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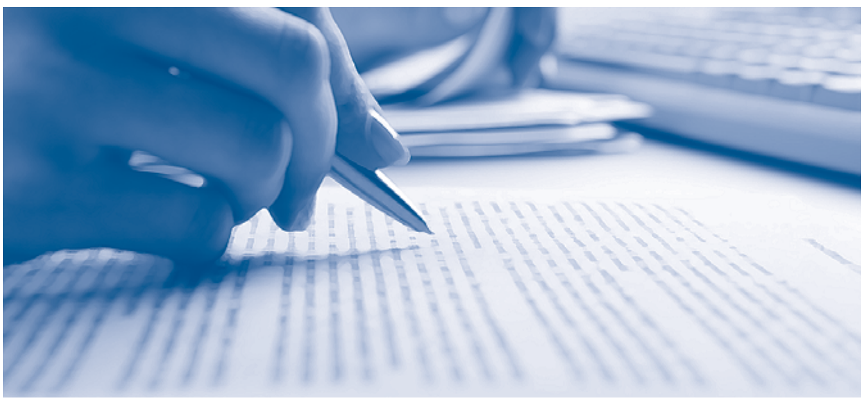

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Insolvency and Contagion in the Brazilian Interbank Market

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Abstract

This paper analyzes the financial institutions (FIs) that operate in the Brazilian Interbank Market, investigating, through simulations, the potential contagion that they present, the contagion losses' and the contagion route associated to FIs' bankruptcies, and the value of the 1-year expected loss of the financial system. The paper also computes the possibility of contagion of other markets triggered by FIs' defaults in the interbank market. Besides, it identifies contagion transmitter FIs and losses amplifier FIs in the market studied. The analyses performed found no particularly important source of stress in the Brazilian financial system, in the period.

Keywords: systemic risk, contagion, interbank market, simulations

JEL Classification: G01, G21, G23, C63

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1. Introduction

The possibility of a large financial crisis and the losses they would inflict to the society justify the effort to identify early signals for these events, their contagion mechanisms, the prudential and risk mitigating actions, and the most effective actions to be taken on an ongoing crisis.

This paper analyzes the financial institutions (FIs) that operate in the Brazilian Interbank Market investigating, through simulations, the potential contagion to which they are subjected, the value of contagion losses due to the FIs crashes, the contagion routes associated to them, the expected financial system loss in 1 year and, finally, it indicates the other markets contagion possibilities due to FIs defaults.

The paper contributes with a framework for the identification and assessment of the financial system vulnerabilities that arise in markets in which their participants' mutual exposures can be represented by a network. We use this framework to analyze the insolvency contagion process that may arise in the Brazilian Interbank Market, presenting: 1) The computation of losses associated to FIs' failures in this market; 2) The contagion route map, which shows the network of contagion propagation paths associated to these failures; 3) The related 1-year horizon financial system expected losses calculation; 4) The estimation of other markets' contagion from contagion processes arisen into this market; 5) The identification of the systematically important FIs and of the ones that amplify losses in the context of the studied contagion process. This framework can be extended to a set of markets and can be used as a tool in policy making or surveillance processes.

We investigate here the contagion potential through simulations, given that contagion data is scarce, since FIs, which failure could start a contagion process, usually receive help before failing[1]. The simulations carried out in this paper have the objective of identifying if, associated with the simulated default of each FI that takes part in the interbank market, the contagion is possible, and, in the affirmative case, the severity of the damage to the Financial System. Even though there are contagion channels through many financial system markets, we choose the interbank

[1] See Upper (2011).

market because it represents about 70% of the non-collateralized exposures among the FIs.

Upper (2011) presents a survey of simulations aimed at the assessment of contagion risk in the interbank market, asking if simulating contagion processes in this market produces valid results. According to him, there is not historical precedent of banks failure due to losses regarding exposures in the interbank market. This may have two meanings: 1) this contagion channel is not relevant and can be ignored, or 2) the channel may be important, but contagious failures are prevented by government bailout operations. On the other hand, the subprime crisis showed that even a crisis in a relatively small-sized market can take large proportions if it triggers a confidence crisis. Another criticism presented by Upper (2011) is that banks and policy makers behaviors are modeled in a very rudimentary way, which makes impossible that simulations reproduce adequately the identified contagion mechanisms, undermining their capacity of forecasting crisis.

Brunnermeier (2009) analyzed the factors related to the emerging bubble in the housing market in the USA, explaining the sequence of events, the contagion and amplification mechanisms of the mortgage market losses in the 2007-2009 crisis. Through the following mechanisms, a relatively small shock can be amplified and cause the evaporation of liquidity:

1) Losses and margins spirals. Losses spirals arise for leveraged investors that seek to keep the leverage ratio in a given level. When the value of investor assets decreases, initially, the loss amount is entirely reflected in its liquid wealth. When this happens, he is forced both to reduce the value of his borrowings in order to not exceed the leverage ratio, in the liability side of his balance sheet, and to sell assets. This sale can force the assets' price to fall again, considering that there can be other investors in the market in the same situation. The margins / haircuts' spirals reinforce losses spirals. When an asset's price drops significantly, the margins calls and the demanded haircuts increase, forcing deleveraging and more asset sales, which can reduce its price even more. This spiral is confirmed empirically by Adrian and Shin (2010).

2) Loan channel. It refers to the restriction of loans granted by lenders with limited capital when their situation is worsening. The precautionary hoarding is one of these mechanisms; it arises when lenders need funds for their projects and strategies and fear losses that can arise from shocks. Another one is the moral hazard in credit operations monitoring. The moral hazard appears in the context of financial intermediaries that monitor borrowers in exchange for participation in the operations profits. When this participation is no longer profitable, they reduce the monitoring effort, leading the market to lend without monitoring.

3) Bank runs. Even that demand deposit holders' runs do not practically occur anymore, runs can occur in other contexts: hedge funds may reduce their liquid assets investment in their counterparties, in the “margin run”, different counterparties increase their margin requirements to keep the contracts open, shareholders from a fund can withdraw their quotes.

4) Network effects: counterparty credit risk and gridlock risk. Risk that arises from an environment of a network of operations in which each participant only knows his own ones. In this case, when there is uncertainty, participants are forced to insure their exposures, as a failure can originate losses to many participants. In this case, a multilateral compensation system could reduce the exposures through the netting of positions.

These mechanisms of increasing losses and contagion are observed in more complex frameworks than that modeled in the financial systems simulations. Besides, the process of the agents’ decision is also more complex.

Upper (2011) is not optimistic about the contagion models’ ability of forecasting crises. In fact, there are two difficulties in modeling contagion processes: the first one is that the processes that have been already identified are complex from the behavioral point of view, and the second comes from the fact that contagion processes change with time, as the financial system, looking for profitability, goes through reorganizations, both structural and operational, originating new contagion possibilities. An example of this is the popularization of credit portfolio securitization, with the creation of all the structures (vehicles) needed for packing and distribution of these bonds, and the role that this had in the amplification of the subprime crisis (Brunnermeier (2009)).

Despite these difficulties, the simulations are useful to characterize the financial system, giving information to support actions of supervision and policy decision making. They also can be used in stress-tests and policy proposal assessments, for instance, to compare alternative capital requirement calculation criteria through their related financial system losses.

This paper uses exposures between FIs in the interbank market and their capital buffer data. Simulating the contagion through the balance sheet, it calculates the systemic losses associated to the failure of each individual FI. It is also considered in this calculation that losses are taken in the short term, i.e., the rate of recovery in case of default is zero, as during the process of liquidation, FIs' assets are frozen. The assets' distribution among creditors occurs in a larger time horizon than that which is considered in this simulation. This paper adopts a FI solvency approach, i.e., if the FI suffers a loss in the interbank market and becomes insolvent, the solution is to inject capital into it. Besides the calculation of losses associated to the default of FIs, the paper also calculates the default probabilities of these FIs in a 1-year horizon, in order to obtain the expected financial system loss associated to the interbank market in 1 year. To do this, we use the structural model of Merton (Merton (1974)) and FIs' accounting data. We also investigate the systemically important FIs, identify the ones that amplify losses in the process of contagion and verify the possibility of contagion of other markets associated to losses.

The paper is structured as follows: the next section presents a literature revision related to the contagion processes in simulations, section 3 describes the methodology used, section 4, the data, section 5, the analyses and results, and section 6 concludes.

2. Literature

The idea that financial crises of a major severity start in a FI, or in a small group of FIs, and then they spread out, has been motivating researches related to contagion processes in FIs networks. Most of these papers use simulations of these processes in FIs interconnected in a network of liabilities.

Allen and Gale (2001) propose an equilibrium model using a network composed of four banks. Studying the equilibrium reaction to liquidity preference shocks suffered by one of the banks, they conclude that the possibility of contagion for the rest of the banks depends on the network structure, and that this structure is more robust when the structure is complete.

A tool widely used in these simulations has been the clearing process of Eisenberg and Noe (2001). This tool is used in this paper and will be addressed in more detail in the following section. This tool was also used in papers that were aimed to reproduce the joint effect of the credit and market risk factors, as well as the ones related to the FIs exposures in the the network. Some of these researches were performed by central banks, due to both the interest of evaluating the financial system risk that they were monitoring, as well as the access restrictions of required data.

