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Research Article

Information Contagion and Stock Price Crash Risk

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We introduce continuity and temporariness into the independent cascade model to depict information diffusion in a social network. Investor behavior changes are determined according to the process of information diffusion, and the investment portfolio model consisting of sentiments is proposed to reveal the fire sales of stocks and the resulting stock price crash risk. Therefore, the relationship between information diffusion and stock price crash risk is established, and the contagion of stock price crash risk is analyzed from the perspective of information diffusion. Furthermore, some immunization strategies of networks are compared to prevent stock price crash risk. The results show that the tendency of stock price crash risk is consistent with that of information diffusion, which indicates that information diffusion before the fire sales is the key to triggering stock price crash risk. Moreover, investors with many ties contribute more to information diffusion than others; hence, immunization strategies of networks based on global information are more effective in preventing stock price crash risk than that based on local information. This study provides a new perspective for the study of contagion risk in the stock market, and it hints at the possibility of regulatory intervention to prevent stock price crash risk.

1. Introduction

The stock market is an important part of the modern financial system, which provides an essential financing environment for the development of the national economy. However, it is prone to crises, especially stock price crash risk, because of the high sensitivity and volatility. As shown in prior studies, one of the fundamental causes of stock price crash risk is owed to the bad news hoarding [1–3]. Concretely, there exists a critical threshold at which it is too costly for management to withhold the bad news. Once the threshold is reached, all the hidden news would come out, leading to an abrupt, dramatic collapse in stock price, that is, a stock price crash [4, 5]. In particular, information diffusion makes it more difficult for managers to withhold egregious bad news once it occurs and triggers the fire sales of stocks. As such, the diffusion of negative information into the social network before the fire sales may lead to panicking investors and irrational sales and result in the stock price crash risk being triggered. In modern society, where internet technology is highly developed, investors can express their opinions through social networks such as Facebook, Twitter, and Message Board, which improves the speed and influence of information diffusion. Therefore, an accurate depiction of information diffusion in an investor's social network is of great importance in analyzing the contagion of stock price crash risk. According to the above mechanism, He and Ren [6] summarized three key drivers of stock price crash risk: the fundamental risk profiles, which generate unexpected, egregious bad news; bad news hoarding; and market frictions that hinder investors' abilities to discern the bad news hoarding. These drivers constitute the assumption underlying our analysis. As a consequence, we extend the study and explore the causation of stock price crash risk from the perspective of information diffusion. Unlike that, we are more attentive to the diffusion process of bad news.

2. Related Literature

Investment decisions are fundamentally determined by information; thus, information diffusion and stock prices are

closely interlinked. Hong and Stein [7] verified the tendency for stock prices to react to information through a behavioral model. Based on this, many studies have directly incorporated information diffusion as an important factor in stock pricing, and the results indicate that information diffusion could explain the fluctuation of stock prices in different periods [8–10]. According to empirical evidence, it was found that proxy variables of information diffusion would exert a great influence on stock price fluctuations [11–13]. In particular, the dramatic diffusion of released bad news would lead to an increase in the stock price fall [3, 14]. However, issues such as how information diffusion affects the stock market and how to quantify such effects remain unknown [15]. Investors' sentiments based on behavioral finance theory provide a new perspective when studying the internal relationship between information diffusion and stock market fluctuations. Studies have shown that sentiments influence investors' risk tolerance and decisions [16]. Yu and Yuan [17] managed to quantify the relationship between investors' sentiments and risk attitudes, thus providing theoretical support to study the mechanism by which information diffusion affects the stock market.

Social networks, the main channel for information diffusion, play a decisive role in the information diffusion process, and they provide ideas for the construction of information diffusion models [18]. Currently, such models mainly include the independent cascade model, linear threshold model, and epidemic model [19–21]. Regarding information diffusion in the stock market, it is exclusively possible for the epidemic model to measure the information diffusion degree instead of the path. Additionally, it is required for the linear threshold model to determine the information diffusion based on the accumulative probability, which ignores the information timeliness. Finally, it is more appropriate to deal with the information for investors through the independent cascade model. Information in the traditional independent cascade model will be diffused synchronously. Saito et al. [22] and Goyal et al. [23] improved its asynchronism and continuity, which renders it with the time property. The time and sequence of information diffusion play a vital role in specific environments, and research on information diffusion through temporal networks continues to increase in recent years [24–28], and it hints at the possibility of studying the information diffusion process among investors in the stock market.

Regarding factors leading to stock price crash risk, traditional studies can be divided into two main types: asymmetric information [4, 29] and irrational investors [30]. Information and investors interact, that is, information influences the stock market only through investor trading behavior. Therefore, it establishes an important direction for the factors influencing stock price crash risk based on the information interaction among investors. Ahern [31] proved this relationship through an empirical study. However, research on the internal mechanism of contagion risk remains scarce. As for the prevention and control of stock price crash risk, studies have been conducted based on macroscopic measures [32, 33]. At the microlevel, most studies centered on improving the insufficient transparency of information disclosure from different kinds of perspectives, such as financial constraint, analyst coverage, insider trading, and corporate tax avoidance [1, 6, 14, 34–36]. However, studies on the control of stock price crash risk starting from information diffusion remain to be expanded.

3. Information Diffusion Model

3.1. Asynchronous Independent Cascade Model. Information in the traditional independent cascade model will be diffused synchronously. In other words, the information will be diffused within a given time step, and all nodes will be activated only if the time step ends. Such a situation does not conform to information diffusion features in the real market. The interaction intensity differs among investors, and the information diffusion time differs among different investors. According to Gruhl et al. [37] and Saito et al. [22], we managed to improve the synchronization problem of information diffusion by introducing an information diffusion delay into the independent cascade model. Therefore, the asynchronous independent cascade model is constructed based on the information diffusion delay.

Generally, the higher the interaction intensity, the shorter the information diffusion delays among investors. Therefore, it makes sense that the information diffusion delay is determined by the interaction intensity. It assumes that the investor u represents the initial active point. At a certain point, the investor u will establish an interactive relationship in the social network with the investor v through the interaction intensity $r_{u,v}$. According to Gruhl et al. [37], the information diffusion delay in the asynchronous independent cascade model is also related to the interaction intensity. Therefore, the information diffusion delay $\tau_{u,v}$ can be determined by the exponential distribution with $\lambda r_{u,v}$ as the parameter:

$$p\left(\tau_{u,v}\right) = \lambda r_{u,v} e^{-\lambda r_{u,u} \tau_{u,v}}, \tag{1}$$

where λ is a constant. Based on the property of exponential distribution, the mean value of the diffusion delay is equal to the reciprocal of its parameter. This is consistent with the feature that the information diffusion delay is short with a strong interaction intensity, and conversely, the information diffusion delay is long with a weak interaction intensity.

The asynchronous independent cascade model can be determined based on the information diffusion delay in the context of the decided interaction intensity $r_{u,v}$. It diffuses the information from investors in the set of initial active nodes at time t, and the process is as follows: it assumes that the investor u represents the active node at time t and that it has a single chance to activate the inactive investor v. The information diffusion delay $\tau_{u,v}$ is still subject to an exponential distribution with $\lambda r_{u,v}$ as the parameter. If the investor v remains inactive before time $t + \tau_{u,v}$, then the investor u tries to activate the investor v with the interaction intensity of $r_{u,v}$. The investor v would be active at time $t + \tau_{u,v}$ under a successful activation. Regardless of the success of the investor u, no attempt can be made to activate the investor v in the subsequent information diffusion process. The information

diffusion process ends with no more potential investors being inactivated in the market.

