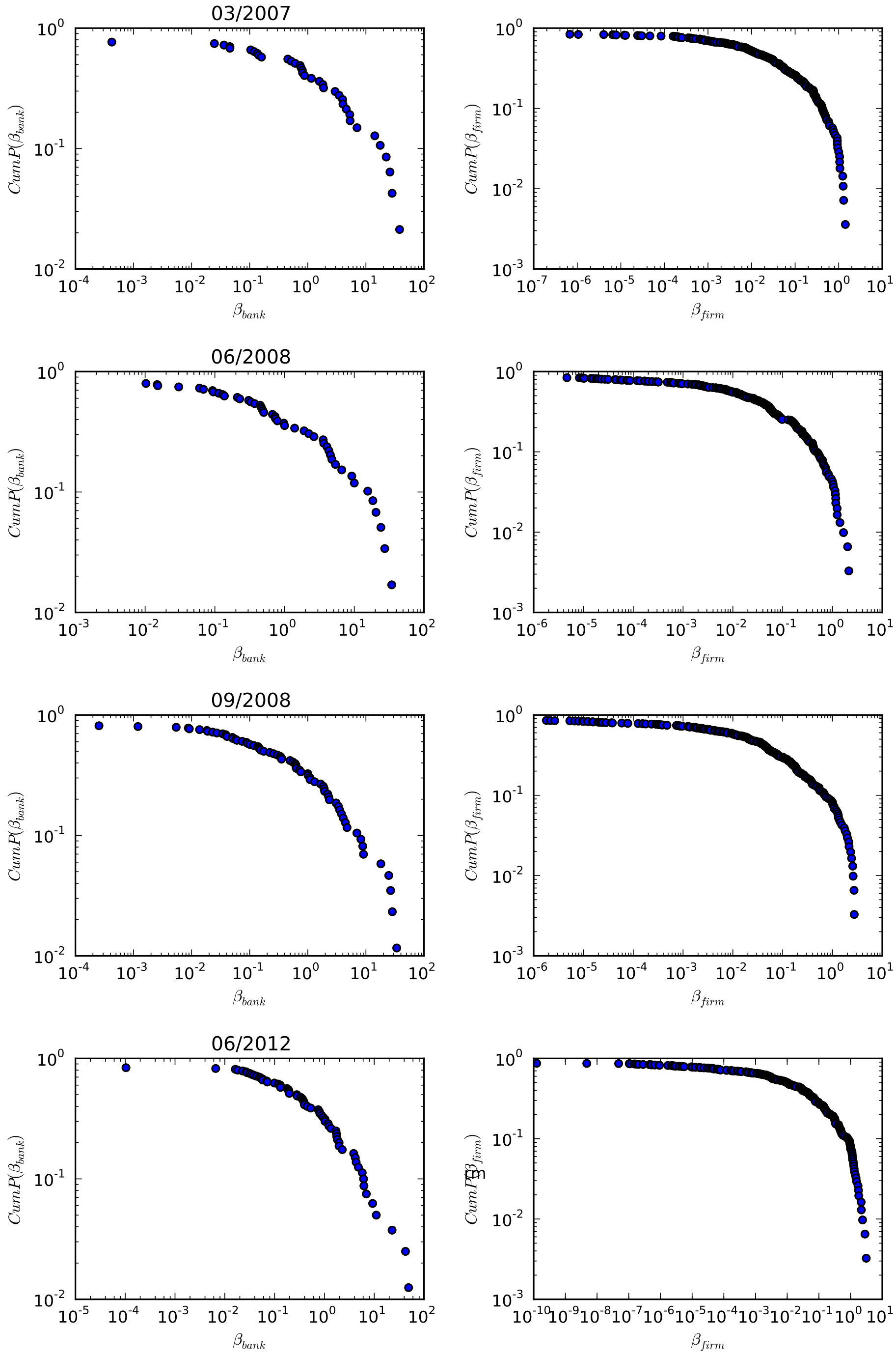

Figure 11: Bank-Firms loan network - distribution of dominance for banks and firms β_{bank} and β_{firm}

