IEEE Access
Multidisciplinary ⁝ Rapid Review ⁝ Open Access Journal

Received May 22, 2020, accepted July 5, 2020, date of publication July 13, 2020, date of current version July 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3008717

Investor Behavior and Risk Contagion in an Information-Based Artificial Stock Market

BINGHUI WU
International Business School, Shaanxi Normal University, Xi'an 710119, China
e-mail: vcmd@163.com

This work was supported by the Program of Humanities and Social Science Youth Foundation of the Ministry of Education of China under Grant 19XJC790014.

ABSTRACT This paper designs an artificial stock market model to discuss investor behavior and risk contagion caused by market information. Considering the investors' trading decisions are attributed to the change of market information, new market information no matter from the macro field or the micro field can influence investor behavior and risk contagion. In our artificial stock market model, we assume new information is the sole factor affecting the fluctuation of stock prices. And investor sentiment is influenced by investor sensitivity to new information, investment decisions of neighboring investors, and investor understanding preference for new information. Through simulation experiments, some conclusions can be drawn as follows. Firstly, stock price volatility becomes stronger with increasing investor sensitivity to new information, under the condition of a smaller fundamental contagion coefficient or larger sensitivity to new information from investor neighbors. Secondly, stock price volatility becomes more moderate with increasing sensitivity to new information from investor neighbors, under the condition of a smaller fundamental contagion coefficient or smaller investor sensitivity to new information. Thirdly, with the increasing fundamental contagion coefficient, stock price volatility may strongly increase under the condition of smaller investor sensitivity to new information and smaller sensitivity to new information from investor neighbors, or slightly increase under the condition of smaller investor sensitivity to new information and larger sensitivity to new information from investor neighbors, or slightly decrease under the condition of larger investor sensitivity to new information and smaller sensitivity to new information from investor neighbors, or show a little change under the condition of larger investor sensitivity to new information and larger sensitivity to new information from investor neighbors.

INDEX TERMS Investor behavior, risk contagion, stock price volatility, market information.

I. INTRODUCTION

The sound development of stock markets plays an important role in promoting the economic growth of a country [1]–[5]. The enterprise raises funds through issuing shares and finishes the centralization and accumulation of capital [6]–[8]. But in investment activities, investors usually adjust their investment decisions under the influences of external factors from stock markets and internal factors from themselves [9], [10]. External factors mainly contain macroeconomic factors, political factors, law factors, cultural factors and regional factors, and so on [11]–[13]. And internal factors mainly emphasize investors' mentality, analysis capabilities, risk preference, and knowledge structures, and so forth [14]–[16]. In the same market environment, investors probably make different decisions under the influence of internal factors. This difference in investment decisions reflects that investors are not the same and have heterogeneous characteristics [17]–[20]. Besides, the behavioral interaction among investors makes investment decisions more complex and increases the difficulties in the studies of risk contagion. It is hard to thoroughly and effectively explain the dynamic features of financial markets through traditional methods based on the analysis of rational investors. Under this background, some research tries to discuss stock market risk through artificial stock markets built by agent technology, such as Krichene and El-Aroui [21], Hafezi *et al.* [22], Manahov and Hudson [23], Liu *et al.* [24], Zhang *et al.* [25], Wu and Duan [26] and Xu *et al.* [27].

The research on stock market risk based on agent technology mainly centers on the analysis of stock price volatility and the construction of artificial stock markets. For example, some studies have found that the random interaction mechanism of agents shows the heavy-tail distribution

The associate editor coordinating the review of this manuscript and approving it for publication was Zhipeng Cai.

of stock price volatility, caused by investor herd behavior [28]–[30]. After analyzing the relationship of asset return distributions, transaction orders, and mutual imitation among investors, the above studies further show that agents make investment decisions in groups and investment incomes obey a power distribution at a low activity level of agents and a critical value of behavior interaction probability [28]–[30]. Based on [28], Iori considered that each agent could receive an information set, including self-information and other-information, and then each agent adjusted the investment decision according to the dynamic change of information set [31]. Lux and Marchesi built a multi-agent stochastic model to analyze risk contagion based on the fluctuation of investor sentiment. They divided investors into two types: fundamental analysts and technical analysts and found the return series having the characteristics of fat-tailed distribution and cluster volatility [32]. Yu and Cao improved the model in [32] and proposed a new entry and exit mechanism, which could be used for building ordinary differential equations to discuss the evolutionary process of agent-based stock markets [33]. To increase the heterogeneity of agents, psychological factors and emotive factors are gradually added into the research of stock market risk [34]–[37]. The Santa Fe Institute Artificial Stock Market model abbreviated SFI-ASM model is the most classical artificial stock market model [38]–[40]. In the SFI-ASM model, investors in the stock market can be seen as independent agents with self-adaptive features [41], [42]. Because agents can buy and sell stocks in the stock market, the time series of stock price reflects the dynamic behavioral characteristics of agents [43], [38]. In recent years, many scholars have built artificial stock market models to study investor behavior and risk contagion, such as Duarte *et al.* [44], Wu and Duan [45], Bertella *et al.* [46], Krichene and Elaroui [47], Tsao and Huang [48], Yang and Chen [49], and Prates *et al.* [50].

The study of risk contagion has always been a hot topic in financial research fields [51]–[56]. And it has broad prospection in the aspect of analyzing the mechanism of risk contagion based on artificial stock market models. However, it isn't hard to find that the most artificial stock market models are constantly revised according to the SFI-ASM model in the available literature, and the investors in artificial stock market models are usually assumed to be rational traders and noise traders, or technical analysts and fundamental analysts. Finally, risk contagion is discussed through the behavior interaction of different investors. Many researchers discuss the macroscopic problem of risk contagion from the microscopic structure of market players, but ignore the risk contagion between the same kind of traders. Thus, this paper designs an artificial stock market model based on investor behavior to study the problem of risk contagion. This model which isn't a revised SFI-ASM model, no longer divides investors into different types. We assume that risk contagion is caused by changing market information. More specifically, investors probably change original strategies according to the changing market information and affect their neighbors' investment decisions. Under this mechanism of influence, financial risk realizes the transmission from one investor to another. The remainder of this paper is organized as follows. Section 2 constructs the artificial stock market model based on market information and investor behavior. Next, section 3 conducts simulation experiments to discuss the influences of different parameters on risk contagion. Finally, the conclusions are drawn in section 4.

