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Research Article

Price Linkage Rumors in the Stock Market and Investor Risk Contagion on Bilayer-Coupled Networks

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Investor heterogeneities include investor risk preference, investor risk cognitive level, information value, and investor influence. From the perspective of the stock price linkage, this article constructs an SCIR contagion model of investor risk on a single-layer network. It digs out the investor risk caused by rumors in the stock market under the stock price linkage and its contagion mechanism. The function and influence of different mechanism probabilities and investor heterogeneities on the effects of risk contagion in the stock market are explored through computer simulation. Based on the SCIR contagion model of investor risk on single-layer network, we construct an SCI_1I_2R contagion model of investor risk on bilayer-coupled networks. Initially, the evolution mechanisms of investor risk contagion in the stock market are compared in single-layer and bilayer-coupled networks. Thereafter, the evolution characteristics and rules of investor risk contagion under different connection modes and heterogeneous mechanism probabilities are compared on bilayer-coupled networks. The results corroborate the following. (1) In the SCIR contagion model of investor risk on a single-layer network, immune failure probability and immune probability have the "global effect". (2) Investor heterogeneities both have "global effect" and "local effect" on investor risk contagion. (3) Compared with the investor risk contagion on a single-layer network, bilayer-coupled networks can expand the investor risk contagion and have a "global enhancement" effect. (4) Among the three interlayer connection modes of the SCI_1I_2R model of investor risk contagion on bilayer-coupled networks, the assortative link has the effect of "local enhancement", while the disassortative link has the effect of "local inhibition". (5) In the SCI_1I_2R model of investor risk contagion on bilayer-coupled networks, heterogeneous mechanism probabilities have "global effect" and "local effect". The research conclusion provides a theoretical basis for regulators to prevent financial risks from spreading among different investors, which is of high theoretical value and practical significance.

1. Introduction

The price linkage can be considered a "barometer" for the stock market [1, 2]. When the price linkage exceeds the investors' expectations, it leads to changes in investors' decision-making behavior. The uncertainty of information in the financial market easily triggers stock market rumors. Stock market rumors refer to special information that begins to circulate in the stock market without confirmation [3]. Stock market rumors turn into investor risk through their contagion and diffusion on investors' networks, which affects the status of investors toward rumors in the stock market in turn and the trading behavior of investors, thereby bringing the stock price linkage. Therefore, clarifying the formation and contagion mechanism of the investor risk caused by rumors in the stock market is important for understanding the actual process of investor stock trading influenced by information including stock market rumors, effective management of stock market rumors, and the management and control of investor risk.

Figure 1 shows that stock price linkage exceeds investors' expectations, thereby affecting investors' investment behavior on the one hand. On the other hand, information advantage investors make use of information asymmetry to spread stock market rumors driven by interests to obtain higher returns in the stock market. In the stock market, investors not only have cognitive and behavioral biases [4], but also have significant herd effects [5–7]. Egan et al. [7] corroborated that, if most investors choose to buy, they are also willing to buy and that, if most investors choose to sell, they are also willing to sell.

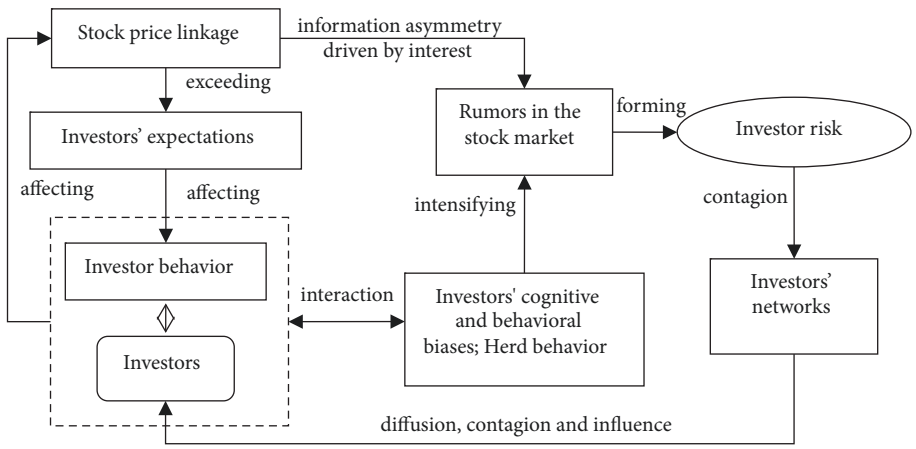


Figure 1: Mechanism analysis of investor risk formed by stock market rumors under the influence of price linkage.

As a result of these factors and influences, the formation of the stock market rumors accelerates. Market rumors can be regarded as "infected market information", which is highly contagious; the essence of investor risk formed by rumors is the interaction and diffusion of information among investors who carry "infected market information". Most investors who receive rumors think that they are in the middle of the rumor transmission sequence and that the stock price moves while rumors intersect with other investors' opinions and behaviors [8]. Therefore, investor risk spreads and diffuses in the investors' networks, such as social networks, kinship networks, friend networks, and work networks [9], thereby affecting investor behavior and decision-making and stock price linkage [10, 11].

In recent years, the impact of stock market rumors on price linkage in the stock market has become increasingly prominent. The investor risk and its evolution brought by stock market rumors under the influence of price linkage have an important impact on the health and stability of the stock market, which has been widely concerned by academic circles and financial regulators. Considerable literature has demonstrated the impact of market rumors on stock market linkage [10, 12, 13], Chen et al. 2010, [11]. For instance, Pound and Zeckhauser [10] contended that the stock price of the takeover target company generally has a significant increase before the takeover rumors published in the Wall Street journal. Clarkson et al. [13] and Gao and Oler [11] affirmed the significant increase in the trading activity of target securities before the announcement of merger rumors. Given the difficult issues of investor psychology and trading data availability, some studies have combined experimental and investigation methods. For instance, using college students in conducting simulated investment experiments, Schinlder [8] deduced that participants who receive rumors would conduct transactions, leading to the linkage of asset prices. Kosfeld [14] and Andrei and Cujean [15] introduced other ways of modeling and analysis. From the perspective of the exchange of information among traders, they believed that the more the exchanges among traders, the more the possible transactions that will be conducted, which will lead to price linkage. Existing literature analysis shows that empirical studies mainly discuss the effect of rumors, while theoretical modeling studies focus on the evolution of investor behavior.

The innovation of this paper focuses on a new perspective, stock price linkage, which considers the investor risk contagion caused by stock market rumors and concentrates on the investor risk contagion path and change rules. We use epidemic models to measure the investor risk. Based on that, we use a broad set of investor heterogeneities to modify the classic models. We use computer simulation to depict investor risk contagion because of the challenge of getting real data.

The structure of this article is as follows. In the second section, on the basis of the definition of investor risk, the research on the diffusion model of rumors is organized and summarized, and the adaptability of the epidemic model is analyzed. In the third section, an investor risk contagion model in the stock market on single-layer networks under the price linkage is constructed. Concurrently, the investor risk contagion probability model in the stock market on single-layer networks is constructed by considering the heterogeneity of investors, and the computer simulation analysis is conducted. In the fourth section, an investor risk contagion model in the stock market on bilayer-coupled networks is constructed, and the computer simulation analysis is implemented. The last section summarizes and concludes the research.

2. Investor Risk and Adaptability of the Epidemic Model

To better analyze the effects and influence factors of investor risk contagion, as well as look for the effective risk control strategy, this section initially defines the concept of investor risk. Studies of the rumor diffusion model, complex network theory, and related research are reviewed, while the adaptability of epidemic model is analyzed.

2.1. Investor Risk. Market rumors, regarded as "infected market information", are highly contagious. In this paper, investor risk is defined as follows: under the diffusion of rumors in the stock market, the investor's risk is formed by the change of his status toward rumors; its essence is the

interaction and diffusion of information between investors carrying "infected market information".

From the idea of the SIR model of infectious disease, Daley and Kendall [16] first proposed the random model of rumor diffusion (DK model). Maki and Thompson [17] further proposed an improved model (MK model). Thereafter, Nokovee et al. [18] combined the MK model and the SIR model and proposed a rumor diffusion model on complex networks. Through theoretical analysis and numerical simulation, the steady state and the evolution of the diffusion process over time in homogeneous networks, ER stochastic maps, and scale-free networks are analyzed comprehensively. Xiong et al. [19] proposed an SCIR diffusion model to describe the diffusion of rumors. In Zhao et al. [20] and Zan et al. [21], the individual is divided into the following categories, respectively: SIHR (ignorant-Spreader-Hibernator-stifler) and SCIR (Susceptible-infective-counter-refractory). These papers considered forgetting and counter mechanism. Jia and Wu [22] proposed a rumor transmission model with incubation period and constant recruitment in social networks. Moreover, the current research on complex network theory is mostly limited to a single network, while a single network is only a subset of a larger complex network, and complex systems are coupled from many networks with different structures and functions [23], Wu et al. 2018, [24]. Wu et al. (2018) found the double transition for information spreading on layered networks. Wang et al. [24] found that the information spreading is suppressed on multirelational networks especially when the average degree of hostile network is large through extensive numerical simulations. Therefore, the social networks are always multirelational, which can be described by using the multilayer network [25–32].

In sum, to make the model closer to the stock market based on the SCIR model, [19], Jia and Wu [22], and consider the heterogeneity of investors and bilayer-coupled structure of investors' networks, this study constructs an investor risk contagion model on bilayer-coupled networks on the basis of establishing an investor risk contagion model on single-layer network in the stock market to explore the path and change rules of investor risk contagion.

2.2. Adaptability of the Epidemic Model. Epidemic models are widely used in the study of diffusion problems, such as the spread and diffusion of public opinions, rumors, and knowledge, and many results have been achieved [24, 33, 34]. The contagion of investor risk in the investors' networks is similar to that of infectious diseases in the population. Specific performances are as follows.

