

Research Article

The Influence of Investor Emotion on the Stock Market: Evidence from an Infectious Disease Model

Yutao Chen ¹, Shuzhen Zhu,¹ and Haoyuan He²

¹Glorious Sun School of Business & Management, Donghua University, Shanghai 20051, China

²University of Illinois, Urbana Champaign, Urbana, IL 61820, USA

Correspondence should be addressed to Yutao Chen; 1054580867@qq.com

Received 21 February 2021; Accepted 8 June 2021; Published 17 June 2021

Academic Editor: Junhai Ma

Copyright © 2021 Yutao Chen et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In March 2020, four consecutive circuit breakers in the US stock market underscored the impact of investor sentiment on the stock market. With the development of technology, public opinion and other information now spread easily through social media and other channels, indirectly affecting investor sentiment. This makes it important to understand the underlying dynamics of such situations to help manage the market impact of such events going forward. To that end, we analyze investor sentiment, investor structures, and the capital market fuse mechanism using infectious disease dynamics. We use an extension of the SIR (susceptible, infectious, and recovered) model, called the dynamic SIRS model (where individuals return to a susceptible state), to simulate the impact of investor sentiment on the stock market. Accordingly, we study the circuit breakers in the US stock market and the simulation results of the model to analyze the fuse mechanism process in China that triggers a pause in the market based on volatile trading. The results of our study show that when the influence rate of investor mutual communication increases or when the emotional calm rate decreases, investor emotions will start to diffuse, leading to an increase in the probability of either a serious stampede or zealous overbuying in the stock market. At the same time, the trading frequency of investors and the ratio of investors in both buying and selling directions will have a certain formal impact on the direction of the stock market, with the final impact determined by the ratio of normal investors to emotional investors. When emotional investors dominate the market, their emotions are diffused throughout. Our study provides the reference for relevant agencies to monitor and improve the stock market fuse mechanism in the future.

1. Introduction

Following the stock market crash of 1987, US regulators put the first circuit breakers in place to prevent the repetition of a swift plunge in the Dow Jones Industrial Average. A circuit breaker is a safeguard that pauses trading for 15 minutes in the hope that the market will calm itself. Since then, a circuit breaker has been triggered only once in 1997, until March 2020 when four consecutive circuit breakers were used in the US stock market—on March 9, March 12, March 16, and March 18—underscoring the strength of the effects of investor sentiment on the stock market. The circuit breaker or fuse mechanism, also known as the automatic suspension mechanism, is meant to control risk when the stock index reaches a specified fusing point. This fuse mechanism, which stops trading to give the market room to recover and calm

down, gives regulatory authorities time to take relevant risk control measures before continuing with trading. The fuse mechanism has been put in place for foreign exchanges and the three major exchanges in China, where it was triggered during the trading of China's A-shares between January 1 and January 8, 2016. The use of the four circuit breakers in the US stocks in March 2020 and the two circuit breakers in China's A-shares in 2016 reinforce the importance of controlling risks in the capital market. However, the factors that cause the circuit breaker environment remain under debate. The objective of this study is to analyze and clarify the process and the phenomena that trigger the circuit breakers. In the fusing process, the most obvious phenomenon is the escalation of public pessimism, leading to an imbalance between trading volume and the trading ratio, and to people stepping on people, reinforcing the importance of investor sentiment.

This study investigates investor sentiment, investor structure, and the capital market fusing system through the infectious disease dynamics. We use an extension of the SIR (susceptible, infectious, and recovered) model (a basic epidemiological model designed to describe the transmission of infectious diseases), called the dynamic SIRS model (where individuals return to a susceptible state), to simulate the impact of investor sentiment on the stock market. We combine the simulation results of the model and study the US stock circuit breakers and the China A-shares fusing process to provide a reference for the relevant agencies to monitor and improve the fuse mechanism going forward.

2. Literature Review

Many scholars have studied the linkage between fluctuations in investor sentiment and stock market returns. Among these, Cui and Zhang [1] indicate that investor sentiment has a significant impact on the risk of collapse. Tang et al. [2] show how the number and tone of media reports lead to a change in investor mood and how the links between media and investors cause a fluctuation in attention and the herd effect. Xiao et al. [3] find that investor enthusiasm can promote information exchange and that investor emotions influence each other. The herd effect is more pronounced when the stock market falls and the impact is relatively less when it rises. Zheng [4] believes that investor emotional intensity affects the herd effect in the stock market: the stronger the emotions, the greater the herd effect. Compared with pessimistic leanings, the herd effect driven by optimism is correspondingly weaker. Zhang [5] finds that the trading frequency of some investors affects the overall market equilibrium in his research on behavioral economics. Lu et al. [6] find a correlation between the Baidu index and stock market returns. Wang and Jia [7] find that investor sentiment can adjust the fluctuation in commodity market prices and changes in the inflation rate, while changes in the commodity price level can reflect the impact of market sentiment and domestic inflation levels as well. Li and Li [8] reveal that the stock market is manipulated by investor sentiment. During the manipulation, investor sentiment is high and a stock price bubble forms; after the manipulation, investor sentiment drops, triggering the risk of stock prices collapsing. These studies prove that public opinion is a factor influencing investor sentiment and that investor sentiment can have either a strong or weak influence. Investor sentiment also spreads through the market network and other communication channels across investors, one of the causes of the herd effect.

According to the research on investor sentiment in the stock market, we can see a byproduct, namely, the similarity of investor sentiments and the spread of emotion, with the media representing public opinion. Some scholars have investigated how these public opinions spread from person to person. The SIR and SIRS models have been used in related research. Ballinari and Behrendt [9] find that investor sentiment has five contagion effects, which are more obvious in a pessimistic environment. Nguyen et al. [10] show how customer sentiment expressed through social media affects investment decision-making and the corporate value of

institutional investors, highlighting the importance of social media. Ji et al. [11] explore public opinion transmission based on a microblog using the SIR model. They consider public opinion transmission similar to that of infectious diseases, with a threshold and a balance point. Ally and Zhang's [12] study concludes that a rewiring model based on linear function generates the fastest spread across networks. Thus, linear function may play a pivotal role in speeding up the spreading process in stochastic modeling. Fan [13] states that the memory effect in a two-layer SIR information propagation model will enable nodes to receive messages gradually and expand the scope of information transmission, which is at the expense of time. Yin [14] finds that a public opinion crisis in a limited group will spread like an infectious disease. In the stock market, similarly, investor emotions spread through the opinions of a limited group in a fixed environment. Zhang et al. [15] use the SIR model to prove that independent communicators are the source of information, leading to a higher transmission probability and a wider transmission range, with investors spreading related emotions and public opinion through the Internet and other channels in the current stock market. In the simulation of these models, a threshold and equilibrium point in the spread of infectious diseases are found. From Fisher's [16] article, within the SIR model, the agent is able to react to a combination of expectations, bullish or bearish, and comparative advantages through the information they received when going into the market for CDS. In Rui et al.'s [17] opinion, the SIR model has high accuracy during the information diffusion process in social media. Wang and Li [18] set up a creative model between different nodes based on the SIR propagation model and proved that the improved model could quickly suppress the rumor propagation in networks. Zhou et al. [19] find that positive energy information would have a great contribution to society when information bombing takes place. Sahafizadeh and Tork Ladani [20] extend the SIR information propagation model and conclude that rumor-spreading behavior in these networks do not make a significant difference if there is rumor propagation in groups. Fibich [21] believes that a small-worlds structure has a negligible effect on the diffusion based on Bass-SIR model. Qian et al. [22] find that independent spreaders can start the information diffusion in remote regions without relying on the bridges between communities. Zhao et al.'s [23] study modifies a flow chart of the rumor-spreading process with the SIR model and finds that rumors are capable of disseminating extensively in a short time and causing social instability. Wang et al. [24] indicate that users with more followers ensure that information diffuses faster and wider. Liu et al. [25] established the SIR model and the MLM organizer to obtain MLM participants' income evolution rules; if the threshold or equilibrium point is exceeded, a series of problems occur, such as over-pessimism or overoptimism in the overall public opinion environment. This is similar to the stock market fuse trigger. The application of the two models is shown in Table 1.

