Research Article

Research on Contagion and the Influencing Factors of Personal Credit Risk based on a Complex Network

Xin Sui,1,2 Hongmei Wen,1 Jing Gao3, and Shaopeng Lu4

1School of Finance, Harbin University of Commerce, Harbin 150028, China
2Department of Risk Management, Harbin Bank, Harbin 150070, China
3School of Management, Harbin Institute of Technology, Harbin 150006, China
4School of Economics, Nankai University, Tianjin 300072, China

Correspondence should be addressed to Hongmei Wen; wen-hm@163.com

Received 15 December 2021; Accepted 2 March 2022; Published 18 March 2022

1. Introduction

Personal credit risk has the characteristics of complexity, controllability, and infectivity. Financial institutions have considered the task of preventing personal credit risk and promoting the effective allocation of credit resources as an important goal for sustainable and healthy development. In recent years, the types of personal credit products have increased, competition between financial institutions has intensified, personal credit business has progressed, and financial technology has promoted the development of personal credit. With the digital transformation of commercial banks and the online migration of credit business, personal credit risk management is facing greater challenges. The reason why traditional risk prevention methods cannot identify and measure personal credit risk scientifically and accurately is that gang fraud is common, the linkage of personal credit risk is enhanced, and the social harm is great.

Preventing the outbreak of personal credit risk groups effectively and analyzing the infectious mechanism of personal credit risk can help make the risk management process effective and scientific. Therefore, this study aimed to use the theory and method of complex networks to explore the contagion and influencing factors of personal credit risk in the associated network to provide effective support for preventing personal credit risk.

In 2007, the United States subprime crisis and the consequent global financial crisis directly led to the bankruptcy or reorganization of many financial institutions. Credit risk linkage is caused by the complexity of the relationship among credit subjects and the spread and evolution of credit risk. Therefore, the impact of credit risk complexity on the credit economy has gradually become the focus of commercial banks and scholars. The nonlinear diffusion and contagion of credit risk in the financial market will affect the operation and efficiency of the financial market.
at a small level and may lead to a credit crisis at a large level. This will create a “domino” effect in the financial market and will have an impact on social and economic development [1]. At present, the global economy is in a state of recovery. There are obvious signs of differentiation between the monetary policy and economic trends of the major economies, and the trend of antiglobalization is gradually emerging. At the same time, China’s domestic economy is still in the stage of structural deceleration, and the impact of decapacity and deleverage actions on the financial system has been highly concerning [2]. The Central Committee of the Communist Party of China has repeatedly pointed out the importance of preventing financial risks and maintaining financial stability. There is an urgent requirement for the effective identification of personal credit risk contagion in the financial system.

Researchers have made remarkable achievements using complex network theory to study the risk contagion mechanism. They have mainly focused on the supply chain, the mechanism of credit risk contagion among enterprises [3–5], the systemic risk of the financial market, liquidity risk, and the mechanism of credit risk contagion [6–10]. The theories and methods regarding these aspects have been substantially revised, but there are few studies on the contagion mechanism of personal credit risk. With the rapid development of credit economy, the relationship between credit subjects were becoming more and more complex. Complex network relationships are formed through multiple cross connections of social relations, such as equity, guarantee or mutual guarantee, account transaction, family relationship, and colleague relationship. The correlation provided the possibility for the spread of credit risk. Behavioral finance puts forward that the borrower is a limited rational credit subject, which is easy to be controlled by emotion and will, and his thinking and cognition are limited. When other credit subjects closely related to the credit subject default, it will have a certain impact on the will and behavior of the credit subject. Therefore, the complexity of credit risk is deepening, and there is a “herding effect” in credit subjects. The contagion of credit risk is increasing, which leads to limitations with personal credit risk prevention measures. In order to improve the ability of financial institutions to prevent personal credit risk, financial institutions must continue to expand their ability in this area and their access to customer information. However, customer default behavior is highly uncertain. Because of the changeable economic situation and the “irrational” behavior of credit subject, it is impossible to identify and measure personal credit risk exclusively through individual customer information.

The contribution of this research is that it uses complex network theory and methods to reveal the infectivity and influencing factors of personal credit risk, and it provides valuable reference for the effective reduction of personal credit risk.

2. Previous Research

In recent years, complex network theory and methods have been widely used to describe network structures and analyze their conductivity. This research includes the analysis of the contagion and diffusion of network structure credit risk. The credit subject is regarded as a node in the network, and the relationship among the credit subjects is the line connecting them. This network construction method has been widely recognized by scholars. A large number of scholars use this method as an effective means to study the relationship. For the research of risk diffusion, scholars have explored the mechanism of risk contagion using a complex network propagation dynamics model. Researchers have used complex network theory and methods to reveal the contagion and influencing factors of credit risk. However, there have been relatively few studies on the contagion aspects of personal credit risk. It has mainly been studied from the following different angles.

