The Effect of Diversification on Financial Contagion

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Abstract
The economic and financial crises of the early 21st century (e.g., 2007–2009 global financial turmoil) have made financial instability, which is induced by financial contagion, as one of the major concerns in the economics or financial field worldwide. In this paper we model a network of financial cross-holdings based on the classic Leontief input–output framework, and study the effect of diversification of interbank exposures and interbank connection on the magnitude of financial contagions. We perform a comprehensive numerical experiment by varying the sequences of interbank exposures and interbank connections, the result shows that the diversification has negative influence on financial stability in some extent. Our study has significant implications on financial regulation and surveillance.

1. Introduction

The increasing frequency and scope of financial crises not only has made the financial stability as one of major concerns for academic researchers and policymakers, but also has revealed the necessary of changing views of the regulation concerning financial risk supervision—from micro-prudential supervisory to macro-prudential supervisory. For example, triggering by the default of Lehman Brothers due to the sharp writedowns of assets related to subprime mortgages, the 2008 financial crisis has been considered as the most serious financial crisis since the Great Depression, as it induced the collapse of the worldwide financial system. A crucial characteristic about this financial crisis is the contagion (or avalanche effect), of distress/failure, which is the potential of shocks hitting an interconnected and complex financial institutions—although not necessarily large in terms of total assets—to quickly spread across the whole financial system in an unexpected domino effect. This characteristic, on the one hand, highlights the importance of financial contagion; on the other hand, calls for the regulators focus on financial institutions that are “too-big-to-fail” (TBTF), as well as institutions that are “too-connected-to-fail” (TCTF). Actually, the financial integration and innovation significantly increases the financial connectivity (holding each other’s shares, claims and obligations) among the banks in a financial system, such connectivity can lead to the so-called financial contagion, and such financial contagion threatens the stability of financial system. So in the aftermath of the recent financial crisis, academics and regulators have made significant efforts to explore our understanding of financial contagion. To this end, the network theory has been intensively used to analyze the financial contagion in general as a financial system can be labeled as a network of interdependencies (the cross holding of claims and obligations) [1-3], and the network reflects the connectivity of the financial system. Financial regulators or supervisors have undoubtedly thought network models as a powerful and flexible tool to identify and quantify the topology of a financial system and a guide to provide operational contents to the prudential regulation and surveillance—designing incentives and regulatory policies that prevent or mitigate the financial contagion.

Indeed, a large body of network literature has developed flourishing theoretical studies [2, 4-6] and empirical applications[1, 3, 7, 8] aimed at analyzing a wide range of issues in financial contagion and financial stability. One particular focus is that how interbank connections and interbank exposures influence the probability and extent of financial contagion, academics usually uses the mean of degree and the mean of exposures to measure the interbank connections and exposures [5, 9-13]. However, the mean of degree and exposures is not sufficient
(insufficient) for depicting the interbank connections and interbank exposures, for example, a regular network and a random network may have the same mean of degree, but the connections of these two networks are obviously not the same. On the other hand, a financial network is formed due to the relationship of cross holdings, such as holding each other’s equity shares, claims and obligation; it is reasonable to consider these cross holding relationships as input-output linkages. E.g. institution A holds a certain share of institution B’s equity, which can be viewed as the input of institution B, or equally, the output of institution A. Those situations motivated our study. In detail, we aim to extend the network approach for studying financial contagion by introducing the classic Leontief input–output framework in financial system because the relationships of cross holdings among financial institutions can be viewed as the input-output linkages. We propose a simple contagion algorithm based on the input-output framework and study the effect of diversification of interbank exposures (reflected by the mean and variance of degree) on financial contagion. We perform a comprehensive numerical experiment by varying the sequences of interbank exposures and interbank connections, the result shows that the diversification has bad influence on financial stability.

The rest of this paper is organized as follows: section 2 analyzes the related literature, section 3 presents the model, section 4 studies the impact of diversification of interbank exposure and interbank connection, and finally, the section 5 presents the conclusions.

