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Narisa Zhao, Xiaokang Cheng, Xianda Guo

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Highlights

· This paper incorporates the information diffusion process in the contagion of investment behaviors to study the diffusion of internet investment products.

· Information spread process, temporary investment, regular investment and divestment are considered

· The positive influence of regular investment and the negative impact of divestment are not sensitive to the time scale.

· Stimulation strategies is more effective at early stages, and information rejection should be avoided with first priority compared with divestment.

Impact of information spread and investment behavior on the diffusion of internet investment products

Narisa Zhao, Xiaokang Cheng*, XiandaGuo

Institute of Systems Engineering, Dalian University of Technology, Dalian, 116023, China

Abstract: Social networks play an important role in financial markets because the information diffusion in social networks influences the participation of investors. Prior studies have investigated the impact of investor social networks, but few have explored the impact of investment behavior based on information spread in social networks. In this paper, we propose a model for studying the influence that information dissemination and investment behavior in social networks have on the adoption of internet investment products. Information spread process, temporary investment, regular investment and divestment are considered. The results show that the positive influence of regular investment and the negative impact of divestment are not sensitive to the time scale. In addition, the positive impact of regular investment rate is obvious only when the temporary investment rate is not too small, and vice versa. Furthermore, the negative influence of divestment and the information rejection can hardly be offset by increasing the regular investment rate.

Key words: Internet investment product diffusion; Social networks; Information spread; Investment behavior.

1. Introduction

Nowadays, investors are faced with an increasingly complex investment environment in which massive amounts of information need to be processed [1]. In financial markets, information diffuses in social networks among investors and influences their investment decisions [2].With the development of online social network and internet finance, the impact of social networks on financial markets, especially on the diffusion of internet investment products, has drawn increasing attention over the years.

An internet investment product is a personal investment product that is designed and issued by commercial banks and other financial institutions, and is presented and available for purchase on online platforms. Investors make investments and get fixed or unfixed returns according to the relevant contract. YuE Bao is the most widely known example in China. YuE Bao is a money market fund product that was launched in June 2013 on the online payment platform Alipay. According to data from Eastmoney, by June 2017, the fund size of YuE Bao had reached 1493.5 billion Yuan, which exceeded the total amount of personal deposits at China Merchants Bank at the end of 2016 [3]. Substantial numbers of internet investment products have emerged ever since. For a newly introduced internet investment product, an investor may adopt it and make investment decisions according to the information gathered from acquaintances, and they may divest for the same reason [4-6]. Thus, the expansion of the market size of an investment product can be mainly dependent on the propagation of its investors, and it is important to study the information diffusion on investors' social networks.

One way to shed light on how investment ideas diffuse among investors via social networks is to study network characters that influence investment behaviors [7]. The most widely used method is to define a network on a certain basis to obtain the whole network topology and then conduct a panel analysis to explore the impact of investor social networks on investment behaviors or asset prices [8-10]. In our study, we aim to conduct an analysis that uses the epidemic-spreading mechanism to explore the diffusion of internet investment products. We propose an investment contagion model that is based on a classic epidemic model to study the effects of information spread and investment behavior on the diffusion of internet investment products. The rest of this paper is organized as follows. In Section 2, we present previous studies on investor networks. In Section 3, we propose a diffusion model

* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023，PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

of internet investment products. Theoretical calculus is conducted to study the investment dynamics. In Section 4, we first conduct a simulation to examine the accuracy of our model. Second, a numerical analysis is performed to explore the time evolution of diffusion of investment behaviors. In Section 5, the main conclusions are summarized, and suggestions for investment product promotion strategies are provided.

2. Literature Review

Investment behavior includes the investment in and divestment of an investment product, and the aggregate data on investment behavior can be used to evaluate the diffusion scale of an investment product. In the field of behavioral finance, it has been noticed and proved that social influence does exist in investment behaviors, and has influence on the investment participation [2, 28-29]. The effect of social networks on investment behaviors has been extensively studied. Tan and Tan [11] investigated the influence of online and offline social networks on investment decisions and found that offline social networks have larger impacts. Such a result is not surprising because in offline social networks, communication often occurs face-to-face and therefore has a larger impact on trading behaviors. Pareek [12] studied the impact of network structure on stock return momentum. The author defined an information network based on common portfolio allocation and applied network density to indicate the information dissemination speed in such a network. The author found that a lower network density results in a stronger return momentum and a slower response to the market information. Liang et al. [7] applied the machine learning method to predict investment behavior in a social network context. The authors defined social and investment networks among investors and companies and found that network closeness has a positive effect on investment probability, whereas common neighbour numbers has a negative effect. Li [13] explored the impact of information sharing among extended family members on stock market participation and discovered that a family bond increases the probability of stock market participation by 30%. One reason behind the significant influence of investor social networks is that investment information and ideas can spread among investors and affect~~ing~~ their investment decisions. It has been pointed out that investment ideas can spread like epidemics among investors. The most widely used epidemic model is the Suspected-Infected-Removed (SIR) model, and sequential models have been developed on its basis in a wide variety of fields, including information diffusion[14-18] and contagion of investment behaviors[19-22].

