A Study of Financial Contagion in Interbank System

Xian Cheng  
University of Science and Technology of China  
chengcx@mail.ustc.edu.cn

Stephen Shaoyi Liao  
City University of Hong Kong  
issliao@cityu.edu.hk

Haichuan Zhao  
USTC-CityU Collaboration Scheme  
zhhc@mail.ustc.edu.cn

Xinbo Sun  
Northeastern University  
xbsun@mail.neu.edu.cn

Zhongsheng Hua  
University of Science and Technology of China  
zshua@ustc.edu.cn

Yujing Xu  
USTC-CityU Collaboration Scheme  
xyjsgdhr@gmail.com

Abstract

Financial contagion was often observed during the recent financial crisis, which indicates a critical need for a new and fundamental understanding of its dynamics. Drawing analogies with the extinction analysis—a technique widely used in the study of ecosystems—we focus on modeling and analyzing the financial contagion in a system where a large number of financial institutions are randomly connected by direct balance sheet linkages owing to their lending or borrowing relationships. We propose a simple contagion algorithm to study the effect of several determinants, such as the topology of a financial network, exposure ratio, leverage ratio, and liquidation ratio. We find that the financial contagion weakens with the growth of a network’s connectivity to some extent. Therefore, a financial system with higher connectivity is more stable or robust. We also find that the exposure ratio increases the risk of financial contagion, but both the leverage ratio and liquidation ratio have negative relationships with financial contagion.

1. Introduction

A crucial characteristic of the recent financial crisis was the contagion (or avalanche effect) of distress/failure, which is the potential of the shocks hitting particular financial institutions to quickly spread across the whole financial system. For example, the default of Lehman Brothers on September 15, 2008 triggered a wave of bankruptcies across the U.S’ financial system, and abroad. Many economists are intrigued by the contagion phenomenon and produce a wealth of studies. The network theory, in particular, is the directive of the research in this field. Indeed, the financial system can be viewed as a network with a structure highly connected by interdependencies due to financial innovation. Those interdependencies can be in the form of obligation, exposure, ownership, and correlation [1]. Building on these interdependencies, the intertwined financial network and the diversified financial institutions offer not only an explanation for the spread of crises throughout the network, but also an implication for policy actions such as government intervention and bailout. These interdependent relationships, built initially with the purpose of risk sharing, have created a channel through which financial distress can spread. As maintained by [2], the financial network exhibits a knife-edge or robust-yet-fragile property: in normal times, the interdependencies between institutions enhance liquidity allocation and increased risk sharing [3]; but in times of financial distress, the same interdependencies can amplify the initial shocks, leading to the insolvency of a large number of institutions or even the collapse of the whole network [4, 5]. Yet the study of the nature and causes of financial contagion indicates uncertainty and conflicting views in the academic literature. For example, in the studies by [3] and [6], the authors argue that with financial networks becoming more dense, the effect of shocks suffered by individual institutions on the rest of the system is diminishing, as the losses of one single distressed bank are divided between more creditors. In contrast to this view, Blume, Easley et al.[7] and Vivier-Lirimont [8] argued that the fragility of a financial network increases with the number of counterparties of a bank. This situation illustrates a critical need for a new and fundamental understanding and analysis of financial contagion.

Motivated by the developments in ecology, we view the financial system as a “financial ecosystem.” Following the idea of financial ecosystems, we study financial contagion from the perspective of the extinction analysis. Indeed, there are some similarities between ecosystems and financial systems. First, both
of them have a network structure of interactions. For example, the nodes in ecosystems are species linked to other species as prey, predator, competitor or mutualist, and the nodes in financial systems are mostly banks linked to other banks by lending-borrowing relationships. Second, we can neither remove species from the special food web structure to study the influence on their sudden extinction, nor can we remove or disable an institution from the financial system to explore the downstream effects. Moreover, since the 1970s, there has been extensive research in ecology into the persistence or stability of ecosystems from the food web structure. Some techniques, for example the extinction analysis, can be used to study financial contagion.