II. THE INFORMATION-BASED ARTIFICIAL STOCK MARKET MODEL

A. THE MODELING IDEA

In the theoretical framework of the efficient market hypothesis, the investor is assumed to have full rationality, and make sound decisions according to all market information [57]. However, it is not possible to have full rationality for an investor in the real stock market [58]. For example, investors' blind overconfidence may lead to overreacting to market news. Moreover, investors' insufficient understanding may lead to underacting to market news.

According to the efficient market hypothesis, asset prices that can fully reflect all information in financial markets, are not higher or lower than the intrinsic value of an asset. With the rise of behavioral finance, the behavioral finance theory is commonly used in the analyses of investor behavior, especially in the deviations of investment decisions [59]. And these deviations are often difficult to be explained through traditional financial theories. In the behavioral finance theory, the investor makes an investment decision with incomplete rationality [60]. This behavior of investment decision may cause systematic biases, which cannot be eliminated by statistics methods [61].

In the information-based artificial stock market model built in this paper, we assume that the investor has bounded rationality and heterogeneity at first. And then, we abandon the traditional research framework based on rational traders and noise traders, or technical analysts and fundamental analysts. We assume that the reason for stock price volatility comes down to investor behavior caused by the change of market information. When the market information changes, we can analyze the influence of market information on investor behavior, and the influence of investor behavior on their neighbors' sentiment through the constructed model. Owing to the changes in neighbors' sentiment, these neighbors probably make new investment decisions and transmit new sentiment to other investors. Finally, stock prices continue to fluctuate, and financial risk finishes contagious processes between investors and their neighbors.

B. THE TRADING MECHANISM

Suppose that new information appears in the stock market on each trading day, and the influence of new information on investor sentiment obeys normal distribution, $N(0,\sigma_{NI}^2)$. On each trading day, an investor is assumed to buy or sell one unit of stock. The information-based artificial stock market model is built through Netlogo software in this paper.

Based on [62], investor sentiment y(t) includes three parts: investor sentiment caused by investor sensitivity to new information, investor sentiment caused by the neighbors, and the random variation of investor sentiment caused by the change of understanding preference for new information. The above three types of investor sentiment can be represented as $x_1(t)$, $x_2(t)$ and $x_3(t)$, in turn. Let's suppose that $s_1(t)$ is investor sensitivity to new information, and $s_1(t)$ varies between 0 and 1 at random. For the investor's neighbors, sensitivity to new information can be expressed as $s_2(t)$. Because of the effect of $s_2(t)$ on investor sensitivity coming from the investor's neighbors, we assume $s_2(t)$ is a random variable varying between 0 and 1. The transition function of new information, which can transform new information into investor sentiment, is represented as $Q_1(t)$. And the value of $Q_1(t)$ is set to 1 or -1. When the investor buys one unit of stock because of positive sentiment caused by new information, Q_1 (t) is equal to 1. Conversely, when the investor sells one unit of stock owing to negative sentiment caused by new information, Q_1 (t) is equal to -1. For the investor's neighbors, the transition function of new information is written as $Q_2(t)$. When an investor's neighbor buys or sells one unit of stock, Q_2 (t) is equal to 0.5 or -0.5. Let c(t) be the contagious coefficient of investors affected by neighbors' sentiment. The number of neighbors can be represented as n(t) for each investor. According to the two-dimensional structured grids of Netlogo software, the investor may have 2, 3, or 4 neighbors. It means that n(t) is equal to 2, 3, or 4. Considering that the influence of new information on investor sentiment obeys normal distribution and the investor should not have sentiment deviation to new information, $x_3(t)$ is assumed to obey the normal distribution with zero mean, $x_3(t) \sim N\left(\mu, \sigma^2\right)$ and $\mu = 0$. The variance of this normal distribution is indicated as σ^2, which is set to be the sum of σ_{NI}^2 and ε. As a small variable, ε has the characteristic of stochastic fluctuation. And we assume that the fluctuation range of ε is between 0 and 0.05. $x_1(t)$, $x_2(t)$ and $x_3(t)$ can be expressed as follows.

$$x_1(t) = s_1(t) \times Q_1(t) \tag{1}$$

$$x_2(t) = c(t) \times n(t) + s_2(t) \times Q_2(t) \times n(t) \tag{2}$$

$$x_3(t) \sim N(0, \sigma_{NI}^2 + \varepsilon) \tag{3}$$

Let's suppose that each new information can influence investor sentiment and transaction decision-making. In the artificial stock market model, the investor generates mood swings after receiving new information and affects the neighbors' decisions. Concretely speaking, there are two situations. In situation 1, the investor thinks that new information can make a positive (or passive) impact on the stock price trend. If this judgment is right, the investor will participate in marketing activities more positively and tend to transmit this sentiment to others. Thus, the contagious coefficient c(t) will probably increase. Conversely, in situation 2, the investor makes a wrong judgment. That means the investor's judgment is inconsistent with the stock price trend. And the investor probably loses the enthusiasm for sentiment contagion to others. Therefore, c(t) will probably decrease. We assume that c(t) includes two parts: the fundamental contagion coefficient c_f and the degree of stock price volatility $s_r(t)$. In situation 1, the investor decides to buy (or sell) one unit of stock, and the degree of stock price volatility is a positive number (or a negative number). However, in situation 2, the investor decides to buy (or sell) one unit of stock, but the degree of stock price volatility is a negative number (or a positive number). The contagious coefficient c(t) can be written as c_1 (t) and c_2 (t). The above evolution rules can be shown as follows. When the investor decides to buy one unit of stock, we adopt the expression (4). And when the investor sells one unit of stock, we choose the expression (5).

$$c_1(t) = c_f + s_r(t) \tag{4}$$

$$c_2(t) = c_f - s_r(t) \tag{5}$$

where the fundamental contagion coefficient c_f is a random value between 0 and 1. And the degree of stock price volatility s_r depends on stock price changes. Because investor sentiment y(t) is a key factor to affect stock price changes, we assume that s_r is calculated by expression (6).

$$s_r(t) = \sum_{i=1}^{T} \frac{d_i(t)}{T} \tag{6}$$

where d_i indicates the i-th investor's decision. If $y_i(t) > 0$, $d_i(t) = 1$. And if $y_i(t) < 0$, $d_i(t) = -1$. Because we have assumed that each new information can influence investor sentiment and transaction decision-making, y (t) is not equal to 0. Besides, the number of traders is written as T in expression (6).