In studying investor sentiment and stock market leverage, Chen et al. [26] find that investor sentiment has a greater impact on the market in terms of trading ratio and trading

TABLE 1: Literature on the application of SIR and SIRS models.

Model	Examples of references	Research objects
Application of SIR and SIRS models	Fan [13]	The memory effect
	Zhang et al. [15]	Independent communicators as the source of information
	Fisher [16]	Market for CDS
	Rui [17]	The information diffusion process in social media
	Wang and Li [18]	Rumor propagation in networks
	Fibich [21]	Negligible effect
	Qian and Zhang [22]	Independent spreaders and information
	Liu et al. [25]	MLM and information

volume than leveraged trading. In studying the trading situation of the CSI 300 stock index (equity index that reflects China's A-share market performance), in addition to noticing abnormal investor sentiment regarding certain data, Yang and Zhang [27] find that the trading volume, active before and after the market triggered fuse, increased abnormally during the fuse period with trading overly volatile. Li [28] believes that stronger trading volume will have a negative feedback effect on the fuse system. In their empirical study, Yang and Jin [29] find that market panic spreads further when stocks drop; however, whether or not stocks fall, selling orders swarm out, and the imbalance of the order flow deteriorates significantly. Tang [30] believes that, in volatile markets, fusing is easier to trigger and will cause vicious panic selling in the market. Hu et al. [31] believe that investor sentiment and stock market returns are negatively correlated in the bear market state and positively correlated in the bull market state. Kim and Kim's [32] study shows that investor sentiment is positively affected by prior stock price performance and the Internet postings have predictive power for volatility and trading volume. Chen et al. [33] find that when investor sentiment rockets, it indicates that the market will experience a shock in the following month. He et al. [34] show that retail sentiment is more likely to infect each other in China's stock market. Janková [35] concludes that the sensitivity of stock indices shows a negative relationship to the volatility of the VIX stock market, especially out of phase and in crisis periods. Živkov et al. [36] examine the interrelationship between national equities and 10Y bonds in six emerging markets. Dash and Maitra [37] examine the relationship between investor sentiments and conclude that whether investors are short- or long-term, their investment activities cannot be stripped of sentiment.

Based on the extant research, although scholars have studied the influence of public and online opinions on the stock market, with some evidence that the fuse and leverage bull markets are affected by extreme emotions, there is no study that looks at how these public opinions affect investor emotions. A number of studies have found that investor sentiment is influenced by public opinion, but have not explained this in terms of reasonable system dynamics. To address this gap, this study examines obvious abnormal data during fusing.

3. The Fuse Mechanism: Analysis of A-Shares and US Stocks

To analyze the A-share data, the number of traded shares, trading time, number of shares traded in a day, trading space

ratio, the Baidu index (Baidu is the major search engine in China and the index is the corresponding keyword retrieval amount), and the trading volume of the Google index and US stocks 17 days before and after the two fuses in 2016 are examined. As shown in Figures 1 and 2, on January 4, 2016, due to the pessimistic A-share market environment, stock market trading stopped after only 2.3 hours. The total number of shares traded had reached 27.488 billion, but the number of shares traded per hour had touched 1.19513 billion. The trading frequency of the day also had peaked at 11.7183 million shares/hour, reaching the highest point ever. The trading ratio of the day was 0.6972. When the fuse mechanism was triggered again in the A-share market on January 7, 2016, trading had lasted 0.25 hours before triggering the fuse and the number of shares traded was the lowest at 10.496 billion shares, while the transactions per hour reached 4.198 billion shares, four times more than that on January 4, 2016. The average number of transactions per hour was stable at 650–800 million shares.

In Figure 3, we analyze market emotions in the United States. In the two weeks around the circuit breakers, the trading volume of US stocks rose overall, similar to China's situation at the time of the fuse in 2015. After the first break, the speed and ratio of the second break increased.

In March, the yield of US stocks after the first circuit breaker was -7.79% ; after the second, it reached -9.99% , and after the third it dropped to -12.93% . Subsequently, due to the Federal Reserve's water release and the federal government's bailout behavior, overall market sentiment recovered after the fourth breaker, with the yield increasing to -6.3% . The trading volume of the market as a whole reached 750.43 million shares after the first breaker and 911.77 million shares after the second. Moreover, after the second, investor sentiment began to change, from the initial aggressive pessimism to a more stable pessimistic market, with the trading volume dropping to 775.91 million shares and 874.09 million shares, respectively, although remaining higher than the previous average trading volume of 300–400 million shares. The search of Google's index for the circuit breaker shows the highest level of 100% at the first circuit breaker; then the search index gradually declines, achieving a small peak for every circuit breaker. These search degrees include the communication query degree in Twitter, which reflects the frequent communication of investors during the transaction process. These data provide some fundamental ideas for building the SIRS model for investor sentiment.

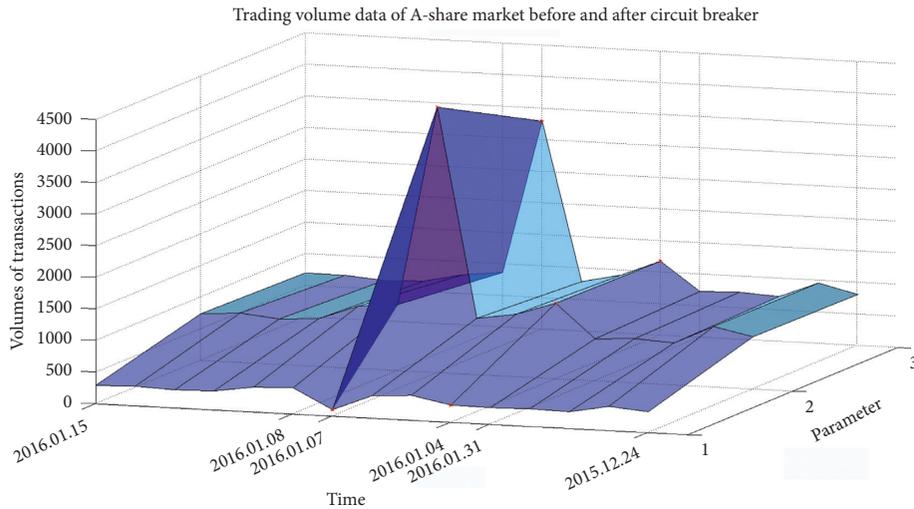


FIGURE 1: Trading day data before and after A-share market fusing.

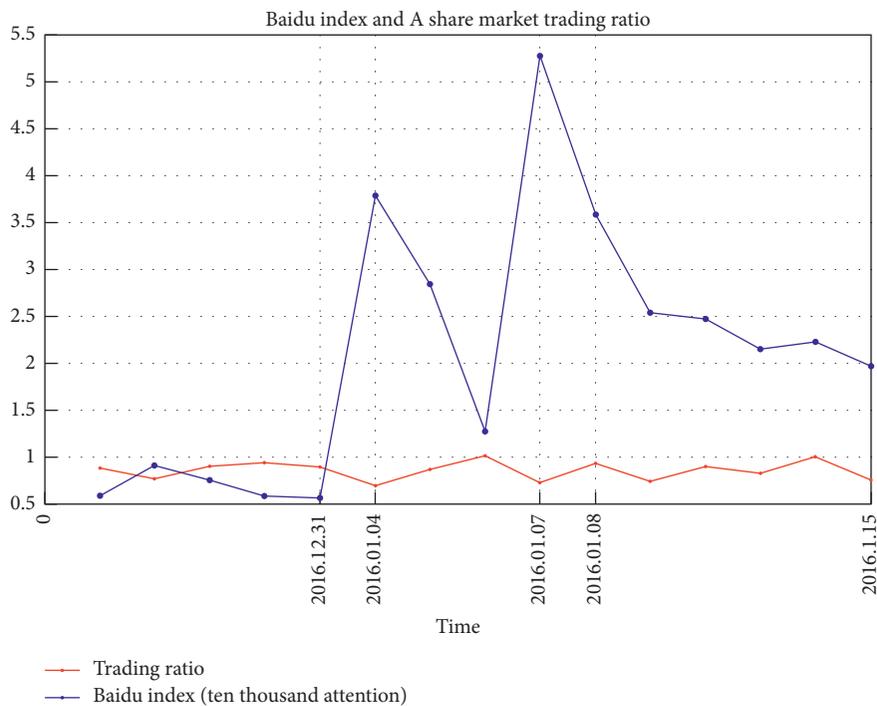


FIGURE 2: The Baidu index and the trading ratio.