Boss et al. (2004b) simulated the Austrian Financial System's reaction to stochastic shocks in market and credit risk factors, calculating the losses, related to these shocks, suffered by the banks network. They conclude that the banking system is very stable and just a few of the banks can be classified as contagious. Elsinger et al. (2006b) claimed that banks regulation and monitoring were carried out for individual banks, based on the hypothesis that the banking system would be healthy if each individual bank was healthy. According to these authors, the analysis of individual banks does not allow to consider two sources of risk that may result in a failure of the financial intermediation on a large scale: correlations in the bank portfolios values and credit interconnections that may transmit contagious insolvency from one bank to the other banks in a domino effect. Using credit and market risks' standard calculation techniques and the clearing process of Eisenberg and Noe (2001), they estimated the amount that a last resort lender must have in order to lend to the banking system to avoid contagious defaults; they also concluded that the exposure correlations is much more important, as a source of systemic risk, than the financial linkages. Following the same way of thinking, Alessandri et al. (2009) presented, for the English interbank market, a model for the quantification of systemic risk using banks' balance sheet data and their network interconnections, in an horizon of 3 years. The calculations are performed for each quarter and the results are used as a starting-point in the following period.

Other papers were focused on studying the relations between the structure and the robustness of the financial system. Boss et al. (2004a) studied the Austrian interbank market network structure using network theory techniques. They found that the connectivity of the nodes in the network had a *power law* distribution, claiming that networks with this type of structure would remain stable if random defaults would appear or if the network suffered intentional attacks. Nier et al. (2007), in turn, investigate how the systemic risk is affected by the financial system structure. In this regard, they construct a network of banks, varying the capitalization level, the degree of connectivity, the value of interbank displays and the concentration level of the system, concluding that 1) the more capitalized the banks are, the more resilient the banking system against defaults contagion; 2) the effect of the connectivity degree on the contagion is not monotonic, i.e., at the beginning, increases in the connectivity increase the contagion effect, however, from a certain point, these increases start increasing the ability of the system to absorb shocks; 3) the value of the interbank debts tend to increase the risk of a contagion cascade, even if banks keep a capital reserve against these exposures, and 4) more concentrated banking systems are more prone to the systemic risk, *ceteris paribus*. Li (2012) related the contagious risk to banking activities in four types of network structures: random, *small-world*, *scale-free* and *tiered*. The results obtained were: 1) the size of bank exposures is the main factor that determines the effect of contagion risks; bigger exposures increase the contagion risk; 2) increases in the liquid assets amounts reduce the contagion effects; 3) the impact of the total loans in the contagion risk depends on the structure of the network, and 4) the contagion effects in heterogeneous banking are greater than in the case of homogeneous networks.

Cifuentes (2005) proposes a model in order to analyze the effect of liquidity problems in the bank solvency, starting with the interbank exposures and the illiquid assets in the balance sheet. He recommends the adoption of liquidity requirements, defending that they can be as efficient as capital requirements in the prevention of contagious failures.

Shin (2008) analyzes the relation between liquidity and risk in a system in which the FIs have interconnected balance sheets. The financial system liquidity as a whole affects the assets prices, which affects the FIs balance sheets. On the other hand, balance sheets affect assets prices, creating a cycle that can increase the shocks in the financial system.

Since the 2007-2009 crisis, new contagion channels have been identified and modeled; also, there has been an increasing concern with the amplification of shocks during the contagion process.

Gai (2010) models two contagion channels: direct contagion among FIs, in which the default of one debtor FI can affect its creditors, and the indirect contagion, in which FIs with liquidity problems sell their illiquid assets, resulting in a price fall of these assets. Due to this fall, FIs who hold these assets in their portfolios are forced to assume losses related to the prices' fall. The simulations results of this model support the claim that financial systems exhibit a robust even if fragile behavior: whereas the probability of contagion can be low, the effects can be widespread when problems occur.

Battiston et al. (2012a) investigate endogenous factors of increasing systemic risk through the contagion channel formed by interconnections of the credit exposures. In this channel, they consider these mechanisms of contagion: interdependence (propagation in space), financial accelerator (propagation along time) and default cascading. The process of the financial accelerator occurs when the effect of a change in the financial condition of the agent in a period generates a feedback that results in a variation of the financial condition of the agent in the same direction, in the next period. This process is associated, for instance, to illiquidity or robustness loss spirals (case in which lenders call for early redemption, forcing the sale of illiquid assets). They conclude that the risk diversification increases the network's resilience: when there is not a financial accelerator, the resiliency of the network increases when diversification. However, in the presence of a financial accelerator, resiliency is maximal for intermediary levels of financial diversification, but it decreases for a higher diversification. Battiston et al. (2012b), in turn, study the default propagation in different conditions of robustness and connectivity, in a network of credit relationships among FIs and, later, they analyze this propagation, adding to the model the possibility of a run of the short term lenders, which do not renew loans when they notice an increase in the fragility of their debtors. They conclude that credit risks' diversification through many borrowers has ambiguous effects in the systemic risk, when there are potential short-term FIs' lenders' runs in the network.

Krause and Giansante (2012) analyze FIs' insolvency and illiquidity effects in the evaluation of the systemic risk in the interbank market and claim that the size of the bank initially failing is the main factor that defines whether there is occurrence of contagion or not, but to determine its extension, the network characteristics of the interbank loans are more important. They suggest that regulate only FIs balance sheets is not sufficient; it is necessary the supplementation by considerations on the structure of the interconnections among banks.

Lee (2013) proposes a method to calculate the systemic liquidity scarcity that includes direct and indirect restrictions of liquidity (they result in chain effects through interbank links). He uses this model to analyze the effect of different network structures on the vulnerability of the banking system on liquidity shocks, concluding that greater inequalities among banks' liquidity positions tend to worsen the lack of liquidity of a borrower bank. Comparing different types of network structures, a core-periphery network with a borrower money center can generate a higher level of scarcity of systemic liquidity. Finally, a banking system becomes as more vulnerable to liquidity shocks as more mismatched it is its interbank network.

Upper (2011), assessing simulation models of the interbank market, claimed that none of these models foresaw the subprime crisis, nor did they have a relevant role in the policy decisions carried out during the period. However, they promoted an advance in the understanding of the contagion process, particularly with regard to the identification of the critical banks for the stability of the system, which are identified not only from balance sheet data, but also from interbank interactions, their capital and their position in the network. Assessing the models analyzed in his paper, he claims they are useful tools when analyzing financial stability, as they put concentrations of risk on evidence; however, they cannot be used as a core of a model that could be used in the prediction of a crisis.

The models that analyze interbank markets have been criticized due to the low exposure risk they found. It should be emphasized that the subprime crises made clear that this market is a fundamental liquidity source. By one side, the freeze of these markets generated a cascading effect among interbank markets across the world, creating liquidity crises and leading FIs to insolvency; by the other side, it generated devastating effects on economic agents' confidence, increasing losses. The potential risks in the interbank markets are high given the speed that the contagion spread among FIs, originating confidence crises in the financial markets and leading to a major crisis.

This paper uses the Eisenberg and Noe (2001) clearing algorithm to analyze the solvency of the interbank market FIs after the failure of one of them, without the simultaneous action of other contagion mechanisms. The calculation of the expected loss in 1 year uses the structural model of Merton (1974). The analyses of the potential contagion of other markets, as with the identification of FIs as loss amplifiers in the context of the interbank market, are not performed in previous papers. A model like the present one can be used as a supporting tool in the process of the financial system supervision. The expected loss value may be a fragility indicator of the financial system, related to the interbank market and to the contagion process modeled. It is not suggested to use this value as a provision for default, since as bailouts represent a resources transfer from the taxpayers to the FIs' lenders and stockholders, in the process of the decision-making, it is necessary to know if this transfer's value is worth the default's social cost.

3. Methodology

In this paper, one calculates the total financial system losses originated by the default of financial institutions (FIs) in the interbank market. The financial system is considered isolated, i.e., it is not a creditor or debtor of external entities to it, with the exception of the FIs' shareholders. The process of losses propagation considered is the contagion through the balance sheet, in which the default of one FI forces its lenders to write-off the corresponding assets from their balances sheets. This can lead FIs that suffered assets losses to insolvency, turning those sources of shocks for their lenders. This paper does not consider other types of contagion processes, as the one originated by the exposure of FIs groups to common risks, the one originated by illiquidity spirals or the one due to the change in prices motivated by fire sales of assets.

For this calculation, one uses the clearing algorithm proposed by Eisenberg and Noe (2001). This process uses a representation of the financial system as a network in which the nodes are the FIs and the edges are the payments that they must do. Given, for every FI, the initial balance and the payments to be done, the process calculates the share of debt effectively paid, considering the possible defaults. This calculation process presents the following advantages: 1) It always has a solution with economic meaning, i.e., the payments vector's components are non-negative; 2) the solution is unique, if the financial system is regular (defined in the next section); 3) the payments vector that solves the problem maximizes the sum of realized payments, and 4) the algorithm is efficient: if the network does not have any cycle, the calculation converges to a solution in a finite number of iterations, at most equal to the maximum distance between any FI of the financial system and a lender of her, direct or indirect.

In the methodology adopted in this paper, it is simulated the fictitious default of every FI of the financial system and identified the defaults provoked by the initial default, and the corresponding additional losses. These losses are computed in monetary units. After the computation of the losses associated to the default of the individual FIs, the default probabilities of these FIs in one year are calculated in order to allow the computation of the expected loss of the financial system associated to the interbank market in one year. The default probabilities are computed using the structural model of Merton (Merton (1974)) and the FIs' accounting data[2]. This expected loss can be regarded as a measure of systemic risk associated to the interbank market, but not as the amount to be provisioned as a bailout fund for FIs, since that: 1) there is a big disparity among the losses provoked by the FIs, and 2) the FIs of more relevance have presented a very low probability of default, although they are able to provoke losses of high severity (they exert little

[2] Stock prices could have been used in the calculation, however, only a few FIs are listed.

influence in the total expected loss). In these conditions, the failure of a FI that induces big losses is not absorbed by the bailout fund.