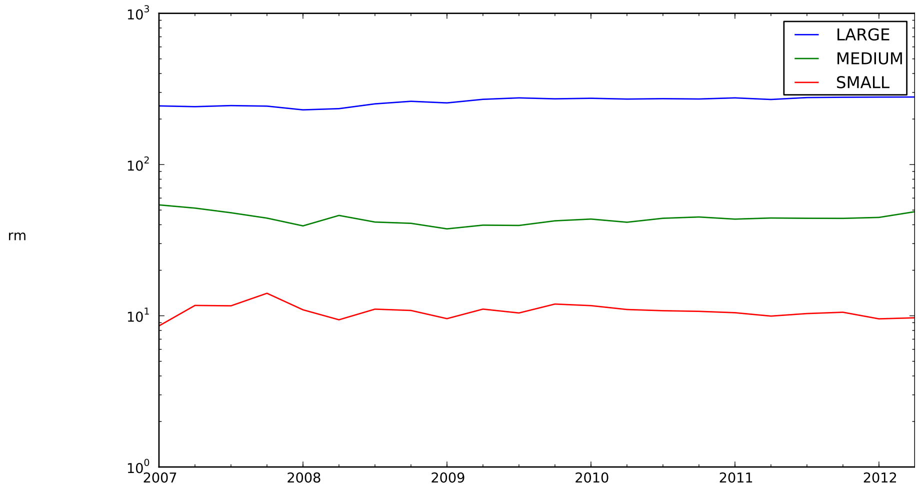

Figure 12: Average degree by bank size

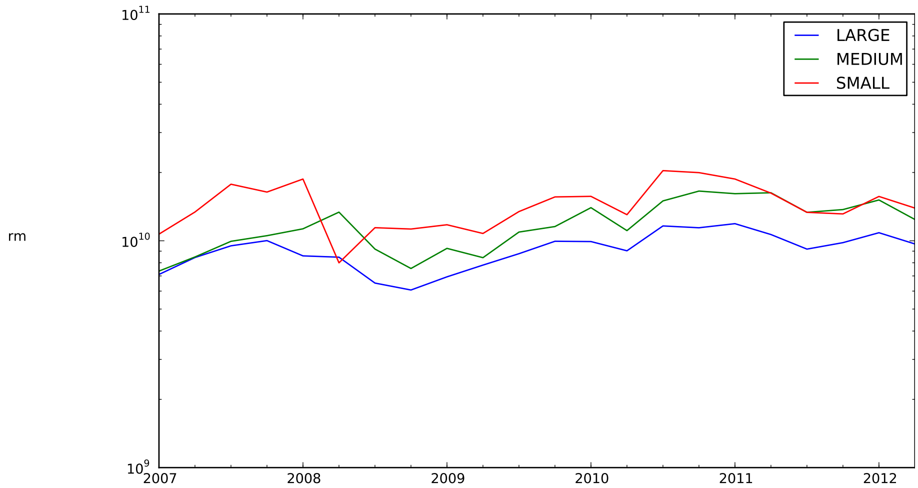

Figure 13: Average firm market value by lending bank size

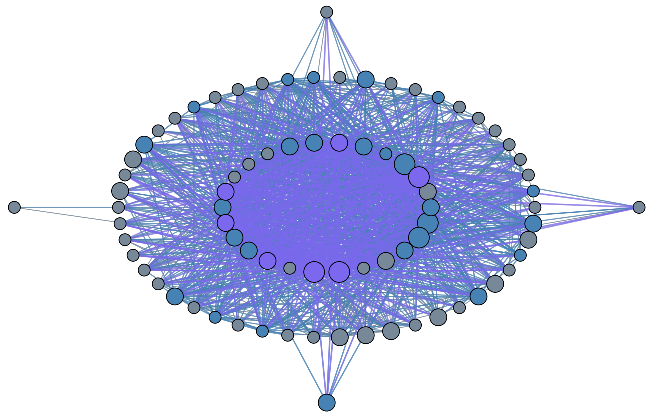

Figure 14: Bank-Firms loan network – Banks projection – Bank are colored according to their component in the interbank network for the same date: – *Core Banks* purple, *Peer Component Banks* Blue, *Isolated Component Banks* gray