3.2. Information Diffusion Decay. In the real market, the influence of information diffusion will decay over time. Therefore, an exponential decay model is proposed in this study based on the studies by Goyal et al. [23] and Barbieri et al. [38]. The model could be applied to depict the decay of interaction intensity among investors over time. For given information, the decay of the interaction intensity between investor u and investor v at time t can be defined as

$$r_{u,v}^{t} = r_{u,v}^{0} e^{-\beta\left(t-t_u\right)}, \tag{2}$$

where $r_{u,v}^{0}$ represents the initial interaction intensity from the investor u to investor v. $t - t_u$ represents the information diffusion delay $\tau_{u,v}$ from the investor u to investor v. Through the combination of information diffusion decay and information diffusion delay, it can be concluded that

$$r_{u,v}^{t} = r_{u,v}^{0} e^{-\beta\tau_{u,v}}. \tag{3}$$

This can be adopted to depict the interaction intensity decay resulting from the information diffusion delay among investors.

3.3. Heterogeneous Information Diffusion. Participants in the stock market can be divided into institutional investors and individual investors, and information interaction intensity differs greatly among different types of investors. Institutional investors are more likely to learn the original information than individual investors are. Furthermore, they are more sensitive to information. Therefore, the information would be diffused more rapidly among institutional investors. However, institutional investors usually deliver information to major clients in private. Consequently, only a few individual investors can access the information, while most individual investors will be inactive in the information acquisition. According to the different features of investors, a heterogeneous information diffusion model is defined where institutional investors and individual investors belong to different social networks, while interactions among different types of investors are depicted through weak ties according to Goldenberg et al. [21].

3.4. Temporal Information Diffusion Network. The information diffusion process refers to the interactive relationship among investors in social networks, which can be presented through a sequence. The information diffusion sequence is constructed based on the time, and it can be expressed as a triplet, $l(u, v, t)$, where u and v refer to the investors of information diffusion, and t refers to the time of information diffusion from investor u to investor v or the so-called information diffusion delay. It is impossible to depict the time features of information diffusion through the traditional network model. Therefore, the temporal information diffusion network was adopted in this study. In a given time window $[0, T]$, the temporal network can be presented as $G = (N, L)$, where N refers to the set of investors in the social network, and $L = \{l(u, v, t), u, v \in N, t \in [0, T]\}$ refers to the set of information diffusion sequences. Under a given time step Δt, the information diffusion within the same discrete time step can be classified into the same network. Such a network is a snapshot of the temporal network within the time step. The temporal information diffusion network $G_w = (N, L_w)$ can be presented as the set of all snapshots within the time window.

3.5. Measures of Information Diffusion. The topological structure of information diffusion should be measured through corresponding metrics. However, when the information diffusion time is included in the network, several metrics of the traditional static network should be revised. Additionally, more metrics should be defined to measure the structure of the temporal information diffusion network structure.

The global structures of information diffusion are measured as follows:

Volume: this metric refers to the degree of information diffusion in social networks. For a social network S, the volume is defined as

$$l_i(S) = \frac{n_i(S)}{N_i(S)}, \tag{4}$$

where i denotes the information, $n_i(S)$ indicates the number of investors that participate in information diffusion, and $N_i(S)$ refers to the number of investors in the social network.

Participation: according to Bakshy et al. [39], participation $p_i(S)$ is defined as the proportion of investors in the activated set that can further activate other investors.

Dissemination: dissemination $d_i(S)$ is defined as the proportion of investors without a parent node in the activated set. In other words, it means the proportion of investors that can learn the original information.

Reach: the reach measures the depth of information diffusion. According to Liben-Nowell and Kleinberg [40], the reach $r_i(S)$ can be defined as the average length of all information diffusion sequences if the length is presented as the number of steps at the end of an information diffusion sequence.

Spread: the spread is adopted to measure the range of information diffusion. According to Liben-Nowell and Kleinberg [40], the spread $f_i(S)$ is defined as the ratio of the maximum number of active investors to $n_i(S)$ in all information diffusion sequences.

The individual structures of information diffusion are measured as follows:

Diffusion: diffusion refers to the information diffusion degree of an individual investor. Therefore, diffusion is defined as the ratio of the leaf nodes of an investor to active investors in all information diffusion sequences.

Cascade: cascade is adopted to depict the influence of an individual investor on further information diffusion by its leaf nodes. Therefore, a cascade is defined as the ratio of investors that can further diffuse the information in the leaf node to all leaf nodes of the individual investor.

The time and sequence of information diffusion are mainly described according to snapshots in each step to show the evolution of the temporal network, and they are defined from the following aspects:

Connectivity: according to Nicosia et al. [41], connectivity in a temporal network is divided into strong connectivity and weak connectivity. The former refers to the existence of a directed path among all pairs of investors, and the latter indicates that there is a path among all pairs of investors if connections are considered useless. The information diffusion in this study has a direction; therefore, strong connectivity will be adopted to measure the temporal network.

Efficiency: the fastest time-respecting path between two investors is called the shortest path of the temporal network. The time for information diffusion through the shortest path between two investors is called latency τ. Many investors in the temporal network cannot be connected through time-respecting paths within a given time window. Therefore, efficiency is defined as a depiction of latency according to Tang et al. [42], that is,

$$e = \frac{1}{N(N-1)} \sum_{ij} \frac{1}{\tau_{ij}}. \tag{5}$$

Centrality: according to Tang et al. [42], the centrality of the investor u in the temporal network is defined as

$$c(u,t) = \frac{1}{(N-1)} \sum_{v \neq u} \frac{1}{\tau_{u,t}(v)}. \tag{6}$$

In the context where there is no time-respecting path among investors, we establish that $(1/\tau_{u,t}(v)) = 0$.

Temporal correlation coefficient: the temporal correlation coefficient is adopted to measure the proportion of the investor u with overlapping information diffusion on two adjacent snapshots. According to Tang et al. [42], the temporal correlation coefficient of the investor u is defined as follows,

$$c(u,t) = \frac{\sum_{v \in \phi(u,t)} a(u,v,t) a(u,v,t+1)}{\sqrt{\sum_{v \in \phi(u,t)} a(u,v,t) \sum_{v \in \phi(u,t)} a(u,v,t+1)}}. \tag{7}$$

If investors u and v have a connection on the snapshot at time t, then $a(u,v,t) = 1$; otherwise, $a(u,v,t) = 0$. $\phi(u,t)$ is the set of indices v such that $a(u,v,t) = 1$ or $a(u,v,t+1) = 1$.

Information diffusion is not only characterized by a temporal network but also meets the rules of an independent cascade model where each investor can only be activated once. In other words, information continues to exert an influence on active investors. Therefore, the temporal correlation coefficient of information diffusion in the stock market can be simplified to

$$c(u,t) = \sqrt{\frac{\sum_{v \in \phi(u,t)} a(u,v,t+1)}{\sum_{v \in \phi(u,t)} a(u,v,t)}}. \tag{8}$$

According to equation (8), the average temporal correlation coefficient of information diffusion in a snapshot can be defined as

$$C = \frac{1}{N} \sum_{u} c(u,t). \tag{9}$$

This can be adopted to measure the probability of a continuous occurrence of a link in the temporal network.