2.2.1. Contagion Environment. Infectious diseases are mainly spread in social networks composed of individuals, and they infect the nodes (people) in social networks through the edges (connections established between people). The contagion of investor risk is spread in the investors' networks, which are composed of shareholding investors. Investor risk infects the nodes (investors) in the investors' networks through the edges (the relationship between investors) in the investors' networks. Therefore, in terms of the contagion environment, the contagion of investor risk is similar to the viral contagion.

2.2.2. Contagion Process. In the transmission of infectious diseases, viruses generally can only spread from infected individuals to those whom they have contact with. Similarly, in the contagion process of investor risk, after a certain node investor is infected with the risk, the associated investor is affected by the risk first, which then impacts the entire investors' network. Therefore, in terms of the contagion process, the contagion of investor risk is similar to the viral contagion.

2.2.3. Contagion Objects. In the transmission process of infectious diseases, the infected object is the individual in the social network. As an independent individual, it has a high degree of autonomy, and its resistance to the virus varies with its immunity. Similarly, given the heterogeneity of investors, investors in the investors' networks have different response levels and tolerance to risk contagion. Therefore, investor risk is similar to infectious disease in terms of contagion objects.

2.2.4. Contagion Direction. The spread of infectious virus in social networks is radiation, not directional. Similarly in the contagion process of investor risk, once a node investor is infected with the risk, the associated investors will be affected, and the contagion is not directional. Therefore, in terms of the contagion direction, investor risk and infectious diseases are similar.

3. Construction and Analysis of Investor Risk Contagion Model on Single-Layer Network in the Stock Market under the Price Linkage

3.1. Investor Risk Contagion Mechanism on Single-Layer Network in the Stock Market. In the stock market, to maximize capital appreciation, investors commonly exchange information and discuss investment strategies together. Therefore, a few informed investors spread market rumors among investors through various interactions of close investors (such as relatives, friends, neighbors, and colleagues) and manipulate the market to increase their trading profits. Concurrently, different investors explain and distinguish the rumors in the market on the basis of their own knowledge of the stock market and investment skills, among which experienced investors become "immune" when they think the rumors cannot be trusted and do not further spread them. That is, investors only believe the market rumors with certain probability and then spread the market rumors. Meanwhile, some investors who spread market rumors find that the news is outdated or untrue in the process of spreading; thus, the market rumors have lost their value, and investors will not continue to spread them.

Suppose that four different types of investors are in the stock market: trusting investors (S), transforming investors (C), infecting investors (I), and immune investors (R). Specifically, trusting investors are those who are likely to receive rumors from other investors but have not received rumors yet. Transforming investors are those who have received

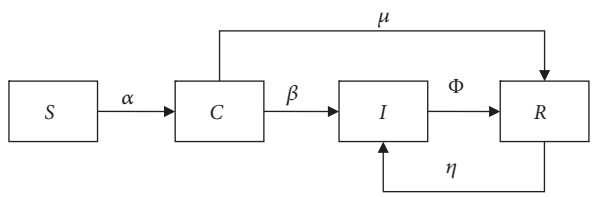


Figure 2: Investor risk contagion mechanism in the stock market.

rumors and have not decided whether to spread them. When transforming investors decide to spread rumors, they become infecting investors who are considered contagious. On the contrary, if transforming investors are immune to the rumors and do not spread them, then transforming investors will turn into immune investors. And if rumors are destructive enough, immune investors will turn into infecting investors. For example, an investor believes that a piece of information in the stock market is a rumor and is immune from it. However, the surrounding relationships of him are believing the information is true (or some top companies in the stock market announced the wrong information). According to the herd effect of investors, he would change his mind and becomes an infecting investor. On the basis of the interaction between different types of investors, this study has constructed an SCIR investor risk contagion model in the stock market, and the contagion process is shown in Figure 2.

Specific contagion process of investor risk is as follows. Assume that there is an investor in the initial time with some unofficial information. The surrounding trusting investors (S) have the opportunity to know this information and become transforming investors (C) in transformation probability α. Transforming investors (C) will learn the information to choose to receive this information and become infecting investors (I) in contagion probability β. These investors also may choose not to believe or reject the information and become immune investors (R) in direct immune probability μ. For infecting investors (I), they choose to believe the information and spread it outward, but after a period of contagion, the infecting investors (I) may gradually lose interest in the information and no longer spread it outward. At this point, the infecting investors (I) may turn into immune investors (R) in immune probability ϕ. Immune investors (R) will not be immune forever; they will potentially be infecting investors (I) in immune failure probability η.

The idea of the SCIR virus epidemic model [19, 22] assumes that there are total Ninvestors in the stock market and that the market size remains unchanged. The sum of different types of investors at any time should be equal to the total number of investors N; that is, the relationship formula is expressed as follows.

$$S(t) + C(t) + I(t) + R(t) = N \tag{1}$$

Accordingly, the ratio of the number of different investors in the total amount $s(t)$, $c(t)$, $i(t)$, $r(t)$ is summed.

$$s(t) + c(t) + i(t) + r(t) = 1 \tag{2}$$

On the basis of the risk contagion mechanism of the SCIR model, the system dynamics characteristics can be described by the following differential equations.

$$\begin{aligned} \frac{dS(t)}{dt} &= -\alpha S(t) I(t) \\ \frac{dC(t)}{dt} &= \alpha S(t) I(t) - (\beta + \mu) C(t) \\ \frac{dI(t)}{dt} &= \beta C(t) - \phi I(t) + \eta R(t) \\ \frac{dR(t)}{dt} &= \mu C(t) + \phi I(t) - \eta R(t) \end{aligned} \tag{3}$$

3.2. Analysis of Transformation Probability of Investor Risk by Considering the Heterogeneity of Investors and Information Function. The heterogeneity of investors can be divided into four aspects: heterogeneous belief, heterogeneous constraint, heterogeneous income, and heterogeneous preference [35–37]. From the point of view of information function, considering the heterogeneity of investors, the transformation probability model of investor risk is constructed.

3.2.1. Investor Risk Preference θ, $0 < \theta < 1$. Combined with the latest research results of behavioral finance, the degree of investor risk preference is an important factor influencing the transformation rate of investor risk [37]. The degree of investor preference promotes and inhibits risk contagion. That is, risk-averse investors help curb the spread and contagion of risk, while risk-appetite investors play a role in promoting risk contagion. The expression $0 < \theta < 0.5$ means that investors are risk-averse; $\theta = 0.5$ means that investors are risk-neutral; and $0.5 < \theta < 1$ means that investors are risk-appetite.

3.2.2. Investor Risk Cognitive Level τ, $0 < \tau < 1$. Investor risk cognitive level includes their own knowledge and skills of stock investment and decision-making ability to face risks [38–40]. The greater the τ, the more analytical and responsive the investors are to stock market rumors. Investors with high risk cognitive level can adopt more prudent and appropriate decision-making behavior through their own stock investment knowledge and analysis of the stock market.

3.2.3. Information Value v_0, $0 \le v_0 \le 1$ [41]. This expression shows the difficulty investors have in obtaining information, where 0 means information is easy to obtain and 1 means information is hard to acquire.

High information value arouses information asymmetry and information distortion, which intensifies investor risk. Information asymmetry influences investor behavior indirectly. As show in Figure 3, when information asymmetry and distortion happens, some investors with low cognitive level of investor risk, poor psychological quality, and poor information decision-making ability cannot recognize or tell rumors. They cause behavior biases, panic, and scare. And in the meantime, investors carrying "investor risk" spread this low-quality information via media channels and

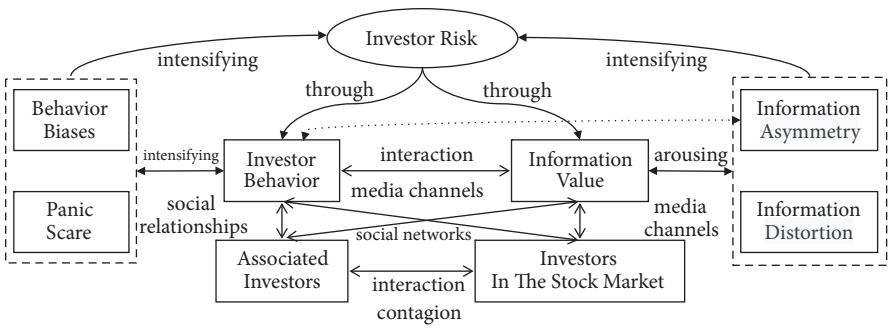


FIGURE 3: Information value, information asymmetry, and investor risk.

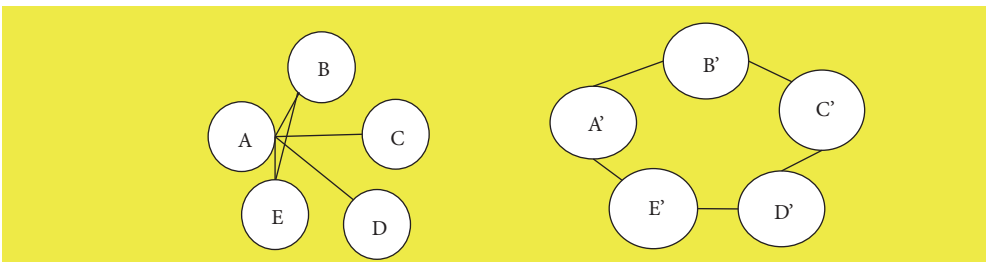


FIGURE 4: A simple example of measuring investor influence.

social networks (relationships). Under the situation, investor risk is enhanced through "investor behavior" and "information value". The information asymmetry phenomenon helps trusting investors to become transforming investors.

3.2.4. Investor Influence λ_i. The influence of investors is related to the topological structure of the investors' networks [34, 42, 43]. In this paper, the investor influence is measured by the edge weight w and the investor's degree K, which represents the weighted average of the edge weight between the investor and the connected K investors:

$$\lambda_i = \frac{\sum w_i}{K_i} \tag{4}$$

where $\sum w_i$ represents the sum of the edge weight associated with investor i; K_i represents the degree of investor i. The edge weight is defined as the interaction frequency between investors, that is, the one-way diffusion times between investors in recent time. The degree of the investor is also called the connectivity, which refers to the number of edges connected between the associated investor and the investor.