Empirically, social network does influence investment behaviors. However, studies on the diffusion mechanism of an investment idea in investor network are still undeveloped. Colapinto et al. [30] studied the interlaced process of awareness diffusion and general innovation adoption, implying that the diffusion of awareness is prior to the adoption, and stylized empirical facts are recovered. In a recent study, based on the classic SIR model, Zhu et al. [22] proposed a Potential-Investor-Divestor (PID) model and studied the spread of a financial scheme in complex networks. The authors explored the diffusion speed and the collapsing time of the scheme using epidemic spreading mechanism. In fact, several recently collapsed Ponzi schemes in China are manipulated by issuing illegally managed internet investment products. The mechanism of how the diffusion of information and contagion of investment ideas on social networks gradually affects the adoption of internet investment products is still to be discovered.

3. Theoretical Framework

Information about internet investment products spreads in social networks, and information recipients choose whether to make an investment. Our model aims to incorporate the information diffusion process into the investment contagion model to study the diffusion of an internet investment product. The diffusion mechanism is developed on the basis of the classical epidemic model [23, 24].

In the investment contagion model in [23], there are three types of entities: potential investors (entities who have not made an investment), investors (entities who have made an investment) and divestors (entities who have divested and no longer make investments), and the transformation follows the epidemic mechanism. [23] studies

* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023，PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

the diffusion of Ponzi scheme in complex network. We extend [23]'s work and studies a general concept of personal investment product. The PID model in [23] is suitable for our study because the investors are in pursuit of profits in both situations. ~~The difference between a Ponzi scheme and a legitimateinternet investment product is that the former will definitely collapse with the fraudulent mechanism, whereasthe latter will develop sustainably as long as the fund is properly managed. The sustainable development of an investment product is ensured by the continuous inflow of capital, which means that there are loyal investors making regular investments in the fund. Therefore, it is reasonable to incorporate regular investors, i.e., investors who continuously invest in the product.~~ In our model, the information dissemination and rejection process was considered for potential investors. Since the information diffusion process is very fast compared with the network lifetime, the network structure is considered to be constant during the given time period in our study [25]. The diffusion process of an internet investment product is illustrated in Fig. 1. Assume that each node in the diagram represents a type of entity. The states of all entities are classified into six categories, and the definitions are as follows:

UP (Uninformed potential investor): The node has not received the product information and will receive the information upon encounter with nodes that carry the information, i.e., informed potential investor, temporary investor, and regular investor nodes.

P (Informed potential investor): The node carries the product information but has not made an investment.

DS (Discarded): The node rejects and will become immune to the information [20], i.e. the node will not be interested in or spread the information ever again.

I (Temporary investor): The node adopts the product and makes temporary investment on the product while holding the product information, and will either quit the investment and become a divestor, or become a loyal investor making regular investments.

RI (Regular investor): The node makes regular investments on the product while holding the product information. Within the given time, a regular investor continuously has investment in the product, and will not quit the investment at the end of the given time.

D (Divestor): The node withdraws all the principal and interest, leaves the process entirely and is no longer contagious.

UP-P-DS is the information diffusion process. P-I-D/RI is the investment decision-making process. States DS, RI and D are absorbing states; i.e., nodes will not transfer to other states once they enter these states. The product information can be spread when a node holding the information encounters a UP node. We denote the number of informed potential investor, uninformed potential investor, and discarded nodes at time t as $X(t)$, $Y(t)$, and $DS(t)$, respectively, and the number of temporary investor, regular investor, and divestor nodes at time t as $I(t)$, $R(t)$, and $D(t)$, respectively.

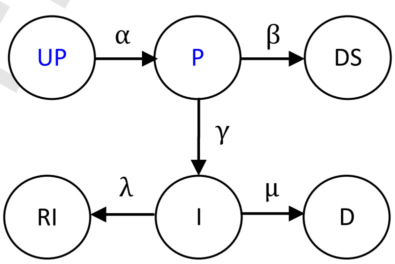

Fig. 1 The diffusion process of an internet investment product

Internet investment products can be of many types. Take mutual fund for example. Some are open ended mutual funds, and are available for purchase and redemption at anytime. In this case, the sustainable management of the product is ensured by the continuous inflow of capital, which means that there are both temporary investors and regular investors, and the diffusion can be studied by our model. Some are close ended mutual funds, and can

* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023，PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

only be purchased during the fund raising period, and there will be no regular investors. In addition, a close ended investment product is not redeemable before expiration date. In this case, we can still study the diffusion by letting the probability of a temporary investor transforming to a regular investor or a divestor equals 0. Therefore, our model is suitable to study the diffusion of various types of internet investment products based on the information dissemination process.