2.1. Research on the Evolution and Contagion of Credit Risk

Behavioral finance proposes that when the actor is in an uncertain environment, environmental factors will have a greater impact on the behavior of the actor, and the actor is a bounded rational actor. There is a “herding effect” in the loan market, and the default behavior of credit subjects is related. Lucas [11] defined the default correlation as the relationship between the default probability of one credit subject and that of another credit subject and used the correlation coefficient between default events to measure the default correlation. Bianco and Nicodano [12] analyzed the contagion of debtor breach and found that when one debtor defaults, the intensity of the other debtors’ breach of contract will increase. Jarrow and Yu [13] took the lead in using the intensity model to consider the one-way contagion of the credit risk of related enterprises. In the loan market, the herding effect exists in varying degrees [14]. There is a herding effect of lenders on the network lending platform. Asymmetric information is an important factor affecting the herding effect of lenders [15]. Chen and He [16] discussed the effects of behavioral factors of credit risk holders and financial market regulators and the social network structure on credit risk contagion through the theoretical analysis and numerical simulation.

2.2. Research on the Contagion and Diffusion of Credit Risk in a Complex Network Structure

At present, the research on the spread of credit risk contagion in complex network structures mainly comprises two aspects: the network structure and the contagion effect of credit risk. In terms of the network structure, Watts and Strogatz [17] and Barabasi and Albert [18] first proposed that a network structure has topological properties; that is, it is “small world” and “scale free.” They found that a large number of real networks have scale-free properties. Scholars build network models based on the characteristics of complex networks. These characteristics exist in the financial network. The scale-free characteristic exists in the previous networks of the Chinese financial market, European overnight lending market, and the American, Japanese, Australian, and Brazilian banks [2, 19–21]. The network structures of supply chain markets...
and stock markets also have a scale-free characteristic [5, 22, 23].

In terms of the diffusion effect of credit risk contagion, Giesecke [24] built a credit risk contagion model based on the reduced model. It was found that the business cooperation among credit subjects is the medium of credit risk transmission. Steinbacher et al. [25] constructed a credit risk contagion model based on an interbank network. The results show that credit risk is highly sensitive to the topology of the network and has nonlinear characteristics. Chen and He [1] built a network model of credit risk contagion with related credit subject behavior factors and applied simulation technology to reveal the relationship between the credit subjects in the social network. Chen et al. [26] measured the contagion intensity of the credit risk among related entities by making assumptions on the distribution of asset values. Chen et al. [27] and Li and Zhou [28] described the contagion of credit risk under the special relationship of the mutual insurance between a parent company and its subsidiary company. Giesecke [29] asserted that information disclosure leads to the change of value among the affiliated enterprises and analyzed the contagion effect of the risk of the related credit on this basis. Berloco et al. [30] showed that the introduction of network features that model the trade credit of firms has a substantial impact on the task of short-term forecasting of defaults of firms. Mark and Lo [31] introduced a contagion model to account for concentration risk in large portfolios of defaultable securities.

In order to explore the contagion of credit risk in the associated network, Chinese and foreign scholars have made extensive research on the contagion effect of credit risk using complex networks. May et al. [32] pointed out that there are similarities between the financial system and the ecosystem, and the spread of financial risk and an epidemic is very similar. Based on an SIS epidemic model of complex network theory, Pastor-Satorras and Vespignani [33] systematically analyzed the diffusion of credit risk in the network and judged the important influencing factors of credit risk diffusion. Yang and Zhang [34] established an SIS RP model of a supply chain network and preliminarily verified the applicability of complex network theory in the study of supply chain risk communication. Hu and Li [2] introduced the transmission dynamic model SIRS into the scale-free financial network and discussed the influence of the model parameters and network tightness on risk contagion. Qian and Zhou [35] used an improved infectious disease model to analyze the stable state and characteristics of associated credit risk infection in the immune situation. Zhao et al. [5] used an SIS epidemic model to simulate the diffusion process of credit risk. Xu et al. [20] based their work on the mean field theory of a complex network, and they used the infectious disease model to describe the infectious mechanism of the associated credit risk in the management agent network. Petrone and Latora [36] introduced a dynamic model to quantify the systemic risk by incorporating credit risks with various transmission mechanisms in the bank credit risk network.