2. Related Literature

2.1. Financial Contagion and Financial Stability

Our work is related to multiple strands of the literature. First, as a modeling of financial network, this paper is closely related to literature on financial contagion and stability in financial system. The seminal literature of [14] pioneer this strand of theoretical study by showing how the network structure affects the risk sharing, they point out that the complete network can absorb idiosyncratic shocks, while the incomplete network might allow negative spillovers to spread throughout the system (financial contagion). After this outstanding work, a large number of literatures on financial contagion employ network or graph model. Financial contagion mainly comes through three mechanisms in a financial system: 1), correlation risk because of overlapping portfolios exposure [9, 15-17]; 2), liquidity hoarding risk because of rumor or imperfect information [18-20]; and 3), counterparty risk because of the direct interbank exposures[10, 21-24]. Our work particularly follows the third mechanism in which the bilateral exposures forms by the relationship of cross holding, so the bilateral exposures can be reflected in a network of interdependency, and the network also reflects the interbank connections of the financial system which act as the channel of contagion transmission.

Indeed, it is now generally accepted that the interbank exposures and interbank connections are considered as the major influence of the financial contagion and the stability of the financial system [5, 9-13, 25]. These papers identify the ’knife-edge’ or “robust-yet-fragile” property of financial networks, whereby the trade-off between risk sharing and risk spreading due to the increasing of interbank connections. Indeed, more connection imply that an idiosyncratic shock can be more easily dissipated and absorbed (risk sharing) when an institution has high connectivity. However, on the flip side of the view, an institution with high connectivity will also have a higher probability of being hit by an idiosyncratic shock through one of its counterparties. What’s more, many counterfactual analysis on either real or artificial data have been adopted to simulate the financial contagion in a target financial system under different assumptions, such as the size and the topology of the independency network[22, 26], the diversification of interbank connections[10, 11] and the level of interbank exposures[21, 27]. We broadly categorize the simulation study of financial contagion into two branches, the first branch is considering financial system as random network, which emphasize the importance of network topology structure, such as network connectivity, degree distribution and density. Those kinds of literatures model financial contagion as a result from an initial idiosyncratic shock to one or few financial institutions and spreading through the entire network in a cascade manner. This group of literatures includes the work of [10, 11, 21, 22, 28]. The other branch is studying the financial contagion in a deterministic network, which considers the financial network as either exogenous or endogenous and examines the impact of initial defaults as predetermined by network externalities, such as the configuration model[4], the tiering banking network[26], nested split graph[29].

2.2. Input-output Analysis

Our work is also partly related to the literature of input-output analysis. Since it was originally developed
by Leontief to study the US economy[30], the input-output analysis has been one of the most widely applied methods in economics[31] and has enjoyed a broad popularity in many fields, e.g. energy and environmental analyses[32]. The fundamental purpose of the input–output framework is to analyze the interdependence of individual parts in an economy system, e.g. the inter-industry analysis [33]; the analysis of cross holding in business[34]; risk analysis of large-scale interdependent systems[35] and the consequences of natural disasters[36, 37].

There are also several papers focusing on financial contagion or systemic risk in the framework of input-output analysis. Acemoglu and his collaborators use the Cobb-Douglas production technologies to study the interaction between the shape of the firm-level shock distributions and the structure of the input-output network[38, 39]; Aldasoro and Angeloni employ the input-output analysis to measure the systemic importance of financial institution[40]. It is worthy to note that the paper of [5] is related to our work, this paper mainly study the effect of integration (the average of exposures) and diversification (the average of degree) on the financial contagion. There is a significant difference comparing with our work, except the average exposures and degree, we also investigate the effect of the variance.