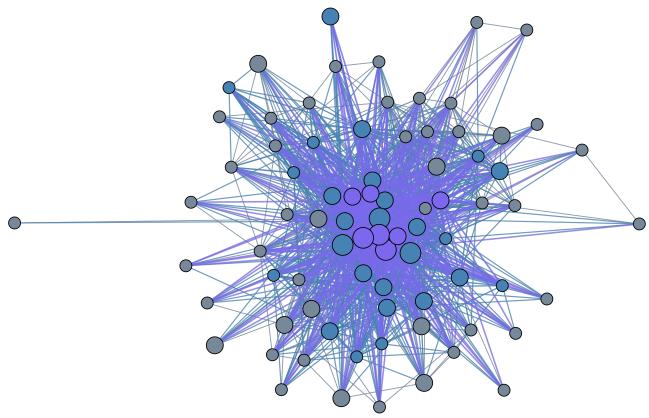

Figure 15: Bank-Firms loan network – Banks projection – Force-based layout – Bank are colored according to their component in the interbank network for the same date: – *Core Banks* purple, *Peer Component Banks* Blue, *Isolated Component Banks* gray

A.3 Results

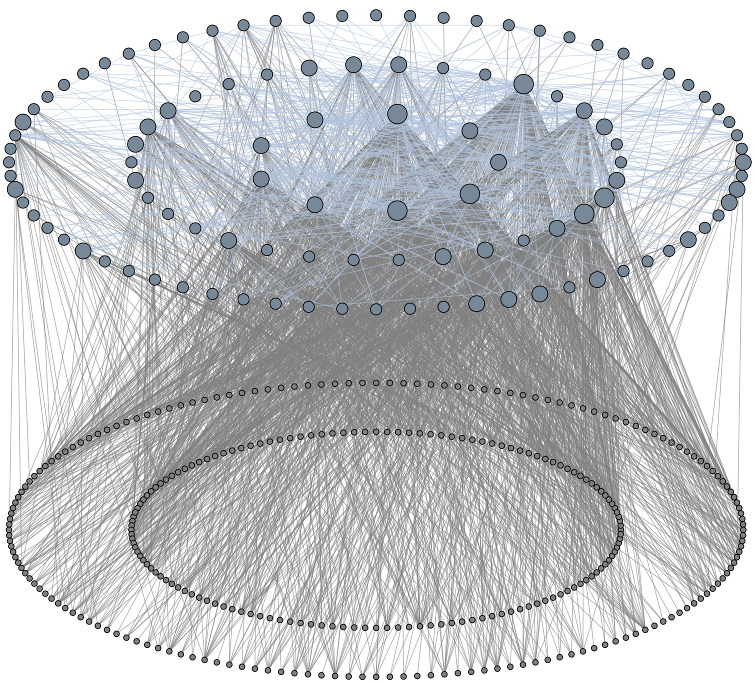

Figure 16: Interbank and Bank-Firms loans Multi-network for June, 2012– Interbank network on top, firms at bottom