In the extinction analysis, one species or a group of species are removed from the ecosystem and then “evolution” occurs according to the simulated knockout experiment. Eventually, the ecosystem either reaches a new stable state (balance of nature) or collapses entirely. The extinction analysis can assess stability or robustness by measuring the strength of extinction cascades induced by the knockout of target species. The extinction analysis model here is simplified, but it is the most widely used mode of assessment [9, 10]. Following the logic of the extinction analysis, we mainly focus on modeling and analyzing the financial contagion in a financial system where a large number of financial institutions are connected by the direct balance sheet linkages owing to their lending or borrowing relationships. In a financial network, one institution interacts with several other institutions. The default of one institution and the resulting shocks will affect its creditors, which, if insolvent, will also suffer default and cause further failures in the financial system. A number of determinants influence this kind of financial contagion, such as the topology of the financial network, the size of exposures, and the capital buffer. We model this kind of financial contagion and propose a simple contagion algorithm to study the role of these determinants. In detail, focusing on a financial system with $n$ banks randomly connected, we take the initial idiosyncratic shock as exogenous or endogenous, and investigate and analyze how it spreads through different financial networks; we also study how it is absorbed or amplified by different sized exposures and the capital buffer. Our contribution is to the ongoing debate on the role of financial integration and diversification in the spreading of financial contagion.

The remaining part of this study is organized as follows: section 2 provides a brief review of relevant literature on the application of network theory to the study of financial contagion; section 3 describes the financial network and balance sheet model; section 4 introduces the contagion mechanism and the algorithm; section 5 presents the results of our simulation experiments; and section 6 outlines our conclusions.

2. Literature Review

Even though financial crises were a frequent feature of the twentieth century, it is only in recent times, following the Subprime Crisis of 2008-2009, that the network theory has been extensively used to study financial contagion by economists and financial regulators [11-13]. The seminal literature of [3] pioneers this strand of theoretical study by showing how the network structure affects risk sharing. They point out that while the complete network can absorb idiosyncratic shocks, it might also allow negative spillovers to spread throughout the system (financial contagion). Following this outstanding work, a large amount of literature on financial contagion uses the network or graph model. Financial contagion mainly happens through three mechanisms: 1) correlation risk due to overlapping portfolio exposure [14-17]; 2) liquidity hoarding risk due to rumors or false information [5, 18, 19]; and 3) counterparty risk due to direct bilateral exposures [11, 20-23]. We mainly focus on the third mechanism, in which the bilateral exposures are the direct balance sheet linkages in the form of lending or borrowing relationships. Indeed, these lending or borrowing relationships act as a channel for spreading contagion.

We broadly categorize the study of financial contagion into two branches. The first branch considers the financial system as a random network, which emphasizes the importance of the topology of network structure, such as network connectivity, average degree, and density. These studies model financial contagion as a result of an initial idiosyncratic shock to one or several financial institutions, which spreads through the entire network in a cascading manner. This group of literature includes the work of [4, 11, 20, 21, 24]. The other branch studies financial contagion in a deterministic network, which considers the financial network as either exogenous or endogenous and examines the effect of initial defaults as predetermined by network externalities, such as the configuration model [25], the tiering banking network [26], and the nested split graph [27].

The above-mentioned theoretical literature investigates the mechanism and influence of financial contagion under a series of determinants by stylized models and a series of assumptions. There is an obvious shortcoming of such branches of research, as Upper said: “Analytical results on the relationship between market structure and contagion have been
obtained only for a limited number of highly stylized structures of interbank markets, which are of limited use when it comes to assessing the scope for contagion in real world banking systems” [28]. “Given the scarcity of theoretical results, researchers have increasingly turned to computer simulations to study contagion.” In fact, Upper presents a comprehensive review on using numerical simulations to study the mechanics of financial contagion in the study of [29]. Further studies on simulation in recent years include [5, 11, 14, 20, 21, 30-37].