Figure 4 shows the way to measure investor influence. Let the left side of the picture be network P and the right side be network P'. Let $\sum w_A = 0.06$, $\sum w_{A'} = 0.04$. Then. In network P, $\lambda_A = 0.015$. In network P', $\lambda_{A'} = 0.02$. For easy analysis, when evaluating λ_i, firstly we settle the investors' network, then we know K_i is a fixed value, and then we assume the $\sum w_i$ is a fixed value. Thus Investor influence λ_i is a fixed value.

The investor risk transformation probability model on single-layer network in the stock market is summarized as follows.

$$\alpha = (v_0 \times \lambda_i)^{(1-\theta)\tau} \tag{5}$$

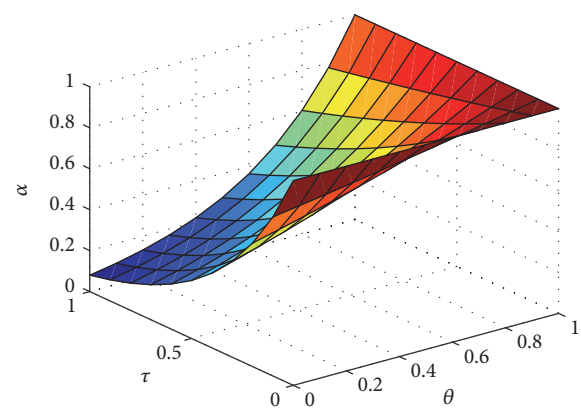


FIGURE 5: Effects of investor risk preference θ and investor risk cognitive level τ on investor transformation probability α when $v_0 = 0.4$ $\lambda_i = 0.2$.

Figure 5 presents the impact of investor risk preference θ and investor risk cognitive level τ on investor risk transformation probability when information value $v_0 = 0.4$ and investor influence $\lambda_i = 0.2$. With the increase of risk preference or the decrease of investor risk cognitive level, the transformation probability of investor risk increases nonlinearly. Combined with the sensitivity analysis in Table 1, the risk preference of investors shows an increasing marginal feature for the transformation probability of investor risk. The risk cognitive level of investors shows a decreasing feature for the transformation probability of investor risk, which is consistent with the actual financial market. Therefore, constructing the investor risk transformation probability model on single-layer network in the stock market is reasonable.

Table 1: Sensitivity analysis of investor risk preference θ and investor risk cognitive level τ to investor transformation probability α.

τ	θ									Expectation	Variance
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9		
0.1	0.796669	0.817047	0.837947	0.859380	0.881362	0.903907	0.927028	0.950740	0.975059	0.883238	0.003729
0.2	0.634682	0.667566	0.702154	0.738535	0.776800	0.817047	0.859380	0.903907	0.950740	0.783423	0.011703
0.3	0.505632	0.545433	0.588368	0.634682	0.684642	0.738535	0.796669	0.859380	0.927028	0.697819	0.020796
0.4	0.402821	0.445645	0.493021	0.545433	0.603418	0.667566	0.738535	0.817047	0.903907	0.624155	0.029389
0.5	0.320915	0.364113	0.413125	0.468735	0.531830	0.603418	0.684642	0.776800	0.881362	0.560549	0.036740
0.6	0.255663	0.297497	0.346177	0.402821	0.468735	0.545433	0.634682	0.738535	0.859380	0.505436	0.042598
0.7	0.203679	0.243069	0.290078	0.346177	0.413125	0.493021	0.588368	0.702154	0.837947	0.457513	0.046973
0.8	0.162265	0.198599	0.243069	0.297497	0.364113	0.445645	0.545433	0.667566	0.817047	0.415693	0.050005
0.9	0.129272	0.162265	0.203679	0.255663	0.320915	0.402821	0.505632	0.634682	0.796669	0.379067	0.051886

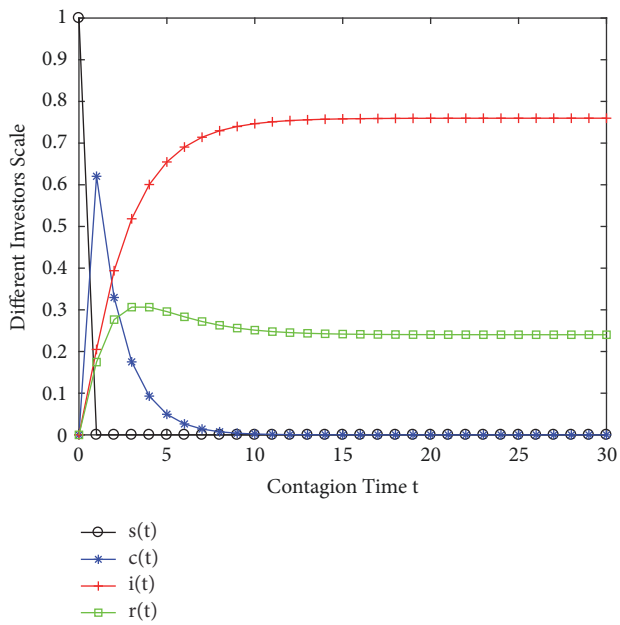


Figure 6: Change of trend of investors' scale in different states in SCIR risk contagion model in the stock market.

3.3. Mechanism Probability. According to Sections 3.1 and 3.2, taking investor heterogeneities into account, mechanism probabilities of SCIR are as in Table 2.

3.4. Computer Simulation Analysis. Suppose that there are N investors in the stock market. Only 1 investor is infected in the initial stage (I), and the rest $N - 1$ investors are all trusting investors (S). $N = 10000$. In the meantime, there are no transforming investors (C) or immune investors (R) in the initial stage. That is, $S(0) = N - 1$, $C(0) = 0$, $I(0) = 1$, $R(0) = 0$. At the moment, the only investor in a contagious state (I) in the system begins to spread rumors to the $N - 1$ trusting investors around.

From the simple analysis above, a basic conclusion can be drawn: the number of trusting investors (S) decreases, while the number of infecting investors (I) increases. However, drawing conclusions directly from the analysis above about the change features of transforming investors (C) and immune investors (R) is impossible. Therefore, by setting the values of different probabilities, the curve of the scale of different types of investors changes with contagion time can be obtained to reveal the characteristics of the scale change of transforming investors (C) and immune investors (R).

Given the absence of a large number of empirical tests of time series data, simulation analysis is relatively the most effective test method. Suppose that the initial parameters of the SCIR model in the stock market are as follows: $\theta = 0.5$, $\tau = 0.5$, $v_0 = 0.5$, $\lambda_i = 0.001$, $\beta' = 0.1$, $\mu' = 0.1$, $\eta' = 0.1$, and $\phi' = 0.01$. The simulation is conducted by Matlab2016b, and Figure 6 shows the graph obtained.

Figure 6 depicts the evolution characteristics of the scale of the different types of investors with the contagion time. In Figure 6, the scale of transforming investors and immune investors shows an increasing trend and then decreases. Additionally, it is consistent with the previous analysis that the scale of trusting investors tends to decrease while the scale of infecting investors tends to increase. When the contagion time reaches a certain value, the scale of all types of investors in the investor network is in a stable state in the stock market, which indicates that the investor network has reached a stable state. We also contend that trusting investors and infecting investors will eventually go to zero and diminish.

Different parameters are changed for simulation to better reveal the impact of different factors on the investor risk contagion mechanism on single-layer network in the stock market. Without changing the value of the transformation probability α, the change trend of the scale of different states of investors in the SCIR investor risk contagion model in the stock market is studied by changing different contagion probability β', direct immune probability μ', immune probability ϕ', and immune failure probability η'. Table 3 shows the original value of SCIR investor risk contagion model in the stock market under different mechanism probability environments.

Figure 7 shows the investor scale trends in different states of the SCIR investor risk contagion model in the stock market under different probability mechanism environments. Table 4 shows infecting investors and immune investors scale changes of SCIR investor risk contagion model in the stock market under different mechanism probability environments. After the contagion time reaches a certain value, that is, when the investor network reaches the steady state of the network, the scales of different types of investors basically remain unchanged.

In Figure 7(a), contagion probability β' increases, while the values of other parameters remain unchanged. Compared with those in Figure 6, combined with Table 4, the scales of investors in each state reach a stable state faster. But there is no obvious change in the scales of the different types of investors in the steady state of the investor network. Moreover, during the risk contagion process of investors, the peak of the scale of transforming investors is lower. This trend shows that the increased contagion probability β' not only enables the investor network to reach the steady state faster, but also plays a significant role in changing investors from transforming to infecting.

In Figure 7(b), direct immunity probability μ' increases, while the values of other parameters remain unchanged. Compared with those in Figure 6, combined with Table 4, there is no obvious change in the contagion time when the scales of the different types of investors reach the steady state of the investor network. However, in the process of investor risk contagion, the peak value of transforming investors is lower than that in Figure 6, while the peak value of the scale of immune investors is higher than that in Figure 6. The increasing to decreasing trend is more evident, thereby indicating that the increase of immune probability μ' not only enables the investor network to reach the steady state faster, but has a significant effect on the transformation from transforming investors to immune investors.

In Figure 7(c), the immune probability ϕ' increases, while the values of other parameters remain unchanged. Compared with those in Figure 6, combined with Table 4,

Table 2: Relationship of mechanism probability and heterogeneous mechanism probability in SCIR.

contagion probability β'	heterogeneous contagion probability β	$\beta = (\beta')^{\sqrt[3]{(1-\theta)\tau(1-\nu_0)}}$
direct immune probability μ'	heterogeneous direct immune probability μ	$\mu = (\mu')^{\sqrt[3]{\theta(1-\tau)\nu_0}}$
immune probability ϕ'	heterogeneous immune probability ϕ	$\phi = (\phi')^{\sqrt[3]{\theta(1-\tau)\nu_0}}$
immune failure probability η'	heterogeneous immune failure probability η	$\eta = (\eta')^{\sqrt[3]{(1-\theta)\tau(1-\nu_0)}}$

Table 3: Numerical changes of SCIR investor risk contagion model in the stock market under different mechanism probability environments.