III. THE SIMULATION EXPERIMENTS

As a continuously evolving system, the stock market shows the feature of risk contagion caused by investors and their neighbors under the influence of market information. According to the trading mechanism in section 2, we need to set the simulation experiment environment at first. The settings of simulation experiments are as follows. All simulation experiments are assumed to be 300 trading days. Because the network structure of Netlogo software is the two-dimensional square lattice, the location of origin is set to (0, 0) in the center of patches. The maximum and minimum of x coordinate for patches are 50 and -50, respectively. Likewise, the y coordinate for patches has the same maximum and minimum, 50 and -50. Thus, the number of agents in the simulation experiments is 10201, calculated by the product of 101 and 101.

Because different investors have different sentiment and sensitivity to the same information, investors can affect their neighbors' investment decisions. Thus, we set two different parameter values for c_f, $s_1(t)$ and $s_2(t)$ to analyze the influence of different parameter values on risk contagion in the stock market. According to the different values of c_f, $s_1(t)$ and $s_2(t)$, we design eight simulation experiments. To be specific, c_f is equal to 0.25 or 0.85; $s_1(t)$ is equal to 0.15 or 0.75; $s_2(t)$ is equal to 0.05 or 0.65. Considering that σ^2 is the sum of σ_{NI}^2

TABLE 1. The parameter values of simulation experiments.

The simulation experiments	The parameter values of simulation experiments
	$[c_f, s_1(t), s_2(t)]$
Experiment 1	(0.25, 0.15, 0.05)
Experiment 2	(0.25, 0.15, 0.65)
Experiment 3	(0.25, 0.75, 0.05)
Experiment 4	(0.25, 0.75, 0.65)
Experiment 5	(0.85, 0.15, 0.05)
Experiment 6	(0.85, 0.15, 0.65)
Experiment 7	(0.85, 0.75, 0.05)
Experiment 8	(0.85, 0.75, 0.65)

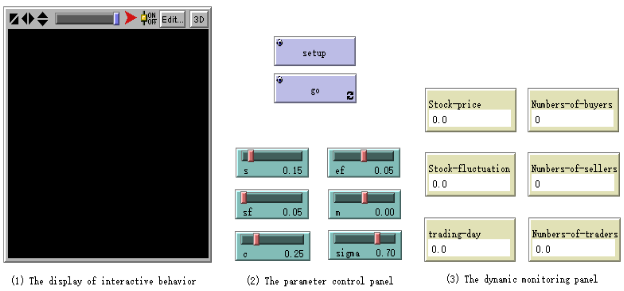

FIGURE 1. The interactive interface of an artificial stock market.

TABLE 2. The parameter meaning of slider in the control panel.

The slider in the control panel	s	sf	c	ef	m	sigma
The meaning of slider	$s_1(t)$	$s_2(t)$	c_f	ε	μ	σ_{NI}^2

and ε in expression (3), we assume σ_{NI}^2 is equal to 0.70 in the following experiments. The parameter values of simulation experiments can be seen in table 1.

Figure 1 shows the interactive interface of an artificial stock market, which contains three parts: (1) the display of interactive behavior, (2) the parameter control panel, and (3) the dynamic monitoring panel. Part 1 displays the dynamic interaction of agents during experimental periods. Through the parameter control panel in part 2, we can adjust these parameters values and discuss the effects of parameters on experimental results. When the model is running, the dynamic monitoring panel shows the real-time data of key variables in part 3. Specifically, the meanings of different sliders in the control panel are shown in table 2.

We assume that the logarithmic value of the stock price is equal to 0 at the initial time. According to all experiment parameters, the results of simulation experiments are shown in figures 2, 3, 4, 5, 6, 7, 8, and 9. For any of

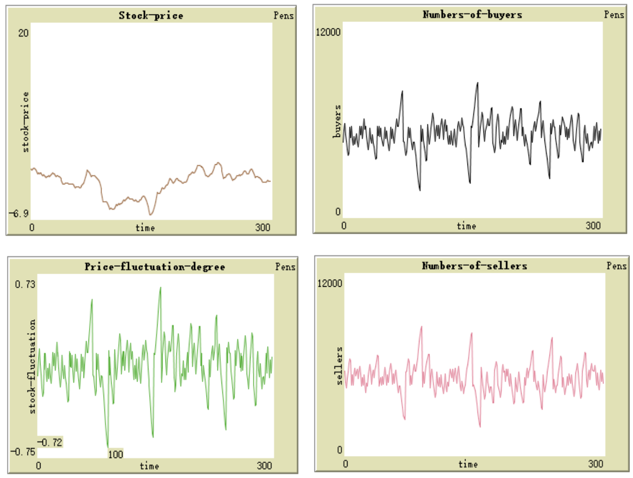

FIGURE 2. The results of experiment 1.

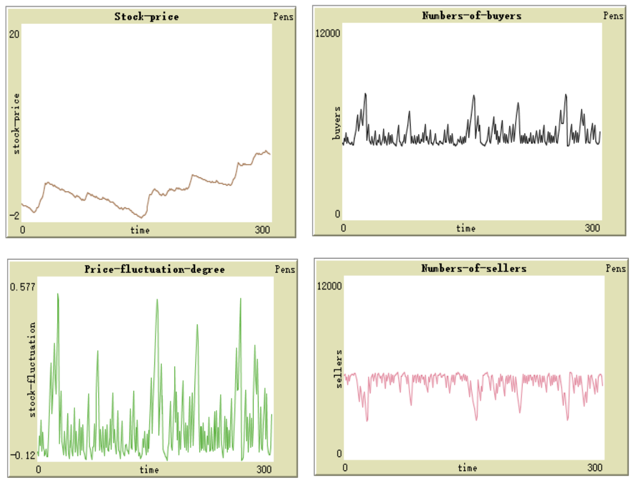

FIGURE 3. The results of experiment 2.