We define $\eta_j(t, t+\Delta t)$ as the indicator function of whether a node transforms from state UP to state P during $[t,\ t+\Delta t]$. $\eta_j(t, t+\Delta t) = 1$ means that the transition occurs, otherwise $\eta_j(t, t+\Delta t) = 0$. Similarly, $\omega_j(t, t+\Delta t)$ indicates whether a node rejects the message during $[t,\ t+\Delta t]$. $\omega_j(t, t+\Delta t) = 1$ means that the message is rejected during the period, otherwise $\omega_j(t, t+\Delta t) = 0$. In addition, let $\varphi_j(t, t+\Delta t)$ denote whether an informed potential investor node adopts the product and becomes a temporary investor during $[t,\ t+\Delta t]$. $\varphi_j(t, t+\Delta t) = 1$ means that the product is adopted and the investment is made during the given time interval, and $\varphi_j(t, t+\Delta t) = 0$ means the opposite. We denote $\{\cdot(t)\}$ as the set of all nodes inside state $\cdot$ at time t. We have

$$X(t+\Delta t) = X(t) + \sum_{j\in\{Y(t)\}} \eta_j(t, t+\Delta t) - \sum_{j\in\{X(t)\}} \omega_j(t, t+\Delta t) - \sum_{j\in\{X(t)\}} \varphi_j(t, t+\Delta t). \tag{1}$$

We denote α as the information spreading rate. Assume that during time interval Δt, the nodes will encounter one another by the probability drawn from exponential distribution with parameter α [24]; we have

$$P\big(\eta_j(t, t+\Delta t) = 1\big) = 1 - (1 - (1 - e^{-\alpha\Delta t})^{X(t)+I(t)+R(t)} = 1 - e^{-\alpha\Delta t(X(t)+I(t)+R(t))}. \tag{2}$$

We assume that β is the information rejection rate and that S nodes will transform into state DS with probability drawn from the exponential distribution, with parameter β [24].With the introduction of acquaintances, the longer a node holds the information of an internet investment product, the more likely it is that the information will be well interpreted; therefore, an investment is more likely to be made. Denoting γ as the temporary investment rate, we assume that S nodes will transform into state I with the exponential probability distribution with parameter γ, i.e.,

$$P\big(\omega_j(t, t+\Delta t) = 1\big) = 1 - e^{-\beta\Delta t}, \tag{3}$$

$$P\left(\varphi_j(t, t+\Delta t) = 1\right) = 1 - e^{-\gamma\Delta t}. \tag{4}$$

By using the mean field approximation [26], we have

$$\lim_{\Delta t\to 0}\frac{E(X(t+\Delta t) - E(X(t))}{\Delta t} = \lim_{\Delta t\to 0}\frac{E(Y(t)E(1 - e^{-\alpha\Delta t(X(t)+I(t)+R(t))})}{\Delta t} - \lim_{\Delta t\to 0}\frac{E(X(t)E(1 - e^{-\beta\Delta t})}{\Delta t} - \lim_{\Delta t\to 0}\frac{E(X(t)E(1 - e^{-\gamma\Delta t})}{\Delta t}$$

$$\Rightarrow E(\dot{X}(t)) = E\big(X(t) + I(t) + R(t)\big)\alpha E(Y(t)) - \beta E(X(t)) - \gamma E(X(t)). \tag{5}$$

Similarly,

$$E(\dot{Y}(t)) = -\alpha E(X(t) + I(t) + R(t))\, E(Y(t)), \tag{6}$$

$$E(D\dot{S}(t)) = \beta E(X(t)). \tag{7}$$

We define $\sigma_j(t, t+\Delta t)$ as the indicator function of whether node j transfers from state I into state D during $[t,\ t+\Delta t]$. $\sigma_j(t, t+\Delta t) = 1$ means that the transition occurs, and $\sigma_j(t, t+\Delta t) = 0$ means the opposite. $\theta_j(t, t+\Delta t)$ represents whether node j changes from state I to state RI during $[t,\ t+\Delta t]$. $\theta_j(t, t+\Delta t) = 1$ indicates that the transition occurs, and $\theta_j(t, t+\Delta t) = 0$ means that it does not. Thus, the following equation can be obtained:

$$I(t+\Delta t) = I(t) + \sum_{j\in\{X(t)\}} \varphi_j(t, t+\Delta t) - \sum_{j\in\{I(t)\}} \sigma_j(t, t+\Delta t) - \sum_{j\in\{I(t)\}} \theta_j(t, t+\Delta t) \tag{8}$$

We define λ as the regular investment rate, representing the likelihood an I node transforms into an RI node, and μ as the divestment rate. Assume the transition probabilities from state I to RI and D are drawn from an exponential distribution with the parameters λ and μ, respectively, we have

* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023，PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

$$P(\theta_j(t, t+\Delta t) = 1) = 1 - e^{-\lambda\Delta t}, \tag{9}$$
$$P(\sigma_j(t, t+\Delta t) = 1) = 1 - e^{-\mu\Delta t}. \tag{10}$$

Note that when $\alpha = 0$, $\beta = 0$ and $\lambda = 0$, our model reduces to the PID model proposed in [23].