4. Contagion Risk

4.1. Information Diffusion and Investor Sentiment. Empirical evidence shows that various psychological biases among investors lead to irrational trading behaviors. Such a phenomenon indicates that psychological influence plays a vital role in investment decisions. The psychological biases of investors can be reflected through investment sentiment. Therefore, it constitutes the key to quantifying the impact of information diffusion on investor sentiments. To this end, the following process is adopted. We assume that investor sentiment is denoted by s. If $s > 0$, then investors have a positive attitude, and if $s < 0$, investors have a negative attitude, otherwise investors are rational. Moreover, the larger the $|s|$ is, the more severe the sentiment is. The initial sentiments of all investors are randomly distributed without information diffusion. This study aims to analyze the stock price crash risk resulting from information diffusion. Consequently, we mainly discuss the information that will lead to negative sentiments. The details are as follows: given the initial investor set N_0, the investor $u \in N_0$ sentiment is changed to

$$s_u(0) = s_u - 1, \tag{10}$$

where s_u refers to the initial sentiment of the investor u, and $s_u(0)$ refers to the sentiment at the beginning of information diffusion. Every time investors are activated, and their sentiments change according to equation (10) until the time window limitation or without information diffusion.

4.2. Sentiment-Based Investment Portfolios. According to Yu and Yuan [17], it can be found that investor's sentiments directly affect risk aversion. Additionally, they quantified the relationship between investor sentiment and risk aversion as

$$A = A_0 f(s), \tag{11}$$

where A_0 represents the rational risk aversion. According to Yu and Yuan [17], $f(s)$ is a monotonically decreasing function of investor sentiment s. Therefore, we assume that $f(s)$ follows a negative exponential function:

$$A = A_0 e^{-\chi s}, \tag{12}$$

where χ is a constant adopted to measure the range of investor sentiment.

Suppose that investors determine investment portfolios using the mean-variance model. In the market with one risk-free asset and M risky assets, the optimal investment portfolio for the investor with risk aversion λ is presented as

$$\max_{w_f, w} E[U(R)] = w_f r_f + w'\mu - \frac{A}{2} w' \Sigma w, \tag{13}$$

additionally meeting the constraint $w_f + \sum_{i=1}^{M} w_i = 1$, where w_f denotes the proportion of risk-free assets, and $w = (w_1, w_2, \ldots, w_M)'$ refers to the proportion of risky assets. Furthermore, r_f represents the risk-free interest rate, $\mu = (\mu_1, \mu_2, \ldots, \mu_M)'$ is the expected return on risky assets, Σ refers to the covariance matrix of risky assets, and $U(R)$ is the utility of the investment portfolio R.

4.3. Fire Sales of Stocks. The empirical results show that stock price variation is subject to lognormal distribution. Therefore, we assume that the variation in the stock price is determined by a series of independent M dimensional random variables $(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_M)$. Furthermore, ε_k follows normal distribution. Consequently, the variation in stock k during the period from $t = \tau$ to $t = \tau + 1$ is presented as

$$p_k^{\tau+1} = p_k^{\tau} e^{\varepsilon_k^{\tau+1}}. \tag{14}$$

The fire sale of stocks is key to studying stock price crash risk raised by information diffusion. Investors may sell off stocks when revising investment portfolios due to information diffusion. According to the theory of supply-demand equilibrium, sales of stocks will devalue prices. Consequently, it results in losses to other investors holding the common stock, who will in turn sell off stocks continuously. According to Cifuentes et al. [43], the dynamic equilibrium of stock prices can be defined as

$$p = e^{-\alpha\left(\sum_i q_i\right)}, \tag{15}$$

where $\alpha > 0$ refers to the stock price elasticity.

4.4. Stock Price Index. Stock price crash risk manages to measure the systemic risk of the stock market. Therefore, a stock price index could be compiled based on variations in all stocks to measure the level of risk. We define the stock price index I as follows:

$$I = \sum_{i=1}^{M} \frac{p_i^t m_i}{p_i^0 m_i}, \tag{16}$$

where M is the type of stock, m_i refers to the number of shares of stock i, and p_i^t denotes the price of the stock i at time t.

4.5. Immunization Strategies. Information diffusion takes place through social networks, while evidence shows that immunization strategies based on network theory could effectively limit information diffusion. It provides an important reference for the prevention of stock price crash risk. Therefore, some immunization strategies have been proposed and compared for the sake of eliminating contagion risks. From the perspective of global information, classic strategies mainly focus on target immunization. Regarding the target immunization in the stock market, it means to rank all investors according to certain measures. Thus, in line with the ranking order, a proportion of investors will be selected for immunization. Consequently, these investors cannot participate in information diffusion. The effects of investors participating in information diffusion are characterized by social network interactions, which are mainly measured by the degree. The degree is further divided into the following aspects: weighted degree, weighted out-degree, weighted in-degree, and unweighted degree. Accordingly, we proposed four immunization strategies, weighted degree immunization (WDI), weighted out-degree immunization (ODI), weighted in-degree immunization (IDI), and unweighted degree immunization (UDI). Furthermore, we managed to conclude a union of all targets of immunization strategies, thus further testing the stock price crash risk by combination immunization. However, it will become difficult for immunization strategies based on global information with the increasing number of investors. Therefore, we further considered random immunization (RI) and acquaintance immunization (AI) based on local information.

5. Results

5.1. Parameterization. We divide investors in the stock market into two types: 100 individual investors and 10 institutional investors. Both types of investors possess the same initial capital of 100. Empirical studies indicate that interaction among individual investors conforms to a scale-free network. However, the interaction among institutional investors is usually characterized by a short path and high clustering. Therefore, the small-world network is adopted to describe the interactions among institutional investors. The connectivity records 0.1 among individual investors and 0.8 among institutional investors. The connection probability between the two types of investors also reaches 0.1. Additionally, the original information acquisition probability reaches 0.02 and 0.1 among individual investors and institutional investors, respectively. Moreover, 10% of investors are immunized in the simulations.

Notably, the time of information diffusion is critical to stock price crash risk. Information diffusion that occurs before the fire sales of stocks would increase stock price crash risk. However, information diffusion that occurs after the fire sales of stocks would not increase stock price crash risk since the fire sales of stocks would push stock prices towards the fundamental value of stocks. Therefore, the information diffusion discussed in the study usually refers to what occurs before the fire sales of stocks.

Conversely, it assumes that 100 stocks are available for investment. The expected returns and volatility of stocks are consistent with the theoretical stock prices. The initial

investment sentiment of investors is the subject to a normal distribution with a mean of 0 and a variance of 0.5. Thus, the parameter is set as $\chi = 0.5$. The information diffusion begins at $t = 10$ with the delay parameter $\lambda = 0.5$ and decay parameter $\beta = 0.5$, which are separately consistent with Saito et al. [22] and Gruhl et al. [37]. It is known that institutional investors have a higher risk tolerance than individual investors. Therefore, it assumes that individual investors will redeem investments if the loss exceeds 10%, while the proportion is 20% for institutional investors. According to Cifuentes et al. [43], the elasticity coefficient of stock prices is $\alpha = 1$.

5.2. Investor Social Network. Information diffusion depends on the social network of investors, and it is more likely to take place among investors with close interactions. Figure 1 shows the social network among investors under the benchmark parameters. In the figure, nodes numbered 1–100 represent individual investors and those numbered 101–110 represent institutional investors. The thickness of the line indicates the interaction intensity among investors. Figure 1 shows that institutional investors and a few individual investors have a relatively closer interaction with other investors, which indicates that those investors play a major role in information diffusion. Figure 2 shows more details by analyzing the degree of individual investors. In the social network, a degree is adopted to depict the interaction intensity among investors. It is believed that investors with a higher degree play a more important role in the social network. Meanwhile, these investors contribute more to information diffusion. Figure 2 shows that institutional investors generally have a higher degree than individual investors do, and only a few individual investors are situated at a similar level to institutional investors, while the degree of others is all at a lower level.