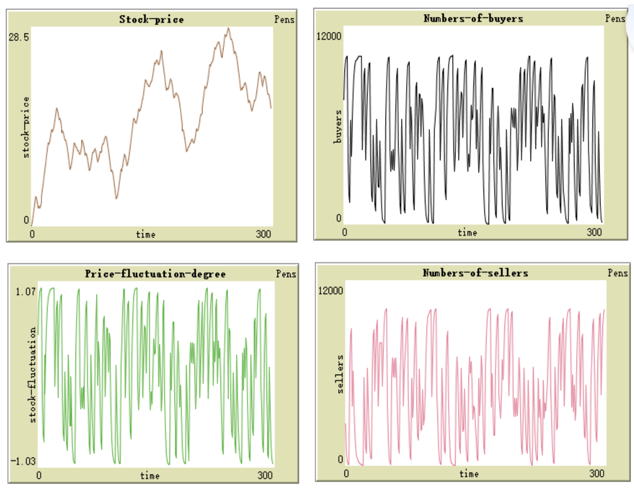

FIGURE 4. The results of experiment 3.

these figures, there are four components: stock-price (drawn by the brown line), price-fluctuation-degree (drawn by the

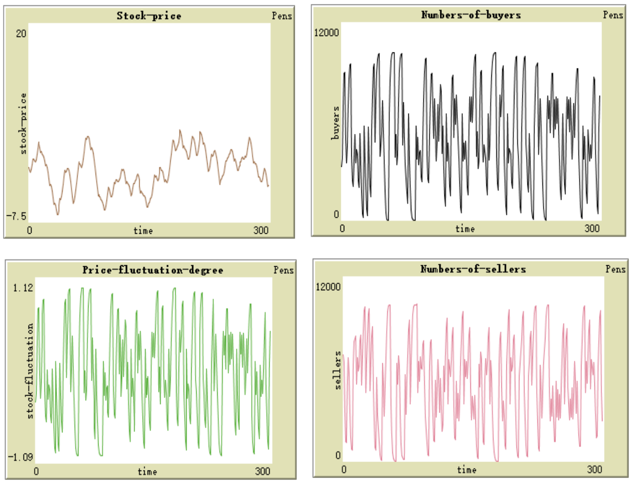

FIGURE 5. The results of experiment 4.

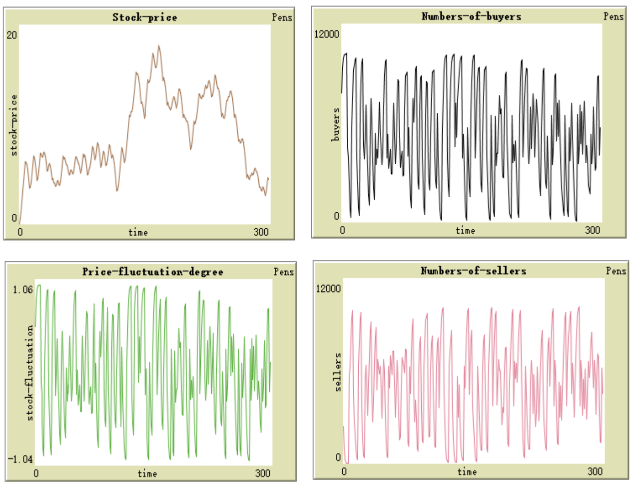

FIGURE 6. The results of experiment 5.

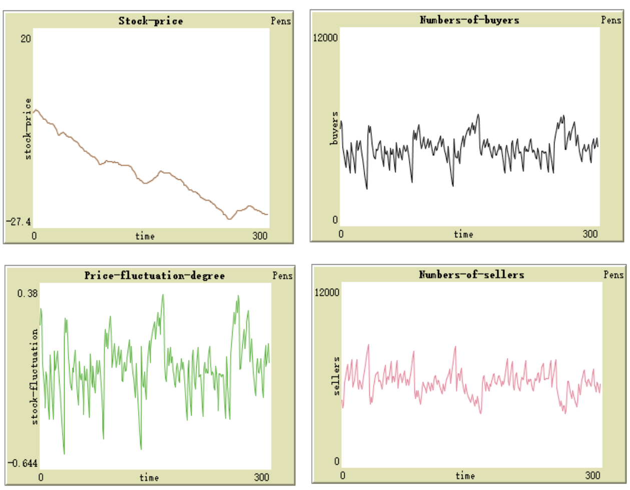

FIGURE 7. The results of experiment 6.

green line), numbers-of-buyers (drawn by the black line) and numbers-of-sellers (drawn by the pink line), successively.

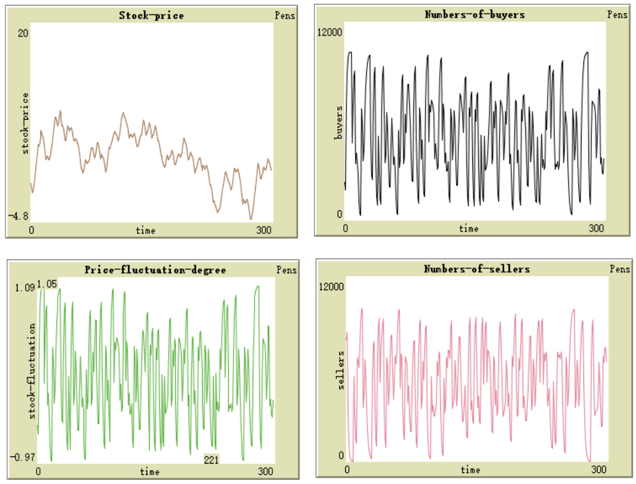

FIGURE 8. The results of experiment 7.