3. Modeling and Contagion Mechanism

3.1. Exposures Matrix and Balance Sheet

Figure 1 shows an illustration of a typical financial system. Here we consider a financial system in which $n$ financial institutions (banks for short) form an interbank network by their claims on each other (cross holdings). In this network, each node is a bank and each link represents a directional holding between two banks, the cross holdings relationships can be represented by an exposure matrix $W \in \mathbb{R}^{n \times n}$, the number $w_{ij}$ is the share of bank $j$ held by bank $i$ where $i, j \in N, N = \{1, 2, ..., n\}$, this share can be viewed as the output of bank $i$ to bank $j$ or the input of bank $j$ from bank $i$. Here we should highlight that $w_{ii} = 0$ for each $i$ in the financial network.

$$W = \begin{bmatrix}
0 & w_{12} & \cdots & w_{1n} \\
w_{21} & 0 & \cdots & w_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
 w_{n1} & w_{n2} & \cdots & 0
\end{bmatrix} \quad (3.1)$$

We denote the corresponding adjacency matrix of $W$ as $G$, where $g_{ij} = 1$ when $w_{ij} > 0$ otherwise 0. Except the cross holding shares, the remains $\bar{w}_{ii} = 1 - \sum_{j=1}^{n} w_{ij}$ of bank $i$ is the share owned by its owners-operators. Actually, this is the part that is owned by outside shareholders, external to the system of cross-holdings. We adopt a diagonal matrix $\bar{W}$ to depict these shares, where the off-diagonal entries of the matrix are defined to be 0.

$$\bar{W} = \begin{bmatrix}
\bar{w}_{11} & 0 & \cdots & 0 \\
0 & \bar{w}_{22} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
 0 & 0 & \cdots & \bar{w}_{nn}
\end{bmatrix} \quad (3.2)$$

Now we turn to consider the structure of assets and liabilities for individual bank. In Figure 1 each individual bank is represented by a deliberately oversimplified balance sheet. On the assets side (the output side), the “Interbank Assets” presents the amount of total shares of other banks (the total intermediate output), the remainder of assets consists a range of “External Assets” which are the holdings of other real economy (the total final output), the external assets can be considered as the investment of the bank, such as high-quality government bonds, mortgages, corporate lending and commercial real estate lending. As our main propose is the study of financial contagion in interbank network, it is worth to note that we assume each bank has a single and independent investment project, this assumption indicates that there is no correlations among the external assets for each bank, facilitating our focusing on directed interbank exposures and ignoring the “fire-sale” of correlated external assets.

![Figure 1. An illustration of a financial system](image-url)
On the other side of the balance sheet, the liabilities consists of the “Deposits” and “Interbank Liabilities”, the deposits is the share of input from outside of the system, as such household, interbank liabilities is the share of input from other banks, the “Equity” is the capital buffer which denotes the excess of total assets (output) over total liabilities (input).

Considering the structure of balance sheet, the following equations are found.

$$A_i = A_i^F + A_i^I$$  \hspace{1cm} \text{(3.3)}
$$L_i = L_i^F + D_i + E_i$$  \hspace{1cm} \text{(3.4)}
$$A_i = L_i$$  \hspace{1cm} \text{(3.5)}

Where $A_i$, $L_i$, $A_i^F$, $D_i$ and $E_i$ denote bank $i$’s total assets, total liabilities, external assets, deposits and equity, respectively.

**Definition 1.** (financial system), a financial system $(W, \{A_i^F\}, \{E_i\})$ is defined by
\begin{enumerate}
\item an exposure matrix $W \in \mathbb{R}^{n \times n}$;
\item a sequence of $\{A_i^F\}_{i=1}^n$;
\item a sequence of $\{E_i\}_{i=1}^n$.
\end{enumerate}

Based on these information, we can get the sequence of interbank exposure $\{a_i\}_{1 \leq i \leq n}$ and the sequence of interbank connection $\{d_i\}_{1 \leq i \leq n}$.

$$a_i = \sum_{j=1}^n w_{ji} = A_i / A_i$$  \hspace{1cm} \text{(3.6)}
$$d_i = d_i^{in} + d_i^{out} = \sum_{j=1}^n g_{ij} + \sum_{j=1}^n g_{ji}$$  \hspace{1cm} \text{(3.7)}