5.3. Information Diffusion Sequence. The information diffusion sequence is obtained by a simulation based on the social network as shown in Figure 1, and the result is shown in Figure 3. In this figure, the values on the lateral axis refer to the information diffusion step, and the values in the box refer to the investor number. Investors in the first column refer to those who can learn the original information. It is worth noting that investors in the same column cannot be compared according to time. Figure 3 also indicates that individual investors with a higher degree tend to exert a greater impact on information diffusion. However, individual investors are inactive in information diffusion compared with institutional investors. Figure 3 shows that institutional investors are more influential than individual investors regarding both range and depth. The reason lies in the following aspects. On the one hand, the social network of institutional investors is more complex. Therefore, institutional investors have a greater impact on others. On the other hand, although weak ties between institutional investors and individual investors have a small impact on individuals, it extends the individuals' social network, thus providing channels for information diffusion in the market.

5.4. Measures of Information Diffusion. The process of information diffusion cannot be completely depicted through the information diffusion sequence, and the above-mentioned measures are more conducive. Global metrics are adopted to depict the information diffusion of the whole social network, and the results are shown in Table 1. According to the results, despite only 4% dissemination, the information diffusion volume has expanded to 87.27% through interactions among investors. It follows that interactions among investors enormously improve information diffusion. However, it can be seen that the participation of investors only records 40%. Such a result shows that, although most investors have learned the information, they are unable to diffuse it further because of their limited capability. Investors have a greater influence that contributes the most to information diffusion. Regarding the information diffusion depth, the reach of information diffusion records 3.63. In other words, the information can only be diffused three to four times in a sequence, on average. The reason for a low average reach lies in individual investors instead of institutional investors. As for the range, the information diffusion spread reaches 17.71%, which indicates an extensive range of influence for some institutional investors.

Global metrics mainly measure information diffusion from the perspective of the whole social network. To gain insight into the information diffusion mechanism, it is necessary to conduct studies on heterogeneous information diffusion from the perspective of individual investors. Figure 4 shows the diffusion of individual information in the experiment. It can be found that the information diffusion of institutional investors is generally higher. However, a few individual investors are also conspicuous. According to Figure 1, we know that these individual investors have something in common. On the one hand, their interactions in the social network are denser. On the other hand, they may also have a close relationship with institutional investors. This is to say, it is more likely for them to reveal information to institutional investors. Consequently, they expand information diffusion. Figure 5 further shows the frequency distribution of individual information diffusion, which is characterized by a long tail. This result can be described through a power-law distribution. In other words, institutional investors and a few individual investors play a major role in information diffusion, while most individual investors are inactive in information diffusion. Based on individual information diffusion, Figure 6 further shows the cascade of individual information diffusion. This result implies that the cascade does not completely consist of diffusion. In contrast, some individual investors have a higher cascade than institutional investors do. Individual investors have close interactions with institutional investors, extending their cascade through institutional investors.

The above measures roughly show the spatial property of information diffusion. However, they cannot depict the temporal properties of information diffusion. Therefore, further studies are required. Figure 7 shows the evolution of connectivity in snapshots of the temporal network during information diffusion. Information diffusion mainly occurs

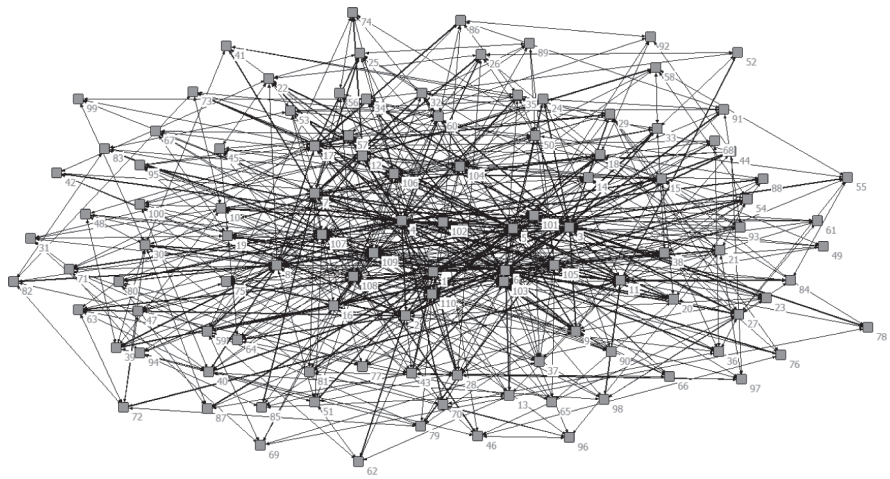

Figure 1: Social network of investors.

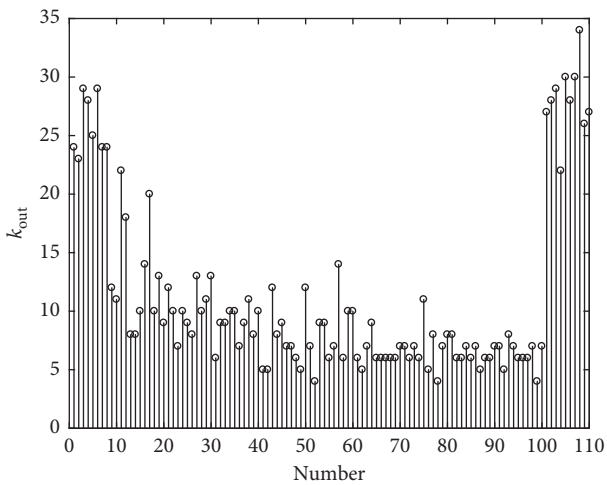

Figure 2: Degree of investors.

in the initial stage, with connectivity close to 0.8. Over time, information diffusion decays rapidly, reducing to below 0.1. In other words, although investors still have interactions in the later stages of information diffusion, it is no longer easy to affect investors. Compared with connectivity, the decay of the efficiency is more rapid. Figure 8 shows that the efficiency is at a high level in the first two stages of information diffusion (especially in the first stage). Afterward, most investors are independent regarding the time-respecting path. Consequently, the efficiency is nearly zero. The evolution of the average temporal correlation coefficient shows the same decay in Figure 9. It is noteworthy that it tends to rise first and fall later in the average temporal correlation coefficient because the metric involves two snapshots in contiguous steps.

Since the snapshot of the information diffusion temporal network depends on the step, the centrality varies within each step. Therefore, we accumulate the centrality regarding time and space, and the results are shown in Figure 10. The left panel indicates that the tendency of centrality conforms to an exponential decay from the perspective of time. Regarding space, it also follows a power-law distribution, where institutional investors and a few individual investors have a larger centrality than others do.