Taking expectations and then limitations on both sides for Eq. (8),

$$\lim_{\Delta t\to 0}\frac{E(I(t+\Delta t) - E(I(t))}{\Delta t} = \lim_{\Delta t\to 0}\frac{E(X(t)E(1-e^{-\gamma\Delta t})}{\Delta t} - \lim_{\Delta t\to 0}\frac{E(I(t)E(1-e^{-\lambda\Delta t})}{\Delta t} - \lim_{\Delta t\to 0}\frac{E(I(t)E(1-e^{-\mu\Delta t})}{\Delta t}$$
$$\Rightarrow E(\dot{I}(t)) = \gamma E(X(t)) - (\mu+\lambda)\, E(I(t)). \tag{11}$$

Similarly,

$$E(\dot{D}(t)) = \mu E(I(t)), \tag{12}$$
$$E(\dot{R}(t)) = \lambda E(I(t)). \tag{13}$$

We have obtained six differential equations with six unknowns. Although analytical solutions are difficult to derive, we can use the Matlab to obtain numerical results [26].

4. Simulation and numerical results

To examine the accuracy of the theoretical solutions, we generated a simulation in Java according to the diffusion mechanism proposed in the prior section. We denote N as the total number of all nodes. Set N=10000 and X(0)=1. According to [24], we set $\alpha = 3.71\times10^{-6}$. In addition, we set $Y(0) = 9999, \beta = 3\times10^{-5}$, $\gamma = 2\times10^{-4}$, $\mu = 1\times10^{-5}$, $\lambda = 5\times10^{-6}$, $T = 4\times10^{5}$. These settings are default settings hereinafter. We divide the total duration T=400000 into 40 equivalent intervals, and simulation values at each epoch are obtained for comparison with the theoretical result. To eliminate occasional errors, we take the mean value of 10 times simulation on each epoch. The comparison result is illustrated in Fig. 2. We calculated the error by taking the average of the deviation of every theoretical and simulation value, and the error is 1.28%, which indicates that our theoretical results are accurate.

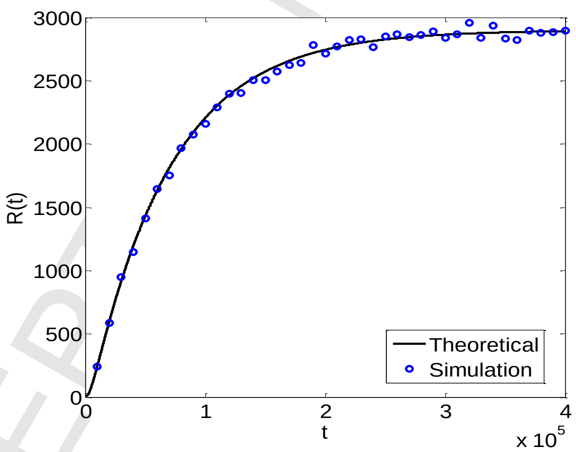

Fig. 2 Comparison between the simulation results and theoretical solution with $X(0) = 1, Y(0) = 9999, \alpha = 3.71\times10^{-6}$, $\beta = 3\times10^{-5}$, $\gamma = 2\times10^{-4}$, $\mu = 1\times10^{-5}$, $\lambda = 5\times10^{-6}$, $T = 4\times10^{5}$.

Next, we investigate the time evolution of the number of nodes in different states with changing parameters. We take the percentage of regular investors at time t as the evaluation of the diffusion of an internet investment product, which is represented by

$$r(t) = R(t)/N. \tag{14}$$

Particularly, r(T) denotes the proportion of regular investor nodes at final time T. To have an intuitive image of how all nodes may change over time, we plotted the proportion of nodes of six states with fixed parameters against time.

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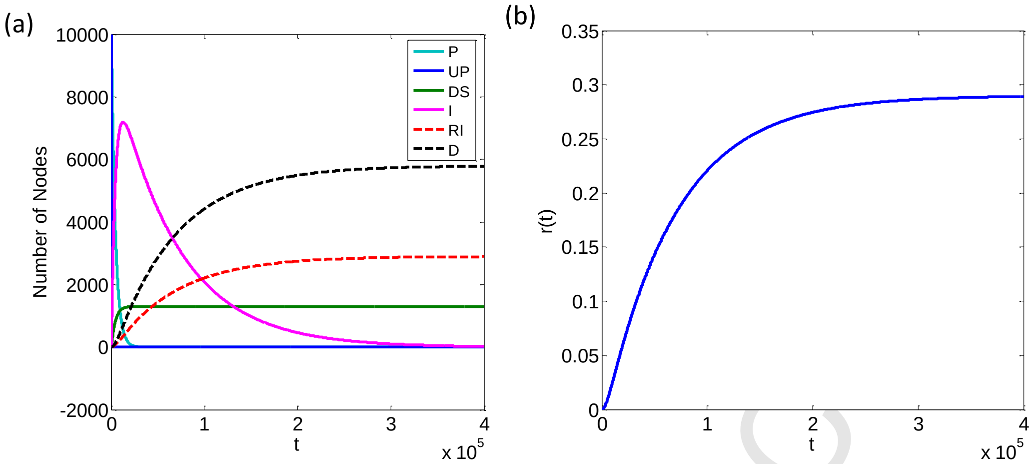

