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Credit Risk Contagion in an Evolving Network Model Integrating Spillover Effects and Behavioral Interventions

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We introduce an evolving network model of credit risk contagion in the credit risk transfer (CRT) market. The model considers the spillover effects of infected investors, behaviors of investors and regulators, emotional disturbance of investors, market noise, and CRT network structure on credit risk contagion. We use theoretical analysis and numerical simulation to describe the influence and active mechanism of the same spillover effects in the CRT market. We also assess the reciprocal effects of market noises, risk preference of investors, and supervisor strength of financial market regulators on credit risk contagion. This model contributes to the explicit investigation of the connection between the factors of market behavior and network structure. It also provides a theoretical framework for considering credit risk contagion in an evolving network context, which is greatly relevant for credit risk management.

1. Introduction

Credit risk is the most important risk in the credit risk transfer (CRT) market, and one of the key issues is dealing with credit risk contagion [1–9]. Modeling credit risk contagion in the CRT network is an important yet challenging problem; credit risk modeling involves examining the role of counterparty risks [2, 4, 6, 9]. If a key investor is in financial distress or default, then any investor who is economically influenced by this given investor will be affected, including the providers and purchasers of credit derivatives and the banks with the investor's credit line. The direct correlation between firms caused by credit contagion leads to further complications in modeling the overall risk level, either portfolio or economy wide [3, 6, 9, 10].

In the CRT market, an intricate web of credit relations links a wide variety of counterparties in a complex system. If a key investor is in financial distress, then credit rating declines, or defaults, which will lead to credit risk contagion. Credit risk will also produce spillover effects of defaults for other investors with indirect correlations. The spillover effects

of credit risk contagion mainly come from the similarities in assets structure and in the effects of some behavior deviations of investors, including credit risk holders and financial market regulators. Thus, the behavioral factors of investors and financial market regulators, particularly investor sentiments, exert important spillover effects of credit risk contagion. The market behavioral approach recognizes that investors are not "rational" but "boundedly rational" and that systematic biases in their beliefs cause them to trade on nonfundamental information called "sentiment" [11]. Several financial economists also recognize that the market exhibits mood swings. The link between asset valuation and investor sentiment will soon become the subject of considerable deliberation among financial economists. Theories departing from rational asset pricing often posit the influence of investor sentiment [12], which leads to price fluctuation, and risk contagion generation. A number of theoretical studies offer models for establishing the relationship between investor sentiment and asset prices [12–15]. In these models, investors are categorized into two types, namely, rational arbitrageurs who are sentiment-free and irrational traders who are prone

to exogenous sentiment [16]. Baker and Stein [16] find that total sentiment, particularly the global component of total sentiment, is a contrarian predictor of country-level market returns. Baker and Wurgler [15, 17] predict that extensive waves of sentiment will exert greater effects on hard-to-arbitrage and hard-to-value stocks, which exhibit high "sentiment beta" [18]. Therefore, given that sentiment influences valuation, taking a position opposite to the prevailing market sentiment can be expensive and risky. Several theoretical studies show that investor sentiment is the most relevant factor in the decision-making domain, which primarily affects an investor's personal investment decisions [19]. Baker and Wurgler [17] pointed out that sentiment-based mispricing is based on the uninformed demand of several investors, noise traders, and a limit to arbitrage. Mispricing can be persistent given that the length of period during which overly optimistic and pessimistic noise traders will continue exerting buying or selling pressures is unknown. Similarly, numerous significant studies in this area are available [20–23]. Recently, theoretical studies have found that investor sentiment is contagious across markets [24], thus providing clues on how investor sentiment induces the spread of risk. The effects of the behaviors of credit risk investors have been a concern of credit risk contagion [4, 8, 9, 25–27]. This concern is also our motivation in considering the effect of the risk sentiment of credit risk investors on the evolving network of credit risk contagion. In addition, the behaviors of regulator and the ability of investors for risk resistance can decrease the influence of credit risk contagion [8, 9, 27, 28]. Thus, we also introduce them to analyze the effect of these factors on credit risk contagion. Our study enhances the understanding of the effects of behaviors of investors and regulators on credit risk contagion.

Given the significant development of complex network theory, a number of scholars have looked for evidence of contagion risk in the financial system which results from complex credit connections. The most well-known contribution to contagion analysis through direct linkages in the financial system is Allen and Gale [29]. This work demonstrates that the spread of contagion depends crucially on the pattern of interconnectedness among banks through a network structure involving four banks. Since the publication of this work, numerous scholars have applied the complex network theory to model the complex structure of the financial system and to analyze risk contagion in the financial system, particularly in banking systems. Several theoretical studies have found that the network structure is crucial to credit risk contagion [10, 30] (Chen et al., 2012), including random [31] (Chen et al., 2012) and tiered structures [30, 32–36]. These theoretical studies examine risk contagion in banking systems via direct linkages among banks, whereas others analyze risk contagion via indirect linkages [30, 37–41] (Jorion and Zhang, 2009). The aforementioned studies show that the network structure can significantly affect credit risk contagion. In our study, we consider the effect of the characteristics of the CRT network structure and behaviors of investors and regulators on credit risk contagion. Our objective is to understand the spillover effects of infected investors, behaviors of investors and regulators, emotional disturbance of investors,

market noise, and CRT network structure on credit risk contagion.

The rest of this paper is organized as follows. Section 2 presents some assumptions and notations for the following investigation. Section 3 defines the contagious process and feature of credit risk and builds an evolving network model of credit risk contagion in the CRT market. Section 4 uses stochastic dominance theory to theoretically study the effects of risk spillover, participants' behavioral factors, and the CRT network structure factors. Section 5 uses numerical simulations to deeply analyze and verify the effects of the aforementioned factors on credit risk contagion. Finally, Section 6 summarizes with some concluding remarks.

2. Notations and Assumptions

This study considers a network of credit risk contagion that evolves through the spillover effects of infected investors and behavioral interventions of investors and regulators. To model the evolving mechanism of credit risk contagion during credit risk transfer, we make the following assumptions. We assume that each node represents one individual investor engaged in the dealing of credit derivatives in the CRT market, and these investors are connected to each other. Thus, investors of the CRT market can use social network for representation. We also assume that the number of individuals N is limited in the evolving network, $N = 1, 2, \ldots, n$. In order to simulate the actual situation of the CRT market, we further assume that the number of the direct connection edges of an investor with other investors is not less than 2, namely, the degree $k \geq 2$ of nodes in the CRT network of credit risk contagion.

In addition, we mark the main variables in this paper and describe their economic and financial meanings. Thus, the notation used in this paper has been summarized as follows:

(i) ϕ_k is the proportion of nodes infected with credit risk by other nodes in the cluster with the degree of nodes equal to k, and $\phi_k \in [0, 1]$.

(ii) α is the degree of the effect of market noises on investors. It is used to depict the influence mechanism of noise attribute on credit risk contagion when market noise attribute is consistent with the emotion, aspirations, or demand of the people. In addition, $\alpha \in [0, 1]$.

(iii) ρ is the malicious attack strength of some institutional investors. ρ indicates that some institutional investors maliciously trigger and strengthen the contagion effects of credit risk by distorting market information and making use of resource advantage. In addition, $\rho \in [0, 1]$.

(iv) β_k is the inherent risk preference level of nodes with the degree of nodes equal to k, and $\beta_k \in [0, 1]$.

(v) θ_k is the resistance of nodes for credit risk contagion. θ_k reflects the risk resistance level and ability of investors under the state of credit risk contagion, and $\theta_k \in [0, 1]$.

(vi) δ is the supervisor strength of financial market regulators, and $\delta \in [0, 1]$.

(vii) η is the initial fitness of credit risk contagion in the network. η is chosen from a fitness distribution $f(\eta)$. It mainly refers to the strength of the impact of credit default behavior of one or a class of investors on others. In other words, η indicates the contagious capacity of credit risk in the CRT network, and $\eta \in [0, 1]$.

(viii) c_k is the emotional disturbance probability of nodes equal to k for credit risk contagion, and $\eta > c_k \geq 0$, where $\partial c_k/\partial \rho > 0$, $\partial^2 c_k/\partial \rho^2 > 0$.

(ix) μ is the spillover effect of credit risk contagion of infected nodes. μ describes the degree of the effect of credit risk of infected investors on other investors that are not directly connected to the infected investors. However, a similar investment assets structure exists between the infected investors and the other investors that are not directly connected to the infected investors, where $\partial \mu/\partial c_k > 0$, $\partial^2 \mu/\partial c_k^2 < 0$, $\partial \mu/\partial \rho > 0$, $\partial^2 \mu/\partial \rho^2 > 0$. And $\mu \in [0, 1]$.

(x) λ is the probability of infected nodes by credit risk to restore the health status. λ indicates the official rescue strength, and $\lambda \in [0, 1]$.