4. Using the Infectious Disease Model to Reflect the Impact of Investor Sentiment

4.1. *Theoretical Analysis.* With the development of Internet technologies, information exchange among investors on the market and its frequency have increased. Due to varied communication modes and self-cognition of investors, changes in emotion transmission in the market are not limited by time and space. The object and path of an emotional transmission in the market can be divided into S or normal investors (susceptible population), I or emotional influence investors (infected population), and R or emotional stability investors (infected immune population). The

main reason investors become calm and stable after emotional influence (hereafter referred to as calm and stable) is the emotional recovery rate; the main factors that affect the emotional recovery rate are factors such as media information and government policies. When emotional investors turn into calm and stable investors, there is a certain probability that they will be less immune to the spread of emotions in the market and turn into normal investors again. For example, due to the impact of performance, investors may be firmly optimistic about a stock, but with the influence of rumors or related emotional news, they may turn bearish on the stock and, after a period, turn optimistic again. The analysis shows that susceptible population,

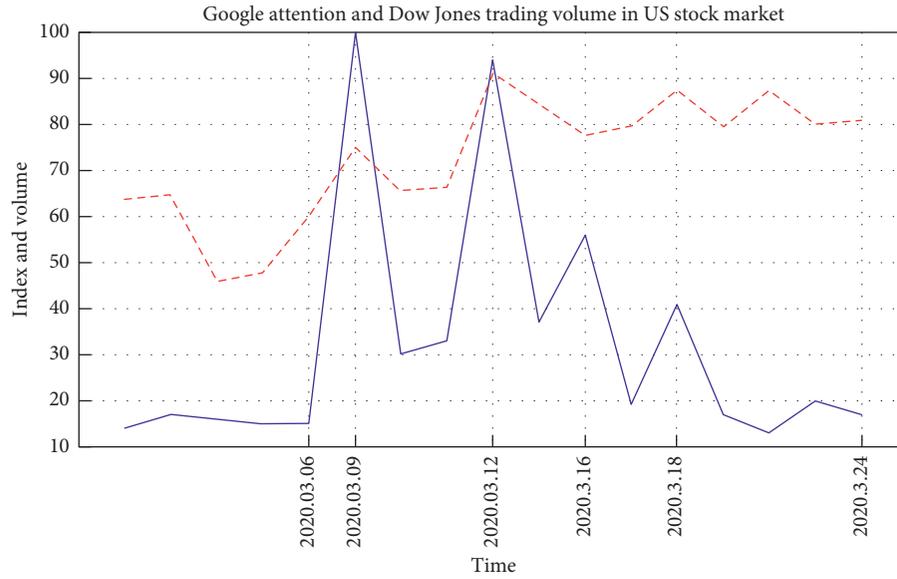


FIGURE 3: The Google index and the trading volume of US stocks.

infected population, infected immune population, nonimmune population, and external media or government are involved in this process.

After determining the boundary of system research, through the analysis of the relationship between the elements in the boundary, we can create the system causality diagram. The information dissemination system is no longer a single linear relationship, but a complex nonlinear system, which is dynamic under the joint action of multiple factors.

We can see from Figure 4 that the causal loop diagram provides several feedback loops in the graph, as follows:

“Normal investors” → “Contact impact rate” → “Investors affected by emotions” → “Calm rate” → “Calm and stable” → “Investors without immunity of emotional information” → “New normal investors.”

As the number of normal investors increases, the number of contact impact rate also increases, resulting in a rising number of investors affected by emotions. When the number of investors affected by emotions is large, the relevant information will be fed back to the government or the media and eventually affect the value of the calm rate. Finally, the number of calm and stable will change. After the increase of calm and stable, a large number of investors will lose immunity and become new normal investors, leading to the increase of normal investors.

“Normal investors” → “Contact impact rate” → “Investors affected by emotions” → “Calm and stable” → “Normal investors.” “Normal investors” → “Contact impact rate” → “Investors affected by emotions” → “Calm rate” → “Calm and stable” → “Normal investors.”

With the increase of normal investors, contact impact rate also increases, resulting in an increase in the number of investors affected by emotions. The increase in the number of investors affected by emotions changes the behavior of the government and influences policies, leads to calm and stable changes, and finally affects normal investors.

4.2. *Theoretical Model and Hypotheses.* According to the above theoretical analysis and based on the accumulation and infection of emotions, overall market sentiment is considered similar to an infectious disease. Although the SIRS model is considered a stable and accurate dynamics model, in using it with investors, the premise is that investors are irrational and the spread of investor sentiment can be compared with that of an infectious disease. In this model, we do not consider that new investors may be joining or withdrawing; instead, we consider only the change in time. We assume the market is a balanced market, meaning buying and selling are balanced and consistent, and no other factors are influencing the overall market.

Supposition 1. The overall market transactions are balanced and the number of investors in the market and the number of institutional investors, N , remain unchanged. The number of retail investors or individual investors dominates the Chinese market, but the opposite is true in the US, and the overall number is regarded as approximately the same large number. Investors are divided into normal investors, investors affected by emotions, and calm and stable. At time t , these three kinds of investors are represented as $s(t)$, $i(t)$, and $r(t)$. Thus,

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

where S , I , and R represent the total number of each type of investor and N all investors in the market.

Supposition 2. Emotion-affected investors can communicate with other normal investors who are not affected by emotions through online and social behaviors. The daily contact impact rate on other investors is λ , while the emotional calm rate of the affected investors is μ .

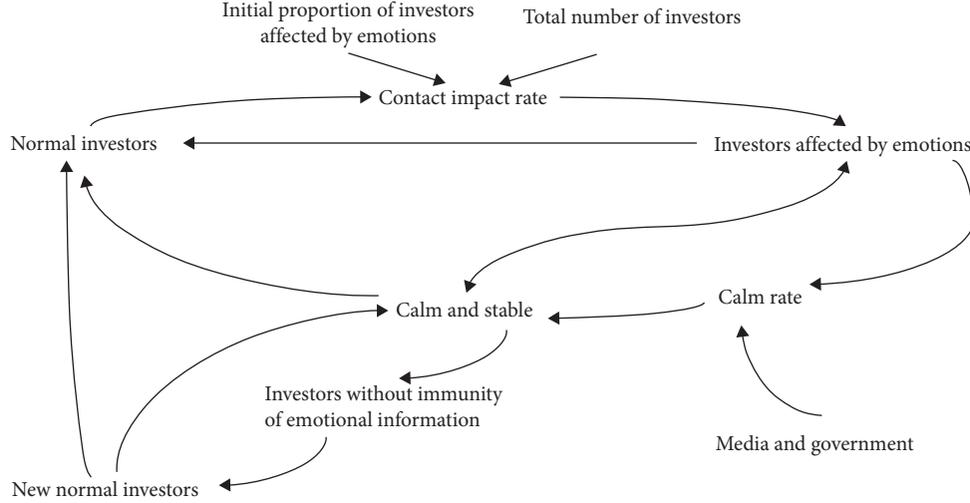


FIGURE 4: Causal loop diagram.

