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*Research Article*

# The Stability of Banking System with Shadow Banking on Different Interbank Network Structures

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With the rapid development of the financial market, the outbreak of systemic risk is affected by many factors, among which shadow banking is considered to be the essential reason to cause financial crisis and destroy the stability of the banking system. In view of the stability of the banking system, considering shadow banking, interbank lending, and complex relationships between banks, a dynamic complex interbank network model with shadow banking under different network structures is proposed. Based on the model, the effects of ROI, investment periods, average deposit, deposit interest rate, the density of shadow banks, and asset loss are studied quantitatively, and the sensitivity and difference of the banking system with shadow banking under different interbank networks are compared and analyzed. The findings indicate that the spread of systemic risks between banks is closely related to the interbank network structures. With the relatively concentrated interbank network structure, it is easier to increase the probability and degree of risk contagion. Under the random, small-world, and scale-free networks, the random network has the strongest ability to resist and absorb risks, while the small-world network is the weakest. However, once the banking network suffers a big shock, excessive risk will directly break through the protection of the banking network, detonate the systematic risk, and destroy the stability of the banking system with shadow banking. This study contributes to a future empirical research agenda on the topic. Moreover, it gives a reference for policymakers and regulatory authorities to prevent systemic risk introduced by shadow banking.

## 1. Introduction

Banking system is a crucial part of modern finance and an indispensable financial subject for maintaining the stable operation of the financial system. Through the interbank market, complex relationships in the form of lending, payment, settlement, discount, acceptance, guarantee, and so on are formed by banks. On the one hand, such complex relationships can make up for the liquidity shortage of banks on time and maintain the stability of the banking system [1, 2]. On the other hand, once a certain bank in the system is impacted and goes bankrupt, this risk will also be transmitted to other banks through the complex interbank relationships, having an effect on the banking system [3, 4]. Therefore, the complex relationship is one of the key factors that cause the fluctuation of the banking system. Employing the complex network theory to describe the interrelationship among bank agents and constructing the complex network of the interbank market has aroused extensive attention of scholars.

In the context of global banking crises, as a carrier of facilitating liquidity exchange [5] and a potential path for risk contagion [6, 7], the interbank network plays a non-negligible role in maintaining the stability of the banking system [8]. Existing research mainly focuses on the interbank network structure [9, 10]. For example, Allen and Gale [11] established a financial contagion model and pointed out that when the banking system faces liquidity shocks, the complete market structure can achieve the optimal risk-sharing of the system better than the incomplete interbank structure. Casser and Duffy [12] confirmed that the risk contagion speed of the local interbank network is slower than that of the globally interbank network, but the liquidity level in the system is lower. Duffy et al. [13] considered complete versus incomplete networks of banks and found that the complete network structure is significantly less

vulnerable to financial contagions than the incomplete network structure under a high liquidation cost. Aleksiejuk et al. [14] proposed a two-dimensional directed interbank network model and found that there is a critical threshold for the average concentration of interbank deposits, and the probability of bank failure at the threshold obeys a power-law distribution. Iori and Jafarey [15] built an interbank network model based on random networks and stressed that the homogeneous interbank market makes the banking system more stable, while heterogeneous banks may cause a chain reaction of contagion between banks. Nier et al. [16] also constructed a simple hierarchical network model based on random networks and observed that a more centralized banking system is often more fragile. Linardi et al. [17] analyzed the interbank network using a dynamic latent space approach and captured the core-periphery structure of financial networks. By investigating the impact of the banking network structure, market liquidity, and idiosyncratic shocks on the stability of the banking system, Gai and Kapadia [18] pointed out the banking system exhibited a robust-yet-fragile tendency. Moreover, Lenzu and Tedeschi [19] established an agent-based interbank network model, which compared the stability of the banking system under the structure of the random network and the scale-free network. The results showed that, in the case of heterogeneity, the random network structure is more stable than the scale-free network structure. Caccioli et al. [20] analyzed the effect of different interbank network structures on the stability of the banking system and found that the scale-free network has better flexibility, but its stability with regard to the banking system is also significantly lower than other networks. Zhang et al. [21] studied the default risk contagion in banking systems under two different network structures and pointed out the default risk contagion is much severer under the random network than the endogenous network. Georg et al. [22, 23] proposed an interbank network system that introduced the central bank as the lender of last resort and demonstrated that the money-center network is more resilient than the random network. Meanwhile, there is a growing body of research on the empirical analysis of the network structure of the interbank network. Soramaki et al. [24] studied the interbank debt connection in Fedwire and found that the interbank network in the United States has the characteristics of a small-world network. When analyzing the CHAPS of British, Becher et al. [25] pointed out that the path length of the British interbank network is close to that of the United States, and the British interbank network is also a small-world network. Souma et al. [26] discovered that the interbank network in Japan has scale-free structure characteristics. Edson and Cont [27] observed that the nodes of the Brazilian interbank network obey a power-law distribution and belong to a scale-free network. Iori et al. [28] found through researching the Italian real interbank lending data that the Italian interbank market network presents a random network structure. Sümer and Özyıldırım [29] used exposure data on the Turkish banking system to study the interbank network structure and showed that the core-peripheral structure centered on highly liquid large banks is the main interbank network structure.

Indeed, as the existing literature has highlighted, the interbank market is an important factor affecting the stability of the banking system. However, from the bubble and collapse of the financial market, the shadow banking has undergone a major dysfunction before and after the crisis. This change made shadow banking to be regarded as an international systemic risk transmitter and the important factor that undermines financial stability in times of crisis. The term shadow banking was coined by McCulley [30] and was picked up by policymakers [31]. According to the Financial Stability Board (FSB) [32], shadow banking is the credit intermediation that channels funding from depositors to investors through a range of securitization and secured funding techniques and may cause systemic financial risks and regulatory arbitrage risks. Although shadow banks conduct credit and maturity transformation similar to that of traditional banks, shadow banks are essentially fragile. Adrian and Ashcraft [33] pointed out that, unlike traditional banks under the policy safety net, the funds of depositors in shadow banks are not protected. Pozsar et al. [34] compared the size of shadow banking during the crisis and found that before the crisis, the size of shadow banking showed a sudden growth trend and reached a peak. Bernanke et al. [35] discussed that shadow banks use maturity transformation to avoid risks, but fragile assets and liabilities caused shadow banks to collapse excessively during the crisis, and systemic risks increased dramatically. By documenting the performance of shadow banking, Wiggers and Ashcraft [36] observed that shadow banks defaulted in large numbers in times of crisis, which destroyed the banking system stability. Nevertheless, Ross [37], Allen, and Gale [38] stressed that the financing expansion of shadow banking is in line with Pareto's optimal improvement, which can share part of the systemic risk and maintain the stability of the banking system. Colombo et al. [39] constructed a shadow banking model and emphasized that the form of propagation after the crisis shock would reduce the system to resist risks and the corresponding stability level of the banking system. An improved shadow banking model is proposed by Gennaioli et al. [40], and the results showed that investors ignore tail risk, which could make the banking system vulnerable to crisis shocks, but under rational expectation, shadow banking would help to resist systemic risk and maintain system stability. Moreira and Savov [41] built a macro-finance model of shadow banking and argued that shadow banking expands the liquidity provision as well as builds up the fragility of the system. Elgin and Oztunali [42] noted through a two-sector dynamic general equilibrium model that the relative size of shadow banking will influence the banking system's stability. Besides, Irani et al. [43] investigated the connections between bank capital regulation and the lightly regulated shadow banks. Loayza et al. [44] and Elias [45] qualitatively analyzed the effect of shadow banking on the banking system's stability from the perspective of the labor market and the money market fund, respectively.

Previous research on the impact of shadow banking on the banking system's stability has been carried out from the aspects of qualitative analysis related to changes in shadow

banks' characteristics and static analysis based on simple models. However, it did not consider the complex relationship between banks, that is, the complex interbank network, and failed to reveal the changes in the stability of the banking system with shadow banking under the dynamic evolution mechanism. As pointed out by the existing research, the complex interbank network not just presents a single network structure but also can be built as a variety of network structures. Different interbank networks have different abilities to contagion and resist risk. It is very meaningful to identify which interbank network used to construct the banking system with shadow banking can disperse and absorb risk more efficiently. To the best of our knowledge, there is no quantitative research on the impact of the sensitivity of different network structures on the stability of the banking system with shadow banking by proposing a variety of interbank network structures. Given the above problems, to explore the stability of the banking system with shadow banking more comprehensively and get rid of the limitation of the single interbank network structure, based on the complex network theory and the dynamic evolution of bank balance sheet, random network, small-world network, and scale-free network are, respectively, used to build the dynamic complex interbank network model with shadow banking. Then, the sensitivity and difference of the banking system with shadow banking under various network structures are compared and analyzed.