3. Definition of the Evolving Network Model of Credit Risk Contagion

We begin by formally defining a dynamic evolving network model in the CRT market that considers the spillover effects of infected investors, behaviors, and emotional disturbance of investors and regulators, market noise, and the CRT network structure on credit risk contagion. Let $P(k)$ represent the probability distribution of nodes with the degree of nodes equal to k in the dynamic evolving network. Then, the average degree $\langle k \rangle$ of the dynamic evolving network is as follows:

$$\langle k \rangle = \sum_k k P(k), \tag{1}$$

where $0 < k < n$.

In the CRT network, the initial fitness η of credit risk contagion mainly depends on the average degree $\langle k \rangle$ of the CRT network, the probability distribution $P(k)$ of nodes that the degree of nodes is equal to k, and the proportion ϕ_k of infected nodes with credit risk in the cluster with the degree of nodes that is equal to k. Thus, the initial fitness η of credit risk contagion in the dynamic evolving network is as follows:

$$\eta = \frac{\sum_k \phi_k k P(k)}{\langle k \rangle}. \tag{2}$$

In the actual financial market, investors are not rational but boundedly rational and systematic biases in their beliefs cause them to trade on nonfundamental information [11]. This will lead to credit asset price fluctuation and induce credit risk contagion generation. In fact, many theoretical studies have found that investor behaviors are contagious across markets [24, 42–44], thus providing clues on how investor behavior induces the spread of risk. In the CRT market, the interactions of credit behavior among investors were more significant [4, 9, 25–27]. Certainly, the regulators' behaviors can restrain irrational behaviors of investors but can also increase the irrational behavior of investors and accelerate its contagion [9, 45–48]. Some literatures of behavioral finance and psychology also show that market noise can also further strengthen the irrational behavior of investors and accelerate its contagion (Aase et al., 2000; Barber and Odean, 2000; Shleifer, 2000; Tumarkin and Whitelaw, 2001; Barber et al., 2009; Gúegan, 2009) [8, 28]. In addition, investors' behaviors can also affect regulators' behaviors and decisions. Thus, in the social network, for investors with degree of nodes equal to k, with the increase in the risk preference level β_k of investors, the contagion effect of credit risk will be intensified in the CRT network, and the emotional disturbance probability of investors and the spillover effect of credit risk contagion of infected nodes will also increase. However, the regulators' behaviors and the investors' ability of risk resistance can change the evolution trend. In other words, with the increasing supervision strength of financial market regulators and the investors' ability of risk resistance, the emotional disturbance probability of nodes and the spillover effect of credit risk contagion of infected nodes can also be reduced. Thus, we assume the fitness η_k of credit risk contagion with the degree of nodes equal to k, the effect degree ρ_k of the malicious attack of some institutional investors on other investors with the degree of nodes equal to k, and the spillover effect μ_k of credit risk contagion of infected nodes with the degree of nodes equal to k could been written as follows:

$$\eta_k = \eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}$$

$$\rho_k = \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} \tag{3}$$

$$\mu_k = \mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)},$$

where η_k depicts the contagion effect of infected investors on healthy investors and represents the change in the average density of infected investors in the CRT network. ρ_k depicts some institutional investors who maliciously trigger or intensify the contagion effect of credit risk by distorting market information and making use of resource advantage. μ_k depicts the effect degree of the default behavior of infected nodes with the degree equal to k on the other nodes that are not directly connected to infected nodes. Their parameter values are independent of k.

In addition, for the infected nodes by credit risk, the probability to restore the health status is opposite to the mechanism above. Thus, we assume that the probability λ_k of nodes infected with credit risk by other nodes to restore the health status can be written as follows:

$$\lambda_k = \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}, \tag{4}$$

where λ_k depicts the evolution behaviors that infected investors restored to health status by the effect of their

own internal and external factors. Its parameter value is independent of k.

In a recent series of literatures, the mean-field approach as a basic tool of dealing with the Markov process has been used to deal with the influence of different things [27, 28, 49–52]. It can convert a multidimensional problem into a low dimensional problem and is also considered as a very important theoretical analysis method in statistical physics. Eboli [53] shows that the infection mechanism in the financial system is similar to the physical phenomenon of network flow. Lopez [54] shows that this kind of problem can been described using the mean-field method. Based on the existing literatures, we adopt the mean-field approach to describe the Markov process of credit risk contagion in the CRT network. Thus, we represent the model of credit risk contagion with the spillover effects of infected investors and behavioral intervention of investors and regulators as follows:

$$\frac{\partial \phi_k}{\partial t} = \rho_k \left(1 - \phi_k\right) \left[k \eta_k + \mu_k\right] - \phi_k \lambda_k. \tag{5}$$

For the contagion system of credit risk, represented by (5), let $\partial \phi_k / \partial t = 0$, and we will get the equilibrium point of the contagion system of credit risk as follows:

$$\phi_k = \frac{\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} \left[k \left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right) + \mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)}\right]}{\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} \left[\mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)} + k \left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right)\right] + \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}}. \tag{6}$$

Equation (6) is the equilibrium probability of the contagion system of credit risk, which describes the proportion of infected investors with credit risk by other investors with the degree of nodes equal to k in the CRT network. Equation (6) describes the mechanism of the effect degree α of market noises, the risk preference level β_k of investors, the risk resistance ability θ_k of investors, the supervision strength δ of financial market regulators, the initial fitness η of credit risk contagion, the emotional disturbance probability c_k of investor, the spillover effect μ of credit risk contagion of infected nodes, the probability λ of infected nodes with credit risk by other nodes restored to the health status, and the degree k of nodes on the proportion ϕ_k of infected nodes under the equilibrium status of the credit risk contagion system. Then, incorporating (6) into (2), we can get the following equation.

$$\eta^* = \frac{1}{\langle k \rangle} \sum_k \frac{kP(k) \left[k \left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right) + \mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)}\right] \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}}{\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} \left[\mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)} + k \left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right)\right] + \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}}. \tag{7}$$

Thus, we derive the fitness η^* of credit risk contagion as (7) under the equilibrium status of the credit risk contagion system. Equation (7) describes the following factors under the equilibrium status of credit risk contagion system, namely, the effect mechanism of the effect degree α of market noises, the risk preference level β_k of investors, the risk resistance ability θ_k of investors, the supervision strength δ of financial market regulators, the fitness η of credit risk contagion, the emotional disturbance probability c_k of investor, the spillover effect μ of credit risk contagion of infected nodes, the probability λ of nodes infected with credit risk by other nodes restored to the health status, the probability distribution $P(k)$ of nodes that the degree of nodes is equal to k, and the average degree $\langle k \rangle$ of the dynamic evolving network on the fitness η^* of credit risk contagion in the CRT network.

4. Evolving Network Analysis of Credit Risk Contagion with Market Participants' Behavioral Factors and Network Structure in the CRT Market

We provide a theoretical analysis of the evolving network of credit risk contagion to study the effect of the effect degree

α of market noises, the risk preference level β_k of investors, the resistance θ_k of investors for credit risk contagion, the supervision strength δ of financial market regulators, the initial fitness η of credit risk contagion, the emotional disturbance probability c_k of investor, the spillover effect μ of credit risk contagion of infected nodes, the probability λ of nodes infected with credit risk by other nodes restored to the health status, the probability distribution $P(k)$ of nodes that the degree of nodes is equal to k, and the average degree $\langle k \rangle$ of the dynamic evolving network on the evolution behaviors of credit risk contagion in the CRT market.

4.1. Influence Mechanism of Market Participants' Behavioral Factors on Credit Risk Contagion

Theorem 1. *For the evolving network with degree equal to F, under the equilibrium status of credit risk contagion system, the evolving behavior of credit risk contagion exists with the following properties. (1) If $\mu = 0$ and $\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} \leq \langle k \rangle / \langle k^2 \rangle$, then the credit risk contagion system exists only at the equilibrium point η^*, and $\eta^* = 0$. (2) If $\mu = 0$ and $\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} > \langle k \rangle / \langle k^2 \rangle$, then the credit risk contagion system exists at two equilibrium points η_1^**

and η_2^*, and $\eta_1^* = 0$, $\eta_2^* > 0$. *(3) If $\mu > 0$, then the credit risk contagion system exists only at the equilibrium point η^*, and $\eta^* > 0$.*

Proof. Let

$$G(\eta) = \sum_k \frac{kP(k)\left[k\left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right) + \mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)}\right]\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}}{\langle k \rangle \left[\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}\left[\mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)} + k\left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right)\right] + \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}\right]}. \quad (8)$$

Let $A = (1 - \beta_k^2)(\ln(\delta^3 + 1) + \theta_k)/(1 + \alpha^2)$, $B = (\ln(\delta^3 + 1) + \theta_k)/(\beta_k^2 + \alpha^2)$. And $A > 0$ and $B > 0$, then (8) can be written as

$$G(\eta) = \sum_k \frac{kP(k)\left[k\left(\eta + c_k^A\right) + \mu_k^A\right]\rho_k^B}{\langle k \rangle \left[\rho_k^B\left[\mu_k^A + k\left(\eta + c_k^A\right)\right] + \lambda_k^{1/B}\right]}. \quad (9)$$

We can get $G'(\eta) = \sum_k(k^2 P(k)\rho_k^B \lambda_k^{1/B}/\langle k \rangle[\rho_k^B[\mu_k^A + k(\eta + c_k^A)] + \lambda_k^{1/B}]^2) > 0$; thus $G(\eta)$ is an increasing function of η. And we can also get $G''(\eta) = -\sum_k(2k^3 P(k)\rho_k^{2B}\lambda_k^{1/B}/\langle k \rangle[\rho_k^B[\mu_k^A + k(\eta + c_k^A)] + \lambda_k^{1/B}]^3) < 0$. Thus $G(\eta)$ is a concave function of η.