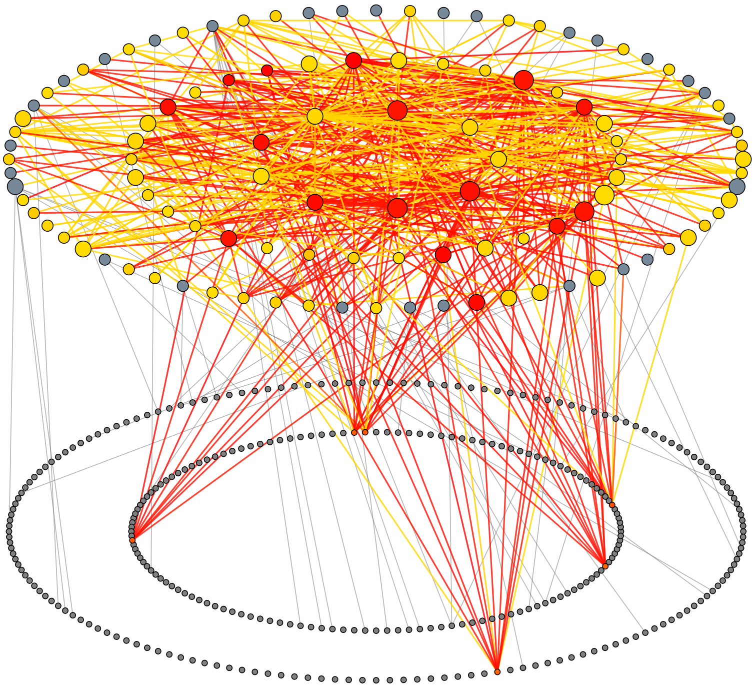

Figure 17: Simulated shock – Most connected firms scenario for June, 2012 – Interbank network on top, firms at bottom – simulated defaulting firms red, directly affected banks red, indirectly affected banks yellow.

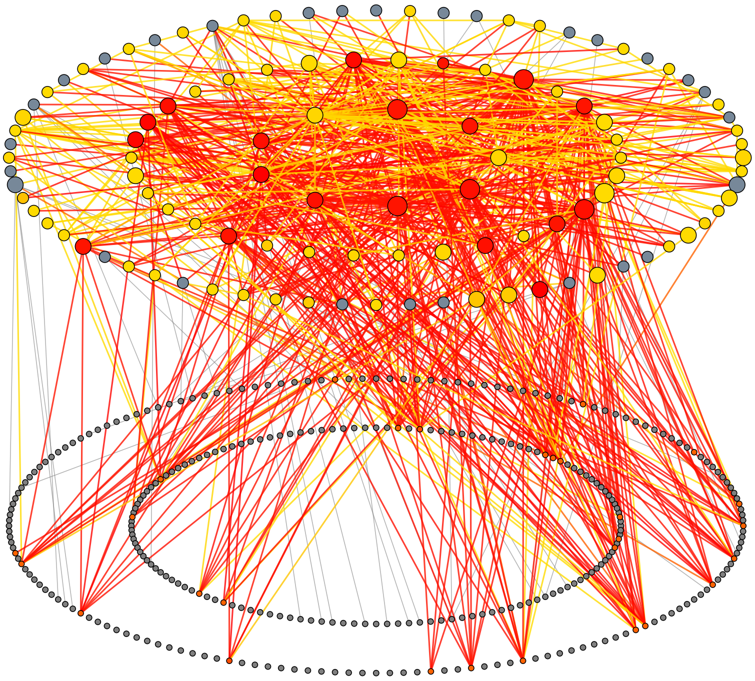

Figure 18: Simulated shock – Most indebted firms scenario for June, 2012 – Interbank network on top, firms at bottom – simulated defaulting firms red, directly affected banks red, indirectly affected banks yellow.