Hypothesis 1. All those who are calm and stable will be transformed into normal investors and investors affected by emotions. Those who remain calm and stable will still be affected by investors affected by emotions. Those who are calm and stable will be converted into investors who are affected by emotions by rate γ in a future unit of time.

Hypothesis 2. The trading frequency of normal investors is φ_1 : daily trading times/annual trading times. Normal investors are two-way traders (both buying and selling stocks) and the ratio is ω and $1 - \omega$. The trading frequency of emotion-affected investors is φ_2 , and emotion-affected investors are one-way traders, with a trading ratio of ξ .

Three equations about $s(t)$, $i(t)$, and $r(t)$ can be obtained from building simultaneous equations for Supposition 2 and Hypothesis 1:

$$\begin{aligned} N[i(t + \Delta t) - i(t)] &= \lambda N s(t) \cdot i(t) \cdot \Delta(t) - \mu N i(t) \cdot \Delta(t), \\ N[s(t + \Delta t) - s(t)] &= -\lambda N s(t) \cdot i(t) \cdot \Delta(t) + \gamma N r(t) \cdot \Delta(t), \\ N[r(t + \Delta t) - r(t)] &= \mu N i(t) \cdot \Delta(t) - \gamma N r(t) \cdot \Delta(t). \end{aligned} \quad (2)$$

At this point, the ratio of normal investors, investors with emotional influence, and those with emotional calm and stability after emotional influence can be recorded as s_0 , i_0 , and r_0 when $(s_0, i_0, r_0 > 0)$. The model of infectious diseases after this change can be transformed into the SIRS model with mutual infection of investors' emotions, which can be written as

$$\begin{aligned} \frac{ds}{dt} &= -\lambda s(t)i(t) + \gamma r(t), \\ \frac{di}{dt} &= \lambda s(t)i(t) - \mu i(t), \\ \frac{dr}{dt} &= \mu i(t) - \gamma r(t). \end{aligned} \quad (3)$$

As $s(t) + i(t) + r(t) = N$ remains constant, the number of calm investors at time t can be obtained by $r(t) = N - s(t) - i(t)$. Then,

$$\frac{ds}{dt} = -\lambda s(t) \cdot i(t) + \gamma N - \gamma s(t) - \gamma i(t), \quad (4)$$

$$\frac{di}{dt} = \lambda s(t)i(t) - \mu i(t).$$

Since S and I must be greater than or equal to 0 and the sum of the two must be less than or equal to 1, we can define the threshold θ , as the ratio of the affected investor emotional communication influence rate to the investor calm rate. When $\theta \leq 1$, the investor emotional calm rate is greater than the investor emotional influence rate, and the overall market situation tends to be stable. The equilibrium point $(n, 0)$ can be obtained through the above formula. If the affected investors inflict a weak emotional contagion and the overall investors remain rational in dealing with external emotions, the overall market will eventually be classified as balanced, and the investors in the market will become normal investors. When $\theta > 1$, the rate of investor calm is less than that of the affected investors' emotional influence rate, so the overall market sentiment will be affected by the affected investor mood and the overall market atmosphere will become unbalanced. At this point, there is an emotional balance point $(\mu/\lambda, \gamma(N - (\mu/\lambda))/\mu + \gamma)$, which means that the overall market will be influenced by emotions where affected investors have a greater influence on other investors' emotions or related public opinion. The final equilibrium state will be dominated by affected investor sentiments, which may also become the state of zealous leverage, rising stock prices, and enlarged trading volume in a mad cow market, or short selling and bearish market sentiment in a bear market.

The equation for the transaction ratio ξ in two directions under the overall market transaction mode as stated in Hypothesis 2 can be obtained as follows:

$$\xi = \frac{\varphi_1 \cdot (1 - \omega) \cdot s(t) + \varphi_2 \cdot i(t)}{\varphi_1 \cdot \omega \cdot s(t)} = \frac{1 - \omega}{\omega} + \frac{\varphi_2}{\varphi_1 \cdot \omega} \cdot \frac{i(t)}{s(t)} \quad (5)$$

That is,

$$\xi = \frac{1 - \omega}{\omega} + \frac{\varphi_2}{\varphi_1 \cdot \omega} \cdot \frac{i(t)}{s(t)} \quad (6)$$

5. Model Simulation and Results

The model simulation is conducted using MATLAB 2014a. In the form of MATLAB programming, the relevant parameters, preset proportion, and data are programmed into the process sequence, and the relevant simulation results are finally run. According to noise theory and equilibrium theory, under the equilibrium trading state, the two-way trading ratio of normal investors is approximately equal; thus, $\omega = 1 - \omega$. According to the herd effect and the agglomeration effect, the trading frequency of investors affected by emotions will be slightly higher than that of normal investors, so $\varphi_2 > \varphi_1$. Three initial values are set at this time and the proportions of investors in these simulations affected by emotions are 20%, 50%, and 70% of the total, respectively. When $\theta \leq 1$, assuming the total number of transactions is 1000, the emotional influence rate of investors is $\lambda = 0.01\%$ and the calming rate is $\mu = 0.1$. Applying dynamical system theory, the phase space curves at a conversion rate $\gamma = 0.05$ change with time as shown in Figures 4 and 5, while other phase space curves with a constant conversion rate $\gamma = 0.5$ change with time as shown in Figures 6 and 7.

We see from the phase space graphs in Figures 5 and 7 and the time-varying graphs of investor ratios in Figures 6 and 8 that initially, when γ is small, the change rate of emotional investors with different initial percentages will be more stable over time, while when γ is high, the change rate of emotional investors will be more dramatic. In different proportions, the final trend and emotion affect the state of the investors being removed. Therefore, irrespective of the proportion of investors affected by emotions, overall investors eventually move to the equilibrium point $(N, 0)$, that is, $(1000, 0)$, and the investors affected by emotions are less and less part of the transaction process, finally resolving to 0. According to the investor proportion curve, in the case of a small γ , a large number of emotional investors recovered at the initial stage of transformation, and the speed of transforming to emotional investors was slow, which caused a decline in the number of normal investors and emotional investors at the beginning. Similarly, in the case of large γ , a large number of investors with emotional recovery will be directly transformed into investors with emotional influence, so the overall change will be dramatic and obvious in the figure. With time, because the exchange rate of emotional people is far less than their recovery rate, all investors with emotional influence will become normal investors. It also shows that when $\theta \leq 1$, the ratio of emotion-affected investors, normal investors, and emotion-calmed investors will change dynamically. Based on the large calming rate and a low conversion rate, the overall market will shift to normal investors, and a large number of calmed investors will also convert to normal investors, leaving fewer and fewer emotion-affected investors in the market. In this way, the capital market returns to equilibrium, while the ratio of buying and selling is also determined by the investors. When the transactions approach equilibrium, the difference is the

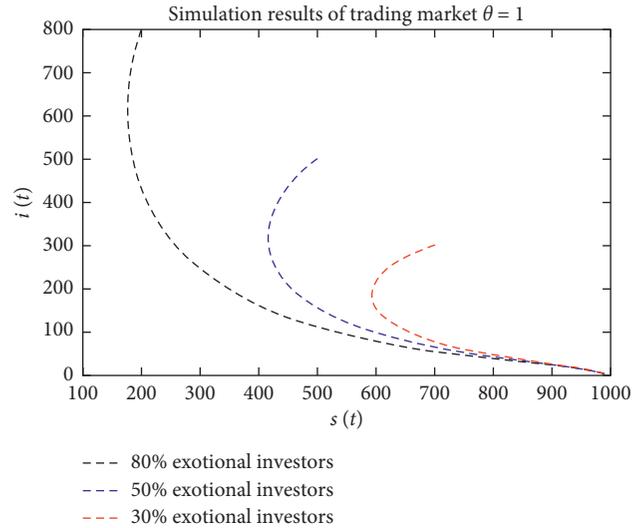


FIGURE 5: Phase space curve $\theta \leq 1, \gamma = 0.05$.