In this paper, we adopt the mean and variance to measure the diversification of the interbank exposure sequence and interbank connection sequence.

$$\bar{a} = \frac{1}{n} \sum_{i=1}^n a_i, \text{ Var}_a = \frac{1}{n} \sum_{i=1}^n (a_i - \bar{a})^2$$  \hspace{1cm} \text{(3.8)}
$$\bar{d} = \frac{1}{n} \sum_{i=1}^n d_i, \text{ Var}_d = \frac{1}{n} \sum_{i=1}^n (d_i - \bar{d})^2$$  \hspace{1cm} \text{(3.9)}

Where $\bar{a}$, $\bar{d}$ denote the mean of interbank exposure and interbank connect, respectively; $\text{Var}_a$, $\text{Var}_d$ denote the variance of interbank exposure and interbank connect, respectively.

**3.2. Book Value and Market Value**

Under the influence of cross holding relationships, the “fair” value of bank can be significantly distorted [41], e.g., focusing on stock market in Japan, French and Poterba argue that the equity market capitalization are inflated due to the double counting of cross-holdings[42]. It is crucial for study financial contagion to calculate the “correct” bank value [5], however, many existing literatures on financial contagion ignore the effect of cross holdings on the bank value, e.g., [9-11, 43]. So in this subsection we calculate the bank value and market value in the framework of input-output analysis.

Without lose the generality, here we just consider the output side (assets) of the financial system. According to the balance sheet, the book value of bank $i$ can be obtained.

$$V_i^{book} = A_i^I + A_i^F = \text{total output}$$
$$= \sum_{j=1}^n w_{ij} V_j^{book} + A_i^F$$  \hspace{1cm} \text{(3.10)}

Equation (3.10) can be written in matrix notation as

$$V_i^{book} = W V_i^{book} + A_i^F$$  \hspace{1cm} \text{(3.11)}

and solved to yield.

$$V_i^{book} = (I - W)^{-1} A_i^F$$  \hspace{1cm} \text{(3.12)}

Where $V_i^{book} = (V_i^{book}, V_2^{book}, \ldots, V_n^{book})^T$, $A_i^F = (A_i^F, A_2^F, \ldots, A_n^F)$ are $n \times 1$ column vectors. The $(I - W)^{-1}$ is the well-known Leontief inverse.

We refer to the market value of an individual bank as the non-inflated value which can be captured by the share of book value that is held by its owners-operators (outside stakeholders). So the market value of bank $i$ is equal to $\bar{w}_i V_i^{book}$, and we can get the equation (3.13)

$$V_i^{market} = \bar{w}_i V_i^{book} = \bar{w} (I - W)^{-1} A_i^F$$  \hspace{1cm} \text{(3.13)}

We refer to $\bar{w} (I - W)^{-1}$ as the **Relevance matrix**. $R$ is column stochastic,

$$\sum_{i=1}^n R_{ij} = 1$$  \hspace{1cm} \text{(3.14)}

**3.3. Contagion Mechanism**

For an individual bank, the value shared by the owners-operators is $\bar{w}_i V_i^{book}$, if this value is sufficiently low, the owners-operators may choose to cease operations and liquidate the bank. If a bank ceases operations and goes to liquidate, its value is sharply decreased due to the liquidation costs, such as the costs of assessing values, the losses involving idle assets and the holding cost for sales assets. So we assume that there is a threshold value $V_i^{market}$ such that if the value $V_i^{market}$ of a bank $i$ falls below this threshold level, then $i$ is said to fail and incurs liquidation costs $C_i^{liq}$. So the book value of bank $i$ becomes:

$$V_i^{book} = \sum_{j=1}^n w_{ij} V_j^{book} + A_i^F - C_i^{liq}$$  \hspace{1cm} \text{(3.15)}
This leads to a new version of (7) and (8) for book value and market value:
\[ V^{\text{book}} = (I - W)^{-1}(A^E - C^{liq}) \]  
\[ V^{\text{market}} = W V^{\text{book}} = R(A^E - C^{liq}) \]  