Fig. 3(a) The number of nodes of six states versus time with T=4×10^5. (b) The proportion of regular investor nodes against time. Other parameters are same as the default setting.

Fig. 3(a) illustrates the change in the number of nodes of the six states over time. We can see that the number of UP nodes decreases rapidly to zero at the beginning[1]. The number of P nodes increases to 10000 and then fell to zero with a decreasing speed. The number of I nodes increases sharply to a peak value and then drops smoothly to zero. The number of DS nodes increases steeply at the beginning and has remained unchanged at an early stage. The number of RI and D nodes shares similar evolution pattern, both of which increases mildly to a maximum value and has remained steady since then. The proportion of RI nodes is presented in Fig. 3(b). There were approximately 28% investors at the end of the given time period. According to the 2015 China securities investment fund fact book, at the end of year 2015, there were 27.62% (187.5855 million/679.1739 million) valid open-ended mutual fund accounts [27], consistent with this percentage.

4.1 Effect of temporary investment rate

When an entity holds the information of an innovative internet investment product, he or she may decide whether to adopt the product and make an investment. The effect of temporary investment rate can be represented by the effect of the parameter γ, which is illustrated in Fig. 4.

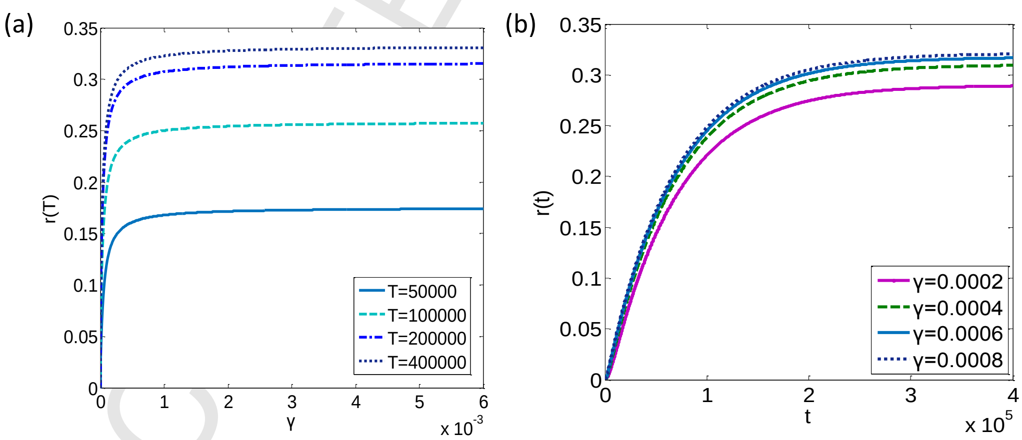

Fig. 4 The proportion of regular investor nodes with different γ and durations. (a) γ changes between 0 and 6×10^{-3} with $T=5\times10^4$, 1×10^5, 2×10^5, 4×10^5, respectively. (b) $T=4\times10^5$ with $\gamma=2\times10^{-4}$, 4×10^{-4}, 6×10^{-4}, 8×10^{-4},

[1] Firstly, it is possible for a piece of information to diffuse explosively with the rapid developing internet technology and social media [31]. Secondly, we can adjust our parameters to fit for different information diffusion speed. The impact of changing α is examined. The results show similar trend in the evolution of r(T) when lifetime T is long enough, suggesting that our results are robust when α changes.

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respectively. Other parameters are same as the default setting.

Fig. 4(a) illustrates the relationship between r(T) and the temporary investment rate γ with a different lifetime. We can see that as γ increases, r(T) would increase sharply at the very beginning and soon reaches a stable status. The extension of lifetime T brings significant increase of r(T) when T is small. Such result suggests that when the promotion strategy is considered for new adopters, expanding the promotion time within a certain range can be beneficial. Fig. 4(b) shows the time evolution of the percentage of RI nodes with different γ. We can see that the increase of γ leads to a slight increase of r(T). In addition, the positive effect of increasing parameter γ shrinks as γ continues to increase, suggesting that increasing the temporary investment rate will boost up the diffusion to a limited extent.