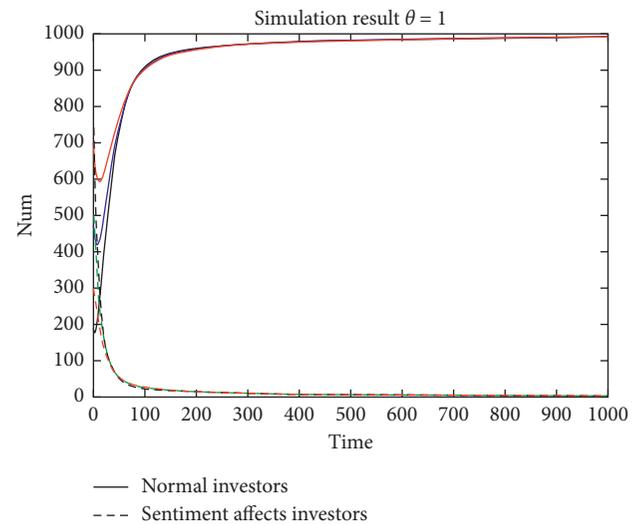
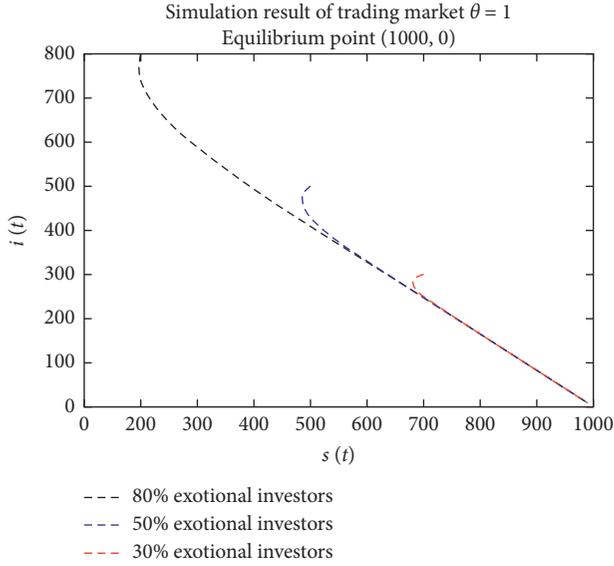
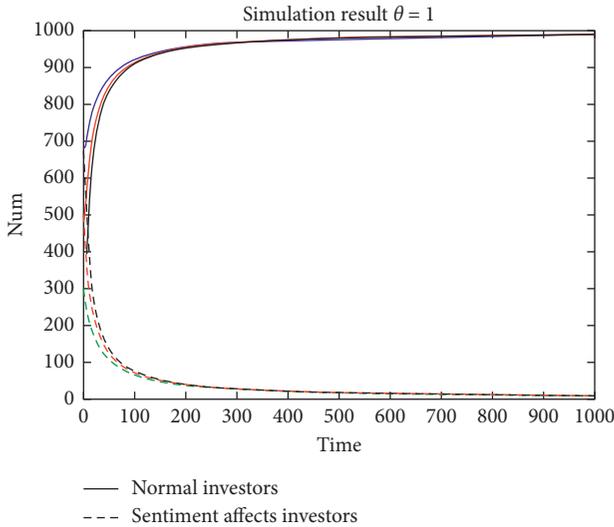


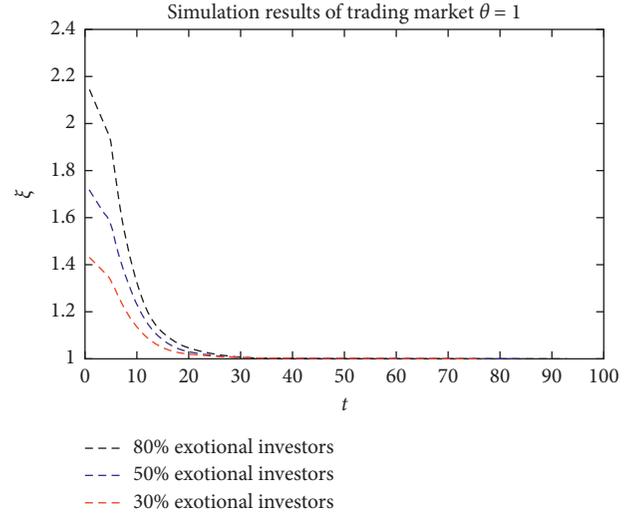
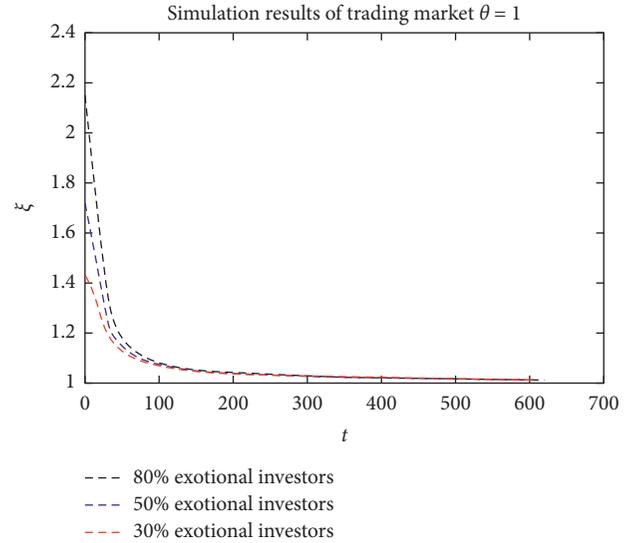
FIGURE 6: Investor proportion curve $\theta \leq 1, \gamma = 0.05$.

change in time and in the ratio. However, due to the different conversion rates for emotionally calm investors, the spatial phase changes are slightly different, with a larger γ meaning slower conversion. The changes in the investor ratios will also change the buying and selling ratio. The simulations of the ratio of buying and selling via changes in two-way transactions are shown in Figures 9 and 10.

We can see in the figures that although the trading frequency of all parties is relatively high at the beginning, the market equilibrium is unbalanced, especially in a market where the proportion of traders affected by emotion is relatively high. As shown in Figure 9, the proportion of investors in the initial mood is 80%. In this case, the proportion of buy/sell transactions will be significantly higher than the equilibrium state of 1, even up to 2.2. This shows that the strength of one side of the multishort side is much greater than that of the other, and the situation is similar in other initial ratios. However, since the recovery rate is much

FIGURE 7: Phase space curve $\theta \leq 1$, $\gamma = 0.5$.FIGURE 8: Investor proportion curve $\theta \leq 1$, $\gamma = 0.5$.

higher than the rate of investor emotional exchange, the emotional impact on investors will eventually be transformed into normal investors, the trading ratio of buying and selling will tend toward 1 after a period of adjustment, and the overall market buying and selling ratio will become balanced. If we compare Figures 9 and 10, we see that, in the case of a small γ , the shorter the change time of buy/sell ratio, the larger the change range. In the case of a large γ , the smaller the change range, the longer the overall continuous change cycle. This shows that when the selling and buying ratio covers most normal investors, the market tends to buy and sell in balance. The difference in γ changes the rate of change in the buying and selling ratio. Comparing the two results, we find that the larger the γ , the slower the rate of change. Therefore, similar to the normal market, when the investor's recovery rate is greater than the exchange rate, the emotion is more balanced. Even if there are so-called noisy

FIGURE 9: Simulation of the buying and selling transaction ratio: $\theta \leq 1$, $\gamma = 0.05$.FIGURE 10: Simulation of the buying and selling transaction ratio: $\theta \leq 1$, $\gamma = 0.5$.

traders or emotional investors, the market will eventually reach an equilibrium due to self-correction. When $\theta > 1$, the overall market situation changes as shown in Figures 10–14. Here, we assume that the total number of transactions is 1000 and the emotional influence rate is $\lambda = 0.1\%$, the calming rate is $\mu = 0.1$, and the conversion rate is $\gamma = 0.05$. Therefore, as calculated, $\theta = 10$ is far greater than 1, while other parameters, such as the calming rate and conversion rate, do not change, and the phase space curve is in proportion to the investors.