According to the above assumptions $\eta > c_k \geq 0$, we can get $G(0) = \sum_k(kP(k)\mu_k^A\rho_k^B/\langle k \rangle(\rho_k^B\mu_k^A + \lambda_k^{1/B}))$, $G(1) = \sum_k(kP(k)[k(1 + c_k^A) + \mu_k^A]\rho_k^B/\langle k \rangle[\rho_k^B[\mu_k^A + k(1 + c_k^A)] + \lambda_k^{1/B}]) < \sum_k(kP(k)[k(1 + c_k^A) + \mu_k^A]\rho_k^B/\langle k \rangle[\mu_k^A + k(1 + c_k^A)]\rho_k^B) = 1$. Thus when $\mu = 0$, the credit risk contagion system has at least one equilibrium point $\eta^* = 0$, but no more than two.

According to $G'(\eta) = \sum_k(k^2 P(k)\rho_k^B \lambda_k^{1/B}/\langle k \rangle[\rho_k^B[\mu_k^A + k(\eta + c_k^A)] + \lambda_k^{1/B}]^2)$, we can get $G'(\eta = 0)|_{\mu=0} = \sum_k(k^2 P(k)\rho_k/\langle k \rangle \lambda_k) = (\rho_k/\lambda_k)(\langle k^2 \rangle/\langle k \rangle)$. Thus when $\mu = 0$ and $\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}/\lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} \leq \langle k \rangle/\langle k^2 \rangle$, $G'(\eta = 0) \leq 1$, which means that the credit risk contagion system exists only at the equilibrium point η^*, and $\eta^* = 0$.

In the same way, when $\mu = 0$ and $\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}/\lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} > \langle k \rangle/\langle k^2 \rangle$, $G'(\eta = 0) > 1$. Thus the credit risk contagion system exists at two equilibrium points η_1^* and η_2^*, and $\eta_1^* = 0$, $\eta_2^* > 0$.

According to the above, for $\mu > 0$, we can get $G(\eta = 0) > 0$ and $G(\eta = 1) < 1$. Thus the credit risk contagion system exists only at equilibrium point η^*, and $\eta^* > 0$. □

Corollary 2. *With increasing market noises and risk preferences of investors, the contagion effect of credit risk and its spillover effect will be intensified, but the effectiveness of market supervision and official rescue will be crippled.*

Proof. According to (3) and (4), we can get $\partial c_k/\partial \alpha > 0$, $\partial \rho_k/\partial \alpha > 0$, $\partial \mu_k/\partial \alpha > 0$, $\partial \lambda_k/\partial \alpha < 0$. And $\partial c_k/\partial \beta > 0$, $\partial \rho_k/\partial \beta > 0$, $\partial \mu_k/\partial \beta > 0$, $\partial \lambda_k/\partial \beta < 0$. Thus we can get $\partial \phi_k/\partial \alpha > 0$, $\partial \phi_k/\partial \beta > 0$, $\partial G(\eta)/\partial \alpha > 0$, and $\partial G(\eta)/\partial \beta > 0$. Thus Corollary 2 is true. □

Corollary 3. *With increasing supervision strength of financial market regulators, the contagion effect of credit risk and its spillover effect, the effect degree of market noises, and the*

malicious attack strength of institutional investors will be crippled. However, the effectiveness of the market supervision and official rescue will be enhanced, such that the recovery probability of investors who are from the infected status to health status will be enhanced.

Proof. In the same way as Corollary 2, Corollary 3 can be proven. □

Conclusion 4. When the degree of the similar investment asset structure among investors in the CRT market is lower, namely, the spillover effect $\mu = 0$ of credit risk contagion, and if the official rescue strength and the supervision strength of financial market regulators are higher, then the effect of credit risk contagion can be quickly controlled, and credit risk will not be contagious and diffusive. However, if the official rescue strength and the supervision strength of financial market regulators are lower, then the contagious and diffusion of credit risk will emerge. When the degree of the similar investment asset structure among investors in the CRT market is higher, namely, the spillover effect $\mu > 0$ of credit risk contagion, then the contagion effect of credit risk will emerge and be difficult to control.

4.2. Influence Mechanism of Network Structure on Credit Risk Contagion. In the above, we have analyzed and studied the influence mechanism of investors' behavior and financial market regulators' behavior on credit risk contagion in the CRT market. We obtained meaningful conclusions for controlling the contagion effects of credit risk. However, the different network structures will cause different market behaviors. Let $P(k)$ and $P'(k)$ represent the degree distribution of two different CRT networks. According to network stochastic dominance theory (e.g., [55–58]), if $P(k)$ strict first order stochastically dominates $P'(k)$, it is equivalent to having $\sum_k P(k)f(k) > \sum_k P'(k)f(k)$ for all monotone increasing function $f(k)$. If $P(k)$ strict second order stochastically dominates $P'(k)$, then it is equivalent to having $\sum_k P(k)f(k) > \sum_k P'(k)f(k)$ for all convex function $f(k)$. In addition, according to the network stochastic dominance theory, if $P(k)$ strict first order stochastically dominates $P'(k)$, then the network average degree of the degree distribution $P(k)$ is greater than the network average degree of the degree distribution $P'(k)$. If $P(k)$ strict second order stochastically dominates $P'(k)$, then the heterogeneity of the network of the degree distribution $P(k)$ is higher than the heterogeneity of the network of the degree distribution $P'(k)$. Thus, we assume the contagion fitness $\eta^* > 0$ and the proportion $\phi^* > 0$ of infected investors are at the equilibrium point of the system

of credit risk contagion in the CRT network, then we can get the following theorems by using the network stochastic dominance theory in this work.

Theorem 5. *CRT networks A and B have degree distributions equal to $P(k)$ and $P'(k)$, respectively. If $P(k)$ strict first order stochastically dominates $P'(k)$, then $\eta_A^* > \eta_B^*$ in the same conditions.*

Proof. We assume Theorem 5 is untenable, then $\eta_A^* \leq \eta_B^*$ is tenable.

Let

$$f(k) = \frac{k\left[k\left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right) + \mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)}\right]\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}}{\langle k\rangle\left[\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}\left[\mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)} + k\left(\eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}\right)\right] + \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}\right]}. \tag{10}$$

Namely,

$$f(k) = \frac{k(k\eta_k + \mu_k)\rho_k}{\langle k\rangle\left[\rho_k(k\eta_k + \mu_k) + \lambda_k\right]}. \tag{11}$$

Then, we can obtain $\partial f(k)/\partial k = ((k\eta_k + \mu_k)^2\rho_k^2 + \rho_k\lambda_k(2k\eta_k + \mu_k))/\langle k\rangle[\rho_k(k\eta_k + \mu_k) + \lambda_k]^2 > 0$, and $\partial^2 f(k)/\partial k^2 = 2\eta_k\rho_k\lambda_k(\rho_k\mu_k + \lambda_k)/\langle k\rangle[\rho_k(k\eta_k + \mu_k) + \lambda_k]^3 > 0$. Thus $f(k)$ is a monotone increasing convex function for all $k \geq 2$. According to the network stochastic dominance theory, $\sum_k P(k)f(k) > \sum_k P'(k)f(k)$ when $P(k)$ strict first order stochastically dominates $P'(k)$, namely, for all $\eta > 0$ having

$$G_p(\eta) > G_{p'}(\eta). \tag{12}$$

According to Theorem 1, $G_p(\eta) \in [0,1)$. We assume η_A^* and η_B^* are the equilibrium point of the system of credit risk contagion in the CRT networks A and B, and $\eta_A^* > 0, \eta_B^* > 0$, thus for all $\eta \in (\eta_A^*, 1]$ having $\eta \geq G_p(\eta)$. According to the assumption $\eta_B^* \geq \eta_A^*$ is tenable, we can get

$$\eta_B^* \geq G_p(\eta_B^*). \tag{13}$$

According to (12), we can get

$$\eta_B^* \geq G_p(\eta_B^*) > G_p'(\eta_B^*). \tag{14}$$

Namely,

$$\eta_B^* > G_p'(\eta_B^*). \tag{15}$$

However, $\eta_B^* = G_p'(\eta_B^*)$ for $\eta_B^* > 0$ is the equilibrium point of the system of credit risk contagion in the CRT network B. Thus the assumption $\eta_B^* \geq \eta_A^*$ is untenable; namely, Theorem 5 is tenable. □

Theorem 6. *CRT networks A and B have degree distributions equal to $P(k)$ and $P'(k)$, respectively. If $P(k)$ strict first order stochastically dominates $P'(k)$, then $\phi_A^* > \phi_B^*$ in the same conditions.*

Proof. According to (6), we can derive the proportion ϕ_k of infected investors that the degree of investors is equal to k as follows:

$$\phi_k = \frac{(k\eta_k + \mu_k)\rho_k}{\rho_k(k\eta_k + \mu_k) + \lambda_k}, \tag{16}$$

where $\eta_k = \eta + c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)}$, $\rho_k = \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)}$, $\mu_k = \mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)}$, and $\lambda_k = \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}$.