Unlike our previous research on the stability of the banking system with shadow banking under macroeconomic fluctuation [46], although the same model of the banking system with shadow banking is used in this paper, however, the interbank network structures are different. The contribution of this paper is that it is the first quantitative investigation into the impact of different interbank network structures on the stability of the dynamically evolving banking system with shadow banking. Compared with the current qualitative and static research, our paper fully considers the complex relationships between banks and the various connections, that is, the diversity characteristic of the interbank network structure, and proposes a dynamic interbank network model under different network structures to effectively simulate the dynamic operation and evolution of the banking system. This enables us to observe the changing trend of systemic risk under various interbank networks, compare and analyze which interbank network structure has a better ability to resist risk, thereby providing more valuable reference results for regulators and policymakers. The remainder of this paper is organized as follows. After this introduction, Section 2 describes the dynamic complex interbank network model with shadow banking under different interbank networks. Section 3 presents the main results, and Section 4 provides a conclusion.

## 2. The Model

A dynamic, complex interbank network model under different interbank networks for the banking system with shadow banking is constructed in this paper. The structure of the banking system with shadow banking is shown in Figure 1. The model takes into account the impact of different interbank network structures (the random network, the small-world network, and the scale-free network), the dynamic evolution of the bank balance sheet, and the central bank as the liquidator and supporter on the stability of the banking system with shadow banking.

*2.1. Interbank Network Structures.* The interbank network is a complex network with multiple characteristics. Hence, to explore the stability of the banking system with shadow banking as comprehensively as possible, we use the random network, the small-world network, and the scale-free network, respectively, to build the interbank network of the banking system, as shown in Figure 1(a). The nodes represent the banks, and the edges between the nodes represent the interbank credit lending relationship. Apart from the central bank, there are $G$ bank nodes in the banking system, among which the number of traditional bank nodes is U, and the number of shadow bank nodes is V, that is, $G = U + V$. At any time, there a finite number of functioning banks. Different interbank network structures may have different influences on the risk contagion.

Inspired by Iori et al. [15], Nier et al. [16], and Georg [23], we first establish the interbank lending network based on the random network. The interbank credit lending relationship is represented by a binary matrix $X$, where $X_{i,j} = 1$ or $X_{i,j} = 0$. $X_{i,j} = 1$ shows that there is a credit connection between bank $i$ and bank $j$, and $X_{i,j} = 0$ indicates there is no credit connection. At each time $t$, a bank connects to any other bank with the probability $c_{i,j}$ $(0 \le c_{i,j} \le 1)$, which forms a new random network of potential interbank lending relationships. The independent and opacity characteristics of shadow banks should be noted [47]; therefore, no credit connection between shadow banks is constructed, as shown in Figure 1.

Next, referring to the work of Watts et al. [48], we propose the interbank lending network based on a small-world network. Firstly, there are $G$ banks, and a one-dimensional interbank network with $K$ nearest neighbors for each bank is formed, in which there is no coupling relationship between shadow banks. Then, at each time $t$, randomly reconnect one of the endpoints of each edge with the probability $p$. When reconnecting, it should not only ensure that there is no self-loop and double edge but also ensure that there is no connection between shadow banks.

We also establish the interbank lending network based on the scale-free network referring to Barabasi et al. [49]. Starting from the interbank network with $m_0$ independent bank, a new bank with $m$ edges is introduced at each time $t$, where $m_0 \ge m$. Simultaneously, the probability $\pi_i$ of the new bank $i$ connected to the old bank $j$ has a relationship with the degree $k_i$ and $k_j$ of the bank $i$ and bank $j$, respectively, that is, $\pi_i = k_i / \sum k_j$. There is no connection between shadow banks.

*2.2. The Banking System with Shadow Banking.* Based on the research of Pan and Fan [46], the banking system with shadow banking is constructed in this paper. Traditional banks, shadow banks, and the central bank are included in

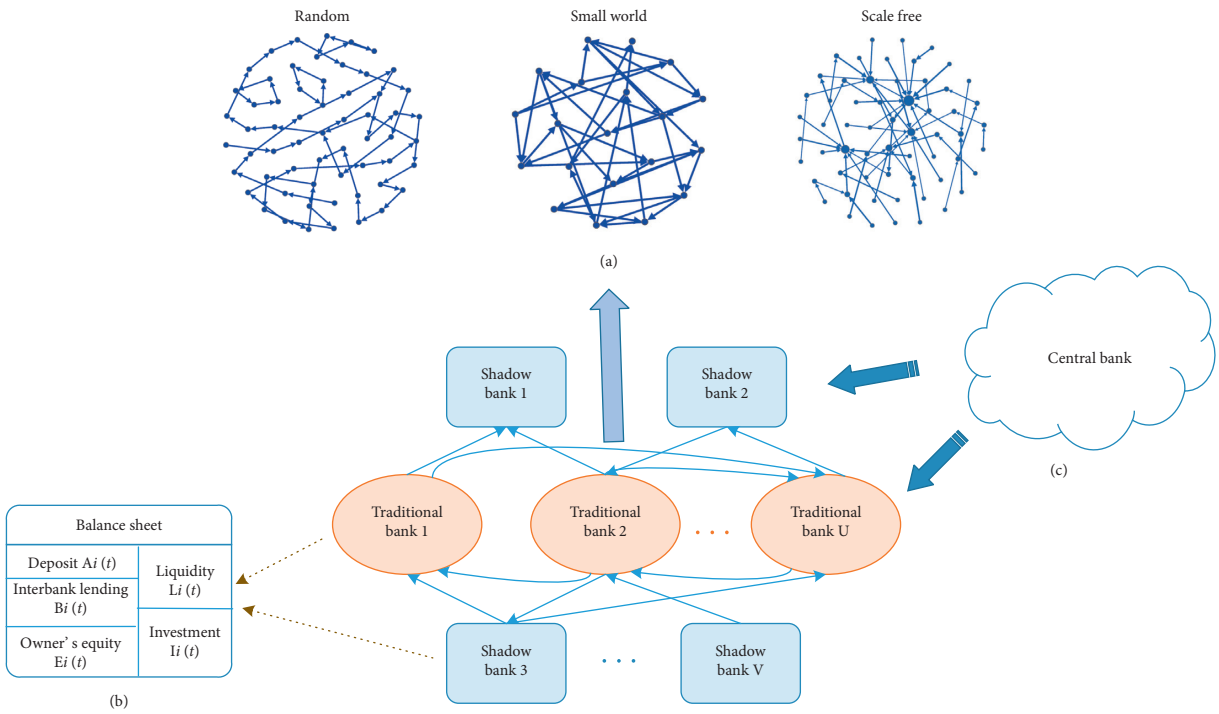


Figure 1: The structure of the banking system with shadow banking under various interbank networks.

the proposed model. The behaviours of each bank are described by the bank balance sheet. Different from previous studies, the bank balance sheet in this paper is dynamically evolved over time. As shown in Figure 1(b), the asset in the bank balance sheet is composed of the liquidity $L$ and investment $I$, and the liability consists of deposit $A$, interbank lending $B$, and owner's equity $E$. The initial bank balance sheet of bank $i$ is described as follows:

$$L_i(t-1) = A_i(t-1) + B_i(t-1) + E_i(t-1) - \sum_{k=1}^{\tau} I_i(t-k), \tag{1}$$

where $L_i(t-1)$ is the liquidity of bank $i$ at time $t-1$; $A_i(t-1)$ and $E_i(t-1)$ are the deposit and the owner's equity of bank $i$ at time $t-1$, respectively; $\sum_{k=1}^{\tau} I_i(t-k)$ is the total investment of bank $i$ in $\tau$ investment periods. $B_i(t-1) = \sum_{k=1}^{G} b_{i,j}(t-1)$ is the total interbank lending amount of bank $i$ at time $t-1$. At time $t-1$, $b_{i,j}(t-1) > 0$ denotes the amount borrowed by bank $i$ from bank $j$, $b_{i,j}(t-1) < 0$ means bank $i$ lends to bank $j$, that is, $b_{i,j}(t-1) = -b_{j,i}(t-1)$. $b_{i,j}(t-1) = -b_{j,i}(t-1) = 0$ shows that there is no lending relationship between banks.