The use of monthly accounting data, both in the calculation of the losses provoked by the FIs, and in the default probabilities calculation, delays the information of the total expected losses provided by the model, once the data of the balances of the FIs are not compiled and published immediately. Thus, in turbulent times, the model is not able to timely detect sudden increases in the expected losses of the financial system. Even with this shortcoming, the measure can identify gradual increases in these losses along time.

3.1. Financial system clearing algorithm

In the following, we present, in a summarized manner, the clearing process proposed by Eisenberg and Noe (2001). The hypotheses carried out in this process are the following:

-The debt payment is limited to what the FI has (its initial endowment plus the amount received);
-Absolute priority of creditors: obligation values must be paid in full, using capital resources of the FI if needed;
-Immediate payment: a FI cannot retain or delay a payment if it has resources to do it.
-Payments are proportional to the debt amount towards each creditor.

Let:

d_i the total debt of the FI i;
e_i the cash flow received by the FI from external sources (operational cash flow);
p_i^* the total effective payment by the i FI, as a result of the clearings process;
$L_{i,j}$ the element of the debt matrix that represents the liability of the i FI towards the j FI, where $d_i = \sum_j L_{i,j}$;
$\Pi_{i,j}$ the matrix of debt proportions of i to be paid to each lender j, i.e., $\Pi_{i,j} = L_{i,j} / d_i$

The payments vector p_i^* is the fixed point of the map:

$$p_i^* = \min(\sum_j \Pi_{j,i} p_j^* + e_i, d_i) \qquad (1)$$

Or, in vector notation:

$$\boldsymbol{p}^* = \min(\boldsymbol{\Pi}^T \boldsymbol{p}^* + \boldsymbol{e}, \boldsymbol{d}) \qquad (2)$$

Eisenberg and Noe (2001) demonstrate that $\boldsymbol{p}^*$ exists and is unique, when the financial system is regular. A financial system is defined as regular if every risk orbit *o(i)* of the *i* FIs that are part of the financial system is a surplus set. Risk orbit of a FI is the set of its direct or indirect creditors. Surplus set is the set of FIs in which none of them has liabilities to a FI that does not belong to the set; besides, in this set, at least one FI has strictly positive operational cash flow. The sufficient condition for regularity, pointed by Eisenberg and Noe (2001) is that every FI has a strictly positive operational cash flow; another possible sufficient condition is that every FI is strongly connected [3] and at least one of them has positive operational cash flow[4].

3.2. Approaches for the losses computation

The computation of the losses resulting from the default of a FI uses the clearing algorithm of Eisenberg and Noe (2001) presented above. In the use of this algorithm, it can be adopted a liquidity or a solvency approach. The first one is associated to the evolution of the availabilities of the FIs as payments among them are carried out in time, and the second one is associated to the identification of

[3] A group of FIs is strongly connected if there is a path from any FI of the group to any other FI of that group.

[4] A practical way for guaranteeing the regularity without imposing a lot of conditions to operational cash flows or to the interconnection of the FIs is to transform the matrix of debts **L**, through permutations of lines and columns in a diagonal matrix in blocks as in the following figure:

$$\begin{bmatrix} A_{11} & 0 & 0 & 0 \\ 0 & A_{22} & A_{23} & A_{24} \\ 0 & 0 & A_{33} & 0 \\ 0 & 0 & 0 & A_{44} \end{bmatrix}$$

In order to guarantee regularity, it is enough to identify the groups of the FIs that correspond to the sub matrix in the diagonal A_{ii} that do not have any non-zero elements above them (in the figure above, the groups are formed by the FIs in the lines of the sub matrix A_{11} and A_{22}). In each one of these groups, there must be at least one FI with a strictly positive operational cash flow for the financial system being regular. This process is only for identifying the bigger set that can be in an isolated risk orbit. In this example, there exist two of these groups: the interconnected FIs in A_{11} and the rest (one can verify that the FIs in A_{22} make payments for the A_{33} and A_{44}, that's why the group formed by the FIs of A_{22}, A_{33} and A_{44} presents the limits of a risk orbit).

insolvency situations that arise when FIs default in their payments. Notice that the insolvent FI can be liquid and in full operation, until supervision determines its liquidation.

The liquidity approach is the more usual. It starts from the initial balance (cash)[5] of the FIs, in the sequence, the payments due in the period are performed[6], resulting in the final balance (cash) and in the values effectively paid at the end of the period. One considers that, in the analysis horizon, there is no entry or exit of resources to/from the financial system. Moreover, one recommends that the matrix of debts L represents a significant share of the debts among the FIs in the network, in the different markets.

The solvency approach is more adequate for analyses related to the impact from the default on payments associated to the FIs liabilities on the capital of its creditors. This type of approach is used in Elsinger et al. (2006a). Under such approach, it is used, as initial balance, the value of the capital buffer in the date of analysis, deducted the assets and liabilities associated to the payments that will be done, i.e., the initial balance is the value that the capital buffer would have if the FI did not have these assets and liabilities. This is done in this way, as the value of the capital presented in the balance sheet considers that payments related to these assets and liabilities were already made. The methodology requires that exposures among FIs must be represented by the matrix of liabilities $\boldsymbol{L}$; its elements represent the liabilities of the FIs in the lines to the FIs in the columns. Starting from this initial balance and performing the payments associated to the FIs' assets and liabilities, one recomposes the value of the capital buffer presented in the balance sheet, i.e., the FIs are brought back to the situation of the date of analysis, without defaulting. With this configuration, this model can be used in order to verify how the FIs' balance sheets are affected when one FI does not honor their liabilities. To do this, we choose a FI and put it in a fictitious default. In this situation, this FI does not pay its liabilities, making its creditors to write-off the correspondent assets from the balance sheet. These write-offs generate capital losses and can lead some of the affected FIs into insolvency. If this happens, this process of assets' write-offs and

[5] The initial cash balance of the FIs substitutes the operating cash flow proposed by Eisenberg e Noe (2001).

[6] For example, until the next working day, a month, a year, etc.

possible default is repeated until no additional default occurs due to the assets' write-offs. The total loss provoked by the original default is the amount not paid by the financial system's FIs, without taking into account the original default value.

Besides these approaches, Elsinger et al. (2006a) suggest two additional approaches: the short and long term approaches. These approaches do not refer to the horizon in which future payments are aggregated into the liabilities matrix, but to the period in which the financial system reaction to the default of the institutions is observed. They consider that, after the default, in the short term[7], all the payments are suspended, i.e., the calculation of losses considers that, if one FI enters in default, it does not make any payment. In long term, creditors receive payments proportional to their exposure, with the recovery rate computed for the debtor FI, as in the traditional Eisenberg and Noe (2001) algorithm. The default effects in the short term are stronger than these in the long term, once in the short term all the payments are suspended.

In this paper, only interbank market liabilities are aggregated; the ideal would be to consider all the network of liabilities among FIs. Taking this restriction into account, additional hypothesis are required:

-Liabilities in the interbank market have the same seniority as the liabilities not represented in the calculation; all these liabilities, in turn, are senior related to the liabilities to the shareholders (capital).

-In some cases, the FI initial balance, calculated as its capital buffer, less the liabilities to be received from other FIs plus the liabilities to pay them, is less than zero. The regularity condition of the financial system associated to positive initial balance values is not satisfied when the FI initial balance is negative. Eisenberg and Noe (2001) demonstrate that the payments vector $\boldsymbol{p}^*$ that clears the financial system exists and is unique when the financial system is regular, i.e., when the risk orbit of every FI contains at least one FI with strictly positive initial endowment. Furthermore, they elaborate the algorithm considering that the initial cash balance e_i is not negative, suggesting that in the cases in which this does not happen, the

[7] That is coherent with the model's hypothesis that the FI is put into a liquidation process immediately after it enters in default. When this happens, in the short-term, payments are frozen.

negative balance should be transformed in a zero balance and in a liability towards an additional node (a fictitious FI), created in order to receive these values. This FI must be created with an initial zero balance and without liabilities towards any other FIs of the system.

Following Eisenberg and Noe (2001), in this paper, FIs with initial negative endowment receive the following treatment: a fictitious FI is created in order to receive payments that correspond to these negative endowments. For these FIs, starting from the initial balance equal to zero and the additional payment to the fictitious FI, one gets the same final balance after the processing of payments.

For every FI in this situation, this negative value is the minimum value borrowed from other markets that are related to applications in the interbank market; so, if the FI loses the total amount of its applications in the interbank market, the impact in other markets will be at least equal to this negative value. Summing these values to the whole financial system, we have a superior limit for losses in other markets motivated by losses in the interbank market.

In this framework, if any FI with a negative initial balance enters in default, in the long-term approach, what it will have received will be divided proportionally among the creditor FIs, including the fictitious FI. In other words, both the creditors of the interbank market, and those from other markets, receive impact from losses in the same proportion, and implicitly are assumed with the same seniority.

After this treatment of negative initial balances of the FIs one uses the clearing algorithm in its original form, if the calculation is performed following the long-term approach.