The entry \( R_{ij} \) of the Relevance matrix describes the proportion of bank \( j \)'s liquidation costs that bank \( i \) bears when \( j \) fails. The liquidation costs of failed banks are distributed in the interbank network through the cross holdings relationships, so small idiosyncratic shock on a single bank may have significant influence on the system by triggering an avalanche effect of failures. In detail, when bank \( j \) fails, thereby incurring liquidation costs of \( C^{liq}_j \), then \( i \)'s value will decrease by \( R_{ij}C^{liq}_j \). If \( \Delta V_i = V^{\text{market}}_i - V^{\text{market}}_{i-1} \) is negative, then bank \( i \) will fail, the liquidation of bank \( i \) lead to the decrease of market value for its creditors, this may cause the fail of creditors and so forth. This depicting illustrates the mechanism of financial contagion through interbank network, the contagion mechanism is the foundation of this study. Here we present a contagion algorithm to trace the propagation of failure, this sort of algorithm also appear in other literature on financial contagion [5, 44, 45].

The algorithm is presented as follow.

**Step 1:** Introducing the initial failures. Random selecting one bank go to fail( \( \#\text{Fail}_0 = 1 \) ), where \( \text{Fail}_t \) be the set of failed banks at time \( t \), letting \( \mathcal{C}_t \) be a vector with element \( \mathcal{C}_i = C^{liq}_i \) if \( i \in \text{Fail}_{t-1} \) and 0 otherwise (\( \geq 1 \)).

**Step 2:** calculating \( \Delta V_t = D(A^E - \mathcal{C}_{t-1}) - V^{\text{market}}_t \).

**Step 3:** comparing \( \Delta V_t \) and \( \Delta V_{t-1} \); if there are new entries of vector \( \Delta V_t \) which are negative, updating \( \mathcal{C}_t \) and \( \text{Fail}_t \) based on these new entries, and returning to step 2; otherwise terminating the algorithm.

If the algorithm is terminated at time \( T \), the set of \( \text{Fail}_T \) corresponds to the set of total failed bank. According to this algorithm, we can find the failed bank at each time by counting the new entries in \( \text{Fail}_t \) compared to \( \text{Fail}_{t-1} \), these new entries are banks whose failures are induced by the aggregated loss of prior lose.

### 4. Diversification of Interbank Exposures and Interbank Connections

Both the intrinsic characteristics of financial institutions and the structure of financial network influence the magnitude of financial contagion and the stability of financial system. The characteristics of financial institutions and the network structure usually are reflected by the diversification of interbank exposures and interbank connections, respectively. Indeed, a special financial network has a particular interbank exposures sequence as well as a particular interbank connections sequence, these unique sequences determine the resilience and the stability of the financial system in distress time. However, the existing researches on financial contagion simply adopt the mean of these sequences to measure the diversifications of them(e.g., the average interbank exposures, the average interbank connections) [5, 9-13], intuition suggests that the average interbank exposures and connections are insufficient to depict the exposures sequence and connections sequence, respectively. Here we adopt the variance of the exposures to measure the diversification, as the variance reflects how far the sequence is spread out.

#### 4.1. Diversification of Interbank Exposures

For simplicity, we consider a financial system as a random network where \( N \) banks randomly connected with each, and each bank has an independent and equal external asset (there are no correlations among those assets). The random network represents the adjacency matrix \( G \), where \( g_{ij} = 1 \) denotes that bank \( i \) has cross-holdings in bank \( j \), and the diagonal entries \( g_{ii} = 0 \).

We assume that the sequence of interbank exposures obeys a normal distribution \( \alpha \sim N(\mu, \sigma) \), where \( \mu \in (0, 1) \) denotes the average exposure. So \( \alpha_i \) indicates the total interbank exposures of bank \( i \), and it spread evenly among the banks in the \( i \)'th column of the adjacency matrix \( G \). According to this depicting, a financial system is constructed; the exposure matrix, the book value and the market value can also be calculated by depicting in section 3.