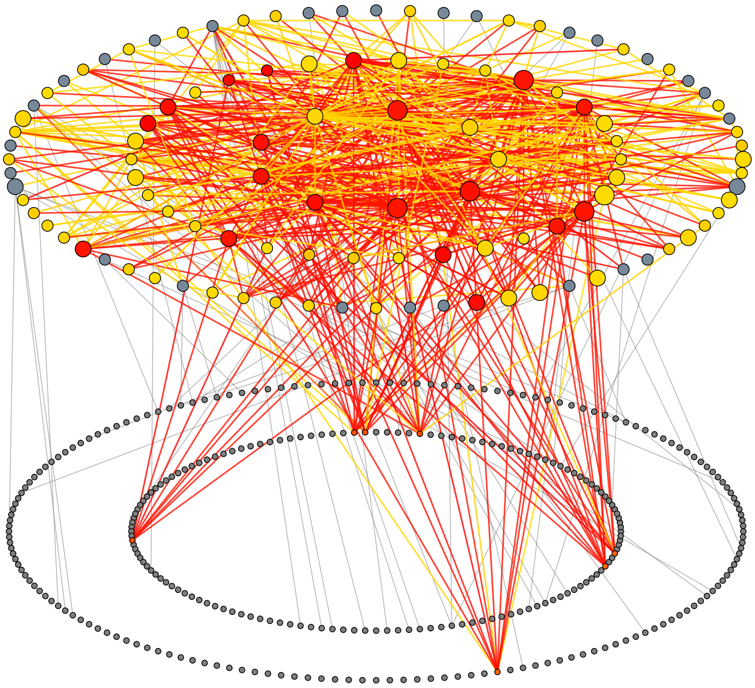

Figure 19: Simulated shock – *Core* banks scenario for June, 2012 – Interbank network on top, firms at bottom – simulated defaulting firms red, directly affected banks red, indirectly affected banks yellow.

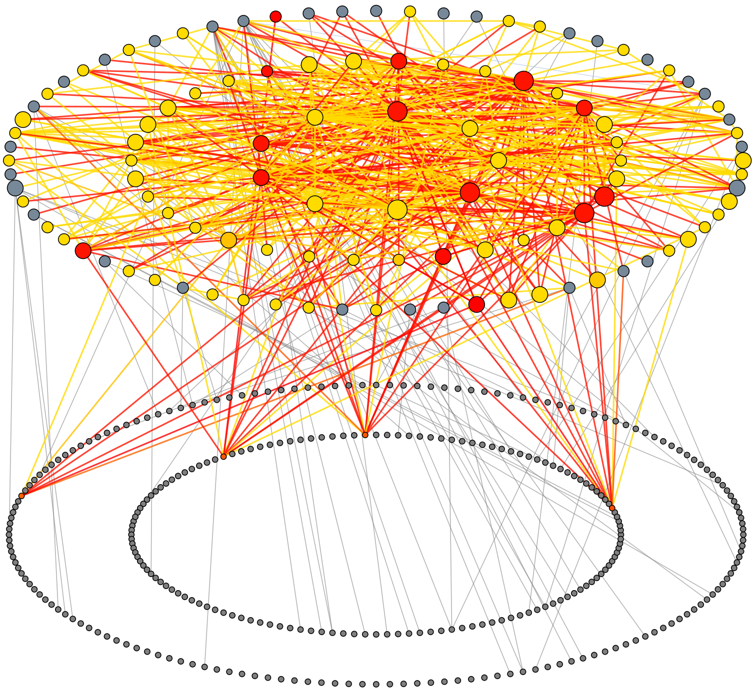

Figure 20: Simulated shock – *Periphery* banks scenario for June, 2012 – Interbank network on top, firms at bottom – simulated defaulting firms red, directly affected banks red, indirectly affected banks yellow.

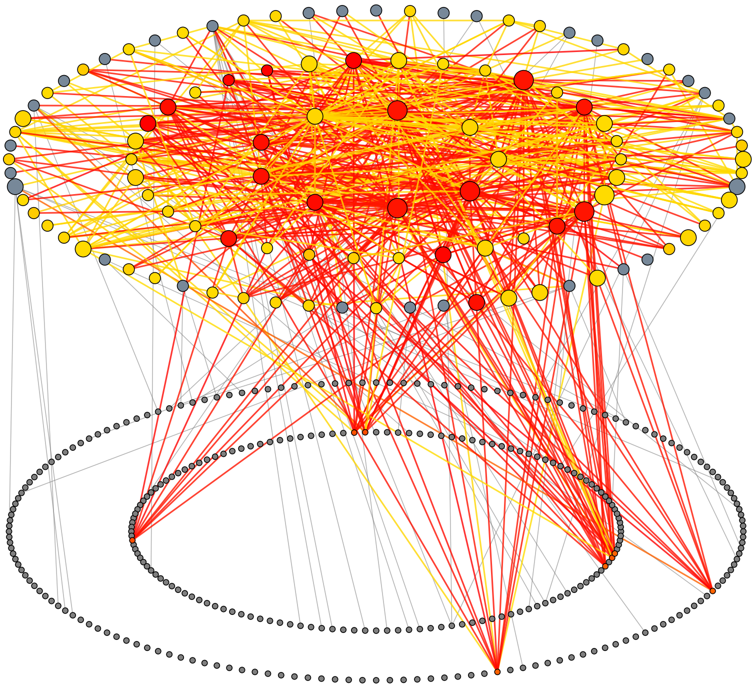

Figure 21: Simulated shock – Most connected banks scenario for June, 2012 – Interbank network on top, firms at bottom – simulated defaulting firms red, directly affected banks red, indirectly affected banks yellow.