5.5. Stock Price Crash Risk. Based on the results of information diffusion among investors that occurs before the fire sales, Figure 11 shows the evolution of stock price crash risk measured by the stock price index. Stock price crash risk caused by information diffusion before the fire sales can be divided into two stages regarding information diffusion at $t = 10$. The former stage shows the evolution of the stock price index without information diffusion, and the latter stage shows the formation of stock price crash risk due to information diffusion. The stock price index fluctuates following intrinsic values in the first stage. When the information is diffused, there is a "cliff-like" drop in the stock price index. Therefore, stock price crash risk emerges. Moreover, due to the continuity of information diffusion and fire sales, the stock price index shows a continuous downward trend after information diffusion. It is worth noting that the stock price index weakens its drop rapidly, which indicates that the evolution of stock price crash risk raised by information diffusion conforms to the information diffusion decay. By recalling the metrics of information diffusion, it can be seen that the evolution of the stock price index during information diffusion also consists of connectivity, efficiency, temporal correlation coefficient, and centrality. In the early stage, metrics of information diffusion are situated at a high level, which implies that investors are sensitive to information diffusion. Therefore, stock price crash risk is prone to the fore sales of investors. Afterward, investors who no longer sell off stocks because of the information would hardly be affected by information diffusion. Consequently, the stock price index returns to normal and the contagion disappears. According to the above analysis, we can see that stock price crash risk corresponds to information diffusion, and the metrics of information diffusion temporal network may indicate the formation of stock price crash risk.

Additionally, it further compares the effect of information diffusion on the stock price that occurs before the fire

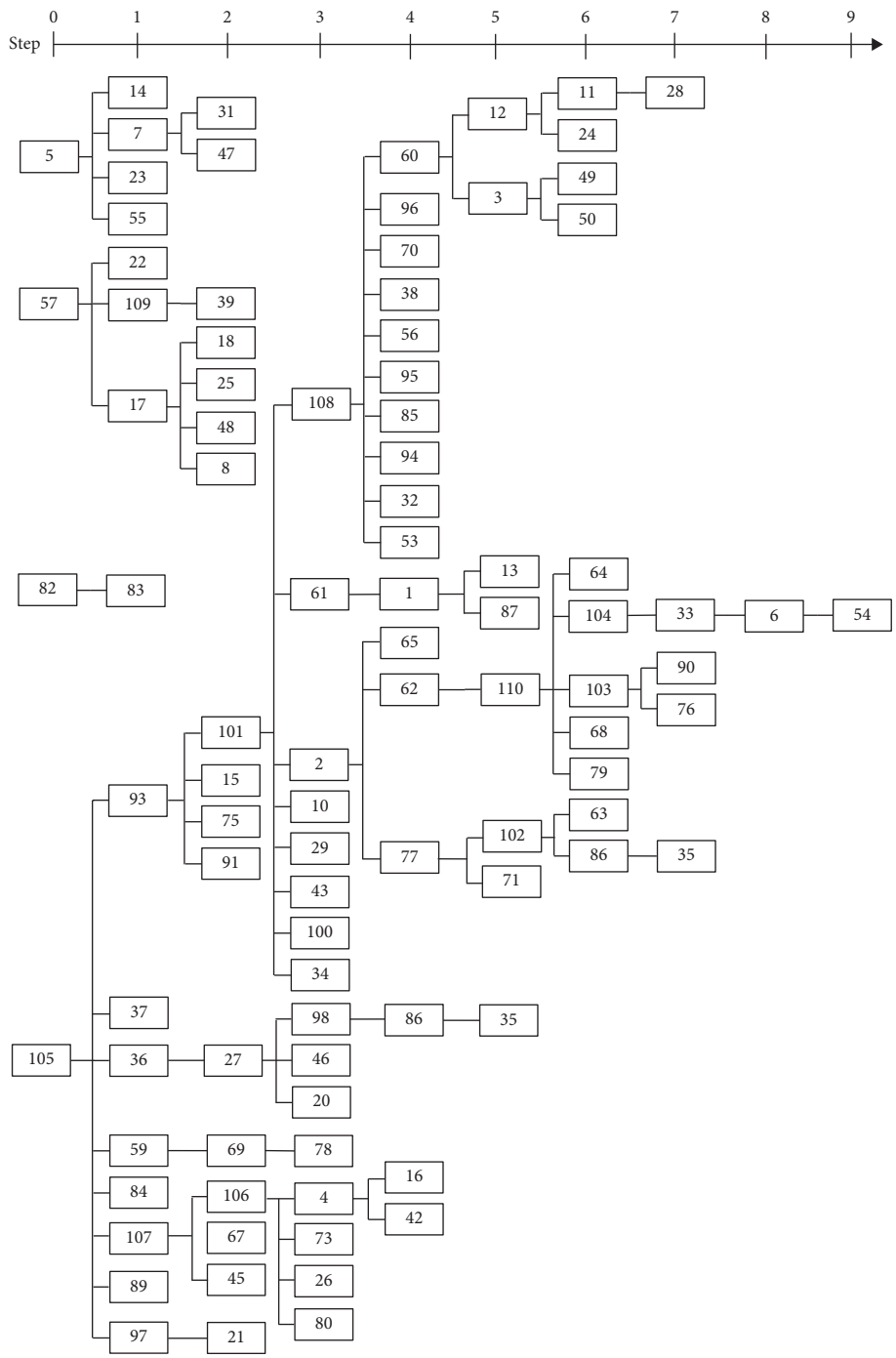

Figure 3: Information diffusion sequence.

Table 1: Global metrics of the information diffusion.

Metrics	Volume	Participation	Dissemination	Reach	Spread
Symbols	l	p	d	r	f
Values	0.8727	0.4000	0.0400	3.6333	0.1771

sales from that occurs after the fire sales. As shown in Figure 11, the evolution of stock price when information diffusion occurs after the fire sales is also simulated. We extend the time of diffusion and moderate the reaction of investors to bad news to simulate the case that information diffusion occurs after the fire sales. As a result, investors can promptly decipher bad news and discount the financially constrained stocks, so that the stock price will be likely to

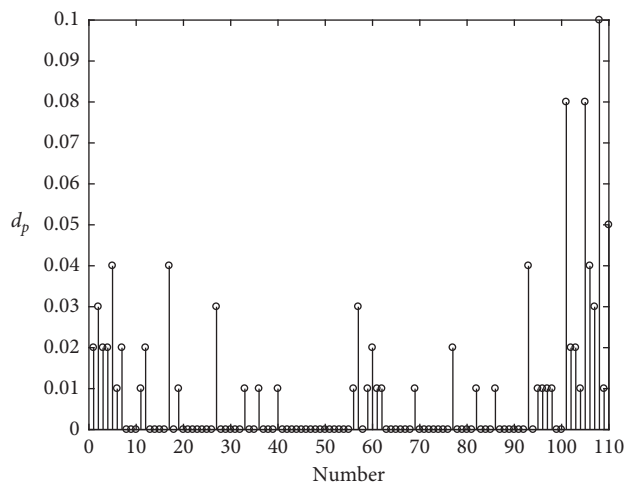

Figure 4: Individual information diffusion.

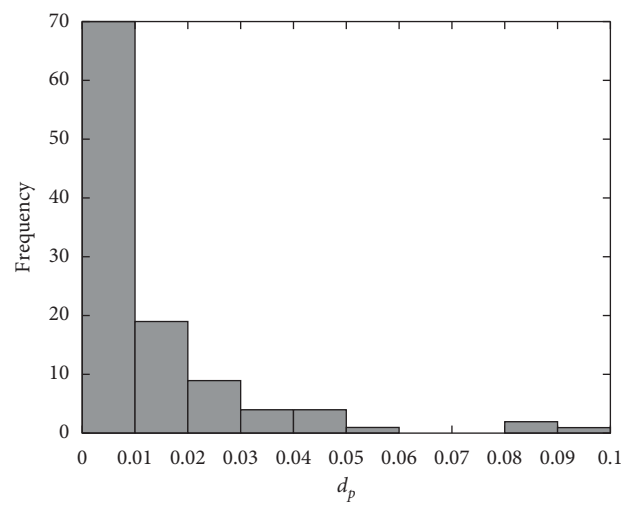

Figure 5: Frequency of individual information diffusion.

