Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.12785/amis/070446

Modeling and Simulation of the Artificial Stock Market Trading System

Jinchuan Ke[1,*], *Yuan Chen*[2]

[1]Beijing Jiaotong University, Beijing 100044, P. R. China
[2]Southwestern University of Finance and Economics, Chengdu 611130, P. R. China

Received: 15 Nov. 2012, Revised: 13 Jan. 2013, Accepted: 19 Jan. 2013
Published online: 1 Jul. 2013

Abstract: By means of computer simulation technique, this paper builds an artificial stock market model consisting of decision making agents. Through the fundamental and technical analysis in the aspects of investors, trading cost, transaction volume, risk-free interest, tick size and price-limit system, the model is used to indicate the volatility and liquidity. The results show that the stock index time series has obtained the characteristics of steep-peak and heavy-tail, which is in accordance with that of real stock market. It is also found that an appropriate increase of tick size or relax of price limit would help improve the market liquidity, but to some extent, increase the market volatility. The irrational behavior of institutional investors and large volume of transaction are also easy to result in stock market fluctuation.

Keywords: Simulation,Artificial Stock market,Volatility,Liquidity.

1. Introduction

The traditional financial theory is based on the premise of effective market, random walk and rational investment, however, the stock market is a complicated adaptive system which provides an environment for interaction between the traders. This makes the traditional theory unable to explain some abnormal phenomena in real market such as calendar effect, week effect and so on. Scholars have realized the limitations of traditional financial theory and begun to pay attention to the behavioral finance theory which is based on psychology and integrates the behavior of investors into the decision-making process, and try to reveal the heterogeneity of stock market investors [1,2]. The explanation is more reasonable to some extent of the market vision, but this new theory also encounters a problem which is difficult to describe with mathematical methods and description. With the development of computer science especially the artificial intelligence techniques, the quantitative simulation of financial markets have made the experimental finance become possible [3].

The artificial stock market came into being with the combination of experimental finance and behavioral finance. An artificial stock market is like any other model to simulate the stock price change of reality. Three types of approaches are used for representation: analytical, experimental and computational. In analytical models, the equations are used to describe market mechanisms; in experimental models, humans are used additionally to represent market participants; while in computational models, market dynamics are represented by means of software programs. The most innovative and most improved formation of computational models is the so-called agent-based artificial stock market. This approach typically uses artificial intelligence technologies to represent the adaptive behavior of market participants [4].

It was not until Lucass Economic Agent that artificial market became an independent study. Lucas (1986) proposed that each agent is a set of decision rules based on the preference and behavior of investors [5]. Holland (1991) brought in the idea of adaptive technology which built a foundation for the Santa Fe Institutes artificial financial market study [6]. In 1994, Palmer and Holland published the first paper on SFI artificial financial market,

* Corresponding author e-mail: jchke99@126.com

creating a precedent for calculating experimental finance. After the SFI stock market, Arthur and Holland (1997) proposed that the stock price is endogenous and has similar characteristics with that of reality [7], such as volatility autocorrelation, speculative bubbles, and so on. Bouchaud (2002) studied on the interaction between technical traders and fundamental traders [1]. LeBaron (2001) made a comprehensive overview of the early research achievements and pointed out that an agent would not have obvious advantages using a long span of historical data when making decisions and that artificial stock market would make a difference in predicting and evaluating the results of financial policies and regulations [8]. Zhang (2010) conducted theoretical analysis and experimental simulation of the artificial financial market [9]. Gao, Dai, and Yi (2005) reproduced the abnormal phenomena in real stock market such as fat-tailed distribution, fluctuations in aggregate and long-term memory by the simulation model [10]. Liu and Han (2007) analyzed individual behavior in a 14-stocks market with the assistance of Markowitzs portfolio theory, perfectly illustrating the combination of financial theory and computer simulation [11]. However, there are shortcomings of existing studies in the following two aspects: First, most of the research focused on reproduction the abnormal phenomena which are difficult to be explained by traditional finance theory and behavior finance theory, such as the works of Liu (2004), Yu (2007), Zeng (2005), and Sun (2007) [12, 13, 14, 15]. Second, most of the simulations are focused on the market-maker system, while China's stock market is a continuous auction mechanism.

Due to the deficiency of existing researches, this paper tries to provide a better simulation by taking into account China stock markets current situation in investor classification, investment strategy, trading mechanism which has great influence on the stock markets efficiency and its stability.

2. Construction of Artificial Stock Market

There are two types of traders in the stock market. One is the "fundamentalists" who are more interested in the fundamental analysis of a company and will buy shares of companies with good value and hold it for a certain period with the expectation of capital gain through the stock price going up. This is the classic Buy and Hold investment strategy. The other one is the "active traders" who often buy or sell shares based on the analysis of the stock price, making use of various technical indicators to make the trading strategy.