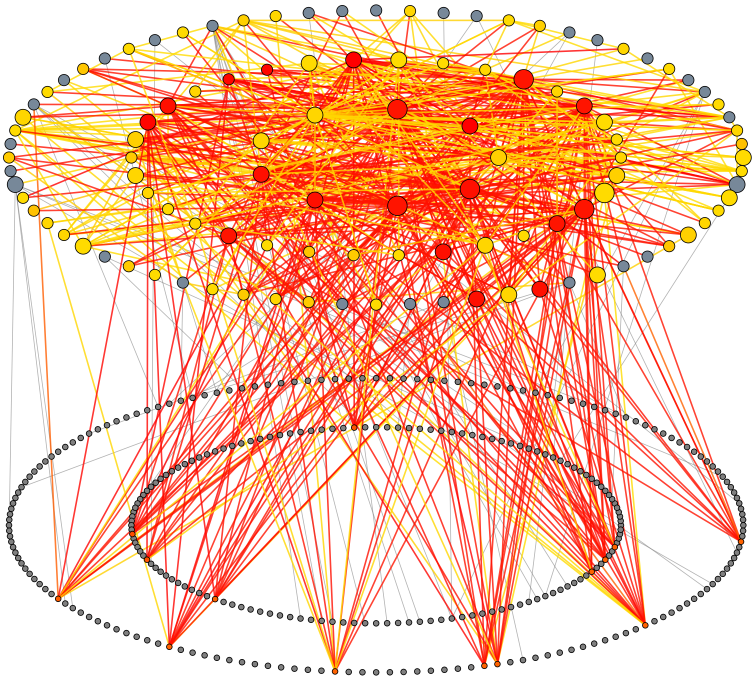

Figure 22: Simulated shock – Most dominant lenders scenario for June, 2012 – Interbank network on top, firms at bottom – simulated defaulting firms red, directly affected banks red, indirectly affected banks yellow.

B Tables

B.1 Number of banks affected

These tables list the number of banks affected by the simulated shocks in each scenario. The **Directly Affected** are the number of banks which suffered direct simulated losses due to the simulated defaults (that is, these banks had outstanding short term or maturing loans invested in the simulated defaulting firms. The **Indirectly Affected** banks are the banks which did not suffer direct simulated losses, but nevertheless their systemic risk score increased due to their connections in the interbank network. The Affected banks are the total number of banks affected, directly and indirectly, divided by the total number of banks in that sample of the interbank network, expressed as a percentage.

	Banks	Directly Affected	Indirectly Affected	% Affected
09/2008	112	20	68	78
12/2008	110	17	71	80
03/2009	104	13	70	79
06/2009	110	19	62	73
09/2009	110	17	61	70
12/2009	112	16	66	73
03/2010	114	19	63	71
06/2010	112	22	54	67
09/2010	116	21	54	64
12/2010	114	22	55	67
03/2011	112	24	54	69
06/2011	108	26	52	72
09/2011	105	22	56	74
12/2011	107	29	53	76
03/2012	109	31	53	77
06/2012	106	20	63	78

Table 2: Banks Affected - Highly indebted firms - Actual capital

	Banks	Directly Affected	Indirectly Affected	% Affected
09/2008	112	16	71	77
12/2008	110	24	64	80
03/2009	104	21	62	79
06/2009	110	18	63	73
09/2009	110	19	59	70
12/2009	112	19	63	73
03/2010	114	22	60	71
06/2010	112	24	53	68
09/2010	116	20	55	64
12/2010	114	22	55	67
03/2011	112	24	55	70
06/2011	108	21	56	71
09/2011	105	19	58	73
12/2011	107	19	61	74
03/2012	109	27	57	77
06/2012	106	16	67	78