The operation of the banking system with shadow banking is regarded to be in discrete time, which is denoted by $t$, $t = 0, 1, 2, \ldots, T$. It is assumed that interbank lending between banks within the system only relies on the latest bank balance sheet. At time $t$, the balance sheet of bank $i$ is updated to

$$L_i(t) = L_i(t-1) + \left(A_i(t) - A_i(t-1)\right) - r_a A_i(t-1) + \rho \sum_{k=1}^{\tau} I_i(t-k) + I_i(t-\tau), \tag{2}$$

where$r_a A_i(t-1)$ is the interest paid by the bank$i$ to depositors,$r_a$ is the deposit interest rate (for simplicity, we use the same terminology "deposits" to represent deposits for traditional banks and funding for shadow banks). In practice, $A_i(t) = |\overline{A} + \overline{A}\delta_A \varepsilon_t|$, where $\overline{A}$ is the mean of random deposits of all banks, $\overline{A}\delta_A$ is the standard deviation of random deposits of all banks, and $\varepsilon_t \sim N(0,1)$. $\rho \sum_{k=1}^{\tau} I_i(t-k)$ and $I_i(t-\tau)$ are the income of bank $i$ from the investment and the expiry investment, respectively, $\tau$ is the investment cycle, $\rho$ is the return on investment of each period. The return on investment $\rho$ can be expressed as

$$\rho = \begin{cases} 0, & 1-q, \\ \rho, & q, \end{cases} \tag{3}$$

where $q$ is the investment recovery probability. After bank $i$ receives the investment profit, it may carry on the dividend and reinvestment. The dividend and reinvestment of traditional banks refer to the model of Iori et al. [15] and is not repeated here. This paper mainly describes the business activities of shadow banks. At time $t$, the dividend of shadow bank $i$ satisfies the following conditions:

$$D_i(t) = \max\left[0, \min\left[\theta\left(\rho \sum_{k=1}^{\tau} I_i(t-k) - r_a A_i(-1)\right), \quad L_i(t)\right]\right], \tag{4}$$

where $\theta$ is the deposit ratio of shadow banks. After the dividend is paid, shadow banks need to invest the remaining liquidity fund to improve their profits. The investment $I_i(t)$ of shadow bank $i$ at time $t$ can be decided by the following equation:

$$I_i(t) = \min[\max[0, L_i(t) - D_i(t)], \omega_i(t)], \tag{5}$$

where $\omega_i(t)$ is the investment opportunity of shadow bank $i$ at time $t$, which is defined as $\omega_i(t) = |\overline{\omega} + \overline{\omega}\delta_\varphi \eta_t|$. $\overline{\omega}$ is the mean value of all shadow banks' investment opportunities, $\overline{\omega}\delta_\varphi$ is the standard deviation of all shadow banks' investment opportunities, and $\eta_t$ obeys the normal distribution $N(0, 1)$.

After dividends and investments, if a bank $i$ still has ample liquidity $L_i(t) \geq 0$ , the bank$i$ is a potential creditor bank, which can provide funds in the interbank market. Conversely, if bank$i$ lacks liquidity $L_i(t) < 0$ it is a debtor bank, it needs to borrow from the interbank market in order to maintain its normal operation. When the lending from the interbank market is sufficient to repay the previous loan, the debtor bank can continue its operation. If the debtor bank fails to borrow enough money from the interbank market to repay its arrears and deposit interest, it will be labelled as a member of the default set $D$ and wait for central bank clearance or support, as shown in Figure 1(c).

The operations of traditional banks are supervised by the central bank, while the activities of shadow banks are free from the scope of the central bank regulation [31]. So, only traditional banks can receive support from the central bank. At time$t$, the assistance of the central bank to the traditional bank $i$ is:

$$H_i(t) = \begin{cases} R_i(t) - L_i(t), & R_i(t) > L_i(t), \\ 0, & \text{otherwise}, \end{cases} \tag{6}$$

where $R_i(t) = \beta A_i(t)$ is the legal deposit reserve required by traditional bank $i$ at time $t$, the deposit reserve ratio is $\beta$. When $R_i(t) > L_i(t)$, $R_i(t) - L_i(t)$ is the assistance of the central bank to the traditional bank $i$. Meanwhile, the liquidity and debts of the assisted traditional bank $i$ both turn to 0 ($B_i(t) = 0$ and $L_i(t) = 0$), the traditional bank $i$ goes out of the default set $D$ and rejoins into the operation of the banking system. Otherwise, the traditional bank $i$ pays legal deposit reserve by itself and continues to operate. When the illiquid bank $i$ is a shadow bank, it is cleared by the central bank and shadow bank $i$'s debts are paid proportionally [50]. The debt repayment is calculated as follows:

$$C_{i,j}(t) = \begin{cases} E_i(t) * \dfrac{b_{i,j}(t)}{\sum_{j=1}^{f} b_{i,j}(t)}, & \text{if } b_{i,j}(t) > 0 \text{ and } E_i(t) > 0, \\ 0, & \text{otherwise}, \end{cases} \tag{7}$$

where $E_i(t)$ represents the owner's equity of the shadow bank $i$, $b_{i,j}(t)$ is the interbank borrowing amount between the shadow bank $i$ and traditional bank $j$, and $\sum_{j=1}^{f} b_{i,j}(t)$ is the total amount of the shadow bank $i$ borrowed from no more than $f$ traditional banks ($f$ is the maximum number of traditional banks that can be borrowed by a shadow bank). Then, the debts of shadow bank$i$ update to 0 ($B_i(t) = 0$), and it remains a member of default set $D$ for all subsequent time.

*2.3. Dynamic Update Algorithm.* The dynamic update algorithm is rendered to determine how the banking system with shadow banking evolves from one state to another. The algorithm is divided into 4 steps that are briefly described as follows:

(i) Step 1: determine and build the interbank network. Random network, small-world network, or scale-free network is constructed according to the demand, and the corresponding initial parameters and variables are, respectively, set.

(ii) Step 2: update the liquidity of the bank and then the dividend and investment. According to (2), the liquidity of the bank $i$ is calculated at time $t$. If the bank $i$ with sufficient liquidity ($L_i(t) \geq 0$), it carries out dividend distribution $D_i(t)$ and investment $I_i(t)$ according to (4) and (5). If the bank $i$ with liquidity shortage ($L_i(t) < 0$), it will go for interbank lending.

(iii) Step 3: interbank lending in the system. After dividend $D_i(t)$ and investment $I_i(t)$ are operated, the liquidity of bank$i$ updates to $L_i(t) = L_i(t) - D_i(t) - I_i(t)$. If the liquidity of bank$i$ is positive, bank $i$ is a creditor bank, which can lend its liquidity to illiquid banks. Otherwise, the bank $i$ is a debtor bank that needs to borrow from flush liquidity banks to pay its loans. After creditor banks and debtor banks are determined, interbank lending activities begin. If the debtor bank $i$ can borrow sufficient funds from the creditor banks to repay the previous loan and interest, i.e., $L_i(t) - (1 + r_b)B_i(t-1) \geq 0$ ($r_b$ is the interbank market interest rate), it can continue to operate; if the debt bank $i$ cannot borrow sufficient funds to repay the previous loan and interest, i.e., $L_i(t) - (1 + r_b)B_i(t-1) < 0$, it becomes a member of the default set $D$ and is then supported or cleared by the central bank.

(iv) Step 4: supported or cleared by the central bank. At time $t$, if the default bank $i$ is a traditional bank, it is aided by the central bank according to (6), then comes out of the default set $D$ and continues to evolve in the system; If the default bank $i$ is a shadow bank, it is cleared by the central bank according to (7) and then remains a member of default set $D$ for all subsequent time. The aided or cleared bank $i$'s liquidity and debts are both updated to 0, i.e., $L_i(t) = 0$ and $B_i(t) = 0$.

## 3. Simulation and Analysis

*3.1. Model Parameters.* To conduct the simulation analysis of the above model, firstly, it is necessary to give the values of model parameters. The maximum simulation time step is set

to 100 (within 100 time steps, the dynamic characteristics of the banking system network can be fully embodied), and referring to the studies of Iori et al. [15], Watts et al. [47], and Barabasi [48], as well the actual banking system, the parameters are set in Table 1.

The systemic risk of the banking network system at time $t$ is determined by the internal state and parameters of the network system. In order to effectively depict the systemic risk of the banking network system, the average number of default banks in $[t+1, t+W]$ time range is the normalized value $R(t)$.$R(t)$ Can be calculated as follows:

$$R(t) = \frac{1}{\mathrm{WO}_e} \sum_{i=1}^{O_e} \sum_{j=t+1}^{t+W} \frac{Y_j^i}{Y_j^i + Z_j^i}, \tag{8}$$

where $W$ is the time interval, and the average proportion of default bank in the future $W$ time can indicate the systemic risk of the system at a certain moment. $W$ is set to$W = 10$ in this paper. $O_e$ is the time number of the simulation. $Y_j^i$ and $Z_j^i$ is the number of default bank and survival bank at time $j$ in the $i$th simulation, respectively. According to the study of Caccioli et al. [51], more than 5% of bank failures in the banking network system consider that risk contagion occurs, that is, risk contagion occurs in a wider range of crisis phenomena. Therefore, given the parameters, assuming that the total number of experiments is $n$ and the number of risk contagion is $n_1$, the average probability of risk contagion (PC) in the banking system is

$$\mathrm{PC} = \frac{n_1}{n}. \tag{9}$$

Record the number of default banks at the $i$th risk contagion occurs as $n_2^i$, then the average degree of risk contagion (DC) is expressed as follows:

$$\mathrm{DC} = \frac{\sum_{i=1}^{n_1} \left(n_2^i / G\right)}{n_1}. \tag{10}$$

Intuitively, $R(t)$ reflects the dynamic change of systemic risk of the banking network with time.PC and DC analyze the risk contagion in the banking network system from the perspective of statistics. The comprehensive application of $R(t)$, PC, and DC carry out a more complete risk analysis on the banking network system with shadow banking.