In the computation of capital losses according to the solvency approach, under the point of view of the short-term effects, the algorithm suffers a small modification, what turns it similar to the algorithm of Furfine (2003), in which it is considered that, if any FI is in default, it does not realize any payment:

$$p_i^* = \begin{cases} d_i \text{ se } \sum_j \Pi_{j,i} p_j^* + e_i \geq d_i \\ 0, \text{otherwise} \end{cases} \quad (6)$$

Figure 1 represents this calculation process:

<FIGURE 1>

3.3. Computation of default probabilities

The computation of the FIs default probabilities is done through the structural model of Merton (see Merton (1974)), which is the contingent claims analysis applied to the measurement and analysis of credit risk[8]. In this model, the balance of an institution is divided in its main components: assets, liabilities and capital (equity). The basic idea of this approach is to model the capital of the institution as a call option, with strike price equal to the value of the liability and time to maturity T. In case of default, shareholders do not receive anything, because assets are not enough for the integral payment of the debts (liability). If an institution does not default, shareholders receive the difference between the assets and liabilities values. Thus, the value to be received by shareholders is given by max[A - DB, 0], being A the value of the assets and DB the total debt. According to Black and Scholes (1973), the value to be received by the shareholders is given by:

$$E = A \ N(d_1) - DB \ e^{-rT} N(d_2) \quad (7)$$

where A is the implicit value of the asset, DB, the debt to be paid, r, the risk-free interest-rate, T is the time to maturity, N(·) is the accumulated normal distribution and d_1 and d_2 are defined as:

$$d_1 = \frac{\ln\left(\frac{A}{DB}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \quad (8)$$

$$d_2 = \frac{\ln\left(\frac{A}{DB}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \quad (9)$$

[8] Contingent claims analysis is a generalization of the Black and Scholes (1973) theory of option pricing.

From Black and Scholes (1973), it is possible to obtain the equation that relates assets' volatilities and equities:

$$\sigma_E = N(d_1)\frac{V}{E}\sigma_A \tag{10}$$

With the market value and the equities' volatility, and with the book value of the liabilities, it is possible to estimate the implicit value of A and σ_A solving the system formed by the equations (7) and (10). The debt to be paid DB is interpreted as a default barrier. If the FI's assets implicit value falls under this barrier, it defaults. The default barrier is given by:

$$DB = STD + \alpha\, LTD \tag{11}$$

where STD are the short term liabilities (expiration until 1 year), LTD are long-term liabilities (expiration above 1 year) and α is the parameter between 0 and 1, assumed by Moody's-KMV, whom we are following, around 0.5[9]. This parameter is a *proxy* of the long term liabilities' share subjected to early redemption in case of stress.

The time to maturity T usually assumed is 1 year and is the horizon for which we calculate default probabilities. Having defined this, one computes the distance to default, which is the number of standard deviations between the value of assets and the default barrier:

$$D2D = -d_2 \tag{12}$$

This distance can be used in the computation of a risk-neutral default probability, assuming that assets are log-normally distributed:

$$DP = N(-d_2) \tag{13}$$

The probability of default is the area under the default barrier shown in figure 2. For more details, see Gray and Malone (2008) and Souto et al. (2009).

< FIGURE 2>

[9] According to Souto et al. (2009), Moody's-KMV uses α between 0.5 and 0.6 based on the calibration of its model. The calibration process aimed the adjustment of the model to the historical probabilities of default.

4. Data

The analysis realized in this paper uses FIs that participate of the interbank Brazilian market[10] exposures data. The exposures refer to interbank deposits operations (85% in volume), debentures (13,4%) and repos (1,6%) among financial conglomerates and individual institutions, which amount to more than 300 participants. Intra-conglomerate exposures are not considered. The exposures of the domestic interbank market represent approximately 70% of the total non-secured exposure among FIs[11]. The total invested in this market by these institutions varied from R$ 55 billion to R$ 71 billion in the period analyzed, corresponding to 1,5% of the total assets of the FIs and the to 14% of the Tier 1 Capital of them.

In Brazil, the domestic interbank market operations must be registered in the CETIP[12]. The operations are not secured and are subjected to early redemption. Based on this, we aggregate and net the open positions between these FIs to create exposures matrices for each date in which analysis is realized. These net exposures are obtained in the last working day of each month in the period from July 2011 thru June 2012. This is done in order to obtain exposures data contemporaneous to the available information of the FIs' capital buffer. The capital buffer we consider is the FI's Total Capital (Tier 1 + Tier 2 capitals) amount that exceeds 8% of its risk-weighted assets (RWA). In Brazil, the capital requirement is 13% or 15%, for specific types of credit unions, and 11% for other FIs, including banks. These FIs usually hold more capital than required and are allowed, temporarily, to hold less than it. For this simulation' purposes, we understand that if a FI holds less than what is recommended by the BCBS[13], i.e., 8% of its RWA, it will take a longer time to adequate its capital level and will suffer intervention, thus we compute capital buffers using 8% RWA as a reference.

[10] Participants in the Brazilian Interbank Market are multiple banks, commercial banks, investment banks, savings banks, development banks, cooperative banks, credit unions, savings and loans associations, credit cooperatives, brokers and dealers of foreign exchange, government securities, corporate bonds, stocks, and commodities and futures contracts.

[11] Credit operations between conglomerations and credit cession are excluded from this total (they are guaranteed).

[12] CETIP (Cetip S.A. – Mercados organizados) is an open capital company that offers services related to registration, custody, trading and settlement of assets and bonds

[13] Basel Committee on Banking Supervision.

The FIs are classified by size (big, medium, small and micro), according to the methodology presented in the Financial Stability Report of the Central Bank of Brazil (see BCB (2012)). Balance sheet data, in turn, are monthly informed to the Central Bank of Brazil by conglomerates and individual FIs, and are used when obtaining the capital buffer and other accounting information used in the calculation of default probabilities.

The analyzed sample is composed by FIs with the following characteristics:

Regarding the control type: 5 federal state-owned, 7 state-owned, 245 domestic private, 55 private with foreign control and 2 private with foreign participation.

Regarding the macro-segment: 94 commercial banks, 29 investment, 142 credit cooperatives, BNDES, 2 development banks, 33 brokers and dealers, and 12 third-party portfolio managers.

5. Results

The values of losses due to contagion calculated in this paper are potential losses (counterfactuals), i.e., they are losses deriving from the fictitious default of FIs. Furthermore, they are additional losses, as they do not include losses from the original fictitious default. These losses refer to the values not paid by FIs that enter in default by contagion originated by direct or indirect exposure to the ones that were put in fictitious default.

Initially, we calculate the value of the contagion losses for every FI in June 2012, relating this value with the FI's assets participation in the total assets of the interbank market and to the leverage of the FI in this market, in order to investigate a possible relation between leverage and contagion. For this calculation, we use the fictitious default algorithm of Eisenberg and Noe (2001), previously modified to compute short-term losses, i.e., losses with zero recuperation rate. The leverage of every FI with resources from the interbank market is given by $F_i = \Sigma_j L_{ij}/E_i$ and indicates both its fragility and its potential of increasing losses. Results are presented in figure 3. In this chart, abscissae axis presents the participation of the FI's assets in the total assets of the interbank market and the ordinate axis shows the ratio between the value of the contagion losses, due to the FI default, and this total. The data points' sizes refer to the fragility of the FIs. The figure shows FIs with a big participation in the interbank market (12% and 14%) and low fragility. The default of the first of these FIs originates almost zero contagion (0.04%); the second FI's default originates contagion losses of the order of 4% of the market assets. The most fragile FIs, with a leverage of 33.6% and 16.3%, have a visibly less expressive participation in the market, but can originate losses of 9.4% and 3.0%, respectively, which are superior to their participation in the market.

<Figure 3>

Figure 4 presents the losses values due to contagion in the interbank market sum by size of the triggering FI. This sum is not the total loss associated to the simultaneous default of the FIs of each category of size; it is the sum of the short-term approach losses due to contagion originated by the fictitious default of each individual FI of each size category of the financial system, computed in different simulations. The number is just a measure of the relative participations of each size category in the sum of all the losses by contagion. We can observe that the losses sum is about 20% of the assets amount of the interbank market, peaking in Nov/2011.

The number of FIs that originate contagion is 10, on average; it is at least 7 and, at most, 11, in the period analyzed. The FI that originates the greatest contagion is medium-sized and remains the same along all the period. From the 2nd position on, there is some alternation among them, which are big and medium-sized ones, with a few exceptions, in which small-sized FIs originate contagion. Just 17 FIs are contagion sources at least once in the period. The losses volume does not seem to indicate an increase in the systemic risk in the period. The peak in November/2011 is associated to the additional default of a big-sized loss-amplifier FI (i.e., it entered in default due to contagion) that did not default (additionally) in other periods. In other words, in this period, in the simulation, the fictitious default of some FI(s) motivated the additional default (i.e., due to contagion) of a FI with a relatively large liability in the interbank market. The non-payment of these debts motivated the observed increase on losses.

We define a FI as a losses amplifier if it has leverage greater than 1. If its losses exceed its capital buffer, it defaults, suspending all the payments of its liabilities. When the FI leverage is greater than 1, the FI transmits to its creditors' group a total loss amount superior to that it suffered, increasing losses in the propagation process[14].

In the analysis period, the number of loss amplifier FIs in default varied from 14 thru 21, being, on average, 18 (on November/2011, their number was 21). The group of FIs is formed by 1 small-sized bank and complemented predominantly by credit cooperatives of big size. Specifically, the loss-amplifier FI that came into additional default in November/2011 was not a contagion agent, (its default did not lead any of its creditors into default, as they were capitalized), but it increased losses in propagation process.

<Figure 4>

The number of FIs which are vulnerable to default due to contagion from the fictitious defaults were almost stable in the period, as we can see in figure 5. Along the period, the volume of losses followed the same pattern.