The existing literature mainly focuses on the contagion mechanism of credit risk in bank or enterprise networks and supply chain enterprise networks rather than personal risk contagion. However, credit risk contagion does not only exist in the enterprise network but also exists in the personal credit subject network. The above literature proves that credit risk has the characteristics of contagion, the associated network has the nature of complex network, and credit risk infection is similar to epidemic. With the development of the credit economy, the contagion of personal credit risk is gradually increasing due to the deepening of the relationship among credit subjects. Therefore, we need to pay attention to the infectivity of personal credit risk and its influencing factors. This study explored the infectivity and influencing factors of personal credit risk from the perspective of a complex network.

3. Model Construction of Personal Credit Risk Contagion

In order to reveal the influencing factors of individual credit risk contagion effectively, one of the keys to constructing the contagious model of personal credit risk is to determine the contagion structure and mode of personal credit risk based on its nature. The association network of a credit subject has the same type of network nature as occurs within society, biology, and communication, and the credit risk infection is similar to the spread of infectious diseases and viruses [37, 38]. Therefore, based on the classical SIR model and the research hypothesis of Xu et al. [39], this study constructed a SEIR model of complex network infectious diseases considering the existence of exposed subjects and discussed the contagion mechanism of personal credit risk. However, the assumptions in the SEIR model cannot accurately describe the state of a personal credit subject. Considering the credit subject’s self-protection consciousness and legal constraints, the SEIR model was adjusted to increase the direct immune coefficient and latent immune repair coefficient. These adjustments enabled us to clarify the contagion mechanism of personal credit risk and explore the infection and influencing factors of personal credit risk effectively.

3.1. Research Hypothesis. In order to explore the contagion of personal credit risk effectively, the following hypotheses are put forward.

Hypothesis 1. There are four independent states of the credit subject in the association network, and the credit subject can change the state through the association relationship: susceptible subject (S), exposed subject (E), infected subject (I), and recovered subject (R). Xu et al. [39] had confirmed that there are the following four types of credit subjects in the affiliated network.

Susceptible subject (S): The credit subject with the possibility of risk contagion due to its low credit level. Exposed subject (E): The credit subject who has contacted the infected subject but does not have the ability to infect other subjects. After the higher latency of its credit risk level, it becomes the main body of infection.
Infected subject (I): The credit subject that has been infected and defaulted; the credit risk will be transmitted to other credit subjects through association.

Recovered subject (R): The credit subject that obtains the ability of risk recovery. This subject has two types: direct recovery and immune recovery. Direct recovery means that based on a good credit mechanism, there is no joint breach of contract due to a relationship connection. Immune recovery means that after the joint and several risks occur due to the relationship connection, under the influence of law or other factors, through their own risk control they continue to make normal repayments to avoid the occurrence of default.

Among them, the credit subject with the ability of risk recovery may become the subject of contagion again.

Hypothesis 2. $\mu_1$ is the coefficient of latency, which refers to the probability of a latent subject that is susceptible to contagion but does not have contagious ability.

Hypothesis 3. $\mu_2$ is the coefficient of risk contagion, which refers to the probability of infection of a susceptible subject through association ($0 < \mu_2 \leq 1$).

Hypothesis 4. $\mu_3$ is the coefficient of direct recovery, which refers to the probability that some susceptible subjects with self-protection and legal restraint consciousness can avoid infection through their own risk prevention consciousness and directly transform into immune subjects ($0 \leq \mu_3 \leq 1$).

Hypothesis 5. $\alpha$ is the coefficient of latent transformation, which refers to the probability that a latent subject is transformed into an infected subject ($0 < \alpha \leq 1$).

Hypothesis 6. $\gamma$ is the coefficient of immune recovery, which is the probability that an infected credit subject can successfully eliminate the credit risk and turn into an immune subject through their own risk control, collection, or legal constraints ($0 < \gamma \leq 1$).

Hypothesis 7. $\beta$ is the coefficient of latent immune recovery, which is the probability that a latent subject can successfully eliminate the credit risk and turn into an immune subject through its own risk control, collection, or legal constraints ($0 < \beta \leq 1$).

Hypothesis 8. A is the newborn rate, which is when the credit subject entering the related network is regarded as born.

In order to show the change of the state of each node credit subject in the process of credit risk contagion more intuitively, Figure 1 describes the process of personal credit risk contagion. The classical SIR model had confirmed the existence and significance of $\mu_2$, $\gamma$, and $\mu_3$. In order to describe the transformation of credit subjects more accurately, and consider the establishment of credit investigation system and legal constraints, this study added exposed subject and added the transformation path between exposed subject and other subjects.