3. Financial Network and Balance Sheet

Here, we consider a financial system in which \( n \) financial institutions (hereinafter referred to as banks) are randomly connected by their exposure to each other. This exposure, which reflects lending or borrowing relationships in the financial system, can be represented by a weighted directed network, denoted by an exposure matrix \( W \in \mathbb{R}^{n \times n} \). In this network, each node is a bank and each link represents a directional lending relationship between two banks. The weight reflects the size of exposure, which comprises assets and liabilities on either side. We should highlight that the magnitude of exposure is important for studying financial contagion. The exposure matrix \( W \) is defined as follows, where \( w_{ij} \) denotes the size of lending by bank \( i \) to bank \( j \), \( (i, j \in N, N = \{1, 2, ..., n\}) \), \( w_{ij} \neq 0 \) reflects the presence of a link, while \( w_{ij} = 0 \) reflects the absence of a link.

\[
W = \begin{bmatrix}
0 & w_{12} & \cdots & w_{1n} \\
w_{21} & 0 & \cdots & w_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
w_{n1} & w_{n2} & \cdots & 0
\end{bmatrix}
\]

Next, we consider the structure of assets and liabilities for an individual bank. Figure 1 shows a stylized balance sheet for a financial institution. In the Assets column, one bank lends to other banks in the financial system, and this forms the “Internal Assets.” The remainder of assets consist of a range of “External Assets,” which are the holdings of other real economy, such as government bonds, mortgages, corporate lending, and commercial real estate lending. The other column of the balance sheet shows the liabilities consisting of “Deposits” and “Internal Liabilities.” Deposits are held to be outside of the system, e.g. household, internal liabilities include borrowing from other banks. The “Equity” is the capital buffer, which denotes the excess of total assets over total liabilities.

Considering the exposure matrix \( W \), we can calculate the total exposure of bank \( i \) to the financial system. The “Internal Assets” held by \( i \), which is denoted by \( A^I_i \), can be determined by \( A^I_i = \sum_j w_{ij} \). The “Internal Liabilities” \( L^I_i \) can be determined by \( L^I_i = \sum_j w_{ji} \)

An internal asset of one bank is an internal liability of another, therefore, internal liabilities are endogenously determined based on the topology of the financial network. The equation of (1) is, thus, obtained.

\[
\sum_i A^I_i = \sum_i L^I_i = S \quad (1)
\]

![Stylized Balance Sheet for a Financial Institution (Bank)](image)

We define the total of internal assets as \( S \), which provides a measure of the total risk exposure of the financial system. Considering the structure of the balance sheet, the following equations are found.

\[
A_i = A^E_i + A^I_i \quad (2)
\]

\[
L_i = L^I_i + D_i + E_i \quad (3)
\]

\[
A_i = L_i \quad (4)
\]

Here, \( A_i, L_i, A^E_i, D_i \) and \( E_i \) denote bank \( i \)’s total assets, total liabilities, external assets, deposits, and equity, respectively.

Further, we introduce two ratios. The exposure ratio, indicated by \( \alpha_i \), is the ratio of internal assets to total assets \( (\alpha_i = A^I_i/A_i) \) The exposure ratio reflects the risk exposure of bank \( i \). The leverage ratio, \( \beta_i \), is the ratio of equity to total assets \( (\beta_i = E_i/A_i) \). Leverage ratio is also called “capital ratio” or “the ratio of net worth,” which represents a bank’s capacity to
absorb losses while remaining solvent. As mentioned, the “Equity” is the excess of total assets over total liabilities, so when the total liabilities exceed the total assets \( E_i \leq 0 \) or \( \beta_i \leq 0 \), the bank becomes insolvent.