On average, the set of FIs led into additional default in the round of fictitious defaults has 27 institutions in each month of analysis. In the period, the greatest number of repetitions is 4; this means there were FIs led into default due to contagion from 4 different debtors in a period. FIs that are led into additional default in a greater number of times in a round of fictitious defaults are subjected to contagion from a greater number of debtors in a given period, i.e., they are in a vulnerable situation in the network.

The FIs in additional default in a period are predominantly big sized non-banking ones (on average,17), followed by medium-sized FIs (on average, 6), small-sized FIs (on average, 2), and micro-sized ones (on average, 2). Regarding the control type, these FIs are, in general, private domestic. The few that are not in this situation are private of foreign control or state-owned.

[14] When the leverage of the FI is superior to 1 and its total assets in the interbank market is inferior to its capital buffer, the FI does not default motivated by this market. However, if it defaulted, it would amplify losses, i.e., it would transmit losses superior to the ones it suffered.

<Figure 5>

In figures 6 and 7, we present the possible contagion routes for the interbank market on June 2012. The information presented in these graphs is a summary of that provided by the fictitious defaults' simulations in each of their iterations along the contagion processes. The pictures provide information on which FIs start contagion processes, which are vulnerable to them, if they are banks or not, if they are locally important or not, and if they contaminate other markets. The graphs on figures 6 and 7 are adapted from minimum spanning trees (MSTs) to represent the largest net exposures among the interbank market network of FIs.[15] Nevertheless, considering that MSTs are undirected graphs without cycles, we initially build the MST considering the net exposures as they were undirected. After building the MST, we add the exposures' directions to the graph and the critical exposures (i.e., those for which the debtor's default leads the creditor FI into default) that may be removed in order to remove the network's cycles. The critical exposures represent stretches of the contagion route originated by a FI's default and are represented by red arrows[16]. The non-critical ones are represented by gray ones. In both figures, banks are red circles, while non-banks are blue diamonds. The green square at the center represent other markets. The banks' and non-banks' symbols' sizes indicate their local importance. The FI's local importance is given by the sum, for all its creditor FIs, of the ratios between the FI's debt towards them and their capital buffer. The local importance of a FI is not directly related to its size, rather, it represents their creditors vulnerabilities, measured by their net exposures/capital buffer ratios.

<Figure 6>

Figure 7 focuses the contagion route area of figure 6. It shows that the contagion processes, on June 2012, always is originated by banks, while almost all FIs contaminated by them are non-banks. There are 11 banks originating contagion; 5

[15] The MST of a weighted network's graph is a tree subgraph (i.e., an undirected graph without cycles, in which every pair of nodes is connected by just one path) with the minimum edges' weights' sum. One can build a MST using the reverse-delete algorithm (see Kruskal (1956)). In this algorithm, basically, one builds a list of the networks' edges in weight decreasing order and tries to delete edges from the network sequentially, in order to eliminate cycles it may have. The edge can be removed if its removal does not separate the network into unconnected graphs.

[16] It is possible to represent defaults caused by simultaneous failures of more than one debtor FI using the same technique. This type of contagion path is not presented in this paper.

are big and 6 are medium-sized ones. The contagion routes are short: at most 2 propagation stages. The figure also shows FIs that are vulnerable to 2 and to 3 debtor FIs. Besides this, almost all contagion vulnerable FIs contaminate other markets.

<Figure 7>

The losses due to contagion computed by now result from a FI's fictitious default. We compute the default probabilities of the FIs that originate contagion in order to obtain the expected contagion loss. The expected contagion loss amount is the sum of the losses caused by the default of the individual FIs weighed by the default probability of them. The default probabilities (DPs) of the FIs have a horizon of 1 year and are computed for the 13 FIs that originate contagion in the analysis period, using the Merton methodology for option pricing. Further details are found in Tabak et al. (2013). The financial system expected loss standard error is computed using a DP covariance's matrix. Calculations were performed in the period of Jan/2012 to Jun/2012, and the results' unit of measure is the same used in other computations of this paper: 1.00 = Σ (Assets invested in the interbank market). Results are presented in figure 8.

The expected value of the losses in a 1-year horizon has not suffered rough variations along the last 6 months. On Jun/2012, the financial system joint expected losses were about 0.56% of the interbank deposits amount of the system. The 1-year horizon expected loss due to contagion, caused by the default of any FI was, at most, about 0.8% of the market assets amount of interbank deposits, according to the proposed methodology.

Tabak et al. (2013) present the same type of computation for the expected impact[17] obtaining a maximum expected impact of about 2.2% interbank market assets amount. The maximum loss values of about 0.8% interbank market assets amount were computed with the same data, considering, for most FIs, a smaller capital buffer and in the same period of the previous calculation. The present results are

[17] The impact measure can be interpreted as the potential loss inducted by a stress situation motivated by one or more FIs and is represented as a fraction of the total assets invested in the market.

smaller, as they only take into account losses that really occur in these defaults, without taking into account fractions of losses related to stress.

<Figure 8>

In the following, we analyze the contagion of other markets caused by FIs' defaults in the interbank market. The FIs that can generate this type of contagion are those which interbank assets' sum (a) is greater than the sum of its capital buffer and interbank liabilities (b). If these FIs lost all their interbank market assets, this would provoke in other markets a loss of, at least:

$$L_{OtherMkts} = a - b \tag{14}$$

In the real world, when a FI defaults and is put into a liquidation process, it is excluded from the market, so, all its creditors from the different markets in which it acts, suffer losses. This other markets contagion loss computation is not performed in this paper. The calculation performed in this paper refers to the minimum losses suffered in other markets motivated by FIs assets losses in the interbank market. The FIs that have interbank market exposures such that their assets losses in this market result in a default in other markets that cannot be prevented by a higher priority in receiving the repayment of debt, are those for which it was necessary to include a debt for the fictitious FI[18] in the beginning of the simulation. These FIs can default in more than one market, if they suffer high enough assets losses. In the analyzed period, the relation between the sum of FI debts to the fictitious FI and the total debts in the interbank market varied from 11.8% to 14.8% being, on average, 13.0%.

In the computation performed in this paper, almost all the FIs that originate contagion originate contagion indirectly in other markets. This happens because virtually all FIs affected by them are potential generators of contagion in other markets: most of them are credit cooperatives without borrowings in the interbank

[18] In this model, debts from a FI to a fictitious FI represent the minimum possible value of that FI liability towards other markets, related to applications of the FI in the interbank market. In other words, if the FI lose all its interbank market assets, the least possible loss to be suffered by other markets is that of the liability towards the fictitious FI.

market and, at the same time, with application volumes higher than their capital buffer.

The results of this analysis, aggregated by FI size categories, are presented in figure 9. Notice that the group of medium-sized FIs provoked indirectly a higher contagion than the big ones group.

The average ratio, in the period, between contagion losses in other markets and total losses is 0.98. It is presented in figure 10.

<Figure 9>

<Figure 10>

The contagion of other markets is related to situations in which the FIs assets loss is higher than the total sum of capital liabilities, and it is not affected by the default of the loss amplifier FIs, unless they cause losses to lenders in the situation above. In the figure 10 specific case, external contagion losses remained constant between Oct/2011 and Dec/2011. The fall verified in Nov/2011 is due to the peak observed in the total contagion losses (figure 4), motivated by the default of the loss amplifier FI.

The expected losses by contagion in other markets are computed and presented in figure 11. These losses present values around the ones found for the total expected losses, presented in figure 8. Among the main reasons for this similarity, we emphasize the following:

1) The value of the expected total losses includes the values of losses suffered by other markets due to contagion. Figure 7 shows that, on June 2102, most of times, the FIs that suffered additional default were sources of contagion to other markets. An analysis of these FIs shows that almost all of them had assets in the interbank market, but not liabilities. In this case, all the non-absorbed losses were transmitted to other markets.

2) The contagion originator FIs with default probabilities significantly higher than the others present high contagion values towards other markets (external contagion) in the propagation chain into the interbank market.

<Figure 11>

Finally, we perform an analysis of FIs systemic importance, based in the identification of contagious FIs. We emphasize that this analysis is done from the point of view of the contagion mechanism studied in this paper, which is the contagion through the balance sheet, without taking into account mechanisms of loss amplification, like depositor's runs and fire sales of illiquid assets. The analysis of systemic importance of FIs is performed based on the set of the FIs characteristics and of the relationships they hold in the network, as presented in Table 1.

<Table 1>

The starting point of the analysis is the identification of the FIs which fictitious default generates internal or external contagion, i.e., it leads at least 1 creditor FI to default and to not pay its own creditors inside or outside the interbank market. Table 1 presents all the FIs that originate contagion by decreasing order of impact in the system (additional losses) on June 2012, when 11 FIs were in this situation. The table also shows the number of FIs that defaulted due to losses associated to fictitious defaults. It is necessary to verify the vulnerability of these FIs of higher impact. To do this, we verify if the FI would need to be rescued if it lost all the assets it owned in the interbank market. The FI would need to be rescued if its total assets in the market were superior to its capital buffer. FIs that do not need this help are safe: they can suffer losses of any magnitude in this market without defaulting. The capital buffer is a good FI resilience indicator. The table shows that there are 9 FIs which capital buffers are superior to the total of assets in the interbank market, so, they are big-sized FIs and are immune to any loss occurred in this market. To less robust FIs, an important indicator is the number of their critical exposures, which is the number of exposures to individual counterparties that are higher than their capital buffer. The maximum individual amount needed to bailout the FI is the maximum amount to be lent to the FI if the counterparty to which it has the highest exposure defaults (this amount is different from zero when the largest exposure is higher than the capital buffer).