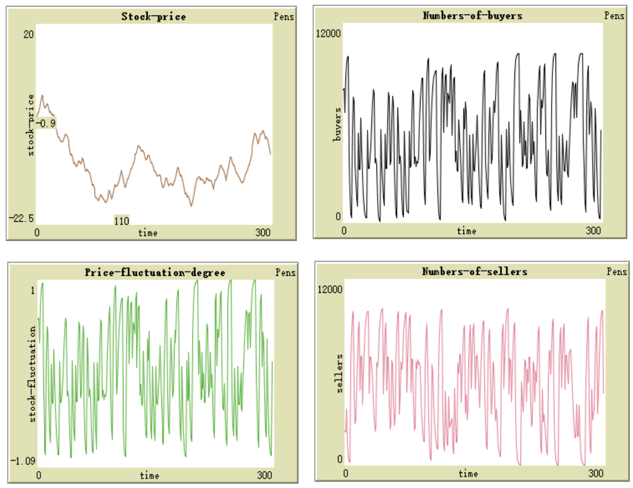

FIGURE 9. The results of experiment 8.

After comparing the simulation results from figure 2 to figure 9, it can be seen that the changes in parameters cause the drastic fluctuation of stock prices. It is necessary to analyze the statistical characteristics of simulation results based on the data in the above figures.

Tables 3 and 4 show the statistical characteristics of key parameters, such as the degree of stock price volatility, the proportion of buyers, and the proportion of sellers. Table 3 shows the statistical description of $s_r(t)$, which contains mean, standard deviation, skewness, kurtosis, minimum, and maximum. According to the statistical description of $s_r(t)$ in table 3, some characteristics can be summarized as follows.

Firstly, all mean values are small and vary between -0.09 and 0.06. The largest mean value is equal to 0.0532 in experiment 3, and the smallest mean value is equal to -0.0811 in experiment 6. The range of minimum and maximum is lower in experiments 1, 2, and 6. And the smallest range, $[-0.1171, 0.5134]$, is in experiment 2. For other experiments, the range of minimum and maximum is close to $[-1, 1]$.

TABLE 3. The statistical description of $s_r(t)$.

Experiment	The degree of stock price volatility					
	Mean	Standard deviation	Skewness	Kurtosis	Minimum	Maximum
1	-0.0056	0.1932	-0.2295	1.4871	-0.6702	0.6267
2	0.0186	0.1319	1.6316	2.5360	-0.1171	0.5134
3	0.0532	0.6399	-0.1236	-1.2242	-0.9955	1.0000
4	-0.0065	0.5757	0.0570	-0.9957	-0.9992	0.9998
5	0.0152	0.5702	0.0737	-1.0240	-0.9871	1.0000
6	-0.0811	0.1585	-0.0780	0.3941	-0.5614	0.3189
7	0.0045	0.5301	0.1005	-1.0045	-0.9461	0.9998
8	-0.0252	0.5757	0.1007	-1.1097	-0.9835	0.9975

TABLE 4. The statistical description of buyers and sellers.

Experiment	The proportion of buyers		The proportion of sellers	
	Mean	Standard deviation	Mean	Standard deviation
1	0.4972	0.0966	0.5028	0.0966
2	0.5093	0.0659	0.4907	0.0659
3	0.5266	0.3199	0.4734	0.3199
4	0.4967	0.2879	0.5033	0.2879
5	0.5076	0.2851	0.4924	0.2851
6	0.4594	0.0793	0.5406	0.0793
7	0.5022	0.2651	0.4978	0.2651
8	0.4874	0.2878	0.5126	0.2878

Secondly, it can be seen that the increase in $s_1(t)$ can enlarge the standard deviation and the value range of stock price volatility for experiments 1 and 3, or experiments 2 and 4, or experiments 6 and 8. In other words, when the investor has a larger sensitivity to new information, stock price volatility is likely to become more obvious. However, this rule doesn't apply to the following case. When c_f has a higher parameter value and $s_2(t)$ has a smaller parameter value, the increase of $s_1(t)$ doesn't make a noticeable difference in stock price volatility. For example, comparing experiments 5 and 7, there is no significant change in other statistical indicators except for the mean value in table 3.

Thirdly, the standard deviation presents a significant decrease from experiment 1 to 2, or experiment 3 to 4, or experiment 5 to 6, by the increase of $s_2(t)$. Similarly, the range of minimum and maximum has a decreasing trend from experiment 1 to 2, or experiment 3 to 4, or experiment 5 to 6. But, this decreasing trend doesn't exist for experiments 7 and 8, with the increase of $s_2(t)$. After comparing experiments 7 and 8, it is easy to be seen that the standard deviation increases from 0.5301 in experiment 7 to 0.5757 in experiment 8. At the same time, other statistical indicators have slightly increasing trends in table 3.

Fourthly, stock price volatility, with the increase of c_f, shows the following characteristics: an obvious rise for experiments 1 and 5, a slight increase for experiments 2 and 6, a slight decrease for experiments 3 and 7, and a little change for experiments 4 and 8. In experiments 1 and 5, both $s_1(t)$ and $s_2(t)$ have a smaller parameter value. When c_f is increased from 0.25 to 0.85, the standard deviation is increased from 0.1932 to 0.5702. And the range of minimum and maximum is enlarged from $[-0.6702, 0.6267]$ to $[-0.9871, 1.0000]$. However, when $s_1(t)$ and $s_2(t)$ take a larger value simultaneously, the increase of c_f doesn't significantly affect the standard deviation and the range of minimum and maximum.

Fifthly, the skewness and kurtosis can be analyzed in table 3 to reveal the distribution features of stock price volatility. At first, the skewness is negative in experiments 1, 3, and 6. It means that stock price volatility has a feature of left-skewed distribution. However, the degree of stock price volatility has a feature of right-skewed distribution in experiments 2, 4, 5, 7, and 8. Then, the kurtosis is a positive value in experiments 1, 2, and 6, and a negative value in other experiments. A positive kurtosis shows stock price volatility has the feature of leptokurtic distribution. Conversely, it presents the feature of platykurtic distribution in experiments 3, 4, 5, 7, and 8.

Also, the proportions of buyers and sellers are shown in table 4. For both the proportion of buyers and the proportion of sellers, the sum equals 1. Thus, the sum of the mean value is also equal to 1, and the standard deviation has the same value for them. But it can be found that the proportion of buyers or sellers has the smallest standard deviation in experiment 2. This indicates that the proportion structure is more stable in experiment 2, relative to that in other experiments. During 300 trading days, the numbers of buyers and sellers are probably close and stable with a larger $s_2(t)$, a smaller c_f, and a smaller $s_1(t)$. On the contrary, some higher standard deviations which are larger than 0.25, appear in experiments 3, 4, 5, 7, and 8.