## 4. Results

The evolutionary process of a bank under three interbank networks is shown in Figure 2. The liquidity, owner's equity, investment, and dividend of banks are all dynamic changes. The banking system evolves over time. In the evolutionary process of the banking network, some banks will go bankrupt and lead to the chain bankruptcy of other banks in the same network. As shown in Figure 2(a), under the random network, the bank owner's equity increases through continuous investment income, and the liquidity is relatively stable. However, at the end of the network evolution, the bank investment has shrunk, assets have been damaged, the owner's equity has fallen to a negative value, liquidity is insufficient, and eventually results in bankruptcy. Figures 2(b) and 2(c), respectively, show the evolution of a bank under the small-world network and scale-free network. Unlike the random network, the time of significant change in bank liquidity, owner's equity, investment, and the dividend of the small-world network and scale-free network are advanced. This shows that a bank's failure may be caused by two aspects. On the one hand, the bank's own poor business strategy makes its income insufficient to pay its deposit interest and loans, leading ultimately to bankruptcy. On the other hand, when a bank in the system fails due to improper operation, it will quickly infect other banks through the interbank network, resulting in a large number of insolvent banks, a huge decline in liquidity, and reduced risk resistance. Different interbank networks have different contagion ability. It can be found from above that the circumstance of a bank is not only related to its own investment strategy but is also closely related to the interbank network structure.

Table 1: Benchmark parameter of the model.

| Parameter | Description | Benchmark value |
|---|---|---|
| $G$ | The total number of banks | 400 |
| $U$ | The number of traditional banks | 100 |
| $V$ | The number of shadow banks | 300 |
| $c$ | Connection probability | 0.03 |
| $K$ | Nearest neighbours for each bank | 2 |
| $p$ | Probability of reconnect one endpoints of each edge | 0.02 |
| $m_0$ | Number of independent banks started | 50 |
| $m$ | Edges of a new bank | 2 |
| $f$ | The maximum number of traditional banks that can be borrowed by a shadow bank | 3 |
| $I$ | Initial investment | 500 |
| $\tau$ | Investment periods | 3 |
| $\theta$ | Deposit ratio | 0.3 |
| $\overline{\omega}$ | Average investment opportunities | 500 |
| $\rho$ | Return on investment (ROI) | 0.045 |
| $q$ | Investment recovery probability | 0.85 |
| $\delta_\varphi$ | Investment volatility | 0.35 |
| $\overline{A}$ | Average deposit | 1000 |
| $\delta_A$ | Deposit volatility | 0.25 |
| $r_a$ | Deposit interest rate | 0.004 |
| $r_b$ | Interbank market interest rate | 0.008 |
| $\beta$ | Deposit reserve ratio | 0.35 |

Figure 3 shows the changes in the survival ratio with time under three interbank networks and the corresponding systemic risk. It can be seen from Figure 3(a) that under any kind of interbank network structure, bank default occurs in the system in the first step, and the bank survival rate begins to decline. This is due to the different initial state and operation strategies of each bank in the banking system. However, unlike the slow decline of the bank survival rate of the random network, the bank survival rate of the small-world network and the scale-free network have undergone significant declines at around 30 steps and 40 steps, respectively, until it was maintained at a low level. The

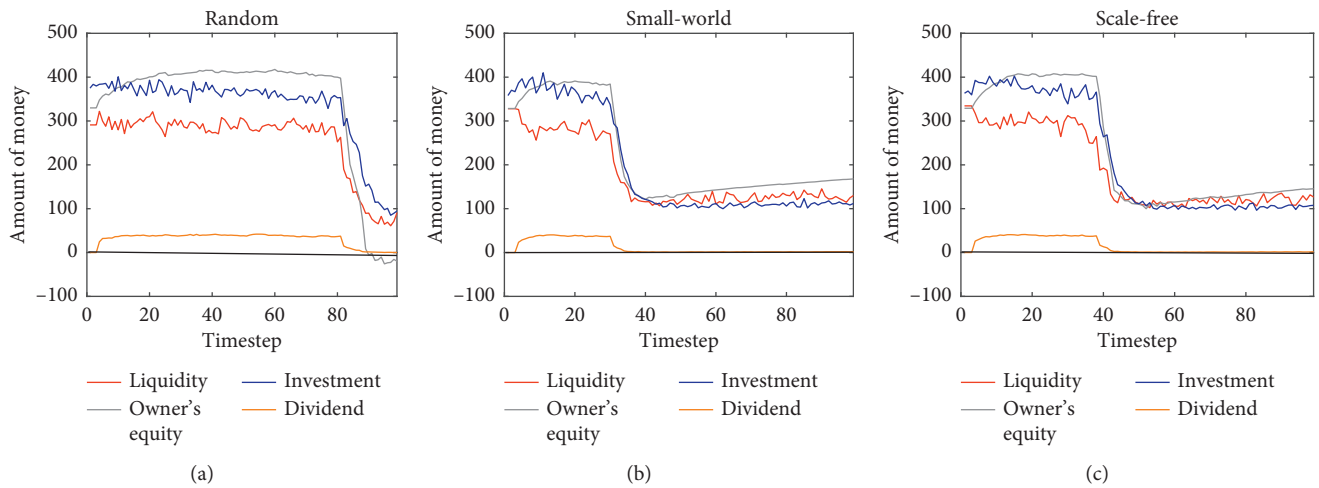


Figure 2: The evolutionary process of a bank under diverse interbank networks.

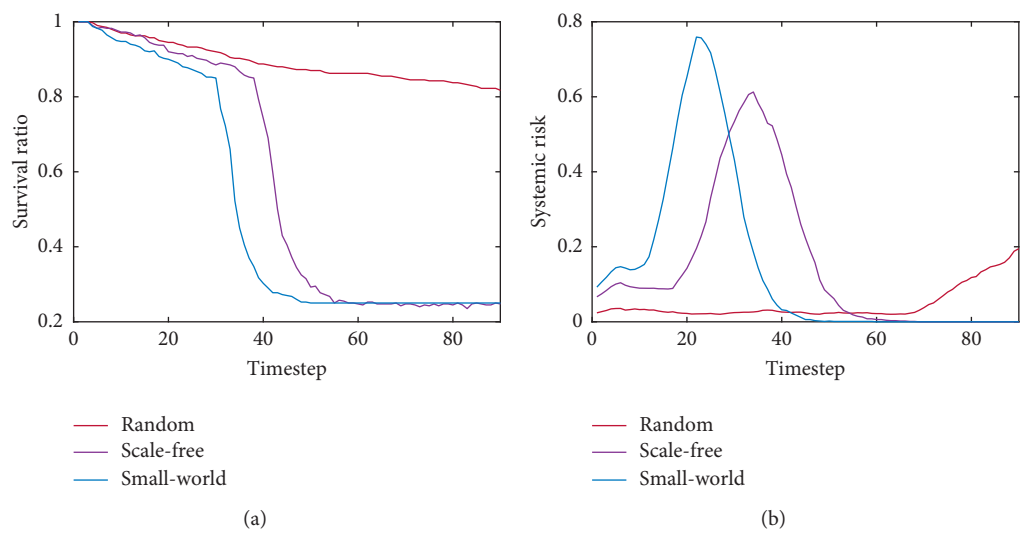


Figure 3: (a) Changes in the survival ratio of diverse interbank networks. (b) Dynamic changes in systemic risk of diverse interbank networks.

corresponding systemic risk Figure 3(b) shows that the banking system based on the small-world network has the largest degree of systemic risk, followed by the scale-free network, and its systemic risk has decreased. The banking system under the random network has always been relatively stable and has a low level of systemic risk. Obviously, from this, different interbank network structures will transmit different levels of systemic risk. This is due to banks establishing direct or indirect linkage through different interbank network structures. The random network randomly connects the banks, and the dispersed network structure can avoid the excessive concentration of risk, reduce the cumulative effect of risk, prevent the occurrence of bank default, and maintain the stability of the system. While under the small-world and the scale-free network structure, the linkage between banks is relatively close. If one bank bankrupts, it will easily lead to a domino effect of bankruptcy due to insolvency and lack of liquidity, accelerate the spread of contagion in the small-world network and the scale-free network, and then detonate systemic risk.