4.2 Effect of regular investment rate

Now we focus on the influence of the regular investment rate λ. The regular investment rate measures the transition probability from state P to state I. The time evolution of the percentage of regular investors under dynamic λ is pictured in Fig. 5.

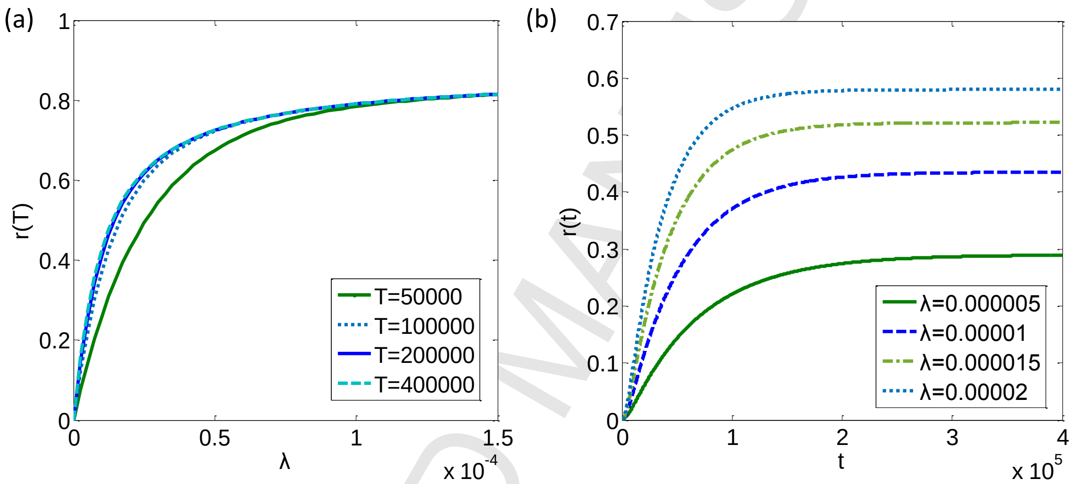

Fig. 5 Proportion of regular investors versus λ and different time scale T. (a) $T = 5\times10^4$, 1×10^5, 2×10^5, 4×10^5. (b) $T = 4\times10^5$, $\lambda = 5\times10^{-6}, 1\times10^{-5}, 1.5\times10^{-5}, 2\times10^{-5}$. Other parameters are same as the default setting.

From Fig. 5(a), we can see that r(T) increases significantly at first, then smoothly with the increase of λ. As shown in the illustration, four lines tend to converge as λ keeps increasing, indicating that the increase of T no longer has an effect on r(T). When λ is not very large, the increase in T has a slight effect on r(T) when T is small, and when T goes beyond 2×10^5, the extension of T does not bring a greater percentage of RI, suggesting that the final effect of the regular investment rate is only slightly dependent on the time scale. Thus we can conclude that when designing the promotion strategy considering regular investors, prolonging time span can barely help. In Fig. 5(b), we can see that the increase of λ brings a faster increase of r(T) at the beginning of the diffusion, indicating that the simulation is more influential at early stage. As λ continues to increase, the positive influence of increasing λ decays.

4.3 Effect of information rejection and divestment

Both the information rejection and the divestment of investors lead to a decrease of the percentage of regular investors. Fig. 6 shows how these two factors affect the diffusion scale of an internet investment product. We can see that both the information rejection and the divestment of investors lead to a decrease of the percentage of regular investors.

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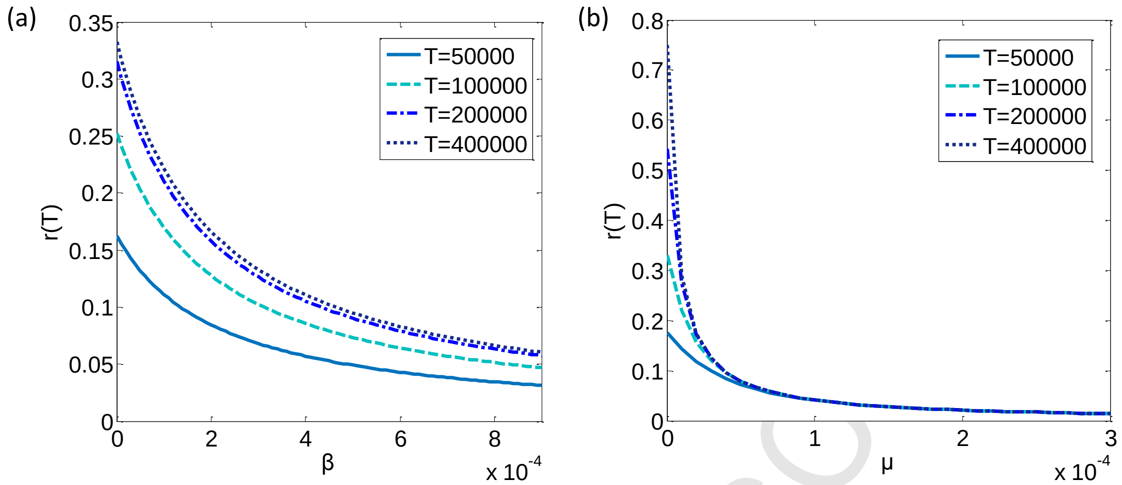

Fig. 6(a) Percentage of regular investors versus information rejection rate β with $T = 5 \times 10^4$, 1×10^5, 2×10^5, 4×10^5, respectively. (b) Percentage of regular investors versus divestment rate μ with $T = 5 \times 10^4, 1 \times 10^5, 2 \times 10^5, 4 \times 10^5$, respectively. Other parameters are same as the default setting.