IV. CONCLUSIONS

This paper analyzes investor behavior and risk contagion based on the information-based artificial stock market model. In the model, we discard the traditional research framework which divides investors into two types: rational traders and noise traders, or technical analysts and fundamental analysts. Considering that new information can cause stock price volatility, we assume the change of new information influences investor sentiment. Under this influence, investors can change their neighbors' sentiment. Finally, the stock price probably rises or drops, owing to the variety of investors' and their neighbors' decisions. Because the market information is changing every day, the stock price is also changing day by day. In the simulation experiments, we obtain eight groups of experimental data with the different parameter combinations for c_f, $s_1(t)$ and $s_2(t)$.

When $s_1(t)$ increases to a larger value, stock price volatility is more intense and risk contagion is more obvious. But, there is an exception. If a larger c_f and a smaller $s_2(t)$ are taken in experiments 5 and 7, the increase of $s_1(t)$ doesn't cause obvious volatility of stock prices. In experiments 5 and 7, when investor neighbors' sensitivity to new information is low, risk contagion mainly depends on the fundamental contagion coefficient of investors affected by neighbors' sentiment rather than investor sensitivity to new information. Except for experiments 5 and 7, other experiments can be divided into two types: type 1 and type 2. The former is the experiment having a smaller c_f, including experiments 1, 2, 3, and 4. The latter is the experiment having a larger $s_2(t)$, including experiments 2, 4, 6, and 8. In the above two types, risk contagion is intensified with the increase of investor sensitivity to new information. In conclusion, a positive correlation exists between investor sensitivity to new information and stock price volatility, under the condition of a smaller fundamental contagion coefficient or larger sensitivity to new information from investor neighbors.

When $s_2(t)$ increases to a larger value, stock price volatility becomes more tempered to some extent. However, this conclusion does not apply to experiments 7 and 8. There are a larger c_f and a larger $s_1(t)$ in these two experiments. Specifically, when the parameter values of simulation experiments are $c_f = 0.85$ and $s_1(t) = 0.75$, stock price volatility shows an increasing trend with the increase of $s_2(t)$. This indicates that investor neighbors' sensitivity to new information can strengthen stock price volatility in the following two conditions: (1) a larger fundamental contagion coefficient and (2) larger investor sensitivity to new information. But, investor neighbors' sensitivity to new information cannot strengthen stock price volatility with a smaller contagion coefficient of investors affected by neighbors' sentiment or smaller investor sensitivity to new information. Because a smaller c_f or $s_1(t)$ can decrease the influences of new information on investor sensitivity, stock price volatility is more moderate with an increasing $s_2(t)$. If both c_f and $s_1(t)$ take larger parameter values, the increasing investor neighbors' sensitivity to new information will make stock price volatility stronger.

When c_f increases to a larger value, stock price volatility becomes more complicated. In simulation experiments, stock price volatility may strongly increase, or slightly increase, or slightly decrease, or show a little change. Concretely speaking, an increasing fundamental contagion coefficient can cause a strong increase in stock price volatility, with smaller investor sensitivity to new information and smaller investor neighbors' sensitivity to new information. When investor neighbors' sensitivity to new information takes a larger parameter value with smaller investor sensitivity to new information, an increasing fundamental contagion coefficient can cause a slight increase in stock price volatility. But, when investor sensitivity to new information takes a larger parameter value with smaller investor neighbors' sensitivity to new information, an increasing fundamental contagion coefficient can cause a slight decrease in stock price volatility. Finally, an increasing fundamental contagion coefficient makes stock price volatility show a little change, when both investor sensitivity to new information and investor neighbors' sensitivity to new information take larger parameter values, simultaneously. In short, the fundamental contagion coefficient of investors affected by neighbors' sentiment plays the important role in risk contagion under the following two conditions: (1) smaller investor sensitivity to new information and (2) smaller investor neighbors' sensitivity to new information.

REFERENCES

[1] T. Beck and R. Levine, "Stock markets, banks, and growth: Panel evidence," *J. Banking Finance*, vol. 28, no. 3, pp. 423–442, Mar. 2004.

[2] G. M. Caporale, P. G. A. Howells, and A. M. Soliman, "Stock market development and economic growth: The causal linkage," *J. Econ. Develop.*, vol. 29, no. 1, pp. 33–50, 2004.

[3] C. K. D. Adjasi and N. B. Biekpe, "Stock market development and economic growth: The case of selected African countries," *Afr. Develop. Rev.*, vol. 18, no. 1, pp. 144–161, Apr. 2006.

[4] A. A. Enisan and A. O. Olufisayo, "Stock market development and economic growth: Evidence from seven sub-Sahara African countries," *J. Econ. Bus.*, vol. 61, no. 2, pp. 162–171, Mar. 2009.

[5] C.-K. Choong, A. Z. Baharumshah, Z. Yusop, and M. S. Habibullah, "Private capital flows, stock market and economic growth in developed and developing countries: A comparative analysis," *Jpn. World Economy*, vol. 22, no. 2, pp. 107–117, Mar. 2010.

[6] J. N. Carpenter and R. F. Whitelaw, "The development of China's stock market and stakes for the global economy," *Annu. Rev. Financial Econ.*, vol. 9, no. 1, pp. 233–257, Nov. 2017.

[7] M. F. Guillén and L. Capron, "State capacity, minority shareholder protections, and stock market development," *Administ. Sci. Quart.*, vol. 61, no. 1, pp. 125–160, Mar. 2016.

[8] K. Adam, A. Marcet, and J. P. Nicolini, "Stock market volatility and learning," *J. Finance*, vol. 71, no. 1, pp. 33–82, Feb. 2016.

[9] T. Sharif, H. Purohit, and R. Pillai, "Analysis of factors affecting share prices: The case of bahrain stock exchange," *Int. J. Econ. Finance*, vol. 7, no. 3, pp. 207–216, Feb. 2015.