Tendency chart	Variation of parameters	β'	μ'	η'	ϕ'	$(s(0), c(0), i(0), r(0))$
Figure 6	None	0.1	0.1	0.1	0.01	(0.999,0,0.001,0)
Figure 7(a)	Increased contagion probability β	0.5	0.1	0.1	0.01	(0.999,0,0.001,0)
Figure 7(b)	Increased direct immune probability μ	0.1	0.5	0.1	0.01	(0.999,0,0.001,0)
Figure 7(c)	Increased immune probability ϕ	0.1	0.1	0.1	0.05	(0.999,0,0.001,0)
Figure 7(d)	Increased immune failure probability η	0.1	0.1	0.6	0.01	(0.999,0,0.001,0)

Table 4: Infecting investors and immune investors scale changes of SCIR investor risk contagion model in the stock market under different mechanism probability environments.

	$s(\infty)$	Δ	$i(\infty)$	Δ
Figure 6	0.7597	-	0.2403	-
Figure 7(a)	0.7597	0	0.2403	0
Figure 7(b)	0.7597	0	0.2403	0
Figure 7(c)	0.5858	-0.1739	0.4142	+0.1739
Figure 7(d)	0.8857	+0.126	0.1143	-0.126

the scales of investors in each state reached a stable state faster. When the investor network reaches steady state, the scale of immune investors is larger and the scale of infecting investors is smaller. This trend shows that the increasing immune probability ϕ' not only enables the investor network to reach the steady state faster, but also plays a significant role in the transformation from infecting investors to immune investors.

In Figure 7(d), the immune failure probability η' increases, while the values of other parameters remain unchanged. Compared with Figure 6, combined with Table 4, the scales of investors in each state reached a stable state faster. In the process of investor risk contagion, the peak of the scale of transforming investors is larger. Immune state investors have smaller peaks. When the investor networks reach steady state, the immune investors are smaller and the infecting investors are larger. This trend shows that the increasing immune failure probability η not only enables the investor network to reach the steady state faster, but also plays a significant role in the transformation of immune investors to infecting investors.

In Figure 7, the transformation probability α and the change trend of the scale of trusting investors remain unchanged. Subsequently, we try to change investor risk preference θ, investor risk cognitive level τ, information value v_0, and investor influence λ_i, to explore the evolution rule of investor risk contagion with the contagion time under the change of different factors.

Figures 8–10 show the variation rules of the scale of infecting investors and immune investors with the contagion time when investor risk preference θ, investor risk cognitive level τ, and information value v_0 are different while the other initial conditions remain unchanged. After reaching a certain contagion time, the scale of the infecting investors and immune investors will tend to a fixed value, at which time the investors' network reaches a steady state. In the process of credit risk contagion, the steady state scale of the infecting investors will increase (or the immune investors will decrease); as the investor risk preference θ and information value v_0 increase, the investor risk cognitive level τ decreases. Moreover, they reduce the contagion time t when the investors' network reaches steady state. Therefore, investor risk preference θ and information value v_0 have "global enhancement" effects on investor risk contagion. Investor risk cognitive level τ has a "global inhibition" effect on investor risk contagion.

Figure 11 shows the variation rules of the scale of infecting investors and immune investors with the contagion time when investor influence λ_i is different while the other initial conditions remain unchanged. Figure 11(a) shows that in the investor risk contagion process, the increase of investor influence λ_i increases the scale of the infecting investors. When the investor network reaches steady state, the scale of infecting investors tends to be fixed under different values of investor influence λ_i. It shows that the increase of investor influence λ_i promotes investor risk contagion and has the "local enhancement" effect. Figure 11(b) shows that in the process of investor risk contagion, the increase of investor influence λ_i shortens the contagion time for immune investors to reach the stable state of the network.

4. Construction and Analysis of Investor Risk Contagion Model on Bilayer-Coupled Networks in the Stock Market under the Price Linkage

4.1. Model Construction. Using multilayer coupling network theory and the propagation dynamics theory for [44], an investor risk contagion model on bilayer-coupled networks in the stock market is constructed based on the SCIR investor risk contagion model. Figure 12 presents the investor risk contagion mechanism on bilayer-coupled networks in the stock market. Figure 12(a) shows the layer process of investor risk contagion on bilayer-coupled networks in the stock market, while Figure 12(b) shows the process of investor risk contagion between layers on bilayer-coupled networks in the stock market.

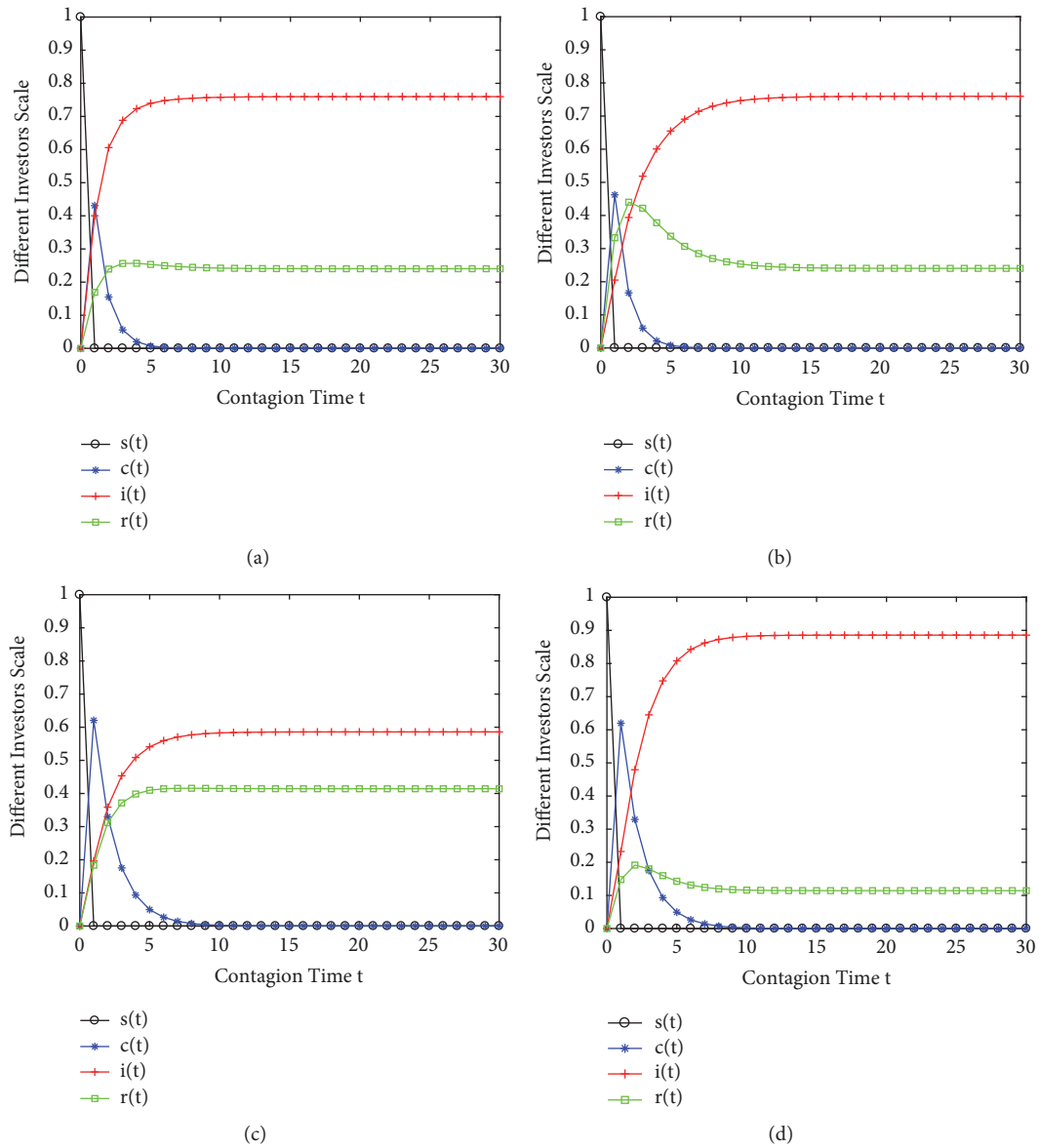


Figure 7: Investor scale trends in different states of SCIR investor risk contagion model in the stock market under different mechanism probability environments.

Suppose there are five different types of investors in the stock market: trusting investors (S), transforming investors (C), intralayer infecting investors (I_1), interlayer infecting investors (I_2), and immune investors (R), and the rumors in the stock market are released in the A-share stock market investor network W. The specific risk contagion process is as follows:

Trusting investors (S) in network W turn to transforming investors (C) with the transformation probability α'. Transforming investors (C) spread stock market rumors to the local network with the intralayer contagion probability β_1 and become intralayer infecting investors (I_1), or spread stock market rumors to the B-share stock market investor network M with the interlayer contagion probability β_2 and become interlayer infecting investors (I_2), or do not spread stock market rumors and become immune investors (R) with the immune probability μ. Intralayer infecting investors (I_1) and interlayer infecting investors (I_2) take the intralayer and interlayer immune probability ϕ_1, ϕ_2, respectively, and change into immune investors (R). Immune investors (R) transform into intralayer infecting investors (I_1) and interlayer infecting investors (I_2) by the intralayer and interlayer immune failure probability η_1, η_2.