3.2. The Establishment of the Model. There are $N$ credit subjects in the network, and the network nodes are composed of credit subjects. The edge of the network is determined by the association among the nodes. The degree of node $i$ and the number of other nodes connected to the node are expressed by $k_i$. The network average degree $<K>$ is the average value of the degree $k_i$ of all nodes in the network. The probability of randomly selecting a node with degree $k_i$ is $P(k_i)$. Therefore, $<K> = \sum_{k=1}^{n} k_i P(k_i)$. In this study, $S_k(t)$, $E_k(t)$, $I_k(t)$, and $R_k(t)$ were used to represent the density of the susceptible subjects, exposed subjects, infected subjects, and recovered subjects with the scale of $k$ at time $t$. Therefore, $S_k(t) + E_k(t) + I_k(t) + R_k(t) = 1$ are included in the structure of the associated network. According to the average field theory, the SEIR model is as follows:

$$\frac{dS_k(t)}{dt} = A - \mu_1 kS_k(t)\Theta(t) - \mu_2 S_k(t) - \mu_3 S_k(t),$$

$$\frac{dE_k(t)}{dt} = \mu_1 kS_k(t)\Theta(t) - (\alpha + \beta)E_k(t),$$

$$\frac{dI_k(t)}{dt} = \mu_2 S_k(t) + \alpha E_k(t) - \gamma I_k(t),$$

$$\frac{dR_k(t)}{dt} = \mu_3 S_k(t) + \beta E_k(t) + \gamma I_k(t),$$

$\Theta(t)$ is the probability that the susceptible subject is randomly connected with the infected subject at time $t$.

$$\Theta(t) = \frac{1}{<K>} \sum_{k=1}^{n} k P(k) I_k(t).$$
3.3. Analysis of Model Contagion Threshold

**Definition 1.** There is a critical value of the risk contagion coefficient in the associated network $\mu_c$. When the risk contagion coefficient $\mu$ is less than $\mu_c$, there is no infectious agent in the associated network. Therefore, $\mu_c$ is called the infection threshold in the association network.

**Theorem 1.** When the threshold of contagion between the credit subjects in the association network is $\mu_c = \gamma(\alpha + \beta)\langle k \rangle/\mu_1 k^2 (\beta \mu_2 + \alpha \mu_1)$, when $\mu < \mu_c$, there is no risk contagion in the associated network. When $\mu > \mu_c$, there is credit risk in the associated network, and the credit risk can be contagious and spread.

It is proved that, in the stable state $dS_k(t)/dt = 0$, $dE_k(t)/dt = 0$, $dI_k(t)/dt = 0$. Therefore, the above equation can be constructed to find the solution of the system of equation (1) as follows:

\[
\begin{align*}
S_k(t) &= \frac{A}{\mu_1 + \mu_2 + \mu_3}, \\
E_k(t) &= \frac{\mu_1 \mu_3 \Theta^*}{(\alpha + \beta)(\mu_1 + \mu_2 + \mu_3)}, \\
I_k(t) &= \frac{\mu_2 A(\alpha + \beta) + \alpha \mu_1 k \Theta^*}{\gamma(\alpha + \beta)(\mu_1 + \mu_2 + \mu_3)}.
\end{align*}
\]

Among them, $\Theta^* = 1/\langle k \rangle \sum_{k=1}^n k P(k) I_k^*$. The $I_k^*$ in (3) is introduced into (2) to obtain the $\Theta$; the self-consistent equation of the model is as follows:

\[
\Theta^* = \frac{1}{\langle k \rangle} \sum_{k=1}^n k P(k) \frac{\mu_2 A(\alpha + \beta) + \alpha \mu_1 k \Theta^*}{\gamma(\alpha + \beta)(\mu_1 + \mu_2 + \mu_3)} = f(\Theta^*).
\]

It is obvious that $\Theta^* = 0$ is a trivial solution of equation (4). In addition, it is continuously differentiable. In addition, $f(\Theta^*)$ is continuously differentiable: $f'(\Theta^*) = \mu_1 k (\beta \mu_2 + \alpha \mu_1) / \gamma(\alpha + \beta)(\mu_1 + \mu_2 + \mu_3) > 0$. That is, $f(\Theta^*)$ increases strictly monotonically with respect to $\Theta^*$.

Therefore, if $f'(\Theta^*)|_{\Theta=0} = \mu_1 k^2 (\beta \mu_2 + \alpha \mu_1) / \gamma(\alpha + \beta)\langle k \rangle > 1$, there is a nonzero solution to equation (4), and the infection threshold is given as $\mu_c = \gamma(\alpha + \beta)\langle k \rangle / \mu_1 k^2 (\beta \mu_2 + \alpha \mu_1)$.

Therefore, the contagion threshold of personal credit risk in the related network is as follows:

\[
\mu_c = \frac{\gamma(\alpha + \beta)\langle k \rangle}{\mu_1 k^2 (\beta \mu_2 + \alpha \mu_3)}.
\]

This is the end of the proof.