[10] A. Majumdar and A. Saha, "Influence of Macroeconomic Variables on Stock Market Volatility: A study on Nifty," *Asian J. Manag. Cases*, vol. 9, no. 1, pp. 440–444, 2018.

[11] C. M. Bilson, T. J. Brailsford, and V. J. Hooper, "Selecting macroeconomic variables as explanatory factors of emerging stock market returns," *Pacific-Basin Finance J.*, vol. 9, no. 4, pp. 401–426, Aug. 2001.

[12] T. Singh, S. Mehta, and M. S. Varsha, "Macroeconomic factors and stock returns: Evidence from Taiwan," *J. Econ. Int. Finance.*, vol. 3, no. 4, pp. 217–227, 2011.

[13] C. A. Yartey, "The institutional and macroeconomic determinants of stock market development in emerging economies," *Appl. Financial Econ.*, vol. 20, no. 21, pp. 1615–1625, Nov. 2010.

[14] Y. Huang and X. Yang, "Managers' overconfidence, risk preference, herd behavior and non-efficient investment," *Independ. J. Manage. Prod.*, vol. 10, no. 1, pp. 56–75, 2019.

[15] H. V. Dang and M. Lin, "Herd mentality in the stock market: On the role of idiosyncratic participants with heterogeneous information," *Int. Rev. Financial Anal.*, vol. 48, pp. 247–260, Dec. 2016.

[16] F. Wen, Z. He, X. Gong, and A. Liu, "Investors' risk preference characteristics based on different reference point," *Discrete Dyn. Nature Soc.*, vol. 2014, pp. 1–9, 2014.

[17] J. Freybote and P. A. Seagraves, "Heterogeneous investor sentiment and institutional real estate investments," *Real Estate Econ.*, vol. 45, no. 1, pp. 154–176, Feb. 2017.

[18] C. Yang and R. Zhang, "Dynamic asset pricing model with heterogeneous sentiments," *Econ. Model.*, vol. 33, pp. 248–253, Jul. 2013.

[19] E. Y. Peng, A. Yan, and M. Yan, "Accounting accruals, heterogeneous investor beliefs, and stock returns," *J. Financial Stability*, vol. 24, pp. 88–103, Jun. 2016.

[20] J. Li, "Investor sentiment, heterogeneous agents and asset pricing model," *North Amer. J. Econ. Finance*, vol. 42, pp. 504–512, Nov. 2017.

[21] H. Krichene and M.-A. El-Aroui, "Agent-based simulation and microstructure modeling of immature stock markets," *Comput. Econ.*, vol. 51, no. 3, pp. 493–511, Mar. 2018.

[22] R. Hafezi, J. Shahrabi, and E. Hadavandi, "A bat-neural network multi-agent system (BNNMAS) for stock price prediction: Case study of DAX stock price," *Appl. Soft Comput.*, vol. 29, pp. 196–210, Apr. 2015.

[23] V. Manahov and R. Hudson, "A note on the relationship between market efficiency and adaptability—New evidence from artificial stock markets," *Expert Syst. Appl.*, vol. 41, no. 16, pp. 7436–7454, Nov. 2014.

[24] Y.-F. Liu, W. Zhang, C. Xu, J. Vitting Andersen, and H.-C. Xu, "Impact of information cost and switching of trading strategies in an artificial stock market," *Phys. A, Stat. Mech. Appl.*, vol. 407, pp. 204–215, Aug. 2014.

[25] X. Zhang, J. Ping, T. Zhu, Y. Li, and X. Xiong, "Are price limits effective? An examination of an artificial stock market," *PLoS ONE*, vol. 11, no. 8, Aug. 2016, Art. no. e0160406.

[26] B. Wu and T. Duan, "Risk contagion and investor behaviour: A new perspective based on agent modelling," *J. Phys., Conf. Ser.*, vol. 1069, Aug. 2018, Art. no. 012028.

[27] H.-C. Xu, W. Zhang, X. Xiong, and W.-X. Zhou, "An agent-based computational model for China's stock market and stock index futures market," *Math. Problems Eng.*, vol. 2014, pp. 1–10, Oct. 2014.

[28] R. Cont and J.-P. Bouchaud, "Herd behavior and aggregate fluctuations in financial markets," *Macroecon. Dyn.*, vol. 4, no. 2, pp. 170–196, Jun. 2000.

[29] L. Feng, B. Li, B. Podobnik, T. Preis, and H. E. Stanley, "Linking agent-based models and stochastic models of financial markets," *Proc. Nat. Acad. Sci. USA*, vol. 109, no. 22, pp. 8388–8393, May 2012.

[30] V. Gontis and A. Kononovicius, "Consentaneous agent-based and stochastic model of the financial markets," *PLoS ONE*, vol. 9, no. 7, Jul. 2014, Art. no. e102201.

[31] G. Iori, "A microsimulation of traders activity in the stock market: The role of heterogeneity, Agents' interactions and trade frictions," *J. Econ. Behav. Organ.*, vol. 49, no. 2, pp. 269–285, 2002.

[32] T. Lux and M. Marchesi, "Scaling and criticality in a stochastic multi-agent model of a financial market," *Nature*, vol. 397, no. 6719, pp. 498–500, Feb. 1999.

[33] T. Yu and G. Cao, "Evolutionary dynamics of a multi-agent stock market model with many states," *J Syst. Eng.*, vol. 24, no. 1, pp. 89–93, 2009.

[34] R. Pascual, B. Pascual-Fuster, and F. Climent, "Cross-listing, price discovery and the informativeness of the trading process," *J. Financial Markets*, vol. 9, no. 2, pp. 144–161, May 2006.

[35] H. P. Boswijk, C. H. Hommes, and S. Manzan, "Behavioral heterogeneity in stock prices," *J. Econ. Dyn. Control*, vol. 31, no. 6, pp. 1938–1970, Jun. 2007.

[36] C. Hommes and D. In't Veld, "Booms, busts and behavioural heterogeneity in stock prices," *J. Econ. Dyn. Control*, vol. 80, pp. 101–124, Jul. 2017.

[37] W. Zhang, Z.-Q. Zhou, and X. Xiong, "Behavioral heterogeneity and excess stock price volatility in China," *Finance Res. Lett.*, vol. 28, pp. 348–354, Mar. 2019.