Given that there are N investors in the stock market at the initial time and the market size remains unchanged. The sum of different types of investors at any given time should be equal to the total number of investors N; that is, the relationship is expressed as

$$S(t) + C(t) + I_1(t) + I_2(t) + R(t) = N. \quad (6)$$

The system dynamics modeling idea is used to establish the investor risk contagion model on bilayer-coupled

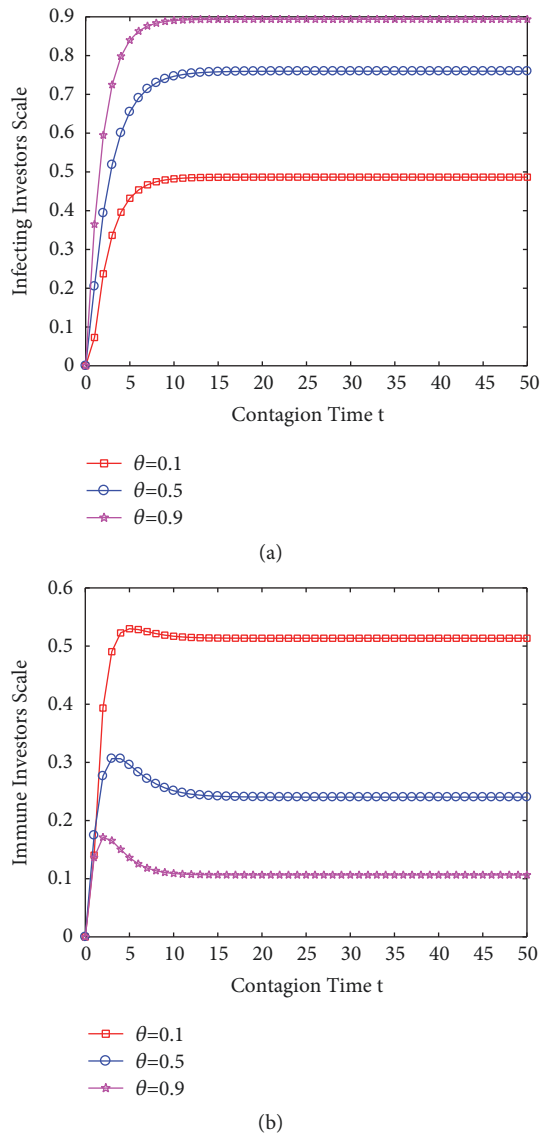


FIGURE 8: Changes in the scale of infecting investors and immune investors with the contagion time under different investor risk preference θ.

networks in the stock market through the differential equations. The corresponding differential equation of this model is as follows.

$$\begin{aligned}
\frac{dS(t)}{dt} &= -\alpha S(t)\left(I_1(t)+I_2(t)\right)\\
\frac{dC(t)}{dt} &= \alpha S(t)\left(I_1(t)+I_2(t)\right)-\left(\beta_1+\beta_2+\mu\right)C(t)\\
\frac{dI_1(t)}{dt} &= \beta_1 C(t)+\eta_1 R(t)-\phi_1 I_1(t)\\
\frac{dI_2(t)}{dt} &= \beta_2 C(t)+\eta_2 R(t)-\phi_2 I_2(t)\\
\frac{dR(t)}{dt} &= \mu C(t)-\left(\eta_1+\eta_2\right)R(t)+\phi_1 I_1(t)+\phi_2 I_2(t)
\end{aligned} \tag{7}$$

4.2. Connection Modes of Bilayer-Coupled Networks. According to the degree correlation of the relational investor nodes between the coupling networks, in the construction of the coupled network structure model of investor risk contagion on bilayer-coupled networks in the stock market, this paper mainly adopts three different coupling connection modes, namely, degree-degree positive correlation, degree-degree negative correlation, and random connection [44]. To simplify the implementation process of the bilayer-coupled networks model analysis, the following provisions are given:

(1) Suppose the A-share stock market investor network and B-share stock market investor network have the same scale and size, and the investors between different networks are one-to-one corresponding connections.

(2) During the construction, all coupling investor nodes are sorted according to the size of degree in their respective investor networks, and then different coupling networks are created according to three different connection modes, namely, interlayer assortative link, interlayer disassortative link, and interlayer random link.

(a) As for interlayer assortative link (AL), investors of A-share stock market investor network W and investors of B-share stock market investor network M are connecting according to the size of the degree of investor nodes. Specifically, large degree of investors of A-share stock market investor network W is connecting with large degree of investors of B-share stock market investor network M, while small degree of investors of A-share stock market investor network W is connecting with small degree of investors of B-share stock market investor network M; this is also called positive correlation link. When the investors' node degrees are the same, investors are randomly selected to set up bilayer-coupled networks in one-to-one node connection mode according to $W_i \longleftrightarrow M_j$.

(b) Interlayer disassortative link (DL) is opposite to AL. Large degree of investors of A-share stock market investor network W is connecting with small degree of investors of B-share stock market investor network M, and small degree of investors of A-share stock market investor network W is connecting with large degree of investors of B-share stock market investor network M; this is also called negative correlation link. The equation $W_i \longleftrightarrow M_j$ $(j = N - i + 1)$ establishes a one-to-one connection mode between the coupling networks.

(c) For interlayer random link (RL), investors of A-share stock market investor network W are randomly connecting with investors of B-share stock market investor network M, which indicates that the nodes connection mode is one-to-one in investor networks in the stock market.

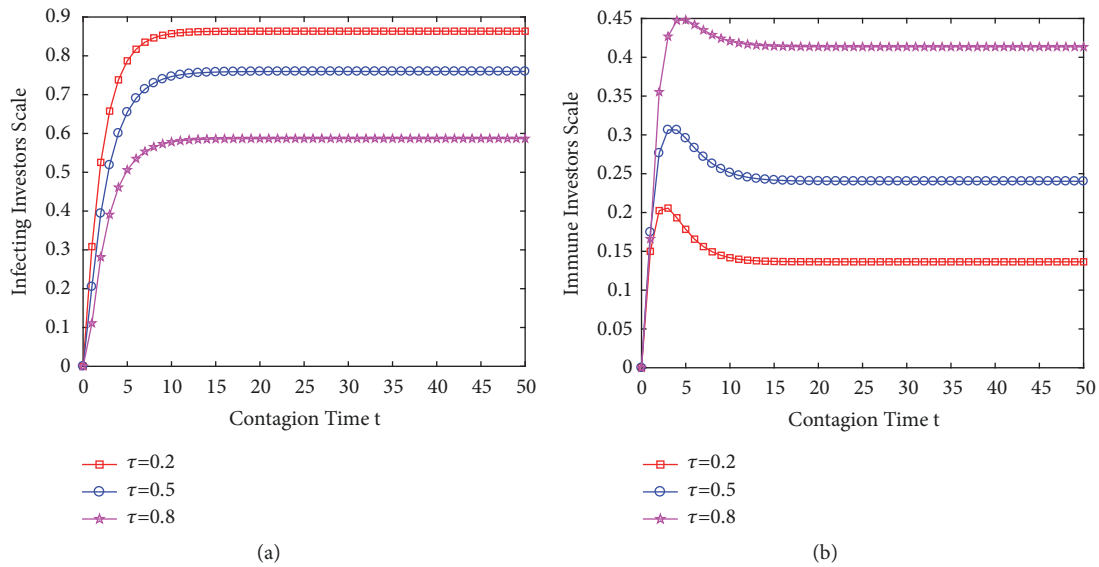


Figure 9: Changes in the scale of infecting investors and immune investors with the contagion time under different investor risk cognitive level τ.

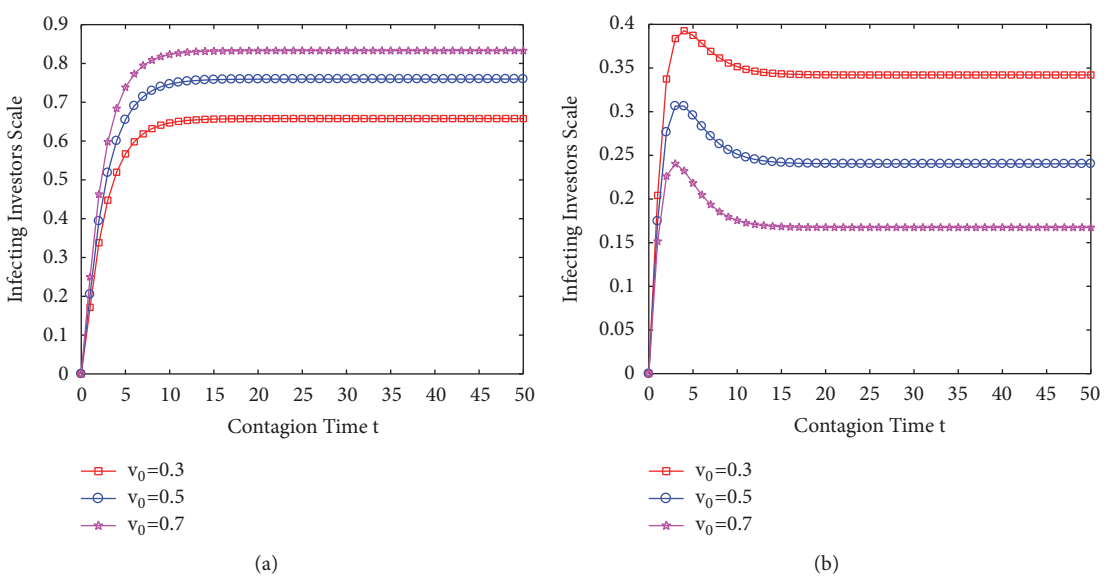


Figure 10: Changes in the scale of infecting investors and immune investors with the contagion time under different information value v_0.

4.3. Transformation Probability of Investor Risk on Bilayer-Coupled Networks. (1) On bilayer-coupled networks, the edge weight of the investor is expressed as the weight of the internal network w_{ij-in} and the weight of the external network w_{ij-out}, representing the edge weight between the investor and the neighboring node investor in this layer and outer layer, respectively.

(2) On bilayer-coupled networks, the degree of investor i is divided into K_{i-in} and K_{i-out}, which represents the number of interactions between investors in local network and outer network, respectively.