In the real financial system, the return on investment represents the overall situation of the current financial market. Therefore, we analyze the impact of ROI change on the systemic risk of the banking system with shadow banking under different interbank networks. Figures 4(a)–4(c) show the systemic risk with different ROI under different interbank networks. From Figures 4(a)–4(c), it can be seen that under the same ROI, the systemic risk of the random network is always lower than that of the small-world network and the scale-free network. With the increase in ROI, the outbreak time of systemic risk in the banking network is delayed, and the level of systemic risk declines. Among the three network structures, the systemic risk level of the random network and the scale-free network decreases significantly with the increase in ROI. For the small-world

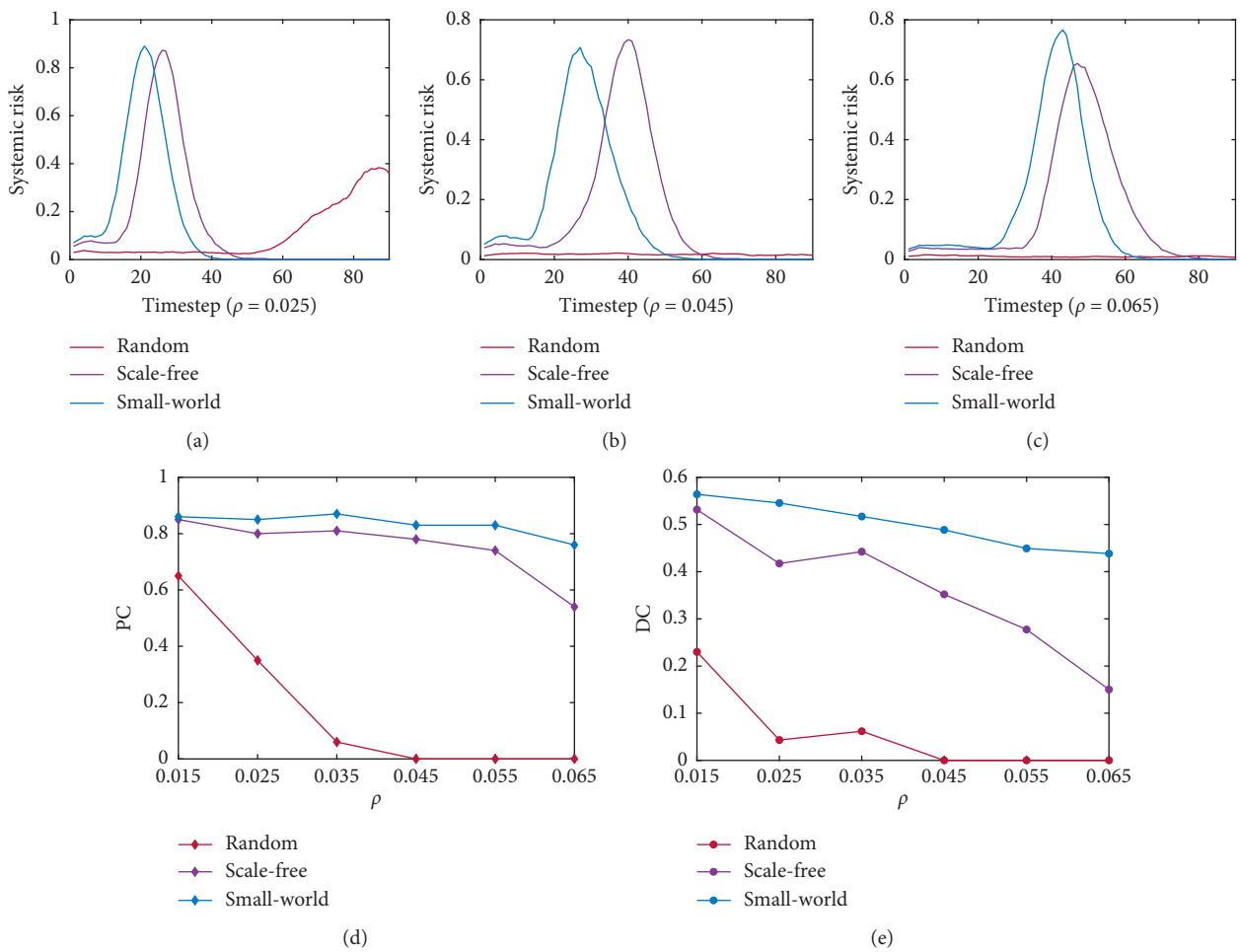


Figure 4: Evolution results of the diverse interbank networks under different ROI.

network, although the time of systemic risk outbreak gradually pushed from 20 steps to 40 steps as the ROI increases, the overall risk level decreases slowly and insignificantly. The explanation is that by increasing the ROI, a sufficient spread between the ROI and the deposit interest rate will be generated, increasing the overall profitability of the bank, which protects banks from illiquidity. Meanwhile, different interbank network structures determine different interbank lending relationships, which in turn determine the liquidity situation of the banking system and affect the stability of the banking system. Figures 4(d) and 4(e) are the average probability of risk contagion and the average degree of risk contagion of different interbank networks under different ROI. Figure 4(d) shows that when the ROI is small, the average probability of risk contagion of three networks is greater than 60%. When the ROI increases, the average probability of risk contagion of the random network drops sharply and drops to 0 when the ROI is 0.045. The average probability of risk contagion of the scale-free network decreases when the ROI exceeds 0.055. Only the average probability of risk contagion of the small-world network remains at a high level. It can be observed from Figure 4(e) that the average degree of risk contagion of the three networks all show a downward trend, but the average degree of risk contagion of the small-world network and the scale-free network is always higher than that of the random network. When the ROI is greater than 0.035, the average degree of risk contagion of the random network and the scale-free network decline obviously compared with the small-world network. When the ROI increased to 0.045, the average degree of risk contagion of the random network decreases to 0, and there is no systemic risk in the banking system with shadow banking under the random network. When the ROI is 0.065, the average degree of risk contagion of the scale-free network is less than 20%, and the systemic risk level reduces, but the small-world network still has a large average degree of risk contagion. The above results show that ROI change has an impact on the stability of the banking system with shadow banking. The sensitivity of different network structures to ROI change is different. The effect on increasing ROI is more significant under the random network, which results in a lower contagion risk because borrowers can get enough liquidity. In contrast, the effect on increasing ROI is weak under the small-world network and the scale-free network because the relatively centralized network structures make lenders overlap and results in limited liquidity available to borrowers. Therefore, the random network has a better resilience to risk.

In addition to ROI, the choice of bank investment strategy has a vital effect on the bank operation and maintaining the banking system stability. In the financial market, different investment products generally have different investment periods. The length of the investment period determines whether the liquidity of the bank is sufficient and thus determines the survival of the bank. Therefore, the reasonable choice of investment periods plays a key role in bank risk control. Figures 5(a)–5(c), respectively, show the systemic risk evolution results of different investment periods under different interbank networks. When the investment period is 2, the systemic risk of the banking system with shadow banking decreases from the small-world network to the scale-free network and then to the random network. The systemic risk value under the three networks is low and less than 1.5%, and the banking system is in a stable state. When the investment period extends to 4 and 6, the systemic risk begins to break out. The small-world network and the scale-free network almost simultaneously erupt with systemic risk, and the time of systemic risk outbreak of the random network also advances with the extension of the investment periods. This is because with the extension of the investment period, the level of liquidity in the banking system decreases. Banks that cannot recover their investment and cannot obtain sufficient funds to repay their debts through interbank lending default, and then the risk is transmitted to more banks through the interbank network, which induces the systemic risk outbreak, and the stability of the banking system is damaged. Figures 5(d) and 5(e) depict the average probability of risk contagion and the average degree of risk contagion of different investment periods under the three networks. We find that the average probability of risk contagion of the three networks increases with the extension of the investment period. When the investment period is greater than or equal to 4, the average probability of risk contagion under the three networks is more than 85%. Meanwhile, with the investment period from 2 to 6, the average degree of risk contagion of the three networks also gradually increased. The above results indicate that the three interbank networks are all sensitive to the change of the investment period, and an increase in the investment period produces an increase of systemic risk. To be specific, the long investment period will result in the decrease of the available liquidity scale in the system. In the process of interbank lending, borrowers are unlikely to get enough amount, and lenders may also default due to the risky loans, which lead to the decline in the bank's survival rate and accumulates the systemic risk. Therefore, setting a reasonable investment period is particularly essential for protecting the stability of the banking system with shadow banking.