[38] C. Liu, Y.-L. Wu, and G.-F. Yan, "Simulation of game analysis based on an agent-based artificial stock market re-examined," *J. Zhejiang Univ.-Sci. A*, vol. 7, no. 4, pp. 564–569, Apr. 2006.

[39] N. Ehrentreich, "The original Santa Fe institute artificial stock market," in *Agent-Based Modeling* (Lecture Notes in Economics and Mathematical Systems), vol. 602. Berlin, Germany: Springer, 2008.

[40] N. Ehrentreich, "Technical trading in the Santa Fe institute artificial stock market revisited," *J. Econ. Behav. Org.*, vol. 61, no. 4, pp. 599–616, Dec. 2006.

[41] Y.-C. Huang and C.-Y. Tsao, "Evolutionary frequency and forecasting accuracy: Simulations based on an agent-based artificial stock market," *Comput. Econ.*, vol. 52, no. 1, pp. 79–104, Jun. 2018.

[42] J. Derveeuw, "Market dynamics and agents behaviors: A computational approach," in *Proc. Artif. Econ.*, vol. 564, 2005, pp. 15–26.

[43] W. Zhang, Z. Wu, Y. Zhang, and X. Xiong, "Adaptive behavior and strategy switching," *Int. J. Inf. Technol. Decis. Making*, vol. 13, no. 3, pp. 567–584, May 2014.

[44] J. B. Duarte Duarte, L. H. Talero Sarmiento, and K. J. Sierra Juárez, "Evaluation of the effect of investor psychology on an artificial stock market through its degree of efficiency," *Contaduría y Administración*, vol. 62, no. 4, pp. 1361–1376, Oct. 2017.

[45] B. Wu and T. Duan, "Agent-based analysis of risk contagion in stock market from perspective of econophysics," *J. Phys., Conf. Ser.*, vol. 1053, Jul. 2018, Art. no. 012109.

[46] M. A. Bertella, F. R. Pires, H. H. Rego, J. N. Silva, I. Vodenska, and H. E. Stanley, "Confidence and self-attribution bias in an artificial stock market," *PLoS ONE*, vol. 12, no. 2, 2017, Art. no. e0172258.

[47] H. Krichene and M.-A. El-Aroui, "Artificial stock markets with different maturity levels: Simulation of information asymmetry and herd behavior using agent-based and network models," *J. Econ. Interact. Coordination*, vol. 13, no. 3, pp. 511–535, Oct. 2018.

[48] C.-Y. Tsao and Y.-C. Huang, "Revisiting the issue of survivability and market efficiency with the Santa Fe artificial stock market," *J. Econ. Interact. Coordination*, vol. 13, no. 3, pp. 537–560, Oct. 2018.

[49] H. Yang and S. Chen, "A heterogeneous artificial stock market model can benefit people against another financial crisis," *PLoS ONE*, vol. 13, no. 6, Jun. 2018, Art. no. e0197935.

[50] W. Prates, N. Da Costa, M. R. Armada, and S. Da Silva, "Propensity to sell stocks in an artificial stock market," *PLoS ONE*, vol. 14, no. 4, Apr. 2019, Art. no. e0215685.

[51] B. Wu and T. Duan, "Nonlinear dynamics characteristic of risk contagion in financial market based on agent modeling and complex network," *Complexity*, vol. 2019, Jun. 2019, Art. no. 2946018.

[52] B. Wu and J. He, "Review of financial contagion in countries under opening economy conditions," *Comparative Econ. Social Syst.*, vol. 30, no. 2, pp. 87–96, 2014.

[53] T. Chen, X. Li, and J. Wang, "Spatial interaction model of credit risk contagion in the CRT market," *Comput. Econ.*, vol. 46, no. 4, pp. 519–537, Dec. 2015.

[54] Y. Dong, J. Wang, and T. Chen, "Price linkage rumors in the stock market and investor risk contagion on bilayer-coupled networks," *Complexity*, vol. 2019, Apr. 2019, Art. no. 4727868.

[55] B. Wu, T. Duan, and J. He, "Dynamics evolution of trading strategies of investors in financial market," *Comput. Econ.*, vol. 51, no. 4, pp. 743–760, Apr. 2018.

[56] S. M. Brooks, R. Cunha, and L. Mosley, "Categories, creditworthiness, and contagion: How Investors' shortcuts affect sovereign debt markets," *Int. Stud. Quart.*, vol. 59, no. 3, pp. 587–601, Sep. 2015.

[57] Q. Ying, T. Yousaf, Q. U. Ain, Y. Akhtar, and M. S. Rasheed, "Stock investment and excess returns: A critical review in the light of the efficient market hypothesis," *J. Risk Financial Manage.*, vol. 12, no. 2, p. 97, Jun. 2019.

[58] B. G. Malkiel, "The efficient market hypothesis and its critics," *J. Econ. Perspect.*, vol. 17, no. 1, pp. 59–82, Feb. 2003.

[59] R. J. Shiller, "From efficient markets theory to behavioral finance," *J. Econ. Perspect.*, vol. 17, no. 1, pp. 83–104, Feb. 2003.

[60] W. Bailey, A. Kumar, and D. Ng, "Behavioral biases of mutual fund investors," *J. Financial Econ.*, vol. 102, no. 1, pp. 1–27, Oct. 2011.

[61] E. I. Hoppe and D. J. Kusterer, "Behavioral biases and cognitive reflection," *Econ. Lett.*, vol. 110, no. 2, pp. 97–100, Feb. 2011.

[62] C. P. Gonçalves. *Artificial Financial Market Model*. Accessed: 2003. [Online]. Available: http://ccl.northwestern.edu/netlogo/models/community/artificial%20financial%20market

BINGHUI WU received the B.S. degree in power engineering from the Anhui University of Technology, China, in 2003, the M.S. degree in finance from the Lanzhou University of Finance and Economics, China, in 2008, and the Ph.D. degree from Southeast University, China, in 2017. He worked at the Lanzhou University of Finance and Economics, from 2008 to 2017. He is currently an Associate Professor with the International Business School, Shaanxi Normal University, China. His current research interests include agent-based computational finance, financial risk analysis, and complex system modeling.