(3) Matching coefficient:

Newman [45] proposed the concept of matching coefficient to quantify the degree correlation between nodes in a complex network:

$$\rho = \frac{\sum_{K_x K_y} K_x K_y \left(e_{K_x K_y} - a_{K_x} b_{K_y}\right)}{\sigma_{K_x} \sigma_{K_y}} \tag{8}$$

where $e_{K_x K_y}$ represents the proportion of all edges in the network whose connection degree is K_x and K_y; a_{K_x}, b_{K_x} denote the proportion of the edge whose degree is K_x, K_y; $\sigma_{K_x} = \sqrt{\mathrm{var}[K_x]}$ is the variance of the random variable K_x.

In $-1 \le \rho \le 1$, $\rho > 0$ denotes AL; that is, large degree nodes tend to connect with other large degree nodes and the larger $|\rho|$ has positive correlation; $\rho < 0$ denotes DL; that is, large degree nodes tend to connect with small degree nodes, and the larger $|\rho|$ has negative correlation. By calculating the extreme value of matching coefficients $\rho_{\max}$ and $\rho_{\min}$ of many real world networks, it is found that the matching coefficient

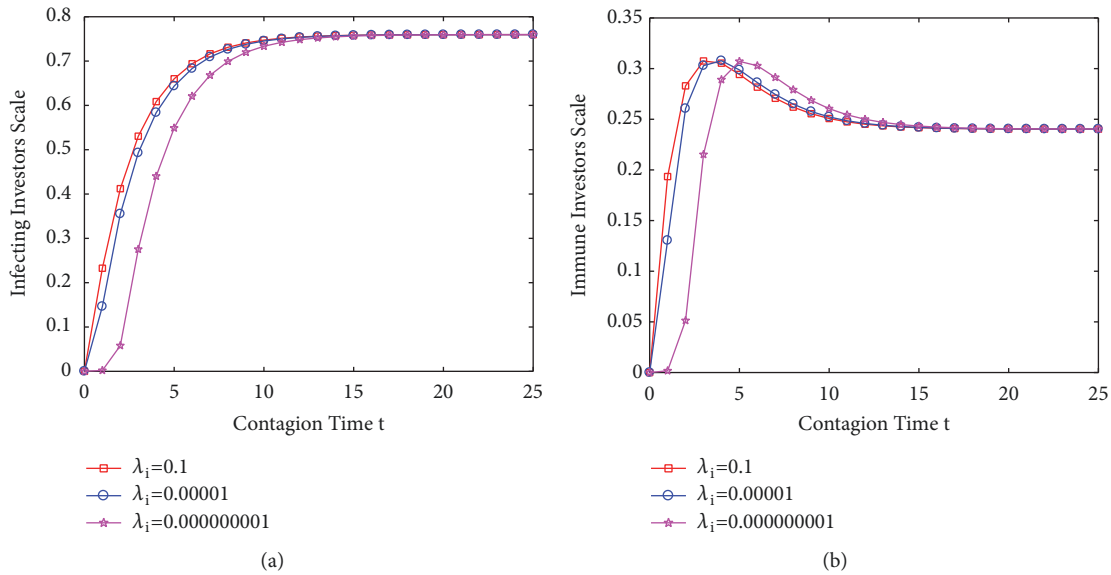
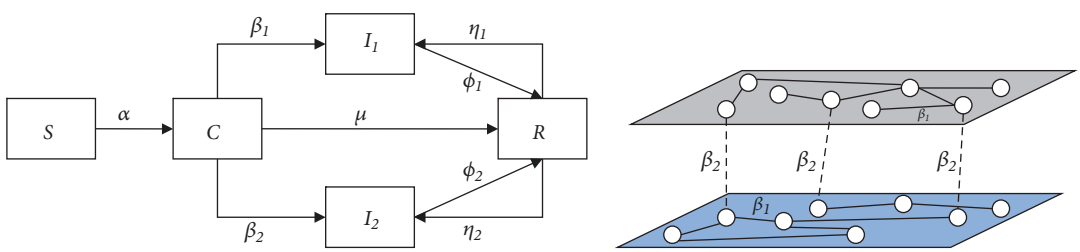


Figure 11: Changes in the scale of infecting investors and immune investors with the contagion time under different investor influence λ_i.



(a) Layer process of investor risk contagion on bilayer-coupled networks in the stock market

(b) Process of investor risk contagion between layers on bilayer-coupled networks in the stock market

Figure 12: Investor risk contagion mechanism on bilayer-coupled networks in the stock market.

of general networks satisfies $-1 < \rho_{\min} < \rho_{\max} < 1$, where $\rho = 1$ when it is completely AL, $\rho = -1$ when it is completely DL, and $\rho = 0$ when it indicates that the network structure has random and irrelevant characteristics (RL).

(4) Investor influence in the stock market on bilayer-coupled networks:

In this paper, the investor influence is expressed as the weighted average of all K edge weights that interact with the investor. The investor influence on bilayer-coupled networks is divided into internal influence λ_{i-in} and external influence λ_{i-out}. The internal influence λ_{i-in} of investor i refers to the influence of investor i in the same layer network, represented by K_{i-in} and w_{ij-in} as follows.

$$\lambda_{i-in} = \frac{\sum_{j=1}^{K_{i-in}} w_{ij-in}}{K_{i-in}} \tag{9}$$

The external influence of investor i represents the influence of investor i in other layer networks, represented by K_{i-out} and w_{ij-out} as follows.

$$\lambda_{i-out} = \frac{\sum_{j=1}^{K_{i-out}} w_{ij-out}}{K_{i-out}} \tag{10}$$

On the basis of the indicator KSCC [46] and the internal and external influences of investors in the stock market on bilayer-coupled networks, this study measures the influence of node investors on bilayer-coupled networks as follows:

$$KSCC\,(i) = x\left[\lambda_{i-in}\right] + y\rho^{|WM|}\left[\lambda_{i-out}\right], \tag{11}$$

where $\rho^{|WM|}$ is the index of degree-degree correlation between network W and M. x, y are internal and external influencing factors, satisfying $x > 0$, $y > 0$, $x + y = 1$.

Combined with the analysis in Section 3.2, transformation probability of investor risk on bilayer-coupled networks is defined as follows.

$$\alpha' = \left(v_0 \times KSCC\,(i)\right)^{(1-\theta)\tau} \times KSCC(i)^{(1-\theta)\tau\rho^{|WM|}} \tag{12}$$

4.4. Mechanism Probability. According to Sections 3.1 and 3.2, taking investor heterogeneities into account, mechanism probabilities of SCI_1I_2R are as in Table 5.

4.5. Computer Simulation Analysis. Simulation analysis is relatively the most effective test method because of the

Table 5: Relationship of mechanism probability and heterogeneous mechanism probability in SCI_1I_2R.

intra-layer contagion probability β_1'	heterogeneous intra-layer contagion probability β_1	$\beta_1 = (\beta_1')^{\sqrt[3]{(1-\theta)\tau(1-\nu_0)}}$
inter-layer contagion probability β_2'	heterogeneous inter-layer contagion probability β_2	$\beta_2 = (\beta_2')^{\sqrt[3]{(1-\theta)\tau(1-\nu_0)}}$
intra-layer immune failure probability η_1'	heterogeneous intra-layer immune failure probability η_1	$\eta_1 = (\eta_1')^{\sqrt[3]{(1-\theta)\tau(1-\nu_0)}}$
inter-layer immune failure probability η_2'	heterogeneous inter-layer immune failure probability η_2	$\eta_2 = (\eta_2')^{\sqrt[3]{(1-\theta)\tau(1-\nu_0)}}$
intra-layer immune probability ϕ_1'	heterogeneous intra-layer immune probability ϕ_1	$\phi_1 = (\phi_1')^{\sqrt[3]{\theta(1-\tau)\nu_0}}$
inter-layer immune probability ϕ_2'	heterogeneous inter-layer immune probability ϕ_2	$\phi_2 = (\phi_2')^{\sqrt[3]{\theta(1-\tau)\nu_0}}$

Table 6: Comparison of initial parameters between single-layer network and bilayer-coupled networks.

Single-layer Network	Bilayer-coupled Networks
$N = 10000$, When $t = 0$, there are: $S(0) = N - 1, C(0) = 0, I(0) = 1, R(0) = 0$	$N_W = N_M = 10000$, When $t = 0$, there are: $S(0) = N - 2, C(0) = 0, I_1(0) = 1, I_2(0) = 1, R(0) = 0$
$\theta = 0.5, \tau = 0.5, v_0 = 0.2, \beta' = 0.07, \mu' = 0.03, \phi' = 0.01, \eta' = 0.03, \lambda_i = 0.02$	$\theta = 0.5, \tau = 0.5, v_0 = 0.2, \beta_1' = 0.07, \beta_2' = 0.07, \mu' = 0.03, \phi_1' = 0.01, \phi_2' = 0.01, \eta_1' = 0.03, \eta_2' = 0.03, x = 0.5, y = 0.5, \rho^{\lvert WM \rvert} = 0$

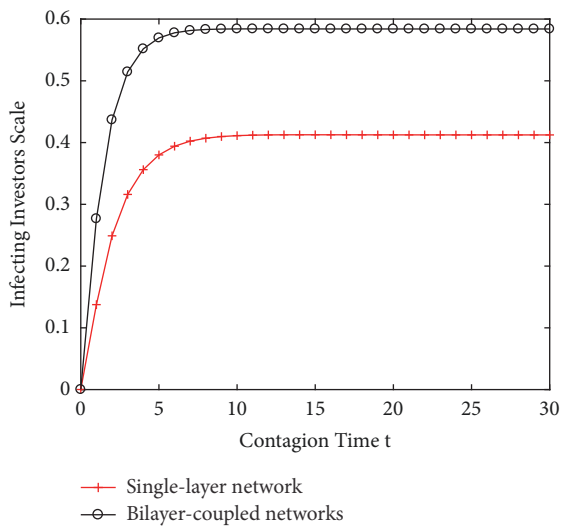


Figure 13: Comparison of investor risk contagion on single-layer network and bilayer-coupled networks in the stock market.

absence of a large number of empirical tests of time series data.