Deposit is a necessary part of the bank balance sheet and the main source of funds. The spread between investment and deposit earns a bank's profit. Therefore, the profitability of the bank is affected by the deposit. Affected by macroeconomic fluctuations, the deposit of the bank always changes. Figure 6 describes the systemic risk evolution results of different average deposits under the three interbank networks. As shown in Figures 6(a)–6(c), the systemic risk of the three interbank networks all decreases with the increase of the average deposit. When the average deposit is 750, the three interbank networks have high systemic risk, and the small-world network has the highest systemic risk. When the average deposit is 1150, the systemic risk of the small-world network and the scale-free network decline significantly, and the systemic risk of the random network disappears. The reason is that the increase in the average deposit provides the bank with sufficient capital, increases liquidity, and reduces systemic risk. Therefore, the increase in the average deposit can improve the stability of the banking system with shadow banking. Figures 6(d) and 6(e) show the average probability of risk contagion and the average degree of risk contagion of different average deposits under the three networks. When the average deposit is less than or equal to 850, the small-world network and the scale-free network have a high and almost the same average probability of risk contagion, and the average degree of risk contagion is also at a high value. As the average deposit increases from 850 to 1150, the average probability of risk contagion and the average degree of risk contagion of three networks are gradually decreased, and the average probability of risk and the average degree of risk contagion of the random network change to 0 when the average deposit is 1150. The above results show that the change in the average deposit has a significant impact on the stability of the banking system with shadow banking. The higher average deposit results in a lower risk of insolvency and a wider range of liquidity fluctuation. Meanwhile, it indicates that different interbank networks have different elastic responses to resist systemic risk under the change of average deposit. Compared with the small-world network and the scale-free network, the random network enables a more balanced distribution of liquidity, guarantees the successful progress of interbank lending, and has a strong ability to resist systemic risk.

It is one of the necessary business activities for banks to pay deposit interest to depositors on schedule. Deposit interest is the main expenditure of banks, so the fluctuation of deposit interest rate will affect the liquidity of banks. Figure 7 gives the evolution results of the diverse interbank networks under different deposit interest rates. As shown in Figures 7(a)–7(c), with the increase of the deposit interest rate, the systemic risk of the three networks has all changed. In the process of the deposit interest rate changing from 0.003 to 0.005, the systemic risk of the random network and the scale-free network gradually increased, and the systemic risk of the small-world fluctuates at a high level. The timing of the outbreak of systemic risk in three interbank networks advances with the increase in the deposit interest rate. This points out that the interbank network is sensitive to the change of the deposit interest rate, which could impact the stability of the banking system to a certain extent. Figures 7(d) and 7(e) show that when the deposit interest rate changes from 0.003 to 0.004, the average probability of risk contagion of three networks increases, while the variation range of the average probability of risk contagion is relatively small in other deposit interest rates. This conclusion enlightens us: there is a deposit interest rate value with maximum contagion ability for the interbank networks.

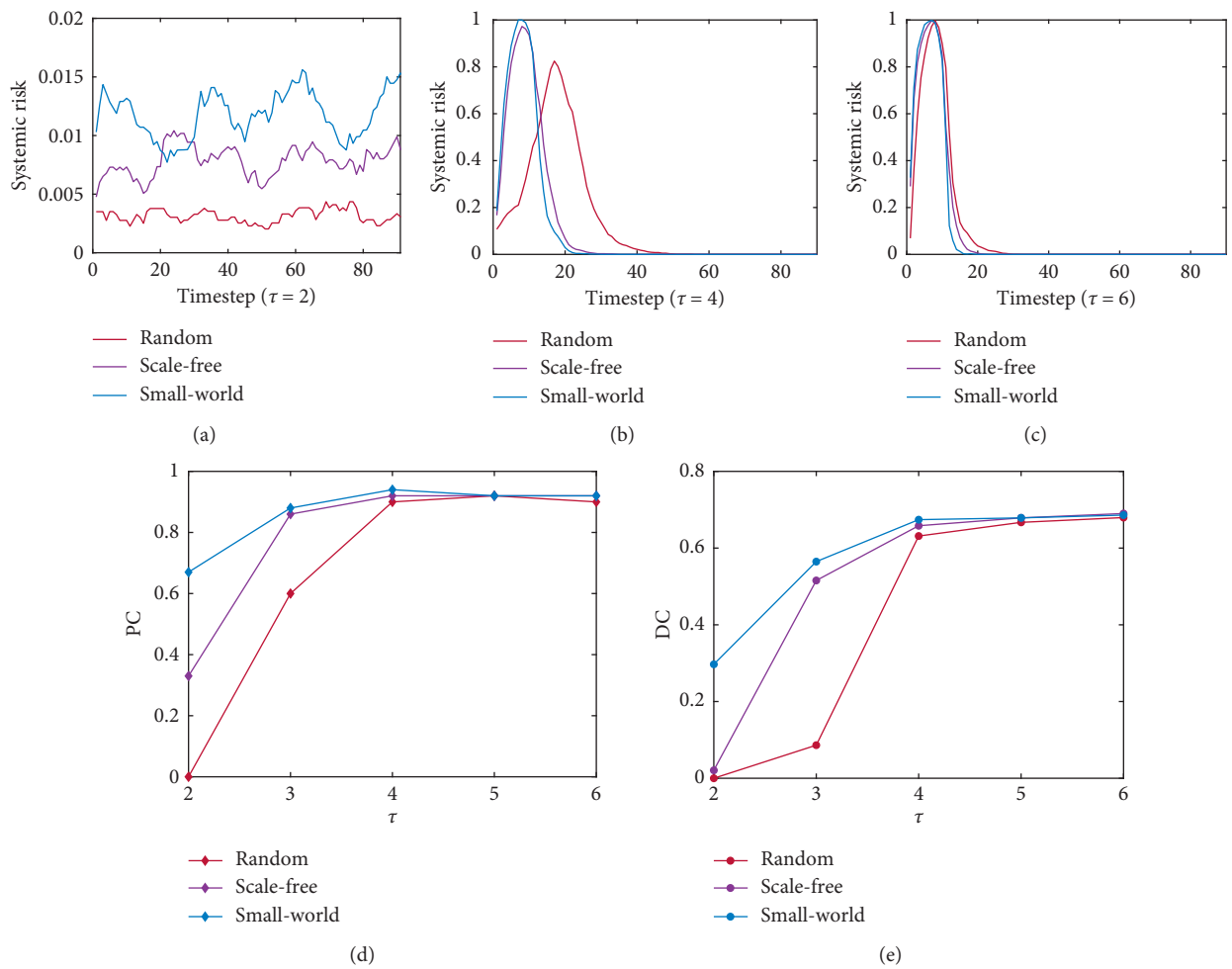


Figure 5: Evolution results of the diverse interbank networks under different $\tau$.

When the deposit interest rate reaches this value, the burdens of the debtor banks aggravate, the risk of insolvency increases, and thus there is a great shock on the banking network, which destroys the stability of the banking system. Meanwhile, among the three interbank networks, the risk contagion probability and risk contagion degree under the small-world network is much higher than that of the random network, because a more centralized interbank network is often more fragile [16]; much more banks default due to illiquidity or insolvency and can neither borrow nor lend in the interbank network.

Shadow banking is one of the main factors that induce financial crises. Therefore, in addition to the operational activities of banks, the density of shadow banking in the system also has an essential impact on the banking system. This paper defines the density of shadow banking $d$ as the ratio of the number of shadow banks $V$ to the total number of banks $G$ in the network, that is, $d = V/G$. Figure 8 shows the evolution results of the diverse interbank networks under different densities of shadow banking. In Figure 8(a), the systemic risk of the three networks is less than 2.5% when the density of shadow banking is 0.2, and the systemic risk of the small-world network and the scale-free network decrease with time. This shows that an appropriate amount of shadow banks can share the systemic risk and maintain the stability of the banking system. However, Figures 8(b) and 8(c) show that with the increase of the density of shadow banking, the systemic risk of the three interbank networks increases. Among them, the systemic risk of the small-world network and the scale-free network increases significantly, which due to the small-world network and the scale-free network are more concentrated than the random network, so the spread of risk is faster and wider. Figures 8(d) and 8(e) show the contagion probability and contagion degree of risk in three networks under the different density of shadow banking. The average probability of risk contagion of the small-world network and scale-free network increases significantly with the rise of the density of shadow banking. The average degree of risk contagion of the small-world network and the scale-free network also obviously go up when the density of shadow banking is greater than or equal to 0.4. The experimental results show that the density of shadow banking is a crucial factor affecting the stability of the banking system. The explanation is that unregulated shadow banking not only promotes interbank lending activities but also accumulates the fragility of the banking system. The increase