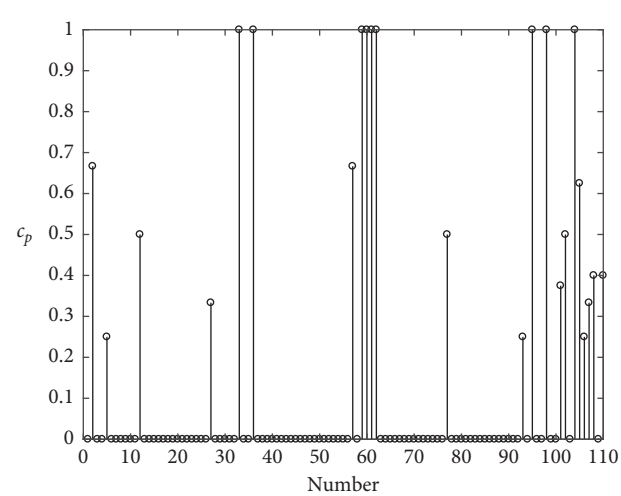

Figure 6: Cascade of individual information diffusion.

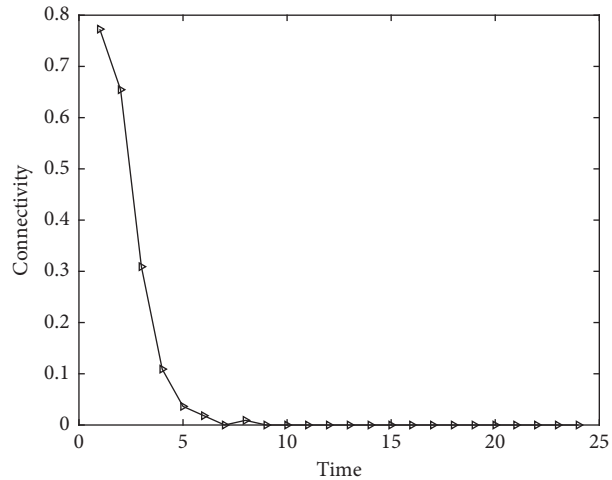

Figure 7: Evolution of connectivity in the temporal network.

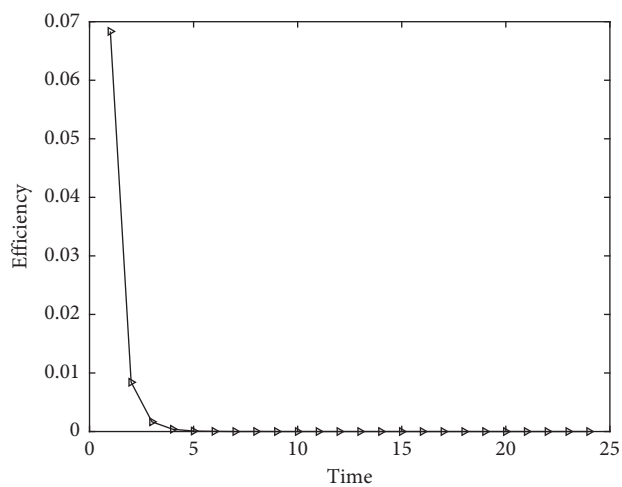

Figure 8: Evolution of efficiency in the temporal network.

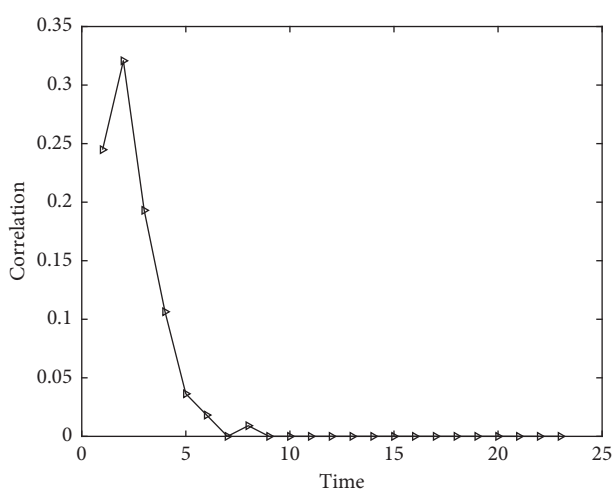

Figure 9: Evolution of average temporal correlation coefficient.

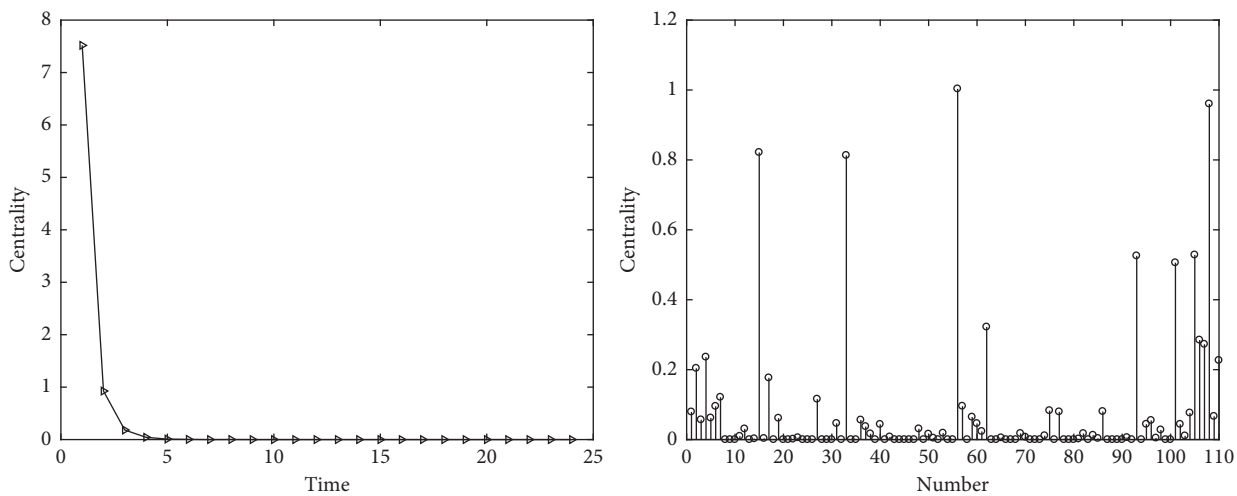

Figure 10: Accumulative centrality of the temporal network.