4. The Contagion Mechanism

4.1. Initial Failures

We assume that the initial failures of a bank in crisis are caused by idiosyncratic shocks occurring due to credit risks (e.g. fraud) or operation risks (e.g. wrong decisions). The idiosyncratic shocks have a bad effect on the external assets of a subset of banks in the financial system (one or several banks) in that they reduce the amount of external assets and hence cause the default of these banks. It is worth noting that the idiosyncratic shocks are not the aggregated or correlated shocks that influence almost all banks simultaneously in the financial system. The bank has to liquidate if it is to default, while its creditors will lose a fraction of claims because the liquidation value of a firm is always smaller than its book value. Formally speaking, bank \( i \) is insolvent when \( E_i \leq 0 \) due to the reduction of external assets, which causes the bank to liquidate; the liquidation of bank \( i \) induces a loss equal to \( y_i w_j \) for its counterparty \( j \), where \( y_i \) is the liquidation ratio of bank \( i \). Therefore, we define the set of initially insolvent banks as follows.

\[
Z_0 = \{ i \in N | \beta_i \leq 0 \} \quad (5)
\]

In this study, we take it that the number of set \( Z_0 \) equals one, which means there is just one default bank initially.

4.2. The Contagion Process

In this financial network, the default of one or several banks may lead to other banks becoming insolvent, which generates a cascade effect of default. Figure 2 illustrates the mechanism of the cascade effect. At some point in this contagion process, bank A and bank B are insolvent and have to be liquidated, which forces them to repay their internal liabilities to banks 1, 2, 3, ...m. Each creditor bank only receives a proportion of its claims. This causes bank 1 to suffer a loss that exceeds its equity, so bank 1 becomes insolvent and is to be liquidated in the subsequent step; bank 3 also becomes insolvent because the cumulative losses incurred from both bank A and bank B, exceed its equity. It should be noted that bank A and bank B are not necessarily liquidated in the same step.

**Figure 2. The contagion mechanism**
To model the dynamics of default contagion, we suppose that all banks in the network are initially solvent and that the network is perturbed at time $T=0$ by the initial failure of one single bank. Considering the set of initially insolvent banks $Z_0$, we calculate the set of banks that become insolvent at time $T=1$ due to their claims to the initial default bank using the following equations.

$$z_1 = \{i \in N| E_t \leq \sum_{j \in Z_0} (1 - \gamma_j)w_{ij}\} \quad (6)$$

$$Z_1 = Z_0 \cup z_1 \quad (7)$$

In fact, when introducing the initial failure for bank $i$, which is not in the set $Z_0$, the internal assets are $A_i' = \sum_{j \in Z_0} \gamma_j w_{ij} + \sum_{j \in Z_0} \hat{w}_{ij}$, so the change of internal assets is $\Delta A_i' = \sum_{j \in Z_0} (1 - \gamma_j)w_{ij}$. According to equations (2), (3), and (4), we can ascertain that bank $i$ will be insolvent when $E_t \leq \Delta A_i'$. Following this procedure, we can calculate the set of default banks at time $T=t$ based on $Z_{t-1}$.

$$z_t = \{i \in N| E_t \leq \sum_{j \in Z_{t-1}} (1 - \gamma_j)w_{ij}\} \quad (8)$$

$$Z_t = Z_{t-1} \cup z_t \quad (9)$$

Iterating equations (8) and (9), we can trace the contagion process initiated by one single bank ($\#Z_0 = 1$). The process will terminate when $Z_t = Z_{t-1}$.

### 4.3. A Simple Contagion Algorithm

This contagion process can be studied by the tool of the branching process, which is widely used in the field of epidemiology [38]. Some scholars already adopt the branching process to study the probability of financial contagion or the extent of contagion [4]. However, there are several challenges to the theoretical analysis of financial contagion. First, the structures of balance sheets for banks are diverse. The size of total assets, the leverage ratio, the exposure ratio, and the in- and out-degrees for different banks may be different. Second, the branching process usually occurs in a tree structure; financial contagion does not necessarily move in the same pattern, but is rather a more general graph. Take the default of bank 3 as illustrated in Figure 2 for example. The default of either bank A or bank B will not induce the default of bank 3, but the default of both bank A and bank B can induce its default. Considering these challenges, we turn to the simulation study of financial contagion with the following contagion algorithm.