Regardless of the proportion of investors affected by emotions, when $\gamma = 0.05$, investors will eventually tip toward the equilibrium point of emotions $(\mu/\lambda, \gamma(N - (\mu/\lambda))/\mu + \gamma)$, that is, (100, 300), while this equilibrium point will reach (100, 750) when $\gamma = 0.5$. According to Figures 11 and 13, in the case of a small γ , the number of investors affected by sentiment will

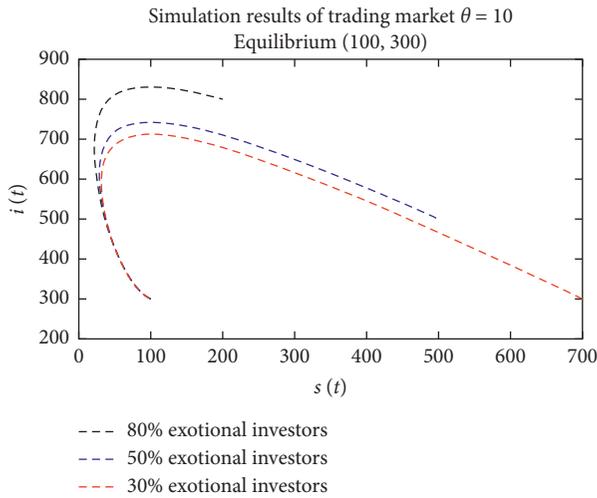


FIGURE 11: Phase space curve with $\theta > 10$, $\gamma = 0.05$.

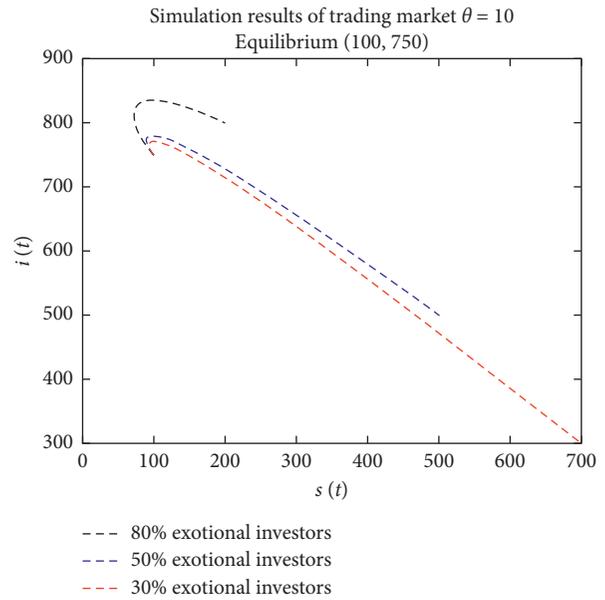


FIGURE 13: Phase space curve with $\theta > 10$, $\gamma = 0.5$.

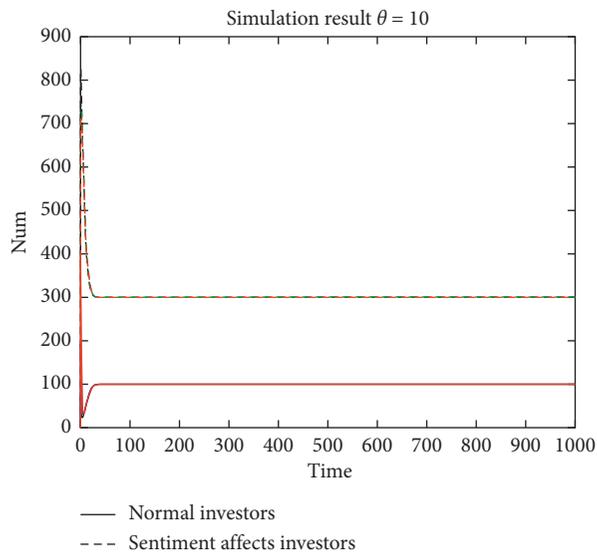


FIGURE 12: Investor ratio curve with $\theta > 10$, $\gamma = 0.05$.

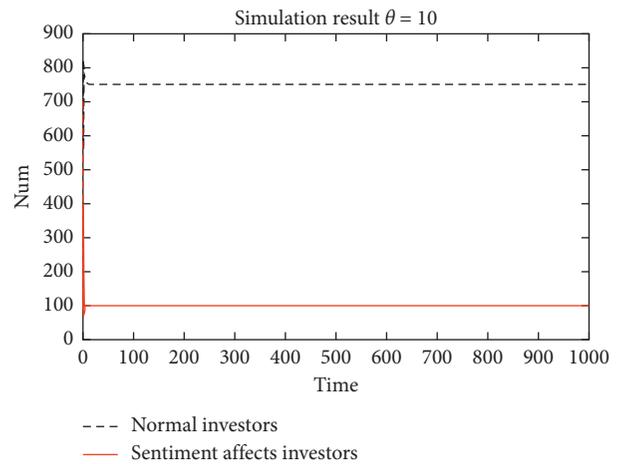


FIGURE 14: Investor ratio curve with $\theta > 10$, $\gamma = 0.5$.

continue to decline due to the influence of recovery rate, and they will turn into those with stable sentiment. After the transformation, calm and stable investors are more likely to return to being emotional investors because of the larger θ . Thus, the number of emotion-affected investors will remain stable in the transaction process, as shown in the simulation. While the number of investors affected by emotion is stable at 300, there will be fewer normal investors than emotion-affected ones. The number of investors in the capital market will return to equilibrium and transactions will tend to be one-sided. When γ is greater than a certain value, the influence of emotion on the investor ratio will be far greater than that of normal investors and in a stable range, as shown in the simulation; the final number of emotional investors will be stable at 750, while the sum of normal investors and calm and stable ones will be steady at 250. Therefore, if θ is greater than 1, regardless of the conversion rate, the attitude of the overall market will change from neutral to positive or negative. The changes in the ratio of

two-way buying and selling transactions are shown in Figures 15 and 16.

The proportion of the two-way buying and selling changes from 1:1 before in the stable market to stabilize at a value greater than 1 in the emotional market, which shows that unilateral buying and selling in the market will be higher than before. When θ is greater than 1 and γ is small, different emotions affect the initial proportion of investors, and the final buying and selling proportion will be different. The higher the initial proportion, the higher the final buying and selling proportion. When γ is large, the final buy/sell ratio is similar to that when γ is small, but when γ is large, the buy/sell ratio will have more concentration effect, and the overall market will be more extreme. However, the change in the θ , that is, the change in λ , shows that if investor sentiment changes through some means such as the Internet, the media, policy interpretation, or other public opinions, it will cause a change in market sentiment. Nowadays, there are many tools to spread investor

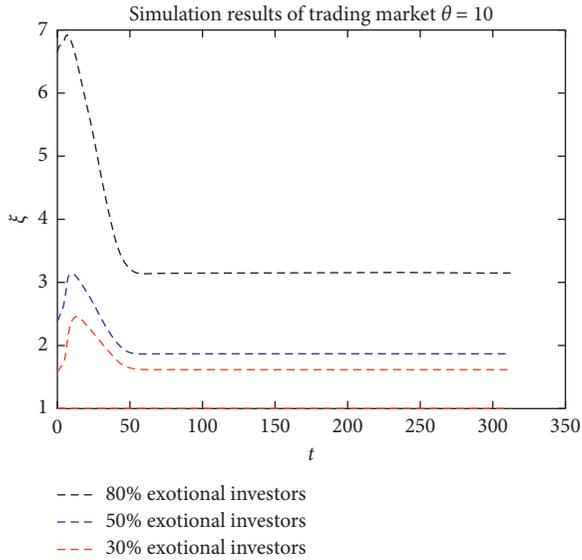


FIGURE 15: Simulation of buying and selling transaction ratio: $\theta > 10$, $\gamma = 0.05$.