4.5.1. Effect of Single-Layer Network and Bilayer-Coupled Networks on Investor Risk Contagion in the Stock Market. To explore the impact of different network structures on investor risk contagion effect in the stock market, the single-layer network with an average degree $< K_i >= 5$ of investor nodes is simulated numerically on the SCIR investor risk contagion model in this section. For the convenience of comparison, the bilayer-coupled networks with an average degree $< K_i >= 5$ of the investor nodes are also simulated on the SCI_1I_2R investor risk contagion model. The risk contagion effect of investor risk in the stock market is measured by the scale of infecting investors (including intralayer infecting investors (I_1) and interlayer infecting investors (I_2) on bilayer-coupled networks). The greater the $s(i)$ is, the greater the scale of risk contagion is, and the more noticeable the contagion effect is. Table 6 shows the initial parameters of the two models.

Using Matlab2016b, the SCIR investor risk contagion model and the SCI_1I_2R investor risk contagion model on bilayer-coupled networks are simulated. The results are shown in Figure 13.

Figure 13 depicts the change rule of the scale of infecting investors with contagion time under the different network structures of the single-layer network and the bilayer-coupled networks. From the simulation results, it is found that the scale of infecting investors increases with the increase of the contagion time whether it is single-layer network or bilayer-coupled networks. After a certain contagion time, the scale of infecting investors on investor networks remains constant, indicating that the investor networks have reached a stable state at this time. We also confirmed the following:

(a) Under the condition that the parameters are all the same, the scale of infecting investors on the bilayer-coupled networks is significantly larger than that of the single-layer network, which indicates that the bilayer-coupled networks expand the investor risk contagion and have the "global enhancement" effect.

(b) For the scale of investor risk contagion of the two network structures, the bilayer-coupled networks structure is not twice as large as the single-layer network, simply. It is a nonlinear positive correlation.

4.5.2. Effect of Interlayer Connection Modes on Investor Risk Contagion in the Stock Market. To eliminate other impacts, the remaining parameters are kept in the initial state of Table 3. The SCI_1I_2R investor risk contagion model on bilayer-coupled networks is simulated by setting $\rho^{\lvert WM \rvert}$ as -0.2,-0.1, 0, 0.5, and 0.9. The simulation results are shown in Figure 14.

Figure 14 depicts the change rule of the scale of infecting investors with contagion time under different connection modes of bilayer-coupled networks. The scale of infecting investors is increasing with the rise of the contagion time no matter what connection modes the bilayer-coupled networks have. Moreover, after a certain contagion time, the scale of infecting investors in the investor networks remains unchanged and tends to have constant value. We also affirmed the following results:

(a) In case that all parameters are the same, in the process of investor risk contagion, the scale of infecting investors is the largest under the AL mode of bilayer-coupled networks, followed by the RL mode. Finally, the scale of infecting investors is the smallest under the mode of DL. Among the three modes of interlayer connection of bilayer-coupled networks, the AL mode has the effect of "local enhancement", while the DL mode has the effect of "local inhibition". In other words, the AL mode is most conducive to the investor risk contagion, while the DL mode is most unfavorable to the investor risk contagion.

(b) In the AL mode, during the contagion process, $|\rho^{\lvert WM \rvert}|$ increases, the positive correlation of the bilayer-coupled networks increases, and the scale of the infecting investors also increases. Under the mode of AL, the increase of $|\rho^{\lvert WM \rvert}|$

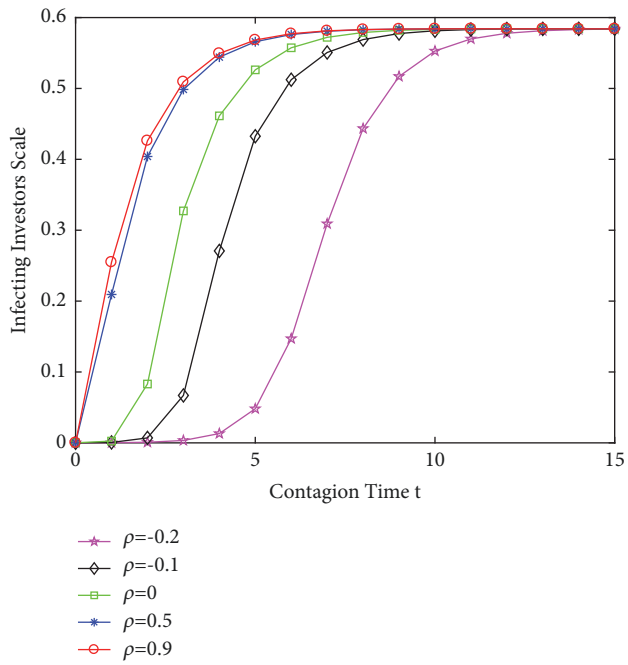


Figure 14: Comparison of investor risk contagion in the stock market under different connection modes of bilayer-coupled networks.

is conducive to the investor risk contagion and has the effect of "local enhancement".

(c) Under the DL mode, during the contagion process, $|\rho^{|WM|}|$ increases and the negative correlation of bilayer-coupled networks increases, while the scale of infecting investors decreases. In the DL mode, the increase of $|\rho^{|WM|}|$ is not conducive to the investor risk contagion and has a "local inhibition" effect.

4.5.3. Effect of Different Heterogeneous Mechanism Probabilities on Investor Risk Contagion in the Stock Market. To better reveal the influence of different factors on investor risk contagion effect on bilayer-coupled networks in the stock market, different heterogeneous mechanism probabilities with fixing transformation probability α' are used to simulate the SCI_1I_2R risk contagion model on the bilayer-coupled networks. Table 7 shows numerical changes of SCI_1I_2R investor risk contagion model under different heterogeneous mechanism probabilities. The simulation results are shown in Figure 15.

Figure 15 depicts the different trends of the investor scale of different states in SCI_1I_2R investor risk contagion model on the bilayer-coupled networks in the stock market under different heterogeneous mechanism probabilities over contagion time. Figure 15(a) shows the variation trend of the investor scale in different states with contagion time in Table 7, while Figures 15(b)–15(f) show the variation trend of the investor scale in different states with changing different mechanism probabilities of Table 7. Given that the transformation probability α' is not changed, the change trend of the scale of trusting investors in Figure 15 also does not change and tends to become zero in a very short contagion time. In Figure 15, the change trend of the scale of transforming investors increases first and then decreases. Compared with Figure 15(a) , except the decreasing peak values of the scale of transforming investors in Figures 15(b), 15(c), and 15(d) , there is little change in the rest of the figures. We focus on the evolution of the scale of intralayer infecting investors, interlayer infecting investors, and immune investors over contagion time t.

Comparing Figures 15(a) and 15(b) , we found an increase in the heterogeneous intralayer contagion probability β_1, an increase in the scale of intralayer infecting investors, and a decrease in the scale of interlayer infecting investors. Comparing Figures 15(a) and 15(c) , we found an increase in the heterogeneous interlayer contagion probability β_2, an increase in the scale of interlayer infecting investors, and an decrease in the scale of intralayer infecting investors. With Figures 15(a) and 15(d) , it is found that the scale of immune investors fluctuates more clearly in the process of investor risk contagion, and the scale of immune investors increases when the network reaches steady state. Comparisons between Figures 15(a), 15(b), 15(c), and 15(d) show that when the heterogeneous intralayer contagion probability β_1 is equal to the heterogeneous interlayer contagion probability β_2, the scale of intralayer infecting investors and the scale of interlayer infecting investors will be consistent on bilayer-coupled networks when the network reaches steady state. However, any change of the heterogeneous intralayer contagion probability β_1 or the heterogeneous interlayer contagion probability β_2 will not change the scale of immune investors when the network reaches steady state, thus indicating that the scale of infecting investors does not change when the network reaches steady state. The only change is the scale of the intralayer or interlayer infecting investors, but their sum does not change.

By comparing Figures 15(a) and 15(e) , it is found that there is an increase in heterogeneous intralayer immune failure probability η_1 and the scale of intralayer infecting investors and a noticeable decrease of the scale of interlayer infecting investors. The scale of immune investors has also decreased significantly. Comparing Figures 15(a) and 15(f) , we can find that there is an increase in heterogeneous interlayer immune failure probability η_2, a noticeable increase of the scale of interlayer infecting investors, and apparent decrease of the scale of intralayer infecting investors. The scale of immune investors has also decreased significantly. Comparing Figures 15(a) and 15(g) , it is found that there is an increase in heterogeneous intralayer immune probability ϕ_1, a noticeable increase of the scale of interlayer infecting investors, and apparent decrease of the scale of intralayer infecting investors. The scale of immune investors has increased significantly. By comparing Figures 15(a) and 15(h) , we can find that there is an increase in heterogeneous interlayer immune probability ϕ_2, noticeable increase of the scale of intralayer infecting investors, and apparent decrease of the scale of interlayer infecting investors. Moreover, the scale of immune investors has increased significantly. Comparisons between Figures 15(a), 15(e), 15(f), 15(g), and 15(h) show that even when the heterogeneous intralayer contagion probability

Table 7: Numerical changes of SCI_1I_2R investor risk contagion model under different heterogeneous mechanism probabilities.