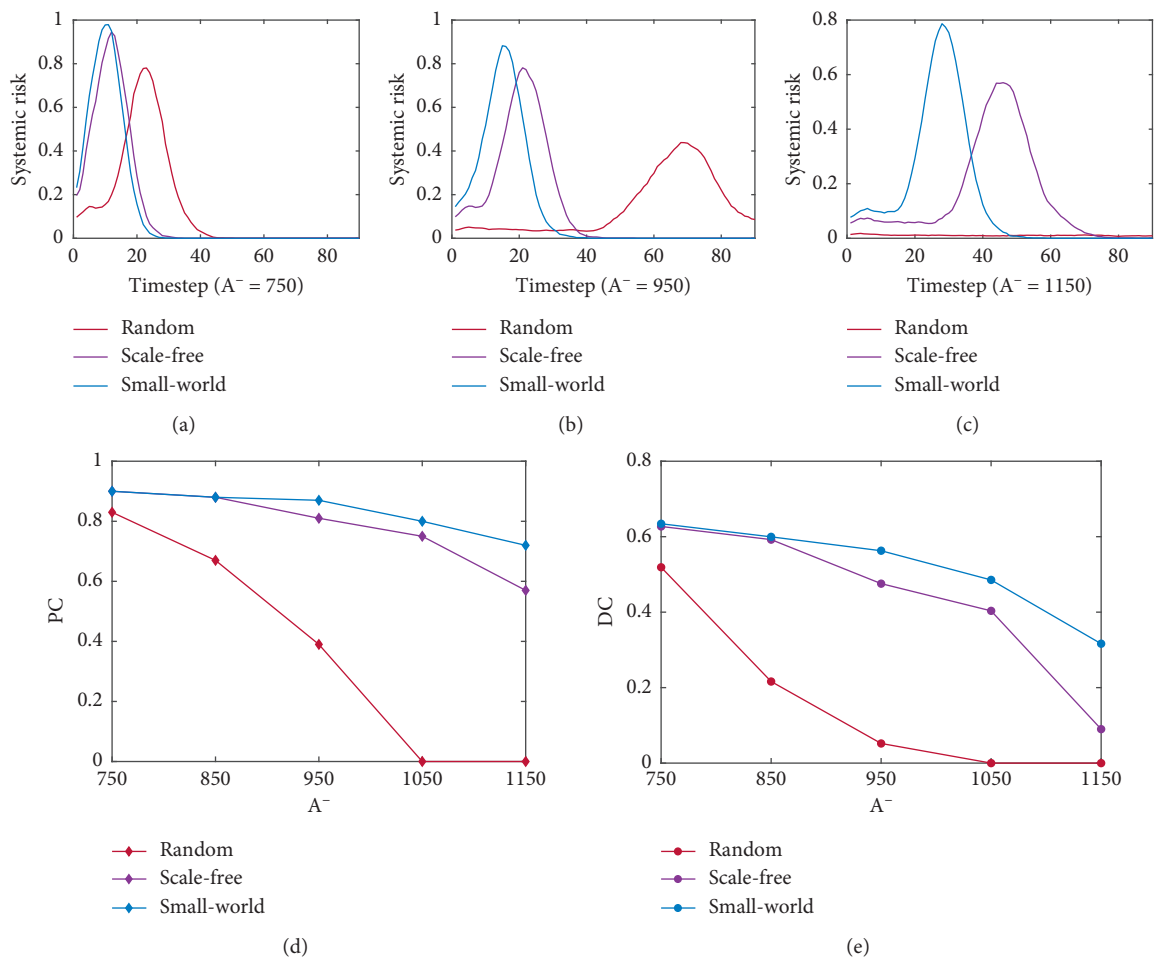


Figure 6: Evolution results of the diverse interbank networks under different $\overline{A}$.

of the density of shadow banking intensifies the accumulation of the systemic risk; once a bank defaults, there will immediately be an outbreak of the systemic risk. Influenced by the network structures, in face of the change in the density of shadow banking, the small-world network and the scale-free network are easier to accumulate and spread systemic risk, while the random network has a better ability to disperse and absorb risk.

Finally, we analyze the changes in the systemic risk of the banking system under three interbank networks when the banking system suffers from asset loss. The impact on the banking system is not only caused by the business activities of banks; during a financial crisis, the instantaneous asset devaluation also causes huge losses to a banks' assets, which will lead to serious damage to the stability of the banking system. Figure 9 shows the systemic risk evolution of different interbank networks that suffered a loss in assets at $t = 20$. As shown in Figures 9(a)–9(c), when the interbank networks are shocked by a loss in assets, the bank default caused by funds shortage will rapidly occur in the small-world network and the scale-free network. The risk of bank default spreads rapidly through the centralized interbank network, which leads to the chain failure reaction of banks and the outbreak of systemic risk. With the increase of a loss in the asset from 15% to 45%, the risk of the small-world network and the scale-free network is expanding in a short period of time, the outbreak time of systemic risk is constantly advanced, the peak value of systemic risk is also increasing, and the stability of the banking system is seriously damaged. However, the random network shows a delayed response to the shock of the asset loss. When the loss in the asset of the banking system is 15% and 30%, bank default does not appear immediately in the random network, as part of the risk is absorbed by the random network. The level of systemic risk is significantly lower than that of the small-world network and the scale-free network. But, when the asset loss reaches 45%, the excessive shock of the asset loss has broken through the ability of the random network to resist risk, and leads to a large number of bank credit defaults, the systemic risk outbreak, and the banking system collapse. The above results show that the larger size of the asset loss shock brings about a higher risk of illiquidity. Besides, the interbank network structure has an important effect on the resistance and contagion of risk. The risk contagion caused by bank illiquidity quickly happens in the relatively centralized small-world network and the scale-free network. The random network generates a dispersed network structure, which provides more chance for interbank

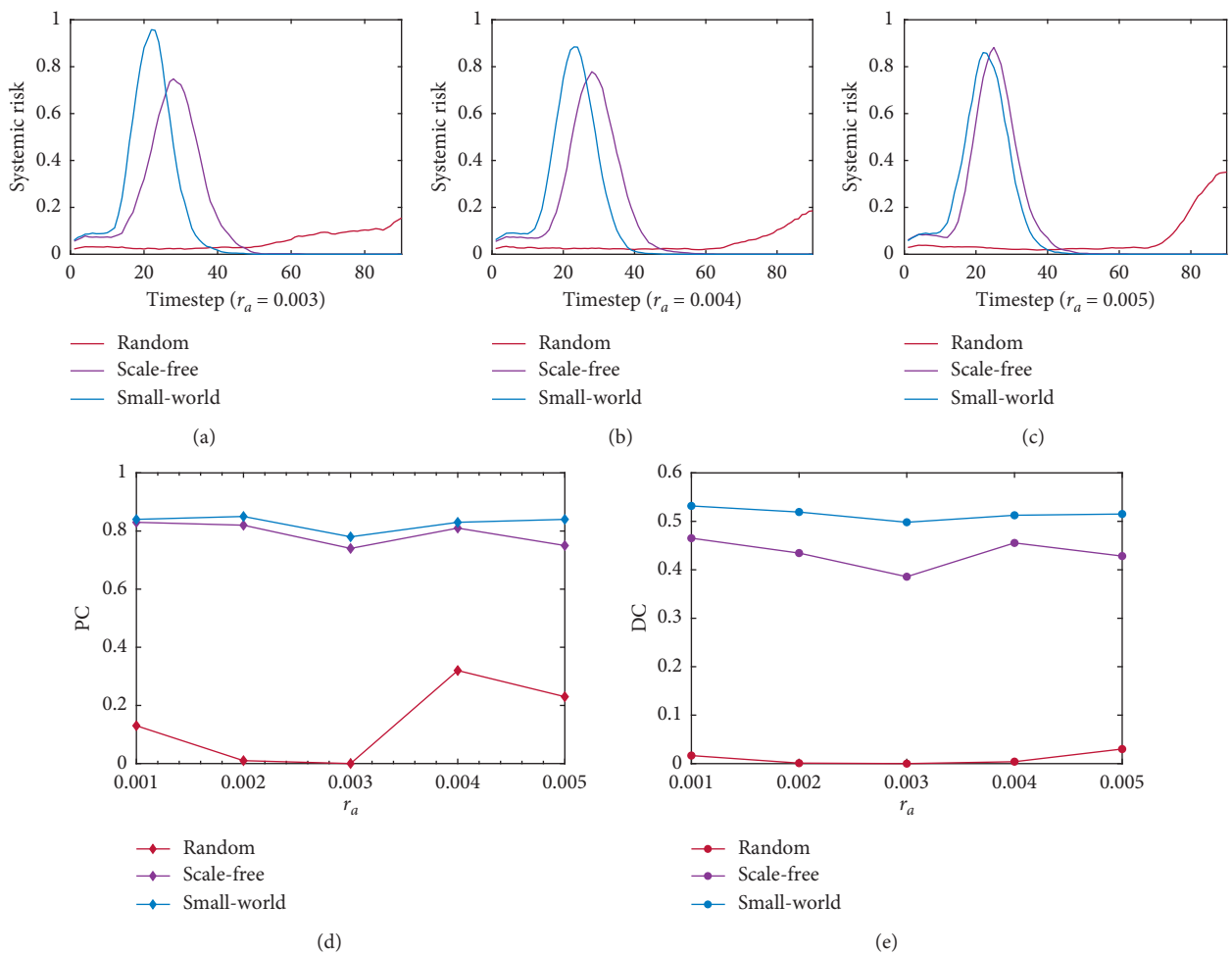


Figure 7: Evolution results of the diverse interbank networks under different $r_a$.