In Fig. 6(a), we can see that as the information rejection rate β increases, r(T) declines smoothly, and the extension of life time is decreasingly effective. In Fig. 6(b), after the convergence of the four lines at an early stage, extending time scale no longer brings increase to r(T). In addition, we can see that compared with the impact of β, the increase of μ results in a more rapid and significant decrease in r(T) at the beginning. Thus it can be concluded that when the information rejection rate is high, r(T) can still be boosted up limitedly by extending the time scale, but if the divestment rate is high, the extension of lifetime would be almost useless.

4.4 How to maintain the positive effect of regular investment rate?

As is discovered above, the regular investment rate λ is the most important positive influencing factor, therefore we now investigate the impact of regular investment rate λ under the dynamic other three parameters.

Firstly, we explore the mutual effect of regular investment rate λ and temporary investment rate γ. As is stated above, the temporary investment rate measures the transition probabilities from state P to I, and regular investment rate indicates that from state I to RI, i.e., γ and λ, respectively. The combined effect of these two parameters is illustrated in Fig. 7. In this section, all parameters are set to change from 0 to 30 times its default setting. For example, the default setting of λ is 5×10^{-6}, then it is set to change from 0 to 1.5×10^{-4} in this section.

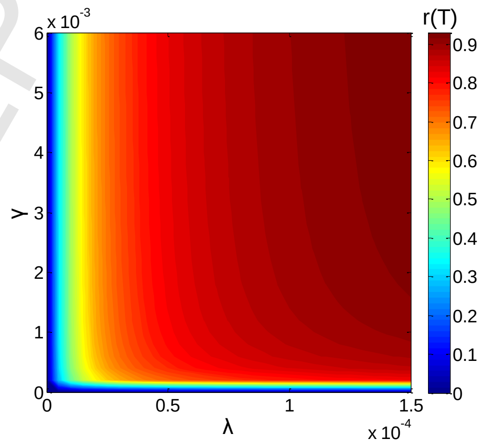

Fig. 7 Percentage of regular investors with changing λ and γ with $N = 10000$, $T = 4 \times 10^5$, $\alpha = 3.71 \times 10^{-6}$, $\beta = 3 \times 10^{-5}$, $\mu=1\times 10^{-5}$.

From Fig. 7 we can see that when λ is extremely small (smaller than 5×10^{-6}), an increase in γ has no

* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023, PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

effect on r(T). As λ keeps increasing, the impact of γ becomes increasingly significant on r(T). The results suggest that the impact of the regular investment rate is obvious only when the temporary investment rate is not too small, and vice versa. However, a low temporary investment rate can still end up with a large proportion of regular investors if the regular investment rate keeps increasing.

Next, we explore the mutual effect of regular investment rate and divestment rate. The divestment can be caused by an increase in perceived risk or competitive financial product information, and it is important to study how the divestment behavior would influence the diffusion of an internet investment product. Fig. 8 presents the mutual effect of λ and μ on the percentage of regular investor nodes.

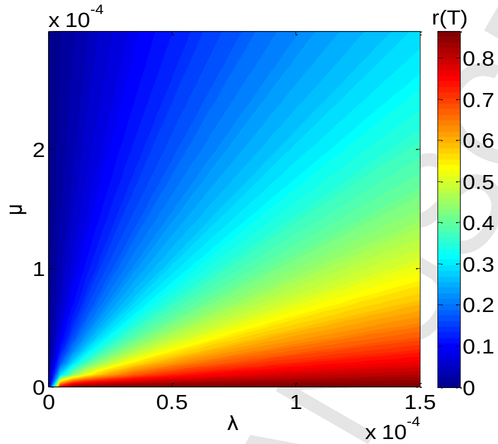

Fig. 8 Percentage of regular investor nodes with changing λ and μwith $N = 10000$, $T = 4 \times 10^5$, $\alpha = 3.71 \times 10^{-6}$, $\beta = 3 \times 10^{-5}$, $\gamma = 2 \times 10^{-4}$.