**Step 1:** Introducing the initial failures. Randomly selecting one bank for default, so the size of the set of initially insolvent banks equals one ($\#Z_0 = 1$);

**Step 2:** Liquidating the default bank. Only repaying one proportion of internal liabilities for the default bank ($\gamma_i w_{ij}$);

**Step 3:** Revising banks’ balance sheets. Mainly focusing on the creditors for default banks and revising these creditors’ balance sheets based on equations (2), (3), and (4);

**Step 4:** Updating the set of default banks. Calculating the set of default banks $Z_t$ based on equations (8) and (9);

**Step 5:** Terminating this algorithm if $Z_t = Z_{t-1}$, otherwise, returning to step 2.

### 5. Simulation Experiments and Results

#### 5.1. Parameters Setting

The algorithm mentioned above allows us to study the contagion process in a financial system when it is in a particular state, corresponding to a particular configuration of the network topology and the balance sheets for each bank. Our main goals are to understand whether and how financial contagion depends on the network properties and the structure of balance sheets. The first step is to formulate specific instructions for the network topology and balance sheets.

#### Table 1. Summary of the variation for parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network topology</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Network</td>
<td>$N$</td>
<td>1000 (fixed)</td>
</tr>
<tr>
<td>$P_{random}$</td>
<td>The probability of forming a link between two nodes</td>
<td>0.01 to 0.30</td>
</tr>
<tr>
<td><strong>Balance Sheet Structure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>The exposure ratio/the internal-assets-to-assets ratio</td>
<td>0.2 to 0.4</td>
</tr>
<tr>
<td>$\beta$</td>
<td>The leverage ratio/the equity-to-assets ratio</td>
<td>0.01 to 0.05</td>
</tr>
</tbody>
</table>

4489
The financial network being studied is based on the Erdoes and Renyi random graph model [39], which can be defined by two parameters: N disconnected nodes and the probability P for forming a link between each couple of nodes. The link formation process is i.i.d. and the degree distribution is binomial. Based on this definition, we can construct a series of financial systems, comprising 1,000 banks. The lending or borrowing relationships in the financial system are represented by the weight in the network, which is assigned according to the findings by [40], where the weight follows a Log-Normal distribution with a mean of 15.2 and standard deviation of 0.8.

With regards the structure of the balance sheet, we assume that all banks have the same exposure and leverage in a financial network, but that there are differences between networks. So in a financial network, we set the same exposure ratio and leverage ratio for all banks, α and β, respectively. We can determine detailed information for each bank’s balance sheet, such as total assets, equity, and deposits, based on the internal assets, internal liabilities, α, and β.

Essentially, a financial system is determined by the matrix W, exposure ratio α and leverage ratio β. So the diversification of the financial system is reflected by the variation of these parameters. Table 1 summarizes the variations that are considered in our simulation study. It is worth noting that we also assume that all banks in the same financial system have the same liquidation ratio.

Finally, to evaluate the magnitude of financial contagion, we introduce two measure indicators. First, we define financial contagion as an event where at least one bank falls into default as a response to an initial failure. Following this definition, two measure indicators are derived: 1) contagion probability, defined as the probability of a contagion event occurring (equation 10); and 2) the extent of contagion, defined as the average number of banks defaulting due to the initial failure in a contagion event (equation 11). These indicators reflect the stability or the robustness of a financial system and, therefore, are suitable gauges of the magnitude of financial contagion. Contagion probability, in particular, indicates the susceptibility of a financial system to experience financial contagion, while the extent of contagion shows the fragility of a financial system. In the following subsections, we present the computational results, which are performed via 1,000 simulations based on these two measure indicators.

### 5.2. Simulation Results

In this subsection, we report the computational results of simulation experiments on the topology structure of random networks according to the contagion algorithm. Figures 4 and 5 show one realization of the financial network, where the probability P, α, and β equal 0.03, 0.2, and 0.05, respectively. Figure 3 shows the density of banks’ internal assets and the best fits for the distribution. Figure 4 reports the probability of net position and the best-fitting distribution for it, where net position is the difference of internal assets and internal liabilities of a bank.