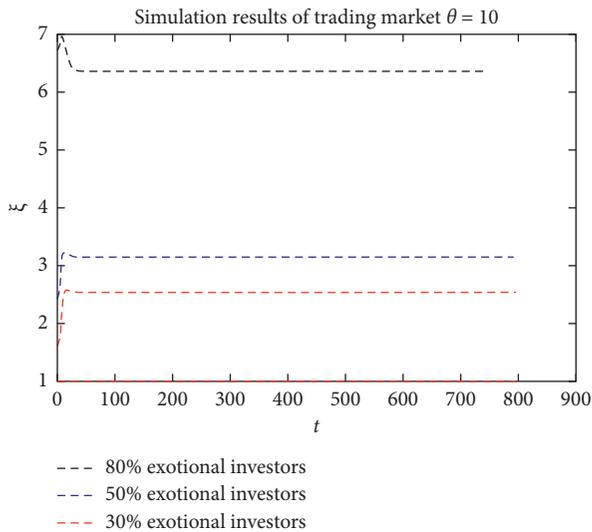


FIGURE 16: Simulation of buying and selling transaction ratio: $\theta > 10$, $\gamma = 0.5$.

sentiment, such as Twitter, Facebook, Baidu post bar, WeChat, or TikTok, not only affecting the overall market, but also affecting individual stocks. Similarly, it can also have a greater impact on individual stocks, such as GameStop (GME.US) which had risen 92.71% and 134.84% in two days in the US and Teli A (000025.SZ) which had risen 15 times trading limited in 17 days in China (stocks in China have 10 percent limited daily). Thus, both the fuse mechanism and bull market behavior are influenced by investor sentiment.

6. Discussion

Using the SIRS model, this paper analyzes the fuse mechanism ignited by the stampede event in China's A-share market in 2016. The results explain the triggering of the

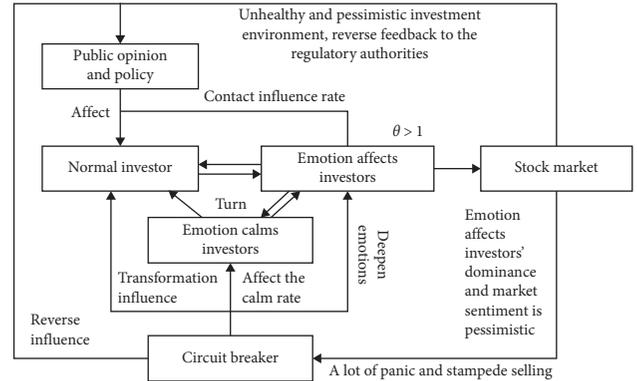


FIGURE 17: Changes in investor sentiments under the circuit breaker.

circuit breakers in US stocks and in China A-shares, through the process shown in Figure 17.

During normal market operations, normal investors are affected by public opinion and certain policies (such as increasing bearish sentiment in the market and media sentiment), and some sentiment-affected investors become bearish and pessimistic investors, while other calm investors are transformed into sentiment-affected investors, further affected by public opinion and the sentiment-affected investors around them. As more and more normal investors become emotional investors, the A-share market changes from normal to emotionally influenced. Pessimistic emotions affect overall investor feelings, the trading volume starts to rise, and a large number of pending sell orders appear, further stimulating investor sentiment and pushing the market quickly to the fuse state. In the fuse mechanism process, investors follow the herd effect, negative emotions spread, and the degree of infection strengthens, causing irreversible transformation.

As the situation analysis shows, the market transaction volume and the number of transactions per hour quickly grow larger and, in the second fuse situation, these numbers are greater than in the first one. This also shows that the contagion of pessimism increases and the calming rate decreases once the fusing mechanism process begins. This is why the second fuse occurs after only 0.25 hours of trading. The recent circuit breaker phenomenon in the US stock market is similar to what happened in the China A-share market. The inertia of trading caused multiple circuit breakers. In 2008 and 2015, a leveraged mad cow market and the stock market crash, along with some internal mechanisms, caused a change in investor sentiments during the fuse mechanism process. Only after this mechanism morphed into a mad cow market, the extraordinary rate of return and media and public opinion further affected the structure of internal investors.

The relationship between investor sentiment and the number of investors in the stock market under a normal healthy trading environment is shown in Figure 18. Because the overall market environment is relatively balanced, even if there are emotional investors, they will eventually shift and become normal investors, and investor mood will rebalance.

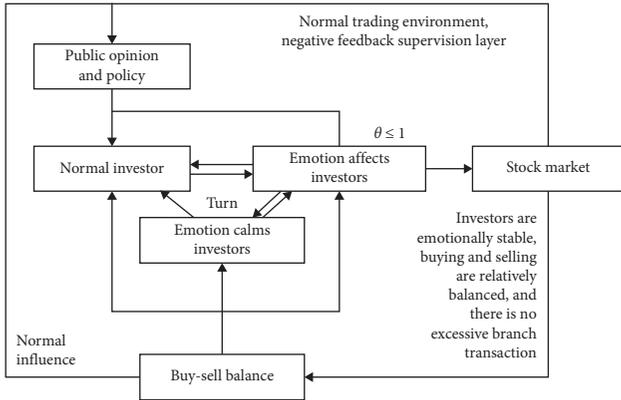


FIGURE 18: Changes in investor sentiments under the normal market.

7. Conclusion and Suggestions

In this study, we use the SIRS model to simulate the change in investor sentiment and the trading ratios in an equilibrium stock market. First, we build a related path graph examining investor sentiment as the direction point. Second, through simulations, the influence of investor sentiment and an infection situation in the capital market is reconstructed. The simulation confirms that investor sentiment can be transmitted through public opinion and other communication mediums in a transmission process similar to that of infectious diseases. Finally, the influence of the change in the related parameters on the whole simulation is studied.

The results are consistent with reality. Under the influence of an extreme market environment, investor sentiment will fluctuate significantly; the process will be infected to a certain extent, as in the case of a disease, and the intensity of the infection may change with changes in the market environment. In addition, the process will be influenced by different information and media, which will change the infection's intensity. In the end, there are a large number of extremely infected investors who will affect the normal, rational, and balanced state of the overall market. The degree of buying and selling is also affected by the investor mood, which creates further imbalance and changes in the market.

In the process of the SIRS simulation, the results show that, when the influence rate λ of all investor mutual communication increases or when the emotional calm rate μ decreases (that is, θ increases), investor emotions will start to spread, leading to an increase in the probability of a serious stampede or zealous overbuying in the stock market. At the same time, the trading frequency of investors, ω , and the ratio of investors in both buying and selling directions will have a certain formal impact on the direction of the stock market, with the final impact determined by the ratio of normal investors to emotional investors. When emotional investors dominate the overall market, emotions spread.

According to the SIRS model simulation results and analysis of investor sentiment changes in the equilibrium market, measures to prevent and control the occurrence and spread of specific emotions in the capital market should be

considered. The balance in the overall market environment can be improved by increasing positive guidance around investor emotions—increasing the calming rate μ or reducing the emotional influence rate λ of overzealous emotional investors. At the same time, the spread of bad news and emotions must be prevented, such as stirring up the market environment through the media, Internet, or public opinion. Some administrative measures could be considered, such as cracking down on illegal stock market news groups on the Internet, controlling and eradicating corrupt self-media or marketing numbers, regulating individuals and groups who earn profits from spreading false news on the Internet, strengthening the controls on online public opinion and media public opinion, and establishing a public opinion index to ensure the healthy operation of the market.