According to Theorem 1, the threshold of personal credit risk contagion is related not only to the network topology but also to the coefficient of latency $\mu_1$, the coefficient of risk contagion $\mu_2$, the coefficient of direct recovery $\mu_3$, the coefficient of latent transformation $\alpha$, the coefficient of immune recovery $\gamma$, and the coefficient of latent immune recovery $\beta$ and the newborn rate $A$ affects the contagion threshold of the personal credit risk.

4. Simulation Experiment based on Scale-Free Network

At present, due to the influence of internal factors and external environmental factors, the associated network presents scale-free characteristics, such as growth and priority connection. The interbank lending network and the stock market correlation are scale-free networks. At the same time, scale-free networks have been used by many scholars in the study of the credit risk contagion mechanism [19, 27]. In view of this, in order to describe the contagion of personal credit risk in the network of related entities and analyze the influencing factors effectively, this study selected the scale-free network to analyze the contagion evolution law of personal credit risk in the network of related entities, and the simulation experiment was realized by MATLAB r2013b.

4.1. The Construction and Degree Distribution of Scale-Free Network. In order to verify the conclusions of the above theoretical analysis, numerical simulation experiments were used to analyze the contagion structure and pattern of personal credit risk in a scale-free network. In terms of the parameter setting, the scale-free network was constructed assuming $n = 400$ and $d = 6$. The distribution of the network nodes and connections and the degree distribution and probability distribution of each node in the scale-free network are shown in Figures 2–4.

4.2. Simulation Experiment. In order to simulate the credit risk contagion in complex networks more effectively, we set different parameter values for simulation to explore the influencing factors of credit risk contagion. In the aspect of parameter selection, this article refers to the research of Zhao et al. [5, 20].

At first, there are only susceptible subjects in the association network, and $S_k(t) = 1$. When there is no latent agent in the network, it is an SIR model; $\mu_1 = 0$. When the coefficient of risk contagion $\mu_2 = 0.5$, the coefficient of direct recovery $\mu_3 = 0.2$ and the coefficient of immune repair $\gamma = 0.1$. The simulation randomly selects an infected individual to run for 40 times and takes the average value to get the density and time $t$ change trend of the susceptible subject $S(T)$, infected subject $I(T)$, and immune subject $R(T)$, as shown in Figure 5. As can be seen from Figure 5, in a scale-free network, when there is no latent subject, the peak of the associated credit risk appears between $T = 0$–5 and the contagion scale of the associated credit risk reaches 0.6.

When there are exposed subjects in the network and $\mu_1 = 0.7$, the coefficient of risk contagion $\mu_2 = 0.15$, the coefficient of direct recovery $\mu_3 = 0.02$, the coefficients of latent transformation were $\alpha = 0.2$ and $\alpha = 0.5$, and the coefficient of immune recovery $\gamma = 1$. The simulation randomly selects an infected individual to run for 40 times and takes the average value to obtain the density and time $t$ change trend...
of the susceptible subject $S(t)$, exposed subject $E(t)$, infected subject $I(t)$, and immune subject $R(t)$, as shown in Figures 6 and 7.

Figures 6 and 7 show that when there are exposed subjects in the scale-free network, the peak of the associated credit risk appears between $t = 5–10$, which reduces the transmission speed of the associated credit risk. It can be seen that the existence of exposed subjects has a significant delaying effect on the arrival of the peak of the related credit risk infection. When the coefficient of latent transformation $\alpha = 0.2$ and $\alpha = 0.5$, the contagion scale of the related credit risk is less than 0.6. The smaller the coefficient of latent transformation is, the smaller the contagion scale is. It can be seen that the existence of latent subjects has a significant inhibitory effect on the contagion scale of the related credit risk. The smaller the coefficient of latent transformation, the stronger the inhibition. In conclusion, when there are exposed subjects in the network, the latent transformation coefficient has a significant delaying and inhibiting effect on the peak period and the scale of infection of the risk of the associated credit.

When there are exposed subjects in the network, and $\mu_1 = 0.4$, the coefficient of risk contagion $\mu_2 = 0.1$, the coefficient of direct recovery $\mu_3 = 0.1$ and $\mu_3 = 0.2$, the coefficients of latent transformation were $\alpha = 0.3$ and $\alpha = 0.4$, and the coefficient of immune recovery $\gamma = 0.1$. The simulation randomly selects an infected individual to run for 40 times and takes the average value to obtain the density and time $t$ change trend of the susceptible subject $S(t)$, exposed subject $E(t)$, infected subject $I(t)$, and recovered subject $R(t)$, as shown in Figures 8 and 9.
Figures 7 and 8 show that the contagion scale of the associated credit risk in Figure 7 is significantly higher than that in Figure 8. It can be seen that the contagion scale of the related credit risk is greatly affected by the coefficient of latent transformation, which changes in the same direction as the contagion scale of the related credit risk. The scale of the related credit risk is greatly affected by the latent coefficient, which changes inversely with the related credit risk.