### 5.2.1. The Probability P and Contagion

We first investigate the effect of probability P, which denotes

\[
\text{Contagion Probability} = \frac{\text{Number of contagion events observed}}{\text{Number of total experiments}}
\]

\[
\text{Extent of Contagion} = \frac{\text{Number of defaulted banks induced by contagion}}{\text{Number of contagion events observed}}
\]
the probability of forming links between each couple of nodes when constructing a financial network. Figure 5 shows the alteration of the contagion probability and the extent of contagion when varying the probability $P$. Here, we also vary the leverage ratio $\beta$ from 0.01 to 0.05. Our first finding is that both the contagion probability and the extent of contagion decrease as probability $P$ increases, regardless of the alteration of $\beta$. In particular, there is a sharp drop when probability $P$ varies from 0.05 to 0.2, approximately. Moreover, considering the same probability $P$, we observe that the higher the value of leverage ratio $\beta$, the lower the contagion probability and the extent of contagion. These observations show the negative influence of the probability $P$ and leverage ratio $\beta$ on the financial contagion.

The negative relationship between probability $P$ and financial contagion can be understood as follows: for a random network, the average degree is approximately $(N - 1)P$. So, the average degree increases as the probability $P$ grows, which reflects a higher level of connectivity in the network; the high level of connectivity indicates that the shocks experienced by defaulted banks can be shared or absorbed by more banks, thus lowering the contagion probability and the extent of contagion. We conclude that the higher the value of probability $P$, which denotes a more stable financial system, the lower the probability of contagion and the lower the extent of contagion. With regards the negative relationship between leverage ratio $\beta$ and financial contagion, the hypothesis is simple: a higher value of leverage ratio $\beta$ reflects a higher capital buffer. This situation suggests that banks can absorb more of the risks induced by other banks. It also leads us to conclude that a financial system with a high leverage ratio is more robust due to the negative influence on financial contagion.

5.2.2. Exposure Ratio and Contagion. Figure 6 depicts the effect of exposure ratio on financial contagion. We find that both the contagion probability and the extent of contagion increase as the exposure ratio grows. For example, when leverage ratio $\beta$ equals 0.03, the contagion probability changes from 0.18 to 0.67, approximately, and the extent of contagion rises from 0 to 400. The probable reason for this is that a high exposure ratio reflects a high risk for banks because it indicates that more assets are held by other banks. From another perspective, the exposure ratio measures the concentration of a bank’s assets. A high exposure ratio implies a lower concentration, so there is a greater effect when failure hits the banks’ counterparty.

However, there are two special cases. In the first case, when the leverage ratio $\beta$ equals 0.01, the contagion probability is always 1 and the extent of contagion is almost 100, although the exposure ratio varies from 0.2 to 0.4. The reason for this is that the financial network is so fragile that it cannot bear any shocks due to a low leverage ratio. In the second case, the leverage ratio $\beta$ equals 0.04 or 0.05, while there is a distinct change in contagion probability. The extent of contagion is almost never altered and this situation implies that financial contagion can occur but to a small extent. The underlying reason is obvious: a high leverage ratio denotes a high level of stability of a financial network, which indicates that the initial idiosyncratic shocks can be absorbed during the first few stages of the contagion process.

5.2.3. Liquidation Ratio and Contagion. Finally, we investigate the effect of the liquidation ratio on financial contagion. The liquidation ratio reflects the proportion of repayments for internal liabilities when a bank is forced to liquidate. The liquidation ratio can also be considered as a measure of the magnitude of the shocks: the higher the liquidation ratio, the lower the magnitude of the shock because a high liquidation ratio indicates that more internal liabilities can be repaid.
Figure 7 shows the changes in the contagion probability and the extent of contagion when the liquidation ratio varies. We find that both the contagion probability and the extent of contagion decrease when the liquidation ratio increases. As discussed above, the reason for this is that high liquidation denotes that the magnitude of shock is small, so the financial contagion is contained. Again, there are two special cases, the first being where the financial system is fragile and the leverage ratio $\beta$ equals 0.01, and the contagion probability and extent of contagion are almost 1 and 1000, respectively; the other is where the financial system is stable when leverage ratio $\beta$ equals 0.04 or 0.05, and the extent of contagion is almost zero.