Table 3: Banks Affected - Highly connected firms - Actual capital

	Banks	**Directly Affected**	**Indirectly Affected**	**% Affected**
09/2008	112	18	70	78
12/2008	110	19	69	80
03/2009	104	17	66	79
06/2009	110	17	64	73
09/2009	110	18	67	77
12/2009	112	19	65	75
03/2010	114	20	62	71
06/2010	112	24	53	68
09/2010	116	22	53	64
12/2010	114	22	55	67
03/2011	112	16	69	75
06/2011	108	23	54	71
09/2011	105	25	51	72
12/2011	107	26	54	74
03/2012	109	28	56	77
06/2012	106	19	64	78

Table 4: Banks Affected - Core Banks - Actual capital

	Banks	Directly Affected	Indirectly Affected	% Affected
09/2008	112	24	64	78
12/2008	110	19	69	80
03/2009	104	18	65	79
06/2009	110	19	62	73
09/2009	110	18	67	77
12/2009	112	20	64	75
03/2010	114	15	67	71
06/2010	112	24	53	68
09/2010	116	22	54	65
12/2010	114	19	58	67
03/2011	112	18	59	68
06/2011	108	16	61	71
09/2011	105	23	54	73
12/2011	107	28	52	74
03/2012	109	32	52	77
06/2012	106	18	65	78

Table 5: Banks Affected - Most Connected Banks - Actual capital

	Banks	**Directly Affected**	**Indirectly Affected**	**% Affected**
09/2008	112	21	67	78
12/2008	110	21	67	80
03/2009	104	16	67	79
06/2009	110	11	69	72
09/2009	110	17	62	71
12/2009	112	16	67	74
03/2010	114	14	68	71
06/2010	112	21	57	69
09/2010	116	17	59	65
12/2010	114	14	63	67
03/2011	112	16	60	67
06/2011	108	17	60	71
09/2011	105	21	56	73
12/2011	107	25	54	73
03/2012	109	21	62	76
06/2012	106	19	64	78

Table 6: Banks Affected - Most Dominant Banks - Actual capital

	Banks	Directly Affected	Indirectly Affected	% Affected
09/2008	112	21	66	77
12/2008	110	23	65	80
03/2009	104	21	63	80
06/2009	110	28	54	74
09/2009	110	8	69	70
12/2009	112	20	65	75
03/2010	114	20	62	71
06/2010	112	25	54	70
09/2010	116	26	49	64
12/2010	114	22	55	67
03/2011	112	10	62	64
06/2011	108	5	71	70
09/2011	105	6	65	67
12/2011	107	15	65	74
03/2012	109	15	64	72
06/2012	106	14	66	75

Table 7: Banks Affected - Periphery Banks - Actual capital

B.2 DebtRank increase

These tables list the increase in the ristemic risk score of banks affected by the simulated shocks in each scenario, and the percentage of the total tier one capital of the sample that was lost to the simulated default in each scenario.

	Systemic Cap Loss (%)	Average Direct DR Increase(%)	Average Indirect DR Increase(%)
09/2008	0.546	3.081	4.563
12/2008	0.317	0.423	1.814
03/2009	0.315	0.356	2.334
06/2009	0.524	0.982	2.199
09/2009	0.519	0.692	2.764
12/2009	0.197	0.208	0.850
03/2010	0.158	0.322	0.937
06/2010	0.187	0.185	0.908
09/2010	0.158	0.300	0.637
12/2010	0.274	0.537	2.930
03/2011	0.208	0.878	0.883
06/2011	0.496	1.190	2.092
09/2011	0.737	1.610	2.011
12/2011	0.894	0.979	1.903
03/2012	0.450	0.271	0.713
06/2012	0.176	0.128	0.686