As can be seen from Figures 8 and 9, the peak of the associated credit risk occurs between $t = 5$ and $t = 10$. The contagion scale of the associated credit risk in Figure 8 is significantly higher than that in Figure 9. The above studies have proved that the coefficient of latent transformation has a significant inhibitory effect on the contagion scale of the related credit risk. The smaller the latent transformation coefficient, the stronger the inhibition. It can be seen that the coefficient of direct recovery has a greater impact on the contagion scale than the coefficient of latent transformation. The larger the coefficient of direct immune is, the smaller the contagion scale is.

In conclusion, when there is no exposed subject in the associated network, the transmission speed and scale of the associated credit risk are at a high level. When there are exposed subjects in the network, the coefficient of latency, the coefficient of risk contagion, and the coefficient of direct recovery are unchanged. The smaller the coefficient of latent conversion is, the more significant the delay and inhibition effect on the peak period and the scale of the infection of the risk transmission of the associated credit is. The coefficient of risk contagion and the coefficient of latent conversion have significant influences on the scale of the risk transmission of the associated credit. The larger the coefficient of risk contagion and coefficient of latent conversion, the larger the scale of the risk transmission of the associated credit. At the same time, considering the influence of the coefficient of direct recovery and the coefficient of latent transformation on the associated credit risk, the coefficient of direct recovery has greater influence on the contagion scale of the associated credit risk than the coefficient of latent transformation, and the larger the coefficient of direct recovery is, the larger the contagion scale of the associated credit risk is.

Figure 10 shows the change trend of $I(t)$ with $t$ under different parameter assignments. When there is no exposed subject in the associated network, the contagion scale and speed of the associated credit risk are the largest. The larger the coefficient of latency is, the larger the contagion scale is. The smaller the coefficient of latent transformation is, the smaller the contagion scale is. The coefficient of direct recovery changes negatively with the contagion scale of the related credit risk and changes in the same direction with the contagion speed of the related credit risk.

4.3. Verification of Interaction. Figure 11 shows the interaction relation among $I$, $\alpha$, and $t$ more intuitively. When $\alpha$ takes a certain value, with the increase of $t$, the density of the infected subjects first increases to the peak and then gradually decreases to 0. The higher the value of $\alpha$, the higher the peak density of the infected subjects. Therefore, the size of $\alpha$ will have a certain impact on the host density $I$. In other
words, the existence of the exposed subjects will affect the density of the infected agents to a certain extent, which is another confirmation of the above simulation experiment.

Figure 12 shows the interaction relation among $I$, $\mu_2$, and $t$ more intuitively. When $\mu_2$ take a certain value, with the increase of $t$, the density of the infected subjects first increases to the peak and then gradually decreases to 0. The higher the value of $\mu_2$, the higher the peak density of the infected subjects. Therefore, the size of $\mu_2$ will have a certain impact on the infection subject density $I$, which also verifies the above simulation experiment.

5. Discussion

We have conducted a systematic analysis of contagion and the influencing factors of personal credit risk. We have demonstrated that credit risk in complex networks had the nature of contagion and diffusion, and commonly used measures of personal credit risk assessment have become less effective due to the neglect of related factors. The decline in the effectiveness of these measures is associated with changing relationship patterns in associated network, including the complexity of the relationship among credit subjects. As behavioral finance puts forward, people's psychological and physiological abilities are restricted by all aspects, and people's rationality is limited. There is a "herding effect" in the loan market. Due to the correlation effect, borrowers form an intertwined credit network, which can easily lead to the evolution and infection of personal credit risk from individual to group. We have also demonstrated that the transmission coefficient among credit subjects had a significant impact on the personal credit risk in the network. In particular, SEIR model effectively revealed the structure and mode of credit risk transmission.

Our analysis also revealed the factors that affect the contagion of personal credit risk. First, the existence of latent subjects had a significant impact on the contagion scale of credit risk. Second, the coefficient of transformation among credit subjects had a significant impact on the contagion scale of credit risk. Finally, we can clearly found the factors of personal credit risk infectivity and influencing through the simulation experiment. In particular, we added the exposed subject, the coefficient of latency, the coefficient of latent, and the coefficient of latent immune recovery to describe the state and transformation process of credit subject in the credit system and the society ruled by law more realistically. Of course, the management of personal credit risk not only stay in the model but also should be based on the actual situation of more accurate analysis.