To illustrate the effect of diversification of interbank exposures, we assume there is a common failure thresholds \( V^{\text{market}}_t = \theta V^{\text{market}}_t \) for a parameter \( \theta \in (0, 1) \); we set \( N = 100 \), and construct 60 random networks by different probability \( P \) for forming a link between each couple of nodes; we perform the contagion algorithm on each random network, each simulation is repeated 100 times to average out stochastic effect and to get robust results.

In order to evaluate the magnitude of financial contagion, we introduce two measure indicators. At first, we define financial contagion as an event that at least one bank fails as a response to the initial failure. Following this definition, two measure indicators are derived: 1), contagion probability, defined as the probability of occurring of a contagion event; 2), extent of contagion, defined as the average banks being defaulted induced by the initial failure if a contagion event occurs. The contagion probability and the extent
of contagion are suitable for measuring the magnitude of financial contagion, further reflecting the stability or the robustness of a financial system. Particularly, contagion probability reflects the sensibility of a financial system for suffering financial contagion, while the extent of contagion reflects the stability of a financial system.

\[ \text{The Probability of Contagion} = \frac{\text{Number of contagion events observed}}{\text{Number of total experiments}} \quad (4.1) \]

\[ \text{The Probability of Contagion} = \frac{\text{Number of total defaulted banks induced by contagion}}{\text{Number of contagion events observed}} \quad (4.2) \]

Figure 2 identifies the 'knife-edge' or 'robust-yet-fragile' property of financial networks (the average exposure is fixed 0.5, and \( \theta = 0.96 \))\([9, 11] \). In detail, figure 2 shows how the extent and probability of contagion changes as the increasing of interbank connections (reflected by degree), both the extent and probability of contagion display the property of non-monotonicity as the inverted U-shaped curves. Particularly focusing on the blue curve, as degree increases in the range of 0 to 5, there is a significant increasing for both the contagion extent and contagion probability as the connectivity acts as a role of 'risk spreading'; as we further increase the degree (in the range of 5 to 20), both contagion extent and contagion probability dramatically decrease as the connectivity acts as a role of 'risk sharing'.

![Figure 2](image)

Figure 2. the “knife-edge” property of interbank network. \( \sigma \) denotes the variance of interbank exposure.

![Figure 3](image)

Figure 3. the effect of diversification of interbank exposures
Besides, figure 2 also shows how these effects vary with $\sigma$ which denotes the variance of interbank exposure. Generally speaking, both the extent and probability increase as the increasing of $\sigma$. Particularly, as the degree varying in the range of 0 to 5, the extent of financial contagion is just slightly changed with the increasing of $\sigma$, however, this is a significant changing for the probability of contagion. One reasonable interpretation is that higher value of $\sigma$ corresponds to the higher diversification of interbank exposures, the diversification make financial system more sensitive to financial contagion, but as the network is incompletely connected (degree is lower), a typical bank has interbank connections through cross-holdings to only a small fraction of other banks, and so financial contagion is limited to a small component (reflected by the small value of the contagion extent). However, on the other side, when degree is in the range of 5 to 20, both the contagion probability and contagion extent is increasing as we continue increase the value of $\sigma$. The difference of change between the contagion probability and contagion extent also can be seen in figure 3. As the variance of exposure varies in the range of 0 to 0.3, the contagion extent is slightly increasing, but the changing of contagion probability is more significant, especially when degree is small.

4.2. Diversification of Interbank Connections

In this subsection, we investigate the effect of the diversification of interbank connection on financial contagion. Actually, we focus on the varying of interbank connections sequences, which have the same mean but different variance. The challenge is constructing a set of networks in which the degree sequences have the same mean but different variance, the Watts and Strogatz (WS) model[46] can be adopted to satisfy this feature. After the inter-woven on a regular network with $n$ nodes and $k$ edges per node, the WS model is based on a rewiring procedure of the links implemented with a probability $p$. Because of the rewiring procedure, the average degree will not be changed as the varying of $p$, but the variance will changed. Figure 4 give an illustration for this changing ($n=20$), actually, for $p = 0$ the network is a regular network (panel A), while for $p = 1$ it is a random network (panel C). Higher rewiring probability increases the randomness of the network, so varying this tunable parameter, we can model numerous different kinds of networks which have the same average degree but different variance.

