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Network topology and interbank credit risk

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ABSTRACT

Modern financial systems are greatly entangled. They exhibit a complex interdependence, including a network of bilateral exposures in the interbank market. The most frequent interaction consists in operations where institutions with surplus liquidity lend to those with a liquidity shortage. These loans may be interpreted as links between the banks and the links display features in some way representative of scale-free networks. While the interbank market is responsible for efficient liquidity allocation, it also introduces the possibility for systemic risk via financial contagion. Insolvency of one bank can propagate through links leading to insolvency of other banks. In this paper, we explore the characteristics of financial contagion in interbank networks whose distribution of links approaches a power law, as well as we improve previous models by introducing a simple mechanism to describe banks' balance sheets, that are obtained from information on network connectivity. By varying the parameters for the creation of the network, several interbank networks are built, in which the concentration of debt and credit comes from the distribution of links. The results suggest that more connected networks that have a high concentration of credit are more resilient to contagion than other types of networks analyzed.

1. Introduction

The financial crisis during 2007–2008 highlighted, once again, the high degree of interdependence of financial systems. A combination of excessive borrowing, risky investments, lack of transparency and high interdependence led the financial system to the worst financial meltdown since the Great Depression. An increasing interest in financial contagion, partially motivated by the crisis, gave rise to several works in this field in the last years (see, for example, [1–4]).

The interdependence of financial systems is manifested in multiple ways. Financial institutions are connected through mutual exposure in the interbank market, through which institutions with surplus liquidity can lend to those with a liquidity shortage. Equally important, financial institutions are indirectly connected because they are exposed in the same assets and share the same depositors.

With respect to the direct connection from having mutual exposure, the structure of interdependence can be easily illustrated in a visual representation of a network, in which the nodes of the network are financial institutions, while the links are the loans–debts between nodes. The direction of the link indicates the cash flow at the time of debt repayment (from debtor to creditor) as well as the direction

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of the impact or financial loss if borrowers default on their repayment. Theoretical works [5,6] have shown that the possibility of contagion via mutual exposure depends on the precise structure of the interbank market. In recent studies, different models have been used to generate artificial interbank networks, in order to identify whether a given network is more or less prone to contagion.

Nier et al. [7] simulate contagion from the initial failure of a bank in an Erdös–Rényi random network, finding a negative nonlinear relationship between contagion and bank connectivity. An increase in the amount of interbank exposure initially has no effect on contagion, since the losses are absorbed by each affected node. However, as the number of connections rises, contagion increases to the point that a further increase in connectivity causes contagion to decline. Studying a similar model on a power-law network, Cont and Moussa [8] find results similar to those of Nier et al. [7] regarding the relation between connectivity, the level of capitalization, and contagion. Battiston et al. [9] simulate contagion in a regular network and find a nonlinear relationship between connectivity and contagion, but with the opposite effect: initially, the increase in the number of connections decreases network contagion, while later additions cause contagion to increase. Ladley [10] evaluates the relation between connectivity and contagion in a partial equilibrium model of heterogeneous banks interacting in the interbank market. The author shows that, under small systemic shocks, higher connectivity increases resilience against contagion, while larger shocks have the opposite effect. The differences in the results indicate that the possibility and extent of contagion depend considerably on the structure of the network and the specific assumptions of each model.

Empirical studies reveal that some interbank networks have features of scale-free networks: this means that the distribution of connections among banks follows a power law [11–14]. However, it is worth to note that other interbank networks do not present scale-free characteristics (on the e-MID electronic money market, see, e.g., ref. [15]). Based on this stylized fact, Montagna and Lux [1] simulate networks whose links distribution follows power laws in order to evaluate the relevance of some known quantities (like the size of the banks) for contagion measures. More recent studies have emphasized core-periphery structures as relevant mechanisms in interbank network formation [2,15]. In such models, the idea is that banks organize themselves around a core of intermediaries, giving rise to a hierarchical structure (interbank tiering).

In general terms, some of the most significant features reported in the literature can be summarized as follows:

1. Networks have a low density of links, that is, they are far from complete.
2. They exhibit asymmetrical in-degree and out-degree distributions.
3. They exhibit approximate power law distributions for in- and out-degree distributions whose exponent varies between 2 and 3.

A characteristic reported in ref. [12] in a study of the Brazilian network is also worth noting: there is a positive association between the size of the exposure (assets) and the number of debtors (in-degree) of an institution and a positive association between the size of liabilities and the number of creditors (out-degree) of an institution. More (less) connected financial institutions have a larger (smaller) exposure.

The goal of this paper is to identify, through simulations of networks whose distributions approach power laws, how scale-free networks behave with regard to financial contagion via mutual exposure and which characteristics make a given network more or less prone to propagate crises. Our particular interest is in evaluating the role of the exponents that characterize a scale-free network, because these exponents determine the concentration of debt (out-degree) and credit (in-degree) in the financial network. We construct networks whose connectivity distribution approaches a power law using the algorithm introduced by Bollobás et al. [16]. In addition to consider the network structure, we have also developed a simple method to determine the banks' balance sheets from the information of connectivity of the interbank network. By varying the parameters for the creation of the network, several interbank networks are built, in which the concentration of debt and credit comes from the distribution of links. Three main types of interbank network are analyzed for their resilience to contagion: (1) those where the concentration of debt is greater than the concentration of credit, (2) those where the concentration of credit is greater than the concentration of debt, and (3) those with similar concentrations of debt and credit. For all the networks that we have generated, the financial contagion starts with the failure of a single node, which affects neighboring nodes by defaulting on its obligations in the interbank lending market. Thus, this work focuses on the problem of credit risk, disregarding other equally important sources of contagion, as the risk of adverse shocks spreads to several institutions at the same time.

The paper is structured as follows: Section 2 describes the model used in the simulation of financial networks and the balance sheet of each node. Section 3 introduces the method used to simulate financial contagion and presents impact indices, by which we evaluate the nodes with respect to their default effect. Section 4 presents the results of the various simulations performed, and Section 5 summarizes the main conclusions.

2. Generating scale free bank networks

In their study on scale free networks, Barabasi and Albert (BA) [17] propose a preferential attachment mechanism to explain the emergence of the power-law degree distribution in nondirected graphs. The algorithm proposed by Bollobás et al. [16] is a generalization for directed networks of the model developed by Barabasi and Albert [17]. The network is formed by preferential attachment that depends on the distribution of in-degree, k_{in}, and out-degree, k_{out}. This algorithm has the advantage of producing different exponents for the in and out degrees, which are necessary to reproduce the characteristics of real networks. The following procedure describes the steps for generating the network according to [16].

Let α, β, γ, δ_{in} and δ_{out} be non-negative real numbers such that $\alpha + \beta + \gamma = 1$. Let G_0 be an initial network, that we assume as two nodes connected through two directed links, and let t_0 be the number of links of G_0. At each step, t,