This analysis may have several limitations. We use the simulation experiment to simulate the contagion process of credit risk in the network only. Although the models and assumptions can simulate the behavior of credit subjects, we do not select the real data for empirical research. In the process of parameter selection, it may deviate from the actual situation based on the parameters in scholars' literature. But through this research, we have got meaningful findings and insights related to this topic.

6. Conclusions

In the postepidemic period, the downward pressure of the economy is greater, and the downward trend of the credit
asset quality is obvious. The credit assets of financial institutions continue to be under pressure, so it is particularly important to effectively prevent credit risk. With the continuous development of the credit economy, the relationship among the credit subjects has become increasingly close, diverse, and complex. The relationship between the credit subjects not only expands the application scope of the credit relationship but also brings potential risk linkage. The research on the influencing factors of the related credit risk can penetrate and visualize the relationship of the credit subjects and provide support for risk early warning and fraud prevention.

In this study, the complex network theory and method were used to study the infectivity and influencing factors of personal credit risk. The complex network theory was used to describe the structure and characteristics of the network of related subjects. Using an SEIR epidemic model, and on the basis of the traditional SEIR model, when we consider the existence of the economic and social legal constraints and the credit subject’s self-protection consciousness, the transmission path of the coefficient of the direct recovery coefficient and the coefficient of latent recovery was found to be increased. The model and structure of the contagion of personal credit risk were revealed by simulation experiments. Based on the model analysis and simulation experiments, this study put forward the factors that affect personal credit risk. The results show that when the coefficient of latency is 0, there is no exposed subject, and the contagion scale and speed of the associated credit risk are the largest. The larger the coefficient of latency, the larger the contagion scale is. The smaller the coefficient of latency is, the smaller the contagion scale of the associated credit risk will be. The coefficient of direct recovery changes in the same direction with the contagion scale of the related credit risk and in the opposite direction with the speed of the related credit risk.

Based on the above analysis and conclusions, the following countermeasures and suggestions are put forward.

(i) Improve personal legal awareness and risk prevention awareness. When the credit subject is infected by the associated credit subject, the credit risk becomes the exposed subject. Before infecting other individuals, the degree of personal legal awareness and risk prevention awareness will greatly affect the scale and speed of the associated network credit risk infection. Therefore, it is important to strengthen personal legal awareness and risk prevention awareness.

(ii) Increase the preloan audit indicators and dimensions. The conclusions of this study confirm the infectivity of credit risk in the network. The traditional preloan audit only considers the indicators of a single customer; it ignores the potential risk exposure due to the relationship. Therefore, commercial banks and other financial institutions should focus on and consider the related information of the credit subject when conducting a preloan audit.

(iii) Improve the ability and means of early warning after the loan is made. The existence of the coefficient of direct recovery and the coefficient of latent immune repair confirm that the scale of the associated credit risk can be reduced by a cure after the credit subject is infected with credit risk. Therefore, an effective postloan early warning ability can help reduce associated credit risk.

This study revealed the reasons for the outbreak of credit risk clusters and provided a new perspective that can help commercial banks and other financial institutions to prevent credit risk.

**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 that they have no conflicts of interest.

**References**

[1] T. Chen and J. He, "Credit risk contagion model based on complex network," *Soft Science*, vol. 28, no. 2, pp. 111–117, 2014.

[2] Z. H. Hu and X. H. Li, "Contagion and bailout strategy in complex financial network—SIRS model on the Chinese scale-free financial network," *Finance & Trade Economics*, vol. 38, no. 4, pp. 101–114, 2017.

[3] Y. K. Li, Y. M. Zhou, and Z. F. Zhou, "Associated credit risk contagion and simulation between enterprises based on the incomplete immune scenario," *Chinese Journal of Management Science*, vol. 25, no. 1, pp. 57–64, 2017.

[4] Z. Gong, "On E-Commerce supply chain risk forecast method based on complex network theory," *Journal of Southwest China Normal University (Natural Science Edition)*, vol. 46, no. 3, pp. 39–44, 2021.

[5] Z. Zhao, D. Chen, L. Wang, and C. Han, "Credit risk diffusion in supply chain finance: a complex networks perspective," *Sustainability*, vol. 10, no. 12, p. 4608, 2018.

[6] G. You, H. Guo, and X. Liu, "The structure evolution and risk contagion of financial market from the perspective of complex networks," *Journal of Financial Development Research*, vol. 2020, no. 1, pp. 30–39, 2020.