Then we can obtain $\partial\phi_k/\partial k = \eta_k\rho_k\lambda_k/[\rho_k(k\eta_k + \mu_k) + \lambda_k]^2 > 0$. Thus ϕ_k is a monotone increasing function for all $k \geq 2$. Since $P(k)$ strict first order stochastically dominates $P'(k)$, then we can derive

$$\sum_k \phi_k^{B^*} P(k) > \sum_k \phi_k^{B^*} P'(k). \tag{17}$$

In addition, due to $\partial\phi_k/\partial\eta = k\rho_k\lambda_k/[\rho_k(k\eta_k + \mu_k) + \lambda_k]^2 > 0$, thus ϕ_k is a monotone increasing function for all $\eta > 0$. According to Theorem 5, if $P(k)$ strict first order stochastically dominates $P'(k)$, then $\eta_A^* > \eta_B^*$. Thus for all $k \geq 2$, we can get

$$\phi_k^{A^*} > \phi_k^{B^*}. \tag{18}$$

Equation (18) is equivalent to having $\sum_k \phi_k^{A^*} > \sum_k \phi_k^{B^*}$ for all $k \geq 2$. Thus we can get

$$\sum_k \phi_k^{A^*} P(k) > \sum_k \phi_k^{B^*} P(k). \tag{19}$$

Thus we can obtain

$$\sum_k \phi_k^{A^*} P(k) > \sum_k \phi_k^{B^*} P'(k). \tag{20}$$

Namely, $\phi_A^* > \phi_B^*$. Thus Theorem 6 is tenable. □

Conclusion 7. Under the same conditions of investor behavior and market supervision, the greater the average degree of CRT network is, the higher the contagion fitness of credit risk and the proportion of infected investors in the CRT network. In other words, the more dense the CRT network is, the higher the similarities are in terms of investment asset structure, the convergence effect of investor behaviors, and

the complexity of market regulation. Thus, the more dense the CRT network is, the greater the influence of the investors' irrational behaviors, the lower the efficiency of the market regulation, and the more significant the contagion effect of credit risk. In addition, the greater the heterogeneity of the CRT network, the higher the contagion fitness of credit risk in the CRT network.

Theorem 8. *CRT networks A and B have degree distributions equal to $P(k)$ and $P'(k)$, respectively. If $P(k)$ strict second order stochastically dominates $P'(k)$, then ξ ($0 < \xi < 1$) is obtained as follows. (1) When $\langle k \rangle / \langle k^2 \rangle < \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} < \xi$, and $\mu^{(1-\beta_k^2)[\ln(\delta^3+1)+\theta_k]/(1+\alpha^2)} \to 0$, then $\phi_A^* > \phi_B^*$ for all $k \geq 2$. (2) When $\langle k \rangle / \langle k^2 \rangle < \xi < \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}$, then $\phi_A^* < \phi_B^*$ for all $k \geq 2$.*

Proof. According to (16), we can get

$$
\left(\rho_k \mu_k + \lambda_k \right) \phi_k P(k) = \eta_k \rho_k k P(k) + \rho_k \mu_k P(k) \\
- \eta_k \rho_k k \phi_k P(k). \tag{21}
$$

In (16) and (21), we know the variables ρ_k, μ_k, λ_k, and η_k are not functions of k; that is, these parameter values are independent of k. Thus, we can further derive

$$
\left(\rho_k \mu_k + \lambda_k \right) \sum_k \phi_k P(k) \\
= \eta_k \rho_k \sum_k k P(k) + \rho_k \mu_k - \eta_k \rho_k \sum_k k \phi_k P(k). \tag{22}
$$

Putting (1) and (2) into (22), we can obtain

$$
\phi = \frac{\langle k \rangle \rho_k \left(\eta_k - \eta \eta_k \right) + \rho_k \mu_k}{\left(\rho_k \mu_k + \lambda_k \right)}. \tag{23}
$$

Thus we can obtain $\partial \phi / \partial \eta$ as follows:

$$
\frac{\partial \phi}{\partial \eta} = \frac{\langle k \rangle \rho_k \left(1 - 2\eta - c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)} \right)}{\left(\rho_k \mu_k + \lambda_k \right)}. \tag{24}
$$

Thus ϕ is an increasing function of η for all $\eta < (1 - c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)})/2$. And ϕ is a decreasing function of η for all $\eta > (1 - c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)})/2$.

According to (10) $\partial f(k)/\partial k = ((k\eta_k + \mu_k)^2 \rho_k^2 + \rho_k \lambda_k (2k\eta_k + \mu_k))/\langle k \rangle [\rho_k(k\eta_k + \mu_k) + \lambda_k]^2 > 0$, and $\partial^2 f(k)/\partial k^2 = 2\eta_k \rho_k \lambda_k (\rho_k \mu_k + \lambda_k)/\langle k \rangle [\rho_k(k\eta_k + \mu_k) + \lambda_k]^3 > 0$. Thus $f(k)$ is a monotone increasing convex function for all $k \geq 2$. According to the network stochastic dominance theory, if $P(k)$ strict second order stochastically dominates $P'(k)$, then it is equivalent to having $\sum_k P(k) f(k) > \sum_k P'(k) f(k)$ for all convex function $f(k)$. According to Theorem 5, we can get $\eta_A^* > \eta_B^*$.

According to Theorem 1, we know that with ξ ($0 < \xi < 1$), when $\langle k \rangle / \langle k^2 \rangle < \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} < \xi$, we can get $\eta < (1 - c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)})/2$. And when $\langle k \rangle / \langle k^2 \rangle < \xi < \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}$, we can get $\eta > (1 - c_k^{(1-\beta_k^2)(\ln(\delta^3+1)+\theta_k)/(1+\alpha^2)})/2$. With ξ ($0 < \xi < 1$), when $\langle k \rangle / \langle k^2 \rangle < \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} < \xi$, ϕ is an increasing function of η. When $\langle k \rangle / \langle k^2 \rangle < \xi < \rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)}$, ϕ is a decreasing function of η. Thus we can get that Theorem 8 is tenable. $\square$

Conclusion 9. In the case of $\rho^{(\ln(\delta^3+1)+\theta_k)/(\beta_k^2+\alpha^2)} / \lambda^{(\beta_k^2+\alpha^2)/(\ln(\delta^3+1)+\theta_k)} > \langle k \rangle / \langle k^2 \rangle$, the effects of network heterogeneity on the contagion scale of credit risk depend on the interaction of the effect degree α of market noises, the risk preference level β_k of investors, the resistance θ_k of investors for credit risk contagion, the supervision strength δ of financial market regulators, the spillover effect μ of credit risk contagion of infected nodes, and the probability λ of nodes infected with credit risk by other nodes restored to the health status. First, decreasing the similarity of investment asset structure, the contagion scale of credit risk will be reduced. However, network heterogeneity promotes the contagion level and scale of credit risk, whereas network homogeneity can decrease the contagion level and scale of credit risk. Second, the malicious attack and market noises can promote the contagion level and scale of credit risk.