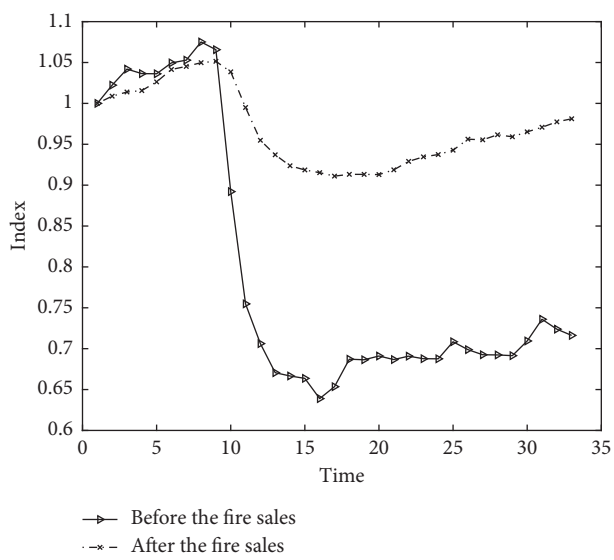

Figure 11: Evolution of stock price crash risk.

decline on a timely basis over time without triggering a crash, thereby lowering stock price crash risk. This is consistent with the result of Figure 11 where there is no stock price crash risk with information diffusion that occurs after the fire sales. Therefore, it verifies the result of He and Ren [6] that information diffusion that occurs before the fire sales of stocks would increase stock price crash risk while information diffusion that occurs after the fire sales of stocks would not increase stock price crash risk.

5.6. Immunization Strategies. To compare the effect on contagion risk, Figure 12 shows the evolution of the stock price index with different immunization strategies. Compared with the without immunization (WOI) case in Figure 12, drops in the stock price index are mitigated when immunization strategies are practiced. This phenomenon indicates that all immunization strategies are effective in reducing stock price crash risk. Moreover, although the effects of various target immunization strategies differ from each other, they are all higher than those of RI and AI are. Therefore, it makes sense that the target immunization strategy provides more accurate protections for investors, thus being more effective for stock market crash risk protection. As for risk immunization strategies based on local information, the effect of AI is higher than that of RI. Regarding AI, it is more helpful in selecting investors with greater influence, thereby enhancing the stability of stock market crash risk.

Notably, Figure 12 shows the comparison of different immunization strategies without considering the number of protected investors. The proportion of investors protected by target immunization and RI was 10%. However, it is more than 10% for the portfolio immunization and less than 10% for AI. It is known that the higher the number of protected investors, the lower the stock market crash risk. Therefore, both the effect of contagion risk and the number of protected investors are taken into consideration to define the efficiency of different immunization strategies in this study. According to Figure 12, the stock price index is influenced by the information diffusion in stages 10–12 and conforms to the intrinsic value thereafter. Therefore, we calculated the efficiency of different immunization strategies using the data of stages 13–15 to promote the robustness of the results. The results are shown in Table 2. According to Table 2, although the most effective result is achieved by portfolio immunization strategy, it is required to protect 14.8 investors on average, thus ranking it the fourth regarding efficiency. Moreover, the efficiency of RI and AI still showed a lower level than that of target immunization. Additionally, AI is more effective in controlling stock price crash risk because of the smaller number of protected investors.

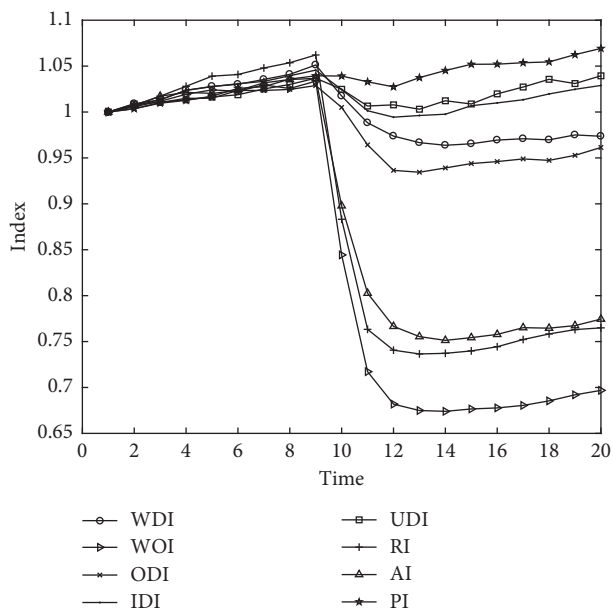

Figure 12: Effect of different immunization strategies.

Table 2: Comparison of different immunization strategies.

Strategy	Effect	Number	Efficiency
WDI	0.2901	11.00	0.0264
ODI	0.2639	11.00	0.0240
IDI	0.3251	11.00	0.0296
UDI	0.3328	11.00	0.0303
PI	0.3697	14.80	0.0250
RI	0.0627	11.00	0.0057
AI	0.0785	9.70	0.0081

6. Conclusions

This study analyzes information diffusion among investors and the accompanying stock price crash risk through investor social networks. Regarding depicting information diffusion in the stock market, the temporal property of information diffusion is incorporated into the independent cascade model. On the one hand, a delay is introduced to improve the continuity of information diffusion. On the other hand, decay is defined to ensure the timeliness of information diffusion. Furthermore, the temporal network with time-respecting paths and topological metrics is defined to depict information diffusion. According to the results, we find that institutional investors in the stock market and a few individual investors with close social interactions have a great impact on information diffusion, while most individual investors are inactive in information diffusion. However, weak ties between institutional investors and individual investors should not be ignored, and they provide channels for global information diffusion. Moreover, information diffusion in the stock market affects most investors in a short time, but it shows an obvious decay, which is characterized by an exponential form. All these results conform to those in a real market, which indicate the effectiveness of our information diffusion model in the stock market.

The results of this study show the correlation between information diffusion and stock price crash risk. It also verifies that the information diffusion that occurs before the fire sale of stocks is the fundamental cause of stock price crash risk. This study provides a new perspective for the study of stock price crash risk. The impact of information diffusion on stock price crash risk is raised by investors' trading behavior. Information diffusion affects investor sentiments and investment portfolios, thus leading to fire sales and contagion risk. From this perspective, it is effective to prevent stock price crash risk by controlling information diffusion among investors. Therefore, the efficiency of some immunization strategies in eliminating stock price crash risk is compared. The results show that various target immunization strategies based on global information are more effective in preventing stock price crash risk. The AI based on local information shows higher efficiency than RI. The results also hint at the promotion of stock market stability from a microscopic perspective.

Data Availability

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

Disclosure

Lei Zhang and Chao Wang should be regarded as co-corresponding authors and co-first authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Lei Zhang and Chao Wang contributed equally to the work..

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References

[1] J.-B. Kim and L. Zhang, "Accounting conservatism and stock price crash risk: firm-level evidence," *Contemporary Accounting Research*, vol. 33, no. 1, pp. 412–441, 2016.

[2] H. A. Hong, J.-B. Kim, and M. Welker, "Divergence of cash flow and voting rights, opacity, and stock price crash risk: international evidence," *Journal of Accounting Research*, vol. 55, no. 5, pp. 1167–1212, 2017.

[3] G. He, H. M. Ren, and R. Taffler, "Do corporate insiders trade on future stock price crash risk?" *Review of Quantitative Finance and Accounting*, pp. 1–31. 2020, In press.

[4] A. P. Hutton, A. J. Marcus, and H. Tehranian, "Opaque financial reports, R2, and crash risk☆," *Journal of Financial Economics*, vol. 94, no. 1, pp. 67–86, 2009.

[5] G. He, "The effect of CEO inside debt holdings on financial reporting quality," *Review of Accounting Studies*, vol. 20, no. 1, pp. 501–536, 2015.

[6] G. He and H. Ren, *Are Financially Constrained Firms Susceptible to a Stock Price Crash? Working Paper*, Durham University, Durham, UK, 2020, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3021307.