[7] C. Li, J. Zhang, P. Li, and X. Feng, "Research of enterprise project chain risk element transmission based on complex network model," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 6, no. 13, pp. 2359–2365, 2013.

[8] H. Ouyang and X. Liu, "An analysis of the systemic importance and systemic risk contagion mechanism of China’s financial institutions based on network analysis," *Chinese Journal of Management Science*, vol. 23, no. 10, pp. 30–37, 2015.

[9] Y. He, S. Wu, and M. Tong, "Systemic risk and liquidity rescue in complex financial networks: pit hole and black hole of liquidity," *Physica A: Statistical Mechanics and Its Applications*, vol. 536, Article ID 121005, 2019.

[10] Y. Ren, J. Xie, J. Zhou, and J. Zhang, "A study of commercial banks’ liquidity risk contagion based on complex network,"
Journal Of Hunan University (Social Sciences), vol. 34, no. 4, pp. 65–73, 2020.
[11] D. J. Lucas, “Default correlation and credit analysis,” The Journal of Fixed Income, vol. 4, no. 4, pp. 76–87, 1995.
[12] M. Bianco and G. Nicodano, “Pyramidal groups and debt,” European Economic Review, vol. 50, no. 4, pp. 937–961, 2006.
[13] R. A. Jarrow and F. Yu, “Counterparty risk and the pricing of defaultable securities,” The Journal of Finance, vol. 56, no. 5, pp. 1765–1799, 2001.
[14] H. Chen, L. Zhang, and Y. Sun, “Empirical research on Commercial Bank credit concentration-based on perspective of herding,” Technoeconomics & Management Research, vol. 1, pp. 86–89, 2012.
[15] K. Zhang and P. Pei, “Information asymmetry, type of lenders and herding effect: the research based on data from Renrendai platform,” Business Process Management Journal, vol. 38, pp. 125–137, 2016.
[16] T. Q. Chen and J. M. He, “A network model of credit risk contagion,” Discrete Dynamics in Nature and Society, vol. 2012, Article ID 513982, 13 pages, 2012.
[17] D. J. Watts and S. H. Strogatz, “Collective dynamics of ‘small-world’ networks,” Nature, vol. 393, no. 6684, pp. 440–442, 1998.
[18] A. L. Barabasi and R. Albert, “Emergence of scaling in random networks,” Science (New York, N.Y.), vol. 286, no. 5439, pp. 509–512, 1999.
[19] H. Inaoka, T. Ninomiya, K. Taniguchi, T. Shimizu, and H. Takeyasu, “Fractal Network derived from banking transaction–An analysis of network structures formed by financial institutions,” Bank Jpn Work Pap, vol. 4, pp. 1–32, 2004.
[20] K. Xu, J. Mo, Q. Qian, F. Zhang, X. Xie, and Z. Zhou, “Associated credit risk contagion with incubatory period: a network-based perspective,” Complexity, vol. 2020, Article ID 5642730, 12 pages, 2020.
[21] W. Liu, Q. Hou, Z. Xie, and X. Mai, “Urban network and regions in china: an analysis of daily migration with Complex Networks Model,” Sustainability, vol. 12, no. 8, Article ID 3208, 2020.
[22] Y. Zhou, S. Cai, and P. Zhou, “Scale-free properties of financial markets,” Journal of University of Science and Technology of China, vol. 39, no. 8, pp. 880–884, 2009.
[23] F. Ma, H. Xue, K. F. Yuen et al., “Assessing the vulnerability of logistics service supply chain based on complex network,” Sustainability, vol. 12, no. 5, Article ID 1991, 2020.
[24] K. Giesecke, “Correlated default with incomplete information,” Journal of Banking & Finance, vol. 28, no. 7, pp. 1521–1545, 2004.
[25] M. Steinbacher, M. Steinbacher, and M. Steinbacher, M. Faggini and A. Parziale, “Interaction-based approach to economics and finance, New Economic Windows,” in Complexity in Economics: Cutting Edge Research, pp. 161–203, Springer, New York, NY, USA, 2014.
[26] L. Chen, Z. Zhou, Y. Peng, and G. Kou, “Structural model for determining enterprise group’s integrated lines of credit,” International Journal of Information Technology & Decision Making, vol. 10, no. 2, pp. 269–285, 2011.
[27] L. Chen, Z. Zhou, and J. Gu, “Evaluation credit risk of an enterprise group’s parent company in view of compound option basket option and ownerships,” Chinese Journal of Management Science, vol. 19, no. 5, pp. 167–172, 2011.
[28] L. Li and Z. Zhou, “Credit contagion mechanism for interrelated guarantee,” Systems Engineering, vol. 33, no. 1, pp. 55–60, 2015.