**Figure 7. The influence of liquidation ratio on financial contagion**

### 6. Discussion and Conclusion

In the past few decades, global financial systems have seen considerable growth in size, complexity, and diversification. However, our understanding of the mechanisms of these systems has not necessarily kept pace. The recent financial crisis has demonstrated that the modern financial structure can amplify and disseminate financial distress on a global scale. Motivated by this situation, in this study we analyze how the topology of a financial network and the balance sheet structure affect financial contagion, which is evaluated by the contagion probability and the extent of contagion, by simulation studies based on a simple contagion algorithm. In detail, by considering the financial systems as “financial ecosystems” and applying the logic of the extinction analysis, we model and analyze financial contagion in a financial system where a large number of financial institutions are connected by direct balance sheet linkages owing to their lending or borrowing relationships. We find that financial contagion weakens as the connectivity of the network grows via the increase in probability $P$. A high level of connectivity indicates that the shock of defaulted banks can be shared or absorbed by more counterparties, so a financial system with a higher probability $P$ is more stable or robust. As for the structure of the balance sheet, which is determined by exposure ratio $\alpha$ and leverage ratio $\beta$, we find that exposure ratio has a positive relationship with financial contagion, but there is a negative relationship for leverage ratio and financial contagion. The exposure ratio measures the concentration of bank’s asset. A high exposure ratio reflects a low concentration, which means that a bank exposes its counterparty to more risks. The leverage ratio determines the magnitude of a bank’s capital buffer, namely, its capacity to absorb shocks. Finally we investigate the role of the liquidation ratio, which evaluates the magnitude of the shocks, on financial contagion. The results show that both the contagion probability and the extent of contagion decrease when the liquidation ratio increases.

Our study partly clarifies the interplay between the network topology and financial integration in disseminating financial contagion. Drawing analogies with the dynamics of ecological food webs, we view the financial systems as “financial ecosystems,” which opens a new perspective on the study of financial contagion. Of course, there are obvious differences between ecosystems and financial systems. For example, in a financial system, there are at least two kinds of incoming links (deposits and internal liability) and two kinds of outgoing links (external assets and internal assets). Another difference is that factors other than failure induced by the lending-borrowing relationship can distress financial institutions. One such factor is “fire sales” where the initial bank’s loss of value for one asset is likely to cause the depreciation of that asset, which in turn can transmit a “liquidity shock” to all other institutions holding the same asset. Another factor is “liquidity hoarding,” where the failure of one institution induces other institutions to take a precautionary policy to increase their capital hoarding by calling in loans. Although these differences exist, some scholars agree that lessons from the ecosystem can be applied to the financial sphere [41-44]. Finally, this study also provides implications for the regulation of financial systems. For example, the regulation of financial stability should seek to minimize the risk of failure not only of individual institutions but of the whole financial system. The strategy of diversification seems to be a sensible solution for sharing risk from the perspective of individual institutions; however, diversification may not be optimal viewed from the systemic perspective, and can even generate a bad result.

Some factors are not taken into account in this study. For a financial network, we assume that banks are randomly connected, but this may not be a reflection of reality because there are many reasons...
why banks lend or borrow money, such as a bank’s credit rating. Therefore, the network topology might not be determined by random connections. For example, Chinazzi, Fagiolo et al. find a core-periphery structure in the International Financial Network (IFN) architecture [45]. The exposure and leverage ratios also may not be the same for all banks. Those factors could be investigated in future studies. Other interesting problems also worth studying include the role of government intervention and bailout under financial crisis conditions and how to respond to individual institutions to mitigate contagion.

7. Acknowledgements
This research is supported by a GRF grant (no 193213) from the Research Grants Council of Hong Kong Special Administrative Region and a development grant (no ZDSYS2014-0509155229805) from the Science and Innovation commission, Shenzhen. We would like to thank the anonymous HICSS-49 reviewers whose constructive comments let us to improve this paper.

8. References