[7] H. Hong and J. C. Stein, "A unified theory of underreaction, momentum trading, and overreaction in asset markets," *The Journal of Finance*, vol. 54, no. 6, pp. 2143–2184, 1999.

[8] H. Ai, "Information quality and long-run risk: asset pricing implications," *The Journal of Finance*, vol. 65, no. 4, pp. 1333–1367, 2010.

[9] Y. Xue and R. Gençay, "Hierarchical information and the rate of information diffusion," *Journal of Economic Dynamics and Control*, vol. 36, no. 9, pp. 1372–1401, 2012.

[10] Z. Li, J. Sun, and S. Wang, "An information diffusion-based model of oil futures price," *Energy Economics*, vol. 36, pp. 518–525, 2013.

[11] C. Curme, T. Preis, H. E. Stanley et al., "Quantifying the semantics of search behavior before stock market moves," *Proceedings of the National Academy of Sciences*, vol. 111, no. 32, pp. 11600–11605, 2014.

[12] X. Moat, D. Shen, and W. Zhang, "Has microblogging changed stock market behavior? Evidence from China," *Physica A: Statistical Mechanics and Its Applications*, vol. 452, pp. 151–156, 2016.

[13] D. Shen, W. Zhang, X. Xiong, and Y. Zhang, "Trading and non-trading period Internet information flow and intraday return volatility," *Physica A: Statistical Mechanics and Its Applications*, vol. 451, pp. 519–524, 2016.

[14] G. Li, L. Bai, and H. M. Ren, "Analyst coverage and future stock price crash risk," *Journal of Applied Accounting Research*, vol. 20, no. 1, pp. 63–77, 2019.

[15] S. Agarwal, S. Kumar, and U. Goel, "Stock market response to information diffusion through internet sources: a literature review," *International Journal of Information Management*, vol. 45, pp. 118–131, 2019.

[16] B. Frijns, E. Koellen, and T. Lehnert, "On the determinants of portfolio choice," *Journal of Economic Behavior & Organization*, vol. 66, no. 2, pp. 373–386, 2008.

[17] J. Yu and Y. Yuan, "Investor sentiment and the mean-variance relation☆," *Journal of Financial Economics*, vol. 100, no. 2, pp. 367–381, 2011.

[18] B. Han and L. Yang, "Social networks, information acquisition, and asset prices," *Management Science*, vol. 59, no. 6, pp. 1444–1457, 2013.

[19] M. S. Granovetter, *The Strength of Weak Ties. Social Networks*, pp. 347–367, Academic Press, Cambridge, MA, USA, 1977.

[20] H. W. Hethcote, "The mathematics of infectious diseases," *SIAM Review*, vol. 42, no. 4, pp. 599–653, 2000.

[21] J. Goldenberg, B. Libai, and E. Muller, "Using complex systems analysis to advance marketing theory development: modeling heterogeneity effects on new product growth through stochastic cellular automata," *Academy of Marketing Science Review*, vol. 9, no. 3, pp. 1–18, 2001.

[22] K. Saito, R. Nakano, and M. Kimura, "Prediction of information diffusion probabilities for independent cascade model," in *Proceedings of International Conference on Knowledge-Based and Intelligent Information and Engineering Systems*, pp. 67–75, Springer, Berlin, Heidelberg, September 2008.

[23] A. Goyal, F. Bonchi, and L. V. S. Lakshmanan, "Learning influence probabilities in social networks," in *Proceedings of the Third ACM International Conference On Web Search And Data Mining*, pp. 241–250, ACM, New York, NY, USA, February 2010.

[24] P. Holme and J. Saramäki, "Temporal networks," *Physics Reports*, vol. 519, no. 3, pp. 97–125, 2012.

[25] B. Ribeiro, N. Perra, and A. Baronchelli, "Quantifying the effect of temporal resolution on time-varying networks," *Scientific Reports*, vol. 3, p. 3006, 2013.

[26] A. Barrat, B. Fernandez, K. K. Lin et al., "Modeling temporal networks using random itineraries," *Physical Review Letters*, vol. 110, no. 15, Article ID 158702, 2013.

[27] I. Scholtes, N. Wider, R. Pfitzner et al., "Causality-driven slow-down and speed-up of diffusion in non-Markovian temporal networks," *Nature Communications*, vol. 5, p. 5024, 2014.

[28] X. X. Zhan, A. Hanjalic, and H. Wang, "Information diffusion backbones in temporal networks," *Scientific Reports*, vol. 9, no. 1, p. 6798, 2019.

[29] L. Jin and S. Myers, "R2 around the world: new theory and new tests☆," *Journal of Financial Economics*, vol. 79, no. 2, pp. 257–292, 2006.

[30] H. Hong and J. C. Stein, "Differences of opinion, short-sales constraints, and market crashes," *Review of Financial Studies*, vol. 16, no. 2, pp. 487–525, 2003.

[31] K. R. Ahern, "Information networks: evidence from illegal insider trading tips," *Journal of Financial Economics*, vol. 125, no. 1, pp. 26–47, 2017.

[32] J. Galí and L. Gambetti, "The effects of monetary policy on stock market bubbles: some evidence," *American Economic Journal: Macroeconomics*, vol. 7, no. 1, pp. 233–257, 2015.

[33] Y. Deng, X. Liu, and S.-J. Wei, "One fundamental and two taxes: when does a Tobin tax reduce financial price volatility?" *Journal of Financial Economics*, vol. 130, no. 3, pp. 663–692, 2018.

[34] H. An and T. Zhang, "Stock price synchronicity, crash risk, and institutional investors," *Journal of Corporate Finance*, vol. 21, pp. 1–15, 2013.

[35] G. He, H. M. Ren, and R. Taffler, "The impact of corporate tax avoidance on analyst coverage and forecasts," *Review of Quantitative Finance and Accounting*, vol. 54, no. 2, pp. 447–477, 2020.

[36] G. He and D. Marginson, "The impact of insider trading on analyst coverage and forecasts," *Accounting Research Journal*, vol. 33, no. 3, pp. 495–521, 2020.

[37] D. Gruhl, R. Guha, D. Liben-Nowell et al., "Information diffusion through blogspace," in *Proceedings of the 13th International Conference on World Wide Web*, pp. 491–501, ACM, New York, NY, USA, January 2004.

[38] N. Barbieri, F. Bonchi, and G. Manco, "Topic-aware social influence propagation models," *Knowledge and Information Systems*, vol. 37, no. 3, pp. 555–584, 2013.

[39] E. Bakshy, B. Karrer, and L. A. Adamic, "Social influence and the diffusion of user-created content," in *Proceedings of the 10th ACM conference on Electronic commerce*, pp. 325–334, ACM, California, MA, USA, July 2009.

[40] D. Liben-Nowell and J. Kleinberg, "Tracing information flow on a global scale using Internet chain-letter data," *Proceedings of the National Academy of Sciences*, vol. 105, no. 12, pp. 4633–4638, 2008.

[41] V. Nicosia, J. Tang, M. Musolesi et al., "Components in time-varying graphs," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 22, no. 2, Article ID 023101, 2012.

[42] J. Tang, M. Musolesi, C. Mascolo et al., "Temporal distance metrics for social network analysis," in *Proceedings of the 2nd ACM workshop on Online social networks*, pp. 31–36, ACM, New York, NY, USA, August 2009.

[43] R. Cifuentes, G. Ferrucci, and H. S. Shin, "Liquidity risk and contagion," *Journal of the European Economic Association*, vol. 3, no. 2-3, pp. 556–566, 2005.