Observing these variables, it becomes clear that there is no FI that originates contagion and has any vulnerability in this market. Other variables, related to bailout actions aimed at the mitigation of contagion, are the amounts to bailout the creditors of the FI in fictitious default. Complete bailout is the amount required to replace all the value not received by the FI creditors, while the required bailout is the amount needed to prevent that all the FI's creditors default, replacing their capital buffer to the level these FIs need to not default. Finally, the external contagion amount is the total of assets losses not offset by the sum of capital buffer and interbank liability of each FI that defaulted in the process of contagion. These values are important only for less robust FIs, i.e., FIs that are vulnerable to the interbank market. These variables are important for the definition of the amount of bailout resources.

The analysis done here for June 2012 shows that none of the FIs originate contagion from losses in the interbank market. This is also true for all the period from July 2011 thru June 2012.

Another approach is that if losses in other markets lead some of these FIs into default, the interbank market may suffer important losses. From this point of view, all FIs that generate contagion losses above a given amount are systematically important.

6. Conclusion and final comments

The proposed framework identified a small number of FIs that originated contagion by insolvency in the interbank market. The contagion losses weren't high and the contagion routes were short, involving, at most, 2 propagation levels. In this market, some big FIs originate contagion losses smaller than some medium FIs. This does not mean that, in general, bigger FIs can be deprived of systemic importance, even that some of them, in this market and in the studied process of contagion, do not have originated contagion. In the analysis that determines if a FI is systemically important, in the context of this paper, the preponderant factor is the condition of the FIs lenders. The FI's size is less important, if it is small or medium. An important issue in the determination of systemic importance of a FI is to verify if it is contagious, i.e., if it has critical exposures and originates contagion. If the contagion originated is relevant, the FI can be classified as systemically important. The identification of contagious FIs, of loss amplifier FIs and of the FIs that can go into default motivated by different FIs (the ones that have more than 1 critical exposure) can be useful in the monitoring of FIs in the process of surveillance. A possible action of risk mitigation is reducing the value of the critical exposures, in order to make them not critical. This framework can be used to simulate new regulatory constraints, to measure their effectiveness.

Concerning the interbank market, it can be assumed that, in the period, it was not identified any relevant source of stress. Regarding the contagion of other markets, it was verified that losses in other markets motivated by contagion are proportionally higher in relation to the total losses. Furthermore, the expected value of contagion losses in 1 year, in other markets, is approximately equal to the value of the total expected losses in 1 year. This happens because the FIs that are sources of contagion of greatest default probability are medium sized and their main lenders are FIs which assets in the interbank market are superior to the sum of its liabilities in this market to its capital buffer (FIs are sensitive to assets' losses and propagate losses for other markets). Therefore, having default, the probability of other markets contagion is big, due to these interconnections in FIs' networks.

In fact, like in other similar papers (for example, Boss et al. (2004b) – Austria, Elsinger et al. (2006b) – United Kingdom), in the Brazilian financial system, it was not found, in the analyzed period, any particularly important source of stress. Moreover, there are few FIs amplifying losses in the context of this contagion mechanism analysis (the contagion through the balance sheet in the interbank market). However, the literature has identified and described other channels of contagion that can operate in times of stress and increase losses, as, for example, bank runs, precautionary hoarding, illiquidity and margin spirals, and the detrimental effect of financial accelerators on risk diversification. These mechanisms affect both the financial system and the real sector, once both interact, and could be added to the process studied in this paper, resulting in the possibility of occurrence of larger losses than those already calculated, due to amplification.

Models incorporating and integrating these mechanisms may not be able to represent the phenomenon of contagion sufficiently well for the quantification of losses, for indicating the imminence of crisis or to support the evaluation of policy actions, given the calibration difficulties they present. However, when one considers that each contagion mechanism represents a stimuli source for FIs in a multi-layer network, and that their reactions depend on decision making, one concludes that, as mentioned by Upper (2011), a good behavioral foundation is necessary to the progress in the area, which would shift towards a more extensive use of Agent-based modeling.

Nevertheless, the framework proposed here is useful as a support to policy making and surveillance, and the follow-up of its results along time can indicate the evolution of risks concentration in the financial system, associated to the studied markets.

The next step to be taken in this research is to extend this framework to assess risks in a set of markets, not necessarily aggregating them. Another one is to include liquidity mechanisms into the analysis, exploring the interface between liquidity and solvency issues. Finally, we intend to seek a better understanding of the behavioral foundation of losses' amplifier mechanisms that may come into action during crises, intending to incorporate them into the model.

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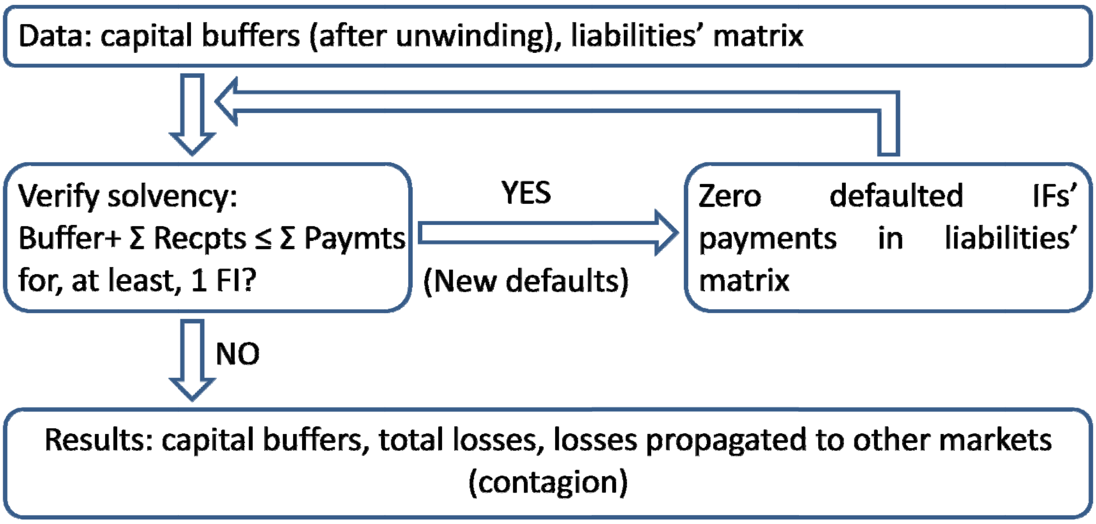

Figure 1: algorithm

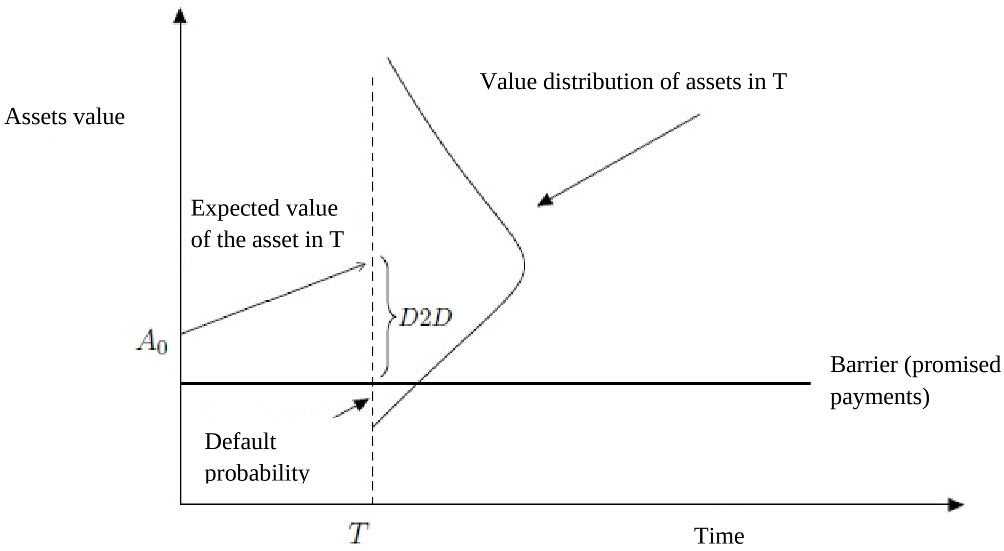

Figure 2: Merton structural model

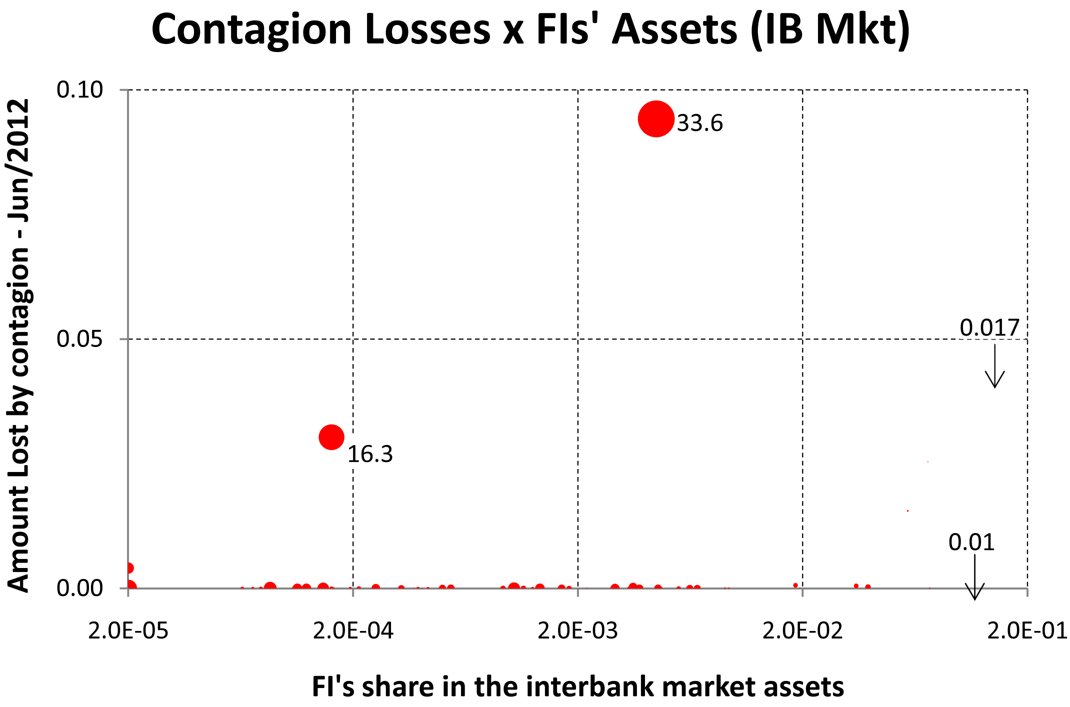

Figure 3: Contagion values originated by the default of individual FIs. Each point refers to one FI. The point's size / number refers to the FI's fragility (loans / capital)