5. Simulation Analysis of the Evolving Network Model of Credit Risk Contagion

Given the absence of a large amount of time series data for empirical tests, numerical simulation analysis is the most effective testing method. Such analysis is conducted by considering the different values of the parameters in the evolving network model of credit risk contagion. The following are assumed: the number of investors $N = 10000$ in the CRT market. We choose the WS small world network and the BA network to conduct numerical simulation, where the probability $p = 0.01$ of the long distance connection of investors in the WS small world network and the degree distributions in the BA network are $P(k) = 2m^2/k^3$. Thus we can find the effects of the effect degree α of market noises, the risk preference level β_k of investors, the resistance θ_k of investors for credit risk contagion, the supervision strength δ of financial market regulators, the initial fitness η of credit risk contagion, the probability c_k of a randomly chosen old node being deleted from the network that degree of nodes is equal to k, the spillover effect μ of credit risk contagion of infected investors, the probability λ of infected investors with credit risk by other nodes restored to the health status, the degree k of investors, the average degree $\langle k \rangle$ of the dynamic evolving network, and the network structure of credit risk contagion on credit risk contagion in the CRT market. Furthermore, with investor behavior and the financial market
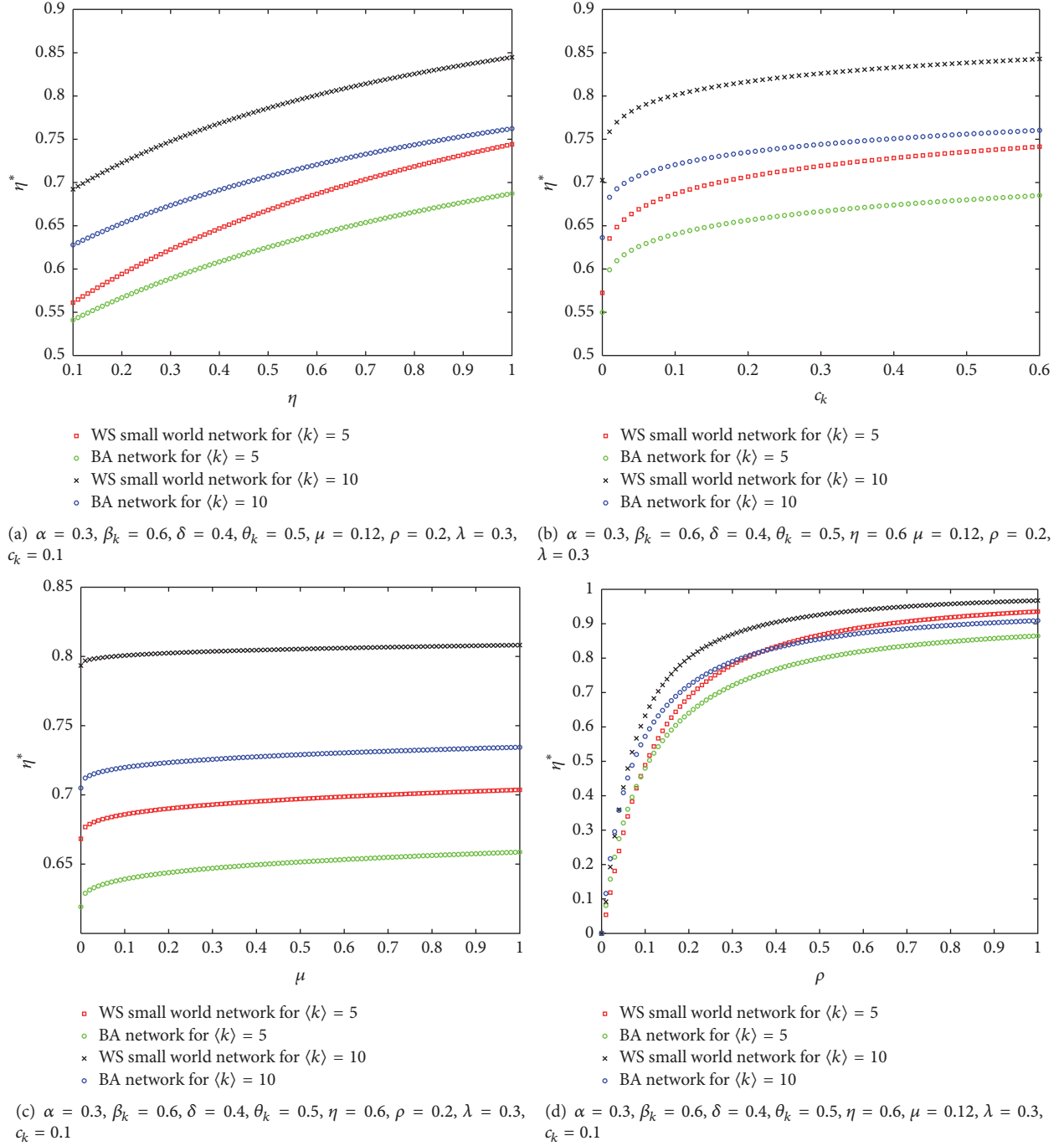
(a) $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta_k = 0.5, \mu = 0.12, \rho = 0.2, \lambda = 0.3,$ $c_k = 0.1$

(b) $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta_k = 0.5, \eta = 0.6\ \mu = 0.12, \rho = 0.2,$ $\lambda = 0.3$

(c) $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta_k = 0.5, \eta = 0.6, \rho = 0.2, \lambda = 0.3,$ $c_k = 0.1$

(d) $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta_k = 0.5, \eta = 0.6, \mu = 0.12, \lambda = 0.3,$ $c_k = 0.1$

FIGURE 1: The evolution function of the equilibrium point η^* of credit risk contagion system as function in the initial fitness η of credit risk contagion, the emotional disturbance probability c_k of investor, the spillover effect μ of credit risk contagion of infected investor, and the malicious attack strength ρ of some institutional investors under the different network structure.

regulators' behaviors, we analyze the evolving properties of the proportion of infected investors ϕ, the global fitness η of credit risk of the contagion network, and the individual fitness η_k of infected investors that the degree of nodes is equal to k. In the numerical simulations, we initialize the contagion network with $m_0 = 10$ nodes being infected with credit risk.

In Figure 1, the equilibrium point η^* of the credit risk contagion system is a concave function of the initial fitness η of credit risk contagion, the emotional disturbance probability c_k of investor, the spillover effect μ of credit risk contagion of infected investor, and the malicious attack strength ρ of some institutional investors. The malicious attack strength ρ of some institutional investors is more significant. The reason is

that the malicious attack of some institutional investors cause market information confusion. It brings about irrational behavior among the majority of small- and medium-sized investors. It also shows that the disturbance effect of private information is more significant on credit risk contagion in the semi-strong valid market. Second, Figure 1 also shows that the contagion rate has a significant positive correlation with network density and has a significant negative correlation with the network heterogeneity. The reason is that the more dense the credit network is, the more significant the interaction between counterparties is. However, network heterogeneity hampers the interaction between investors. Thus the higher the network heterogeneity is, the more unfavorable it is to the credit risk contagion in the CRT market. In the same case of network density, the effect of the network heterogeneity is the most significant on credit risk contagion by inducing in the spillover effect of credit risk contagion of infected investor. This also confirms Conclusions 4 and 7.

In fact, credit risk contagion is a complex process in the CRT market. The process is mixed with complex interactions of the behaviors of counterparties and financial market regulators, and market noises. This adds to the probability of the uncertainty, unpredictability, and uncontrollability of credit risk contagion. Figure 2 shows the following factors under the different network structure, namely, the interaction mechanism of the effect degree α of market noises, the risk preference level β_k of investors, and the supervision strength δ of financial market regulators on the equilibrium point η^* of the credit risk contagion system. First, Figure 1 shows the differential effect of the network heterogeneity. The lower the network heterogeneity, the more significant the reciprocal effects of the effect degree α of market noises, the risk preference level β_k of investors, and the supervision strength δ of financial market regulators on credit risk contagion. Second, market noises and the risk preference of investors have a strengthening effect, and the supervision behaviors of financial market regulators exert weakening effects. Figures 2(a) and 2(b) show the mutual reinforcing effects between market noises and the risk preference of investors. Namely, with increasing market noises, the effects of the risk preference of investors on the infectious rate of credit risk will be promoted. With increasing risk preference of investors, the effects of the market noises on the infectious rate of credit risk will be also promoted. In Figures 2(c), 2(d), 2(e), and 2(f), we found the supervision behaviors of financial market regulators will reduce the effect of the market noises and the risk preference of investors on credit risk contagion. With increasing supervision strength δ of financial market regulators, the effects of the market noises and the risk preference of investors on the infectious rate of credit risk will be reduced. Thus, the behaviors of counterparties and the market noises can promote the contagious rate of credit risk and have the mutual reinforcing effects on the contagious speed of credit risk in the CRT market. However, the supervision behaviors of financial market regulators will weaken the effects of the external disturbance factors and reduce the contagious speed of credit

risk in the CRT market. This confirms Corollaries 2 and 3.

Figures 3 and 4 depict the effect mechanism of the initial contagious fitness of credit risk, the spillover effect of credit risk contagion of infected investor, the emotional disturbance probability of investor, the malicious attack strength of institutional investors, and the official rescue strength on the contagious scale of the credit risk in the CRT market under the different network structures. First, Figures 3 and 4 show that the contagious scale of credit risk has a significant positive correlation with network density. The sparser the CRT network, the weaker the effect of the CRT network heterogeneity on the contagious scale of credit risk. However, with increasing average degree of the CRT network, the effect of the CRT network heterogeneity on the contagious scale of credit risk will be significantly promoted. When the average degree of the CRT network is greater than a certain threshold, the higher the CRT network heterogeneity, the greater the contagious scale of credit risk. Second, Figure 4(b) shows that the official market rescue will restrain the contagious scale of credit risk. With increasing official rescue strength, the contagious scale of credit risk will be reduced. On the contrary, with increasing network density, the efficiency of the official market rescue will be reduced. When the average degree of the CRT network is greater than a certain threshold, the higher the CRT network heterogeneity, the lower the efficiency of the official market rescue.