This study has some limitations in that it still has to address how to calculate more scientifically the influence rate λ of all investors' mutual communication and how to incorporate other public opinion indicators into investor sentiment indicators. These problems are expected to be addressed in future research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request (e-mail: 1179188@mail.dhu.edu.cn).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] H. Cui and Y. Zhang, "Does investor sentiment affect stock price crash risk?" *Applied Economics Letters*, vol. 27, no. 7, pp. 564–568, 2020.
- [2] Y. Tang, X. Hong, and P. Zhu, "Limited attention and abnormal characteristics of stock market and herd effect," *Financial Theory and Practice*, vol. 1, pp. 11–20, 2020.
- [3] Z. Xiao, X. Zhou, and S. Zhou, "Can online sentiment affect the herd effect of stock market?" *Financial Research*, vol. 9, pp. 62–71, 2019.
- [4] Y. Zheng, D. Dong, and H. Zhu, "Does heterogeneous emotion affect herd effect in stock market?—evidence from internet stock community," *Systems Engineering*, vol. 34, no. 9, pp. 9–14, 2016.
- [5] J. Zhang, "The influence of investor sentiment on stock price from the perspective of behavioural economics," *Social Science Front*, vol. 12, pp. 235–239, 2019.
- [6] H. Lu, Y. Wei, and K.-K. Wang, "Micro-index, Baidu index and Shanghai composite index yield forecast," *Journal of Information Systems*, vol. 1, pp. 87–98, 2018.
- [7] D. Wang and Y. Jia, "Investor sentiment, commodity price and inflation—analysis based on micro survey data 'commodity confidence index'," *International Finance Research*, vol. 2, pp. 77–86, 2018.
- [8] M. Li and Z. Li, "Market manipulation and stock price crash risk: path analysis based on investor emotion," *International Finance Research*, vol. 4, pp. 87–96, 2019.

- [9] D. Ballinari and S. Behrendt, "Structural breaks in online investor sentiment: a note on the nonstationary of financial chatter," *Finance Research Letters*, vol. 35, Article ID 101479, 2020.
- [10] H. Nguyen, R. Calantone, and R. Krishnan, "Influence of social media emotional word of mouth on institutional investors' decisions and firm value," *Management Science*, vol. 66, no. 2, pp. 887–910, 2020.
- [11] W. Ji, Y.-H. Huang, P. Lin, and R. Song, "Research on public opinion communication on weibo network based on improved SIR model," *Information Science*, vol. 37, no. 6, pp. 16–22, 2019.
- [12] A. F. Ally and N. Zhang, "Effects of rewiring strategies on information spreading in complex dynamic networks," *Communications in Nonlinear Science and Numerical Simulation*, vol. 57, pp. 97–110, 2018.
- [13] T. Fan, W. Qin, W. Zhao, F. Wu, and J. Wang, "A two-layer SIR information propagation model with heterogeneity based on coupled network," *The Journal of Supercomputing*, vol. 76, no. 3, pp. 1657–1679, 2019.
- [14] N. Yin, "SIR model of public opinion crisis diffusion in limited groups and its simulation realization," *Statistics and Decision*, vol. 34, no. 18, pp. 62–66, 2018.
- [15] L. Zhang, C. Su, Y. Jin, M. Goh, and Z. Wu, "Cross-network dissemination model of public opinion in coupled networks," *Information Sciences*, vol. 451–452, pp. 240–252, 2018.
- [16] E. Fisher, "A biological approach for financial network contagion based on the Susceptible-infected-recovered (SIR) model," *Análisis Económico*, vol. 28, no. 69, pp. 109–128, 2013.
- [17] X. Rui, F. Meng, Z. Wang, G. Yuan, and C. Du, "SPIR: the potential spreaders involved SIR model for information diffusion in social networks," *Physica A: Statistical Mechanics and Its Applications*, vol. 506, pp. 254–269, 2018.
- [18] F. Wang and F. Li, "Rumor propagation model considering different propagation probability in social networks," *Application Research of Computers/Jisuanji Yingyong Yanjiu*, vol. 36, no. 11, pp. 3294–3296, 2021.
- [19] X. Zhou, Y. Hu, Y. Wu, and X. Xiong, "Influence analysis of information erupted on social networks based on SIR model," *International Journal of Modern Physics C: Computational Physics & Physical Computation*, vol. 26, no. 2, 2015.
- [20] E. Sahafizadeh and B. Tork Ladani, "The impact of group propagation on rumor spreading in mobile social networks," *Physica A: Statistical Mechanics and Its Applications*, vol. 506, pp. 412–423, 2018.
- [21] G. Fibich, "Bass-SIR model for diffusion of new products in social networks," *Physical Review E*, vol. 94, no. 3, Article ID 032305, 2016.
- [22] Z. Qian, S. Tang, X. Zhang, and Z. Zheng, "The independent spreaders involved SIR Rumor model in complex networks," *Physica A: Statistical Mechanics and Its Applications*, vol. 429, pp. 95–102, 2015.
- [23] L. Zhao, H. Cui, X. Qiu, X. Wang, and J. Wang, "SIR rumor spreading model in the new media age," *Physica A: Statistical Mechanics and Its Applications*, vol. 392, no. 4, pp. 995–1003, 2013.
- [24] Y. Wang, J. Wang, H. Wang, R. Zhang, and M. Li, "Users' mobility enhances information diffusion in online social networks," *Information Sciences*, vol. 546, pp. 329–348, 2021.
- [25] C. Liu, R. Han, X. Huang, H. Yang, and X. Liu, "SIR propagation model of network MLM," *Journal of Chongqing University of Technology (Natural Science)*, vol. 35, no. 1, pp. 161–167, 2021.
- [26] Z. Chen, Y. Dong, and S. Zhang, "Who has a greater impact on the development of the stock market—investor sentiment or leveraged trading?" *Systems Science and Mathematics*, vol. 39, no. 10, pp. 1655–1671, 2019.
- [27] J. Yang and Y. Zhang, "Empirical analysis of the impact of fuse mechanism on China's A-share market," *Statistics and Decision*, vol. 13, pp. 153–155, 2017.
- [28] M. Li, "American regulatory experience and enlightenment of flash crash," *China Finance*, vol. 19, pp. 65–66, 2017.
- [29] X. Yang and X. Jin, "Magneto mechanical effect of the fuse mechanism in China's stock market: evidence based on natural experiments," *Financial Research*, vol. 9, pp. 161–177, 2017.
- [30] X. Tang, "Research on the causes of fuse mechanism failure in China's stock market under Poisson distribution principle," *Technical Economics and Management Research*, vol. 4, pp. 83–86, 2018.
- [31] J. Hu, Y. Sui, and F. Ma, "The measurement method of investor sentiment and its relationship with stock market," *Computational Intelligence and Neuroscience*, vol. 2021, Article ID 6672677, 11 pages, 2021.
- [32] S.-H. Kim and D. Kim, "Investor sentiment from internet message postings and the predictability of stock returns," *Journal of Economic Behavior & Organization*, vol. 107, pp. 708–729, 2014.
- [33] Y. Chen, H. Zhao, Z. Li, and J. Lu, "A dynamic analysis of the relationship between investor sentiment and stock market realized volatility: evidence from China," *PLoS One*, vol. 15, no. 12, Article ID e0243080–18, 2020.
- [34] G. He, S. Zhu, and H. Gu, "The nonlinear relationship between investor sentiment, stock return, and volatility," *Discrete Dynamics in Nature and Society*, vol. 2020, pp. 1–11, 2020.
- [35] Z. Janková, "Sentiment on the stock markets: evidence from the wavelet coherence analysis," *Scientific Papers of the University of Pardubice, Series D, Faculty of Economics & Administration*, vol. 28, no. 3, pp. 1–10, 2020.
- [36] D. Živkov, J. Njegić, and M. Pečanac, "Wavelet analysis of the interdependence between stocks and bonds in the selected East European and Eurasian emerging markets," *Ekonomicky Casopis*, vol. 67, no. 2, pp. 175–194, 2019.
- [37] S. R. Dash and D. Maitra, "Does sentiment matter for stock returns? evidence from Indian stock market using wavelet approach," *Finance Research Letters*, vol. 26, pp. 32–39, 2018.