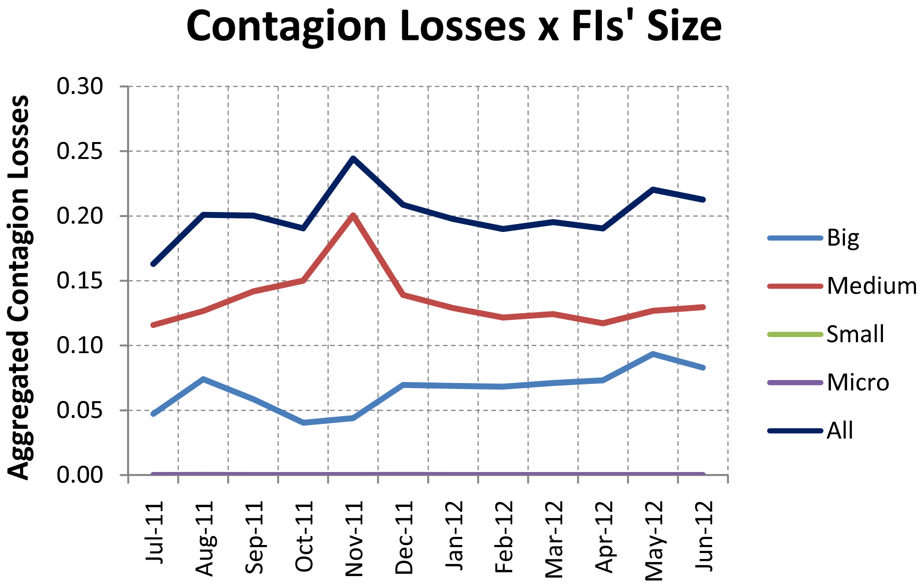

Figure 4: Contagion losses in the interbank market aggregated by FI size.

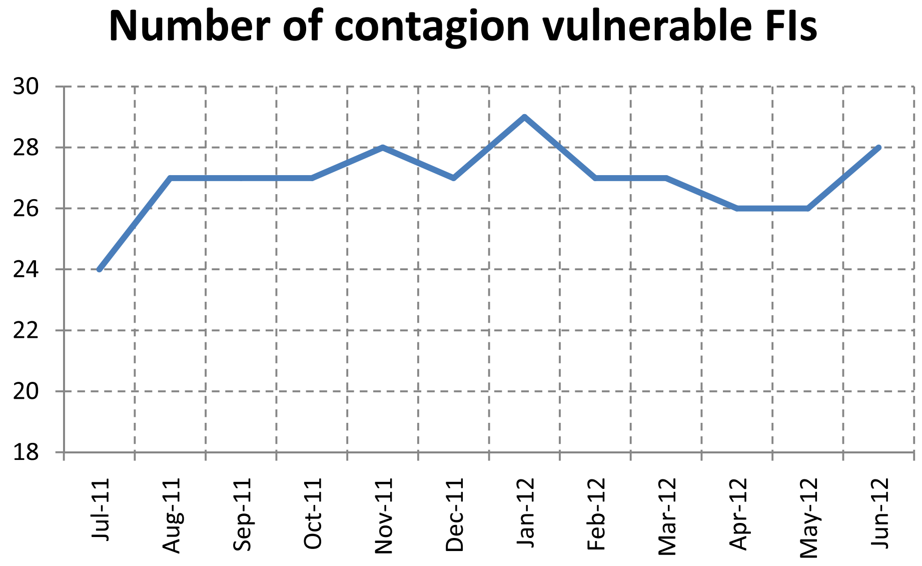

Figure 5: Number of FIs vulnerable to contagion along the period.

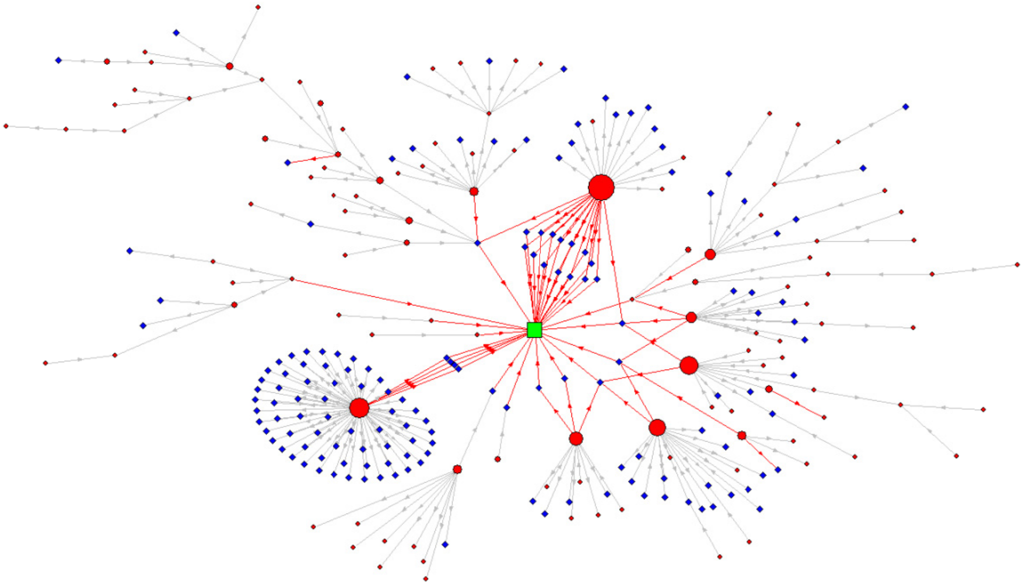

Figure 6: Contagion route into the financial system - June / 2012.

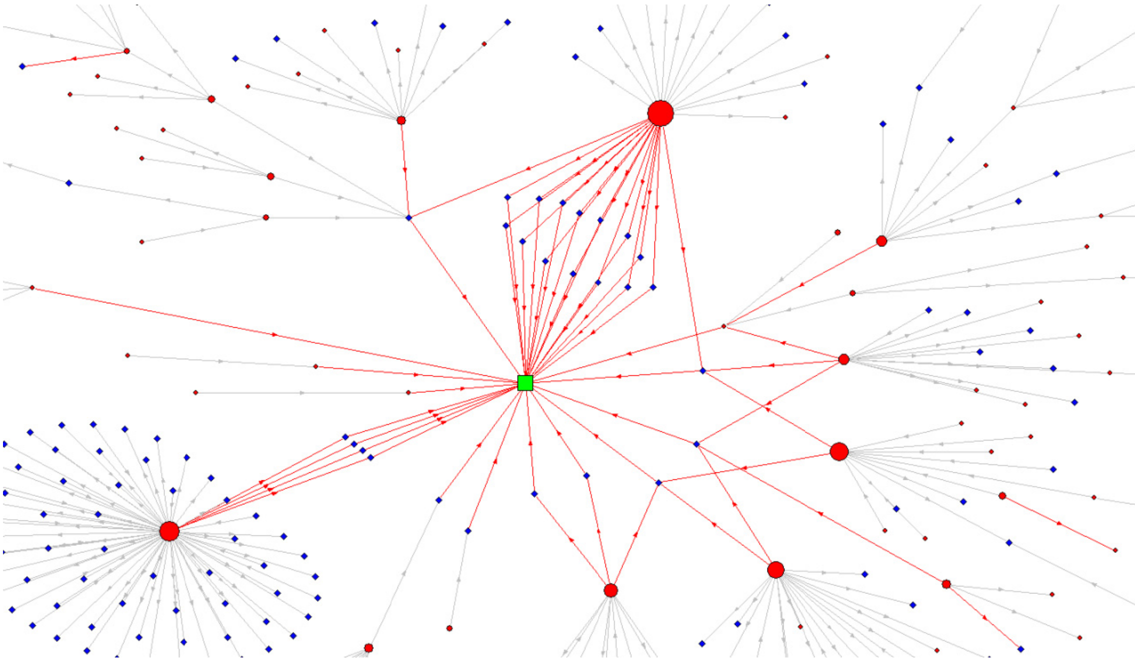

Figure 7: Contagion route (detail) - June/2012.