Figure 5 depicts the effects of the risk preference of investors, the effect degree of market noises, the supervisor strength of financial market regulators, and the risk resistance ability of investors on credit risk contagion. Figure 5(a) shows that when the risk preference of investors is infinitesimally small, credit risk contagion will be controlled, and the contagious scale of credit risk will be also infinitesimally small. With increasing risk preference level β_k of investors, credit risk contagion presents the concavity evolution of monotone increasing. However, when the risk preference of investors is greater than a certain threshold, credit risk contagion presents the convexity evolution of monotone increasing. Figure 5(b) shows that when the market noise is smaller than a certain threshold, credit risk contagion presents the concavity evolution of monotone increasing along with the increasing of the effect degree of market noises. In contrast, when the market noise is greater than the threshold, credit risk contagion presents the convexity evolution of monotone increasing along with the increasing of the effect degree of market noises. In addition, Figures 5(a) and 5(b) also depict, with increasing network density, the contagion effect of credit risk which is amplified and the effects of the CRT network heterogeneity which will be significantly promoted. When the average degree of the CRT network is greater than a certain threshold, the higher the CRT network heterogeneity, the more significant the effects of the risk preference of investors and the market noises on credit risk contagion. Figures 5(c) and 5(d) depict the inhibiting effect of the supervisor strength of financial market regulators and the risk resistance ability of investors
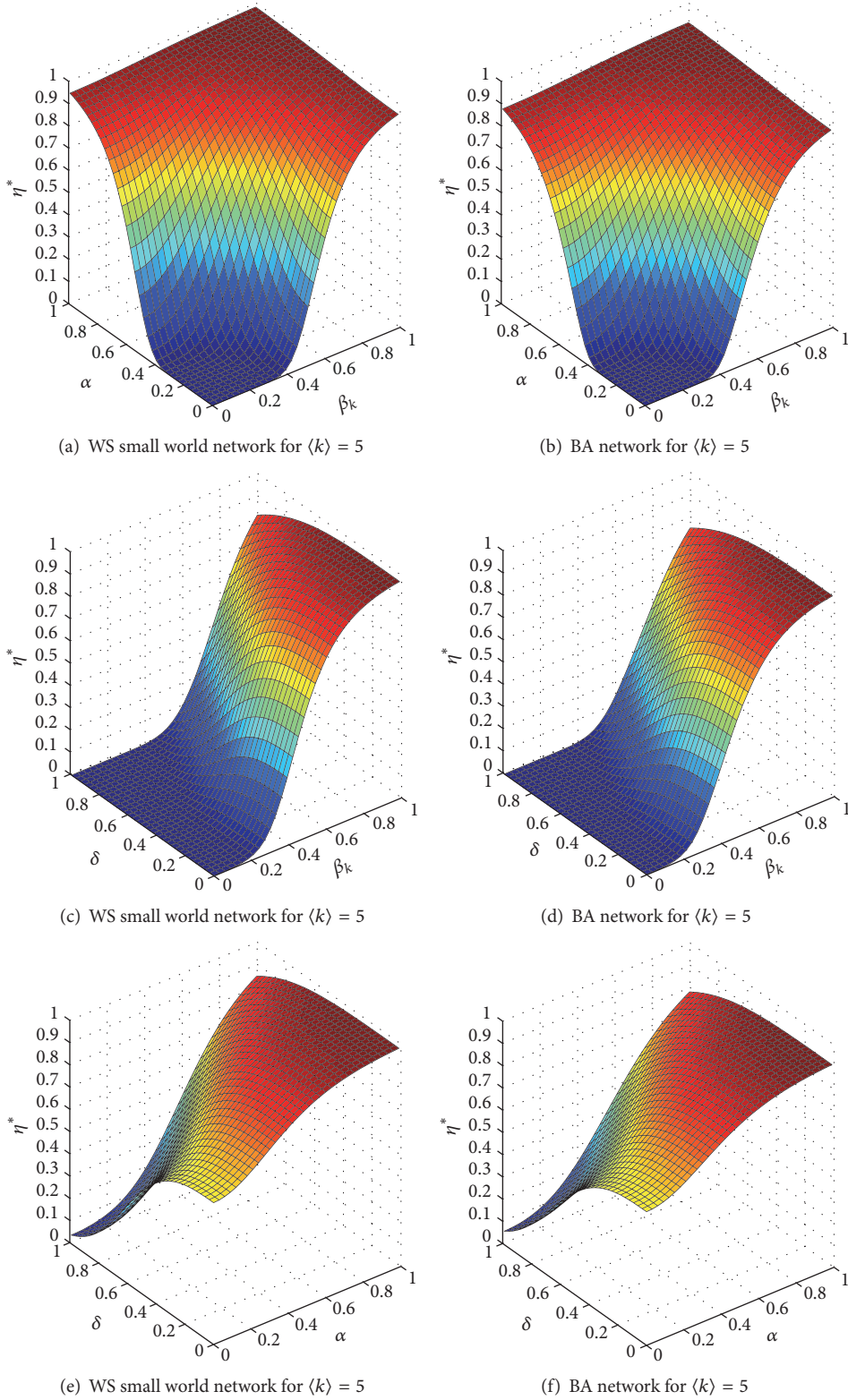
(a) WS small world network for $\langle k \rangle = 5$

(b) BA network for $\langle k \rangle = 5$

(c) WS small world network for $\langle k \rangle = 5$

(d) BA network for $\langle k \rangle = 5$

(e) WS small world network for $\langle k \rangle = 5$

(f) BA network for $\langle k \rangle = 5$

FIGURE 2: The influencing mechanism of the interaction among the effect degree α of market noises, the risk preference level β_k of investors, and the supervision strength δ of financial market regulators on the equilibrium point η^* of the credit risk contagion system under the different network structure. (a) and (b) for $\delta = 0.4, \theta = 0.5, \eta = 0.6, \mu = 0.3, \rho = 0.2, \lambda = 0.3, c_k = 0.1$; (c) and (d) for $\alpha = 0.3, \theta = 0.5, \eta = 0.6, \mu = 0.3, \rho = 0.2, \lambda = 0.3, c_k = 0.1$; (e) and (f) for $\beta_k = 0.6, \theta = 0.5, \eta = 0.6, \mu = 0.3, \rho = 0.2, \lambda = 0.3, c_k = 0.1$.
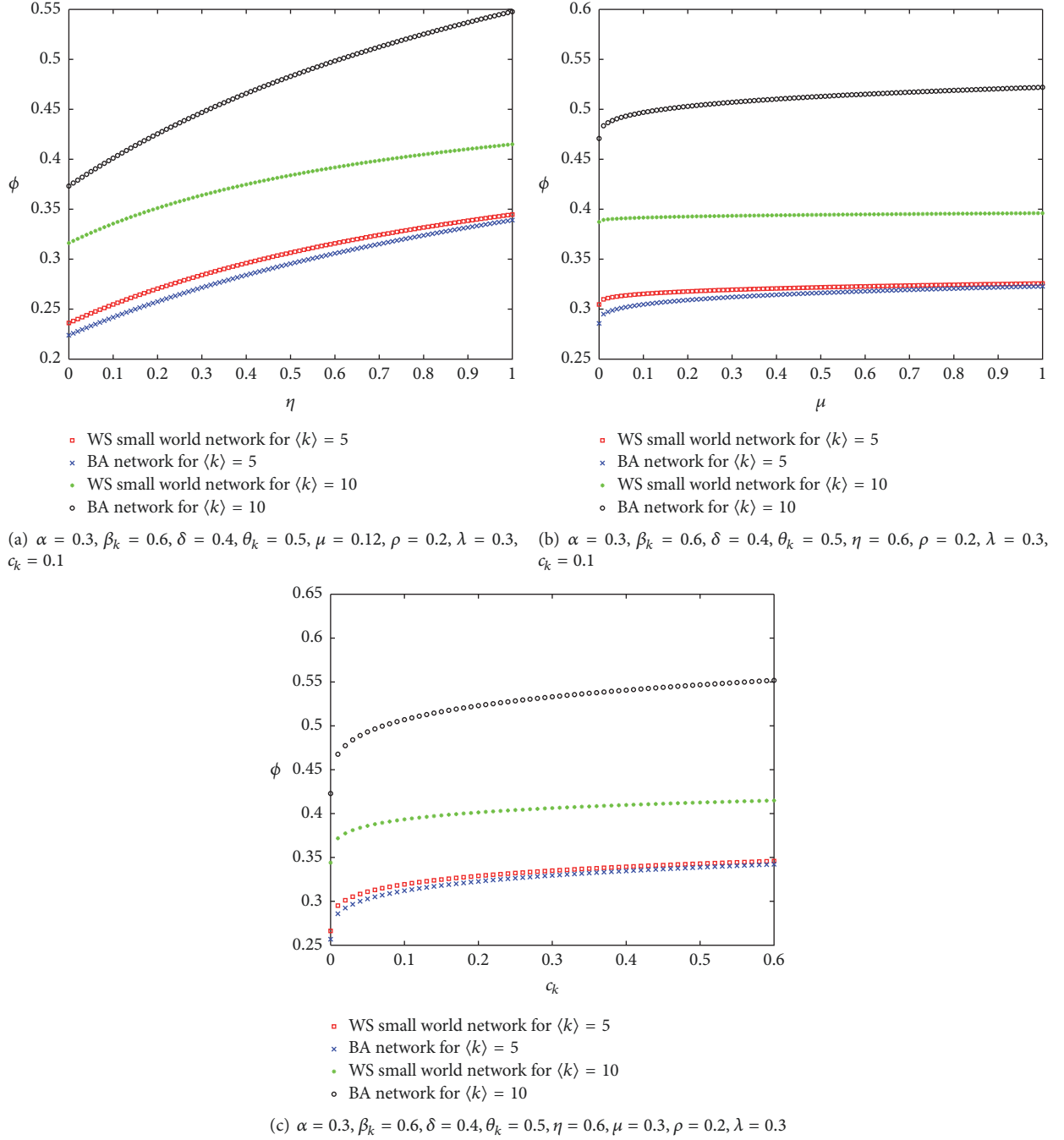
(a) $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta_k = 0.5, \mu = 0.12, \rho = 0.2, \lambda = 0.3, c_k = 0.1$