**Figure 4** the illustration of network topology for different rewiring probability based on WS.
Based on the WS model, we construct a set of networks and perform the contagion algorithm on these financial systems. Figure 5 shows the effect of the diversification of interbank connections (reflected by the varying of variance of degree), here we set the average exposure is 0.5, and the average degree is 12. We find that both the extent of contagion and the probability of contagion slightly increase as the variance of degree varies in the range of 0 to 1.5; however, when the variance of degree is continuously growing (in the range of 1.5 to 3), both the contagion extent and probability significantly increase. Figure 5 also illustrates the effect of varying the θ, both the contagion extent and probability increase as the growing of θ, the intuition is that higher value of θ indicates higher failures threshold, so the financial system becomes easier to induce financial contagion.

In this section, we investigate the effect of diversification of interbank exposure and interbank connection on financial contagion. We find that the increasing of diversifications, which reflect by the varying of variance of exposure and variance of degree, have bad influence on financial contagion.

5. Conclusions and Discussions

Recent financial crises have highlighted that the interbank exposure and interbank connection cross financial institutions linked through cross-holding linkages might create the avalanche effect as the shocks to some institutions may spread to the rest of the financial system. In this paper, we model the financial system as a network by introducing the classic Leontief input–output framework in financial system because the relationships of cross holdings among financial institutions can be viewed as the input-output linkages. And then we propose a simple contagion algorithm based on the input-output framework and study the effect of diversification of interbank exposure (reflected by the mean and variance of exposure) and interbank connections (reflected by the mean and variance of degree) on financial contagion. By varying the sequences of interbank exposure and interbank connection, we find that the diversification has bad influence on financial stability in some extent based on the result of our numerical experiment. In detail, firstly we study the diversification of interbank exposure under the structure of random network and assume the sequence of interbank exposure follows the normal distribution. The results reveal that the diversification of interbank exposure may increase the probability and extent of financial contagion. And then we investigate the impact of the diversification of interbank connection. In order to vary the sequence of interbank connection, we adopt the WS model to construct the financial network in which the mean of degree can keep constant, but the variance of degree is varying with the changing of rewiring probability in WS model. The results show that the diversification of interbank connection also can increase the probability and extent of financial contagion.
contagion. Our study has significant implications on financial regulation and surveillance.

Firstly, our work is a supplement for the network approach for financial contagion by introducing the classic Leontief input–output analysis. Our motivation is that the input–output analysis has been widely used for the study of cross holdings in business groups for risk management [35-37]. We partly clarify the impact of the diversification of interbank exposure and interbank connections on financial contagion.

Secondly, this modeling approach and the analysis framework can be applied in the empirical study for stress testing the real financial system, for example, to study the ongoing Eurozone sovereign credit crisis. There are intertwined relations for countries inside and outside the Eurozone, so a distress even in a very small economy (e.g. Greece) can trigger a large-scale systemic risk due to contagion.

Thirdly, our work can provide policy suggestions for the surveillance and regulation of a particular financial system. From a regulatory perspective, financial supervision should be thought as a systemic work, focusing not only on role of nodes — the particular financial institution or banks, but also on the interdependency relationships among these nodes to unravel the structure of the system under surveillance, e.g. a financial early warning system[47].

However, some shortcoming exists in this research. As mentioned in the introduction section, there are three mechanisms for financial contagion but we only study the counterparty risk (the third mechanisms). Besides, we just focus on the interbank network, while there are some other networks in a financial systems, e.g. Bank-Assets network[15, 16, 48]. These issues can be studied in the future by open up our research.

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8. References