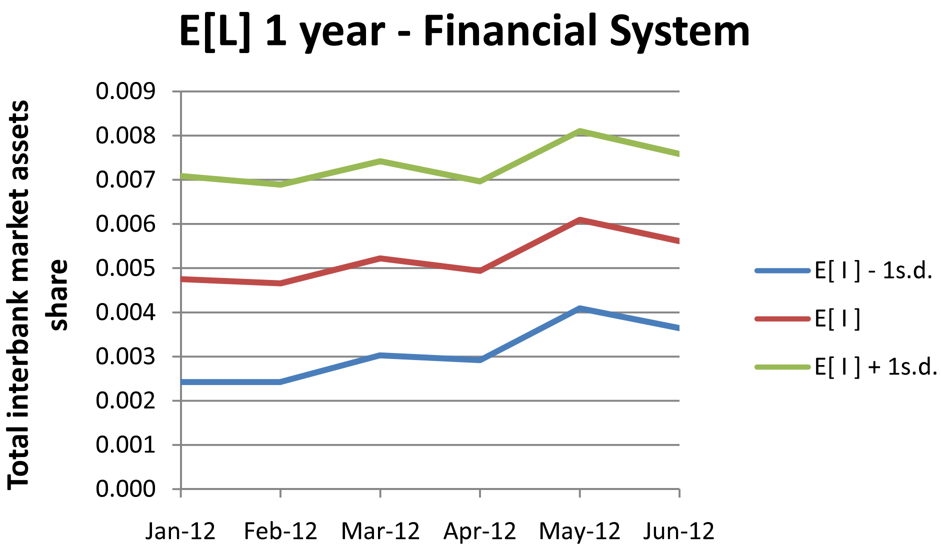

Figure 8: Expected default losses on the horizon of 1 year.

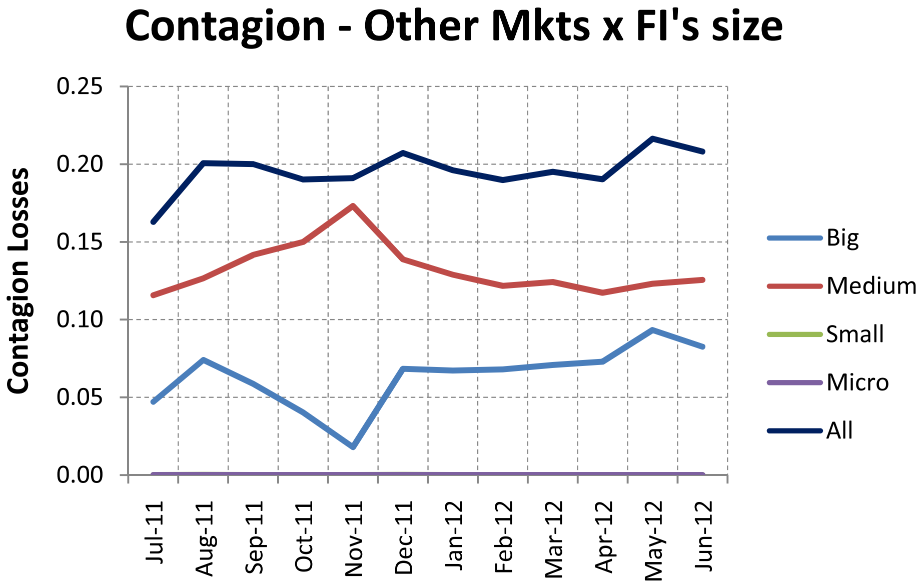

Figure 9: Other markets' losses, due to contagion, aggregated by the triggering FI's size category.

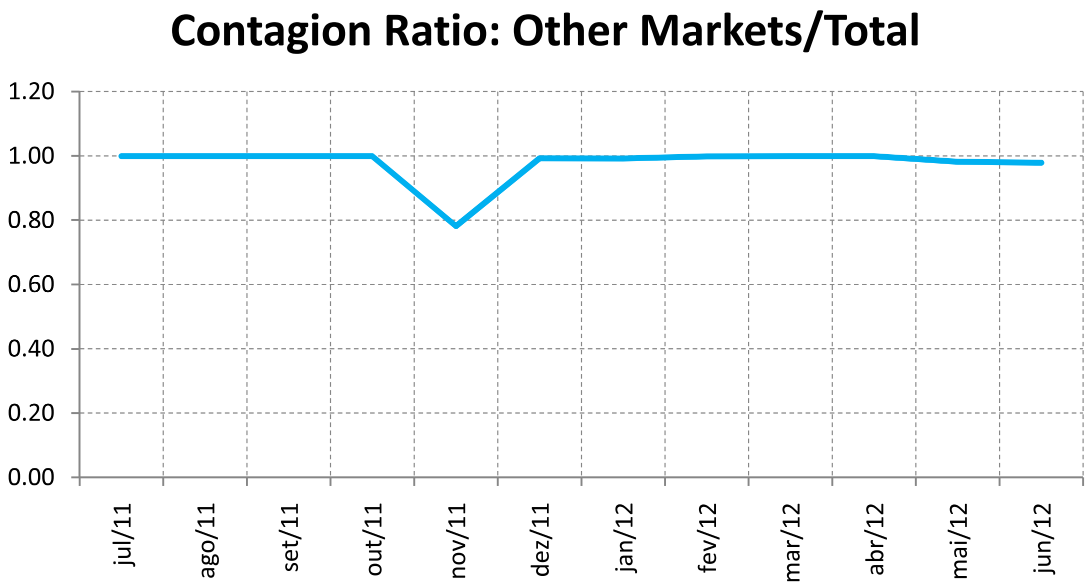

Figure 10: Ratio of losses suffered by other markets due to contagion to total losses due to contagion.

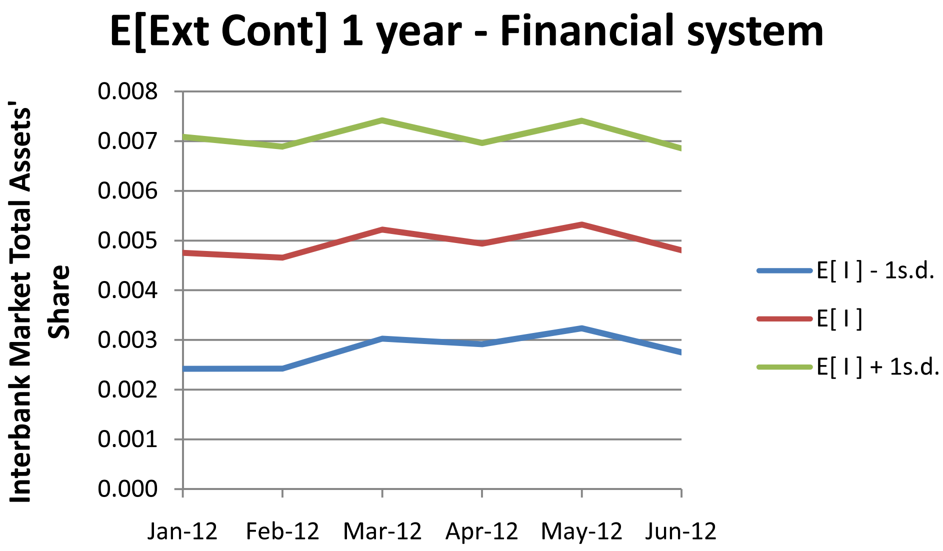

Figure 11: Expected value of other markets' losses due to contagion in the horizon of 1 year.

Table 1 - Impact indicators of contagious fictitious default FIs, by descending order of contagion losses in the interbank market – June/2012

Total Contagion	Ad Def	Max IF Bailout	Num Crit Exp	Max Crit Bailout	Cred T Bailout	Cred N Bailout	Capital Buffer	External Contagion
0.0942	16	0.0015	0	0.0000	0.1035	0.0921	0.0030	0.0942
0.0411	3	0.0000	0	0.0000	0.0133	0.0020	0.7756	0.0411
0.0303	4	0.0000	0	0.0000	0.0743	0.0305	0.0045	0.0303
0.0254	2	0.0000	0	0.0000	0.0019	0.0008	0.0779	0.0254
0.0156	1	0.0000	0	0.0000	0.0461	0.0062	0.6357	0.0156
0.0041	1	0.0000	0	0.0000	0.0266	0.0018	0.0071	0.0006
0.0006	1	0.0000	0	0.0000	0.0530	0.0001	0.1002	0.0004
0.0005	2	0.0000	0	0.0000	0.1170	0.0002	0.2297	0.0003
0.0004	2	0.0000	0	0.0000	0.0078	0.0001	0.7384	0.0003
0.0003	3	0.0000	0	0.0000	0.0368	0.0001	0.0468	0.0000
0.0002	1	0.0002	0	0.0000	0.0066	0.0000	0.0033	0.0000

Total Contagion: amount not paid by FIs that defaulted due to contagion in the interbank market, added to the losses suffered by other markets from contagion; Ad Def: number of FIs in additional default due to contagion; Max IF Bailout: bailout amount for the FI in fictitious default, considering the loss of all of its' interbank market assets; Num Crit Exp: number of individual counterparties to which the FI has an above the capital buffer (critical) exposure; Max Crit Bailout: maximum bailout amount for an FI in fictitious default related to the highest critical exposure; Cred T Bailout: bailout that covers the total amount not received by the creditors of the FI in fictitious default; Cred N Bailout: bailout the fictitious default IFs' creditors requires to not default: (it covers, for every FI creditor, its loss excess relative to its capital buffer); Capital Buffer: it is the Total Capital (Tier 1 + Tier 2) amount that exceeds 8% RWA of the FI in fictitious default; External Contagion: liabilities not repaid in other markets due to the fictitious default.

Amounts are expressed as fractions of the total interbank market assets.

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