In Fig. 8 we can see that when λ is small, the change of μ has a heavy effect on r(T), and r(T) decreases rapidly with the increase of μ. However, the increase of λ leads to a declining influence of μ and vice versa. This indicates that the negative influence of divestment declines as the regular investment rate goes up. In addition, when the divestment rateμis high, the increase of λ can only slightly boost up r(T), but when λ is high, the increase of μ leads to a significant decrease in r(T), suggesting that the negative impact of divestment can hardly be offset by increasing the regular investment rate.

Thirdly, we study the impact of regular investment rate under dynamic information rejection rate. The result is illustrated in Fig. 9.

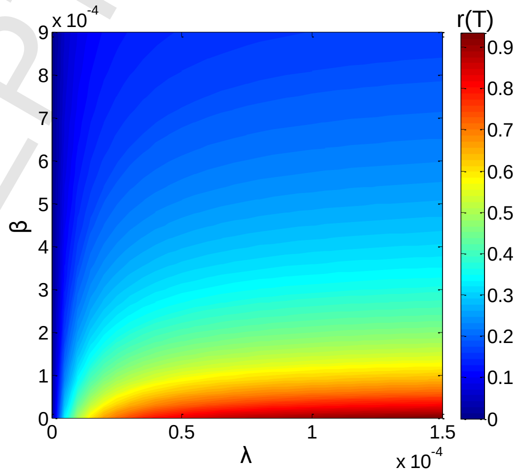

Fig. 9 Percentage of regular investor nodes with changing λ and β with $N = 10000$, $T = 4 \times 10^5$, $\alpha = 3.71 \times 10^{-6}$, $\gamma = 2 \times 10^{-4}$, $\mu = 1 \times 10^{-5}$.

We can see that when λ is smaller than 5×10^{-5}, the negative effect of β declines significantly with the

* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023, PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

increase of λ. When λ is larger than 5×10^{-5}, the impact of information rejection is almost static, indicating that compare with divestment, the information rejection rate should be avoided with first priority. Such result also implies that when it comes to fraudulent investment, increasing information rejection rate would be a useful countermeasure. In contrast, as the information rejection rate increases, the positive effect of the regular investment rate decreases significantly, faster than that when divestment rate increases. A large rejection rate means that the information is rejected and discarded before it is processed among nodes; as a result, the diffusion is interdicted at the beginning stage.

To summarize, the positive impact of regular investment is obvious only when the temporary investment rate is not too small, and vice versa. In addition, the negative influence of information rejection and divestment can hardly be eliminated by increasing the regular investment rate, and information rejection is more harmful than divestment.

5. Conclusions

Epidemic interacting mechanism has been proved valid in explaining behavioral patterns in financial market [20]. In this paper, we propose an epidemic investment contagion model to study the impact of information dissemination and investor behavior on the diffusion of internet investment products. Information rejection, temporary investment, regular investment and divestment are considered. The accuracy of our model is examined by simulation.

Our analysis suggests that the positive effect of temporary investment rate increases with the expansion of total duration, while that of regular investment rate is not sensitive to time scale. Such finding suggests that when the promotion strategy is considered for new adopters, expanding the promotion time within a certain range can be profitable. As for the existing investors, the expansion of time span can hardly help. Secondly, the increment of both temporary investment rate and regular investment rate give significant rise to the adoption rate at early times, indicating that stimulation strategies are more influential at the early stage. The impact of the regular investment rate is obvious only when the temporary investment rate is not too small, and vice versa. Thirdly, information rejection and divestment behavior impact the adoption in different ways. When the information rejection rate is high, the number of regular investors can still be boosted up limitedly by extending the time scale, but if the divestment rate is high, the extension of lifetime would be almost useless. The negative influence of divestment declines as the regular investment rate goes up, but the negative influence of information rejection barely decreases even the regular investment rate keeps increasing, implying that when limited budget is available, compared with divestment, it is more important to avoid information rejection. Such finding also suggests that when it comes to financial schemes, increasing information rejection rate would be a useful immune strategy. In addition, the influence of these two negative factors can hardly be offset by increasing the regular investment rate.

Theoretically, our study introduces a variation of the classic SIR model to study the impact of information dissemination on the diffusion of an internet financial product. Our work is an extension of [23]'s study by considering regular investor nodes and incorporating information diffusion process, and is suitable to study the diffusion of various types of internet investment products by adjusting the parameters. Furthermore, our work provides a foundation for future studies on the diffusion of internet investment product on networks with higher complexity. Practically, our study offers an enlightening insight for internet investment product managers to understand how to effectively boost up the diffusion or avoid the depression of an internet investment product.

In future research, it will be interesting to study the role of innovators and imitators in the adoption process [30]. In addition, the cash balance problem, drawn from our analysis of the dynamics of investor numbers, the competitive information problem and the social network structure can be considered.

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* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023，PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

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* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023，PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.

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* Correspondence to: Institute of Systems Engineering, Dalian University of Technology, Liaoning, Dalian, 116023，PR China. Tel: +86 18504259007. Email address: chengxk@mail.dlut.edu.cn.