(b) $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta_k = 0.5, \eta = 0.6, \rho = 0.2, \lambda = 0.3, c_k = 0.1$

(c) $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta_k = 0.5, \eta = 0.6, \mu = 0.3, \rho = 0.2, \lambda = 0.3$

FIGURE 3: The evolution function of the contagious scale ϕ of credit risk as function in the initial fitness η of credit risk contagion, the spillover effect μ of credit risk contagion of infected investor, and the emotional disturbance probability c_k of investor under the different network structure. (a) for $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta = 0.5, \mu = 0.12, \rho = 0.2, \lambda = 0.3, c_k = 0.1$; (b) for $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta = 0.5, \eta = 0.6, \rho = 0.2, \lambda = 0.3, c_k = 0.1$; (c) for $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \theta = 0.5, \eta = 0.6, \mu = 0.12, \rho = 0.2, \lambda = 0.3$.

on credit risk contagion. With increasing network density, the inhibiting effect of the supervision of financial market regulators and the risk resistance ability of investors on credit risk contagion will be reduced. When the average degree of the CRT network is greater than a certain threshold, the higher the CRT network heterogeneity, the lower the control

efficiency of the supervision of financial market regulators and the risk resistance ability of investors on credit risk contagion.

Figure 6 depicts the reciprocal effect of the market noises, the risk preference of investors, and the supervisor strength of financial market regulators on credit risk
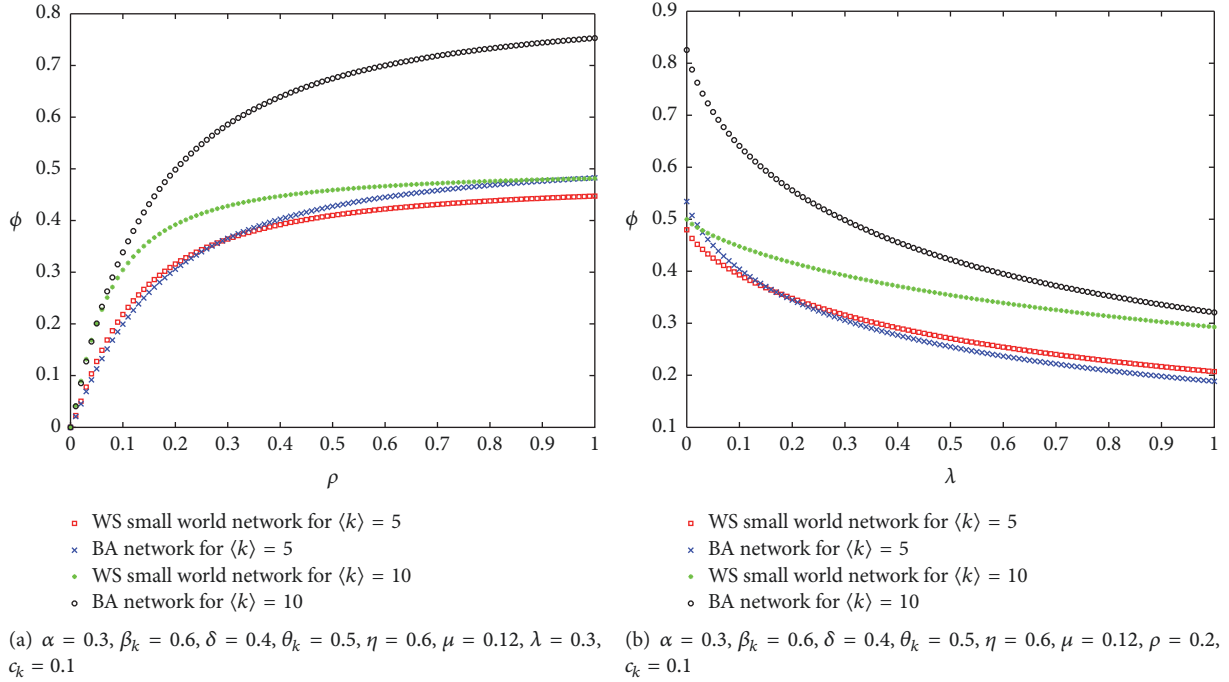
(a) $\alpha = 0.3$, $\beta_k = 0.6$, $\delta = 0.4$, $\theta_k = 0.5$, $\eta = 0.6$, $\mu = 0.12$, $\lambda = 0.3$, $c_k = 0.1$

(b) $\alpha = 0.3$, $\beta_k = 0.6$, $\delta = 0.4$, $\theta_k = 0.5$, $\eta = 0.6$, $\mu = 0.12$, $\rho = 0.2$, $c_k = 0.1$

FIGURE 4: The evolution function of the contagious scale ϕ of credit risk as function in the malicious attack strength ρ of some institutional investors and the official rescue strength λ under the different network structure. (a) for $\alpha = 0.3$, $\beta_k = 0.6$, $\delta = 0.4$, $\theta = 0.5$, $\eta = 0.6$, $\mu = 0.12$, $\lambda = 0.3$, $c_k = 0.1$; (b) for $\alpha = 0.3$, $\beta_k = 0.6$, $\delta = 0.4$, $\theta = 0.5$, $\eta = 0.6$, $\mu = 0.12$, $\rho = 0.2$, $c_k = 0.1$.

contagion. First, Figure 6 shows that the higher the CRT network heterogeneity, the more significant the reciprocal effect of the market noises and the risk preference of investors on credit risk contagion. Second, the reciprocal effect of the market noises and the risk preference of investors will promote the contagious scale of credit risk in the CRT market. However, the supervisor strength of financial market regulators will reduce the effect of the market noises and the risk preference of investors on credit risk contagion.

6. Conclusion

In this paper, we design an evolving network model of credit risk contagion that considers the spillover effects of infected investors, behaviors and emotional disturbance of investors and regulators, market noise, and the CRT network structure on credit risk contagion. We use theoretical analysis and numerical simulation to investigate the effect mechanism of the spillover effects and behavioral intervention on credit risk contagion in the CRT market. We find the strengthening effects of the spillover effects of infected investors, the emotional disturbance of investors and the malicious attack behaviors of some institutional investors, the restraining effects of the official market rescue and the risk resistance ability of investors for credit risk contagion, and the density effects and heterogeneous effects of the CRT network on credit risk contagion. In addition, we also investigate the

reciprocal effects of the market noises, the risk preference of investors, and the supervisor strength of financial market regulators on credit risk contagion. We further find the interactive facilitation effect of the market noises and the risk preference of investors on credit risk contagion, and the restraining effects of the supervisor strength of financial market regulators on credit risk contagion. Certainly, we acknowledge several limitations in the modeling method and process, and the testing method and way. Due to these limitations, the investigation results in the paper are considered exploratory and suggestive rather than conclusive. Therefore, future studies can further deepen and expand the results presented in this paper.