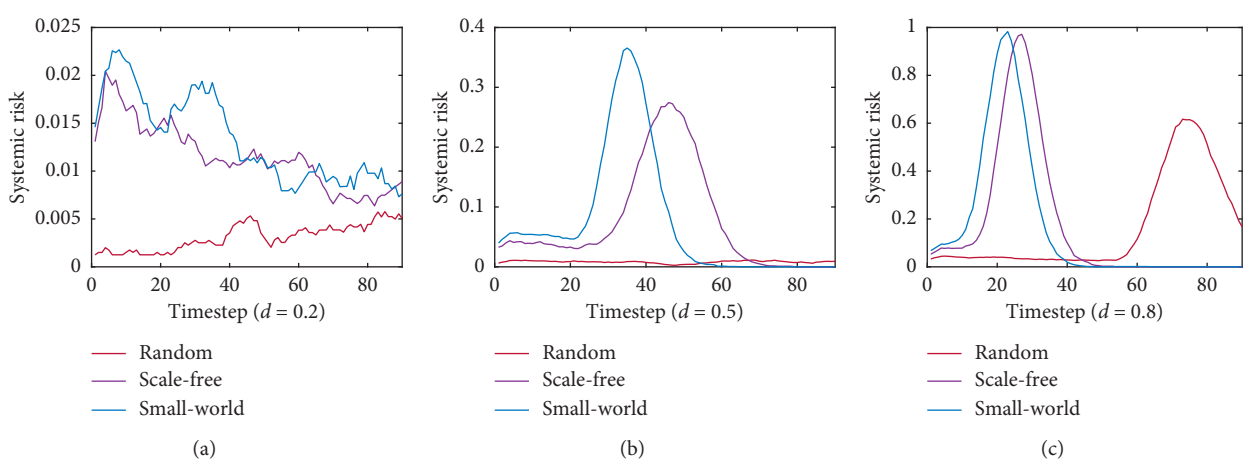


Figure 8: Continued.

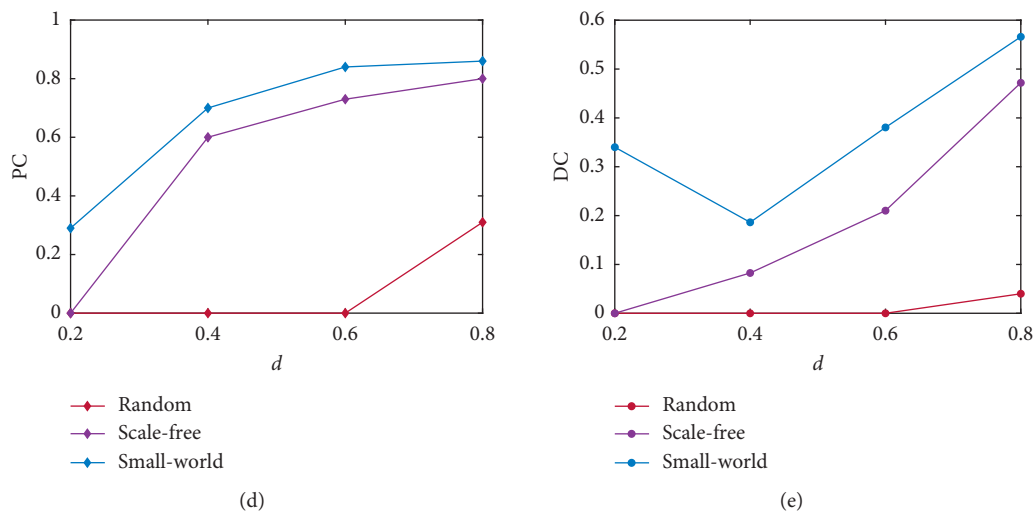


Figure 8: Evolution results of the diverse interbank networks under different $d$.

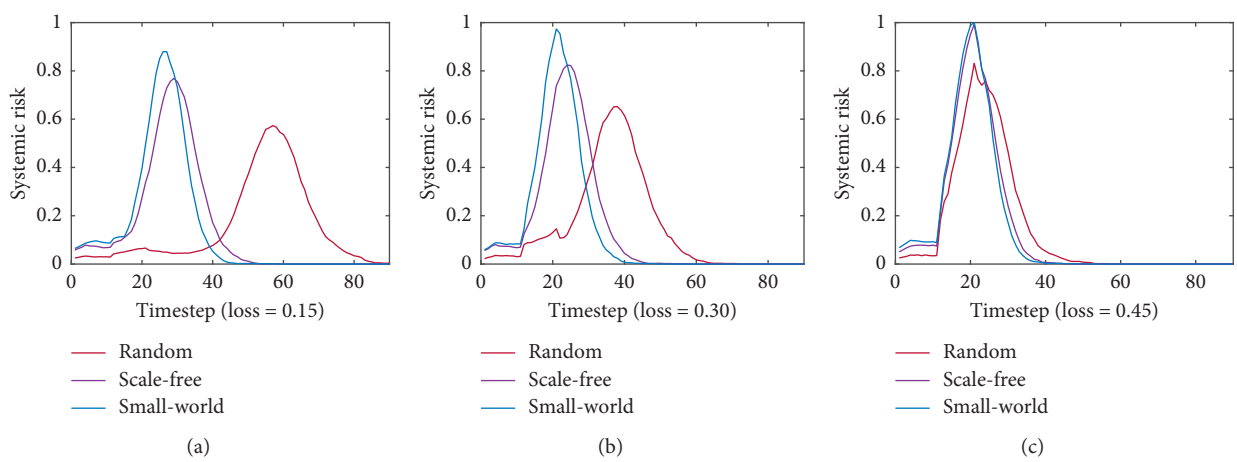


Figure 9: Evolution results of the diverse interbank networks suffer a loss at step 20.

lending and absorbs part of the risk. But, it should be noted that the interbank network will lose the ability to protect the stability of the banking system if the shock of the asset loss is too extensive.

## 5. Conclusions

From the perspective of the stability of the financial system, not only interbank market structure but also shadow banking affects the stability of the financial system. However, the current research on the impact of shadow banking on the stability of the banking system did not consider the complex relationship between banks and failed to reveal the changes of the stability of the banking system under the dynamic evolution mechanism of shadow banking. In order to explore the stability of the banking system with shadow banking more comprehensively, based on the complex network theory and the dynamic evolution of the bank balance sheet, the random network, the small-world network, and the scale-free network were used to establish the dynamic complex interbank network model with shadow banking in this paper. Through the proposed model, the sensitivity and difference of the banking system with shadow banking under various network structures were compared and analyzed. A series of conclusions are as follows:

(i) Different interbank network structures have different abilities to contagion and resist the systemic risk of the banking system with shadow banking. With the relatively centralized interbank network, it is easier to increase the contagion probability and contagion degree of risk. Generally, the system risk is severer under the small-world network and the scale-free network than the random network.

(ii) Changes in ROI have an impact on the stability of the banking system with shadow banking. The greater the ROI, the more stable the banking system with shadow banking. The resilience of the different

interbank networks to the changes in ROI is different, and the resilience of the random network is better than that of the small-world network and scale-free network.

(iii) The banking system with shadow banking is very sensitive to changes in the investment periods. The extension of the investment period significantly increases the systemic risk of the banking system. The random network, the small-world network, and the scale-free network are all sensitive to the change in the investment period. It is very essential to set a reasonable investment period for banks to maintain the stability of the banking system.

(iv) The increase in the average deposit of banks can improve the stability of the banking system with shadow banking. Under the changes in the average deposit of banks, the random network has a better ability to resist risks than the small-world network and the scale-free network.

(v) The increased deposit interest rate reduces the liquidity of banks and promotes the systemic risk of the banking system. There is a deposit interest rate value with maximum contagion ability for the interbank networks, and it has a great shock on the stability of the banking system. Among the three interbank networks, the risk contagion probability and risk contagion degree of the small-world network is the highest, while that of the random network is the lowest.

(vi) The greater the density of shadow banking, the higher the contagion probability and contagion degree of risk in the system. The shadow banking density is an important factor affecting the stability of the banking system with shadow banking. Facing a change in the density of shadow banking, the small-world network and the scale-free network easily accumulate systemic risk, while the random network has a better ability to disperse and absorb risk.

(vii) When the banking system with shadow banking is affected by the loss in assets, compared with the small-world network and the scale-free network, the random network has better ability to resist and absorb the risk. However, the shock of excessive loss in assets will directly break through the protection of the bank network, detonate systemic risk, and destroy the stability of the banking system with shadow banking.

This paper provides a scheme for quantitatively investigating the impact of different interbank network structures on the stability of the banking system with shadow banking. Meanwhile, it gives a reference for policymakers and regulatory authorities to prevent systemic risk introduced by shadow banking. The dynamic evolution interbank network model proposed in this paper provides a basic framework for the study of the systemic risk of shadow banking. In the future, the actual data can be used to make an empirical analysis based on this framework.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare no conflicts of interest.

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