Table 8: DebtRank Increase - Highly indebted firms - Actual capital

	Systemic Cap Loss (%)	**Average Direct DR Increase(%)**	**Average Indirect DR Increase(%)**
09/2008	0.303	0.669	2.747
12/2008	0.305	2.755	4.644
03/2009	0.329	0.880	1.947
06/2009	0.473	2.819	6.463
09/2009	0.415	0.614	2.789
12/2009	0.186	0.373	1.694
03/2010	0.190	0.319	1.703
06/2010	0.190	0.392	0.739
09/2010	0.165	1.011	1.603
12/2010	0.215	1.009	1.791
03/2011	0.199	0.981	1.506
06/2011	0.468	2.306	3.743
09/2011	0.796	3.539	3.647
12/2011	1.422	74.427	10.269
03/2012	1.406	0.363	1.422
06/2012	0.247	0.151	1.279

Table 9: DebtRank Increase - Highly connected firms - Actual capital

	Systemic Cap Loss (%)	**Average Direct DR Increase(%)**	**Average Indirect DR Increase(%)**
09/2008	0.342	0.682	2.774
12/2008	0.390	2.239	4.945
03/2009	0.353	0.418	2.151
06/2009	0.395	0.491	2.132
09/2009	0.136	53.812	2481.002
12/2009	0.215	0.382	1.836
03/2010	0.186	0.269	1.650
06/2010	0.192	0.602	0.743
09/2010	0.173	0.896	0.892
12/2010	0.216	1.021	1.801
03/2011	0.284	286.595	1343324.219
06/2011	0.207	2.103	2.131
09/2011	0.317	4.862	2.493
12/2011	1.632	55.584	7.140
03/2012	1.485	0.444	1.503
06/2012	0.212	0.149	1.001

Table 10: DebtRank Increase - Core Banks - Actual capital

	Systemic Cap Loss (%)	Average Direct DR Increase(%)	Average Indirect DR Increase(%)
09/2008	0.495	1.161	2.601
12/2008	0.347	0.753	2.803
03/2009	0.355	0.687	1.746
06/2009	0.400	0.515	1.851
09/2009	0.139	53.814	2481.009
12/2009	0.215	0.419	1.689
03/2010	0.168	0.270	1.846
06/2010	0.191	0.385	0.701
09/2010	0.160	0.866	0.968
12/2010	0.185	0.547	1.237
03/2011	0.211	1.211	1.636
06/2011	0.201	2.029	3.173
09/2011	0.327	3.129	2.092
12/2011	1.648	51.971	6.374
03/2012	0.434	0.480	1.136
06/2012	0.185	0.138	0.971

Table 11: DebtRank Increase - Most Connected Banks - Actual capital

	Systemic Cap Loss (%)	Average Direct DR Increase(%)	Average Indirect DR Increase(%)
09/2008	0.343	13.026	11.964
12/2008	0.396	1.163	2.953
03/2009	0.377	0.511	2.137
06/2009	0.372	0.320	3.160
09/2009	0.263	0.411	1.390
12/2009	0.200	0.453	1.922
03/2010	0.156	0.176	1.883
06/2010	0.259	0.487	1.111
09/2010	0.160	0.819	1.690
12/2010	0.192	1.214	2.670
03/2011	0.210	1.296	1.938
06/2011	0.207	1.912	3.278
09/2011	0.317	2.019	3.779
12/2011	0.487	4.019	3.537
03/2012	1.311	0.259	1.575
06/2012	0.188	0.278	1.465

Table 12: DebtRank Increase - Most Dominant Banks - Actual capital

	Systemic Cap Loss (%)	Average Direct DR Increase(%)	Average Indirect DR Increase(%)
09/2008	0.310	1.069	1.580
12/2008	0.484	1.847	3.333
03/2009	0.188	360.150	1455.936
06/2009	0.476	2.092	3.992
09/2009	0.342	0.524	5.788
12/2009	0.176	0.270	1.270
03/2010	0.183	0.214	1.449
06/2010	0.203	0.464	0.836
09/2010	0.187	0.919	1.256
12/2010	0.178	0.585	1.102
03/2011	0.234	0.074	2.691
06/2011	0.353	0.180	7.144
09/2011	0.627	0.127	5.281
12/2011	0.666	0.180	2.335
03/2012	0.429	0.050	0.473
06/2012	0.198	0.093	1.064

Table 13: DebtRank Increase - Periphery Banks - Actual capital

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