Disclosure

Tingqiang Chen and Binqing Xiao are co-first authors.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.
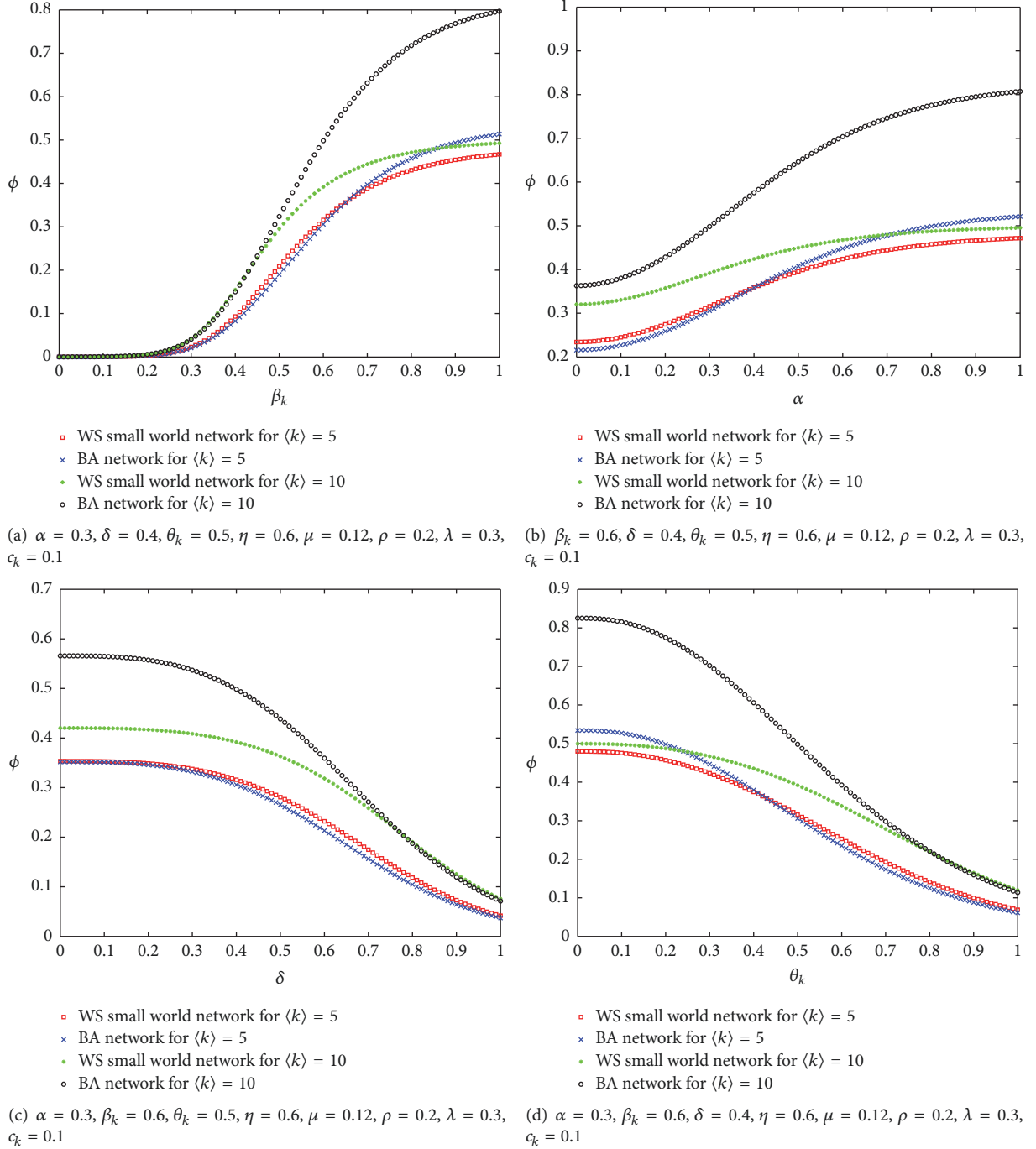
Acknowledgments

FIGURE 5: The evolution function of the contagious scale ϕ of credit risk as function in the risk preference level β_k of investors, the effect degree α of market noises, the supervision strength δ of financial market regulators, and the resistance θ_k of investors for credit risk contagion. (a) for $\alpha = 0.3, \delta = 0.4, \theta = 0.5, \eta = 0.6, \mu = 0.12, \rho = 0.2, \lambda = 0.3, c_k = 0.1$; (b) for $\beta_k = 0.6, \delta = 0.4, \theta = 0.5, \eta = 0.6, \mu = 0.12, \rho = 0.2, \lambda = 0.3, c_k = 0.1$; (c) for $\alpha = 0.3, \beta_k = 0.6, \theta = 0.5, \eta = 0.6, \mu = 0.12, \rho = 0.2, \lambda = 0.3, c_k = 0.1$; (d) for $\alpha = 0.3, \beta_k = 0.6, \delta = 0.4, \eta = 0.6, \mu = 0.12, \rho = 0.2, \lambda = 0.3, c_k = 0.1$.

(a) WS small world network for $\langle k \rangle = 5$

(b) BA network for $\langle k \rangle = 5$

(c) WS small world network for $\langle k \rangle = 5$

(d) BA network for $\langle k \rangle = 5$

(e) WS small world network for $\langle k \rangle = 5$

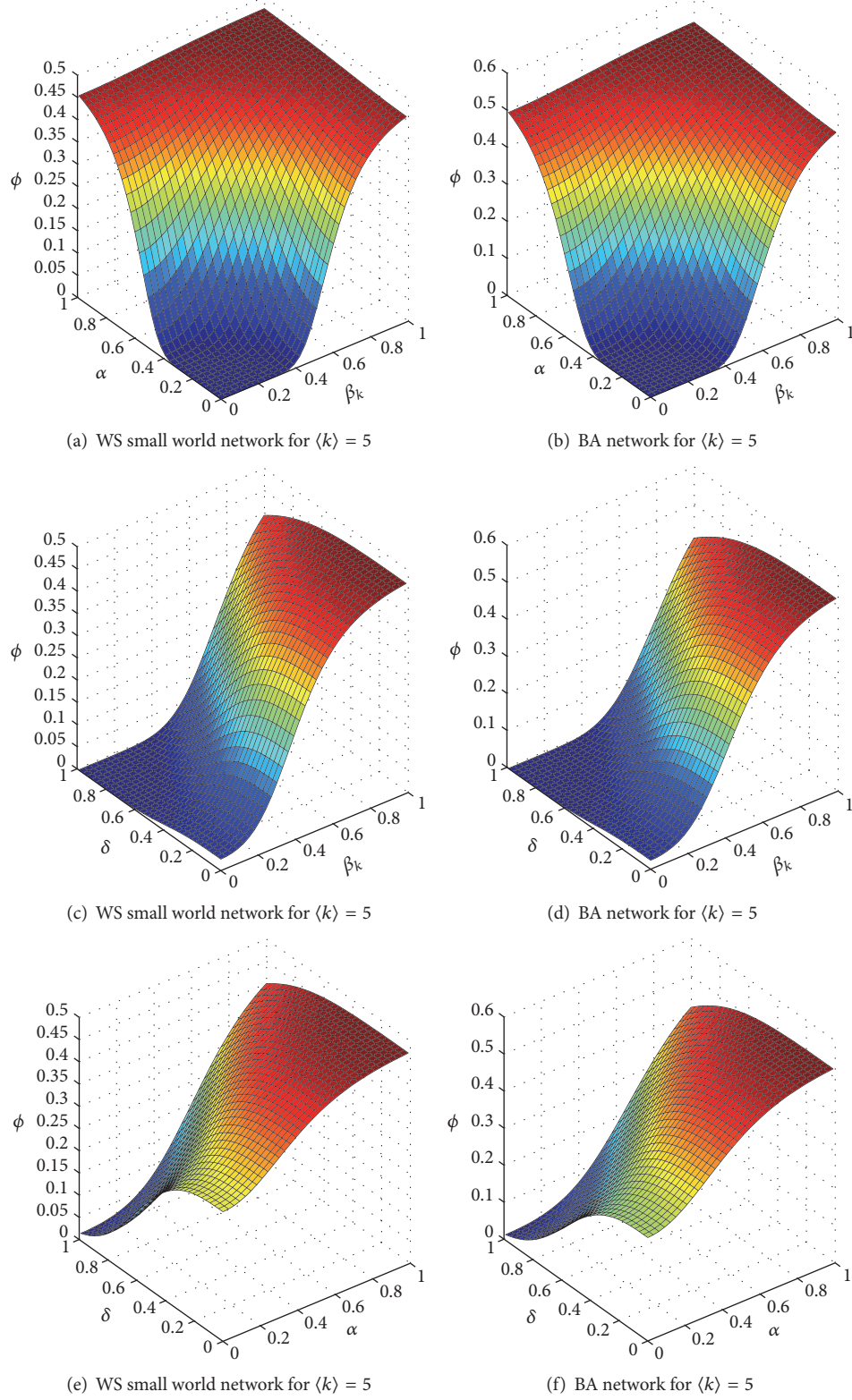(f) BA network for $\langle k \rangle = 5$

FIGURE 6: The influencing mechanism of the interaction among the effect degree α of market noises, the risk preference level β_k of investors, and the supervision strength δ of financial market regulators on the contagious scale ϕ of credit risk under the different network structure. (a) and (b) for $\delta = 0.4$, $\theta = 0.5$, $\eta = 0.6$, $\mu = 0.3$, $\rho = 0.2$, $\lambda = 0.3$, $c_k = 0.1$; (c) and (d) for $\alpha = 0.3$, $\theta = 0.5$, $\eta = 0.6$, $\mu = 0.3$, $\rho = 0.2$, $\lambda = 0.3$, $c_k = 0.1$; (e) and (f) for $\beta_k = 0.6$, $\theta = 0.5$, $\eta = 0.6$, $\mu = 0.3$, $\rho = 0.2$, $\lambda = 0.3$, $c_k = 0.1$.

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