Tendency chart	Variation of parameters	β_1	β_2	μ	η_1	η_2	ϕ_1	ϕ_2	$(s(0), c(0), i_1(0), i_2(0), r(0))$
Figure 15(a)	None	0.07	0.07	0.03	0.03	0.03	0.01	0.01	(0.9999,0,0.00005.0.00005,0)
Figure 15(b)	Increased intra-layer contagion probability β_1	0.2	0.07	0.03	0.03	0.03	0.01	0.01	(0.9999,0,0.00005.0.00005,0)
Figure 15(c)	Increased inter-layer contagion probability β_2	0.07	0.1	0.03	0.03	0.03	0.01	0.01	(0.9999,0,0.00005.0.00005,0)
Figure 15(d)	Increased direct immune probability μ	0.07	0.07	0.1	0.03	0.03	0.01	0.01	(0.9999,0,0.00005.0.00005,0)
Figure 15(e)	Increased intra-layer immune failure probability η_1	0.07	0.07	0.03	0.2	0.03	0.01	0.01	(0.9999,0,0.00005.0.00005,0)
Figure 15(f)	Increased inter-layer immune failure probability η_2	0.07	0.07	0.03	0.03	0.1	0.01	0.01	(0.9999,0,0.00005.0.00005,0)
Figure 15(g)	Increased intra-layer immune probability ϕ_1	0.07	0.07	0.03	0.03	0.03	0.05	0.01	(0.9999,0,0.00005.0.00005,0)
Figure 15(h)	Increased inter-layer immune probability ϕ_2	0.07	0.07	0.03	0.03	0.03	0.01	0.1	(0.9999,0,0.00005.0.00005,0)

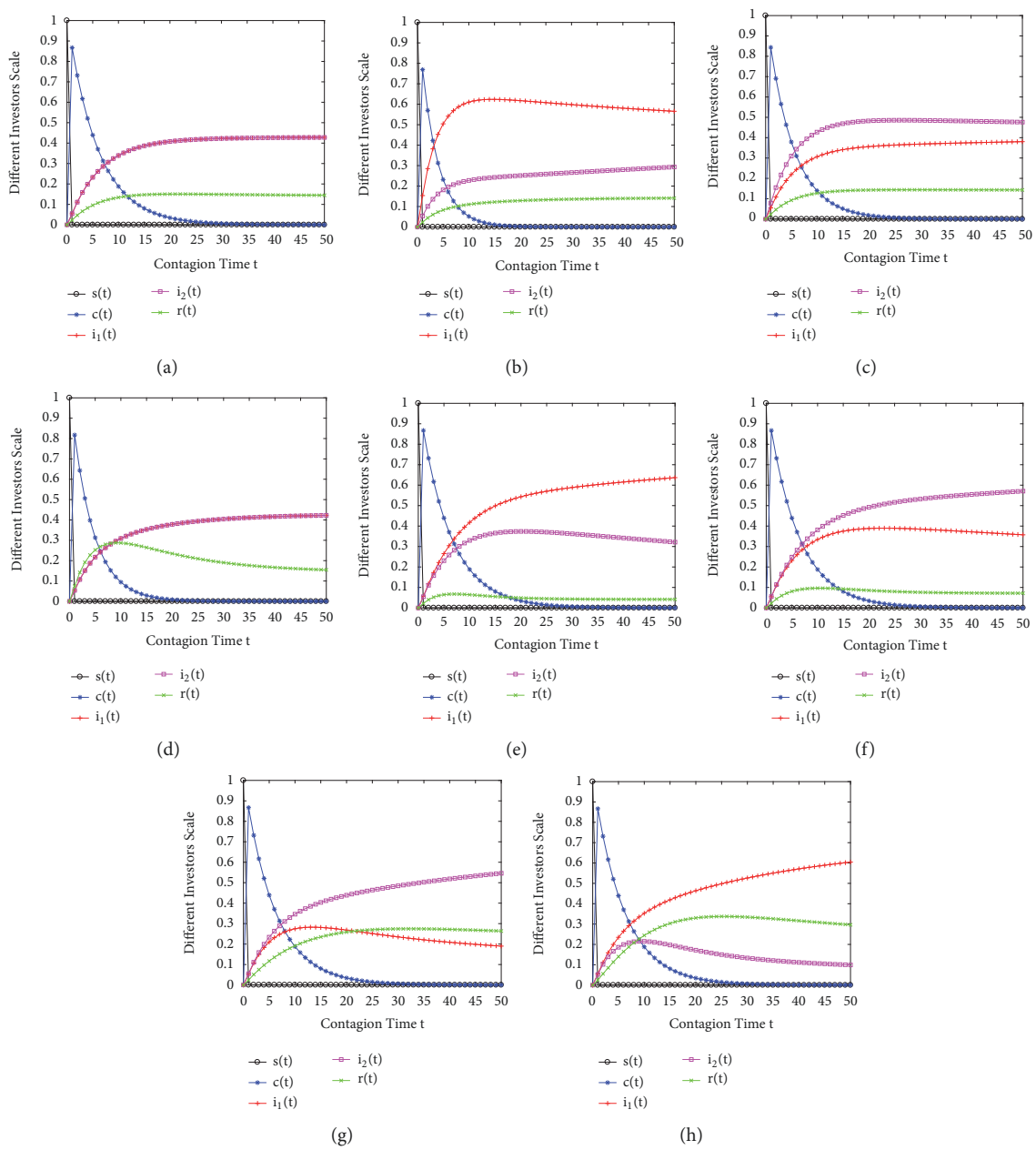


Figure 15: Investor scale trends of different states in SCI_1I_2R investor risk contagion model on bilayer-coupled networks in the stock market under different heterogeneous mechanism probability environments.

β_1 is equal to the heterogeneous interlayer contagion probability β_2, any change in the heterogeneous intralayer immune failure probability η_1, heterogeneous interlayer immune failure probability η_2, heterogeneous intralayer immune probability ϕ_1, or heterogeneous interlayer immune probability ϕ_2 will change the scale of intralayer or interlayer infecting investors. Additionally, increasing heterogeneous immune failure probability reduces the scale of immune investors, and increasing heterogeneous immune probability increases the scale of immune investors.

To sum up, heterogeneous intralayer contagion probability β_1 and heterogeneous interlayer contagion probability β_2 have "local regulation" effect, while the heterogeneous direct immune probability μ, heterogeneous immune failure probability η_1, η_2, and heterogeneous immune probability ϕ_1, ϕ_2 have "global regulation" effect.

5. Conclusion

From the perspective of the stock price linkage, considering the heterogeneities of investors, including investor risk preference, investor risk cognitive level, information value, and investor influence, this article constructs an SCIR contagion model of investor risk on single-layer network to remove investor risk caused by rumors in the stock market under the stock price linkage and its contagion mechanism. Through

computer simulation, this study explores the function and influence of different mechanism probabilities and investor heterogeneity on the effects of risk contagion in the stock market. On the basis of the SCIR contagion model of investor risk on single-layer networks, we construct a SCI_1I_2R contagion model of investor risk on bilayer-coupled networks. Initially, the evolution mechanism of investor risk contagion in the stock market is compared between single-layer and bilayer-coupled networks. Thereafter, the evolution characteristics and rules of investor risk contagion under different connection modes and different mechanism probabilities are compared on bilayer-coupled networks. The conclusions of this paper are as follows:

(1) In the SCIR contagion model of investor risk on single-layer network, some mechanism probabilities have "global effect"; immune failure probability η' has a "global enhancement" effect; and immune probability ϕ' has a "global inhibition" effect. The increase of contagion probability β' not only enables the investor network to reach the steady state faster, but also plays a significant role in the change from transforming investor to infecting investors. The increase of direct immune probability μ' has an evident effect on the transformation from transforming investors to immune investors. The increase of immune probability ϕ' not only enables the investor network to reach the steady state faster, but also plays a significant role in the transformation from infecting investors to immune investors. The increase of immune failure probability η' plays a significant role in the transformation from immune investors to infecting investors.

(2) Investor heterogeneities have "global effect" and "local effect" on investor risk contagion. The increase of investor risk preference θ and information value v_0 can promote the investor risk contagion and has the effect of "global enhancement". Investor risk cognitive level τ can inhibit the investor risk contagion and has the effect of "global inhibition". The increase of investor influence λ_i can promote the investor risk contagion and has the effect of "local enhancement".

(3) Compared with the investor risk contagion on single-layer network, bilayer-coupled networks can expand the investor risk contagion and have the "global enhancement" effect; it is not twice as large as the single-layer network, simply. It is a nonlinear positive correlation.

(4) Among the three interlayer connection modes of the SCI_1I_2R model of investor risk contagion on bilayer-coupled networks, the assortative link has the effect of "local enhancement", while the disassortative link has the effect of "local inhibition". In AL connection mode, the increase of $|\rho^{|WM|}|$ promotes investor risk contagion and has "local enhancement" effect. In DL connection mode, the increase of $|\rho^{|WM|}|$ is not conducive to investor risk contagion and has "local inhibition" effect.

(5) In the SCI_1I_2R model of investor risk contagion on bilayer-coupled networks, heterogeneous mechanism probabilities have "global effect" and "local effect". There is an increase of heterogeneous intralayer contagion probability β_1, heterogeneous intralayer immune failure probability η_1, and heterogeneous interlayer immunity probability ϕ_2; a noticeable increase of the scale of intralayer infecting investors; and a decrease of interlayer infecting investors. Similarly, there is an increase of heterogeneous interlayer contagion probability β_2, heterogeneous interlayer immune failure probability η_2, and heterogeneous intralayer immunity probability ϕ_1; a noticeable increase of the scale of interlayer infecting investors; and a decrease of intralayer infecting investors. Heterogeneous intralayer contagion probability β_1 and heterogeneous interlayer contagion probability β_2 have "local regulation" effect on investor risk contagion, while the heterogeneous direct immune probability μ, heterogeneous immune failure probability η_1, η_2, and heterogeneous immune probability ϕ_1, ϕ_2 have "global regulation" effect on investor risk contagion.

To a certain extent, the research conclusions have expounded the key factors and contagion path of investor risk contagion evolution, have revealed the changing rules of investor risk, and have provided a certain theoretical support for the financial management department to formulate macro policies.

Data Availability

The method in this article is computer mathematical simulation. Numerical simulation analysis is the most effective way to test real-time dynamic data without a large number of empirical validations. The authors use simulation to explore the evolution mechanisms and characteristics of investor risk contagion in the stock market, compared in single-layer and bilayer-coupled networks by using Matlab2016b software. This paper does not have the data that can be obtained because they directly use the plot function of Matlab2016b software to make the images.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Yue Dong, Jiepeng Wang, and Tingqiang Chen contributed equally to this work. They are co-first authors.

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