Traders make the investment decision according to the environment which would give rise to the price fluctuation, and the price fluctuation would in turn affect the trading behavior of investors. In this procedure of iteration, the artificial market will demonstrate the complicated self-adjustment simulation on the real stock market, where the typical simulation structure is shown in Figure 1.

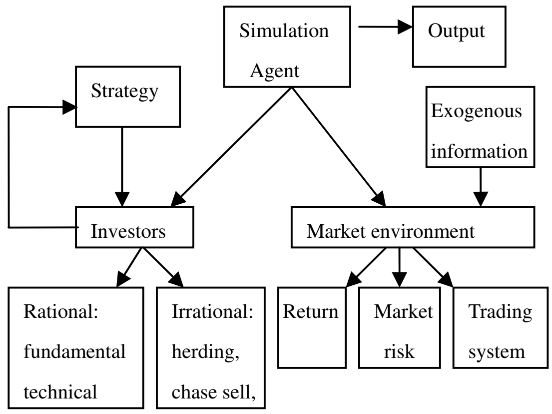

Figure 1: Module structure of the artificial stock market

In the experiment, the simulated stock market model is tested on a single stock where the artificial active traders demonstrated strong learning abilities and dynamic learning behaviors. Assuming that the market is made up of one stock which has fixed amount Q and does not provide dividend, the risk free interest rate is r_f, the interest income of cash will not be used for stock investment. In the stock market, supposed there are institutional investors and individual investors only with the proportion of 1 to n. The risk aversion coefficient of each investor is η_i and each investor's initial shares and cash are randomly distributed by the system. The stock market is a two-way continuous auction system. The transaction cost is f, the price limit is τ, the tick size is ρ, and short selling is not allowed. Meanwhile, the market will disclose the information such as closing price, trading volume, dividend, highest price, current lowest price, and so on.

2.1. Strategy Set

The investors trading strategies consist of the rational such as fundamental analysis and technical analysis, and of the irrational such as herding, chase selling, disposition, and so on. In certain stock environment, the investors will first choose a single strategy and make prediction based on the markets disclosed information, and then decide whether or not to trade by submitting the corresponding order based on their own profit requirement.

2.1.1. titleThe Strategy of Fundamental Analysis

The strategy of fundamental analysis is to compare the theoretical stock price with the market and then to see if the price is devalued or over-valued.

If $\frac{P_{*i}-P_{t-1}}{P_{t-1}} < -r_1$, then the price is over-valued, the future stock price will fall.

If $\frac{P_{*i}-P_{t-1}}{P_{t-1}} > r_1$, then the price is devalued, the future stock price will rise.

Where P_{*i} represents the theoretical stock price, P_{t-1} is the actual stock price on phase t-1. The value of r_1 is supposed to be selected randomly in the range within 5 percent and 10 percent.

Assuming the investor adjusts the stock price every 1000 phases, P_{*i} is the average of the stock price during the phases.

2.1.2. The Strategy of Technical Analysis

1) Moving average

This study sets up the moving average lines of 5 days, 10 days, 30 days, 60 days and 120 days, which are expressed by $MA_{x,t}$, $x \in \{5,10,30,60,120\}$, where x represents the type and t represents the time interval.

If $MA_{5,t-1} > MA_{10,t-1} > MA_{30,t-1} > MA_{60,t-1} > MA_{120,t-1}$, the moving average is lined in long, the price will rise.

If $MA_{5,t-1} < MA_{10,t-1} < MA_{30,t-1} < MA_{60,t-1} < MA_{120,t-1}$, the moving average is lined in short, the price will fall.

If $MA_{x,t-2} > MA_{y,t-2}$, $MA_{x,t-1} > MA_{y,t-1}$, and $x < y$, $x \in \{1,5,10,30,60,120\}$, $y \in \{5,10,30,60,120\}$, the short average line will go up and cross the long average line, the price will rise.

If $MA_{x,t-2} > MA_{y,t-2}$, $MA_{x,t-1} < MA_{y,t-1}$, and $x < y$, $x \in \{1,5,10,30,60,120\}$, $y \in \{5,10,30,60,120\}$, the short average line will go down and cross the long average line, the price will fall.

2) Volume /price theory

If $\frac{P_{t-1}-P_{t-2}}{P_{t-2}} > r_2, \frac{q_{t-1}-q_{t-2}}{q_{t-2}} > r_2$, then the trading volume and price both go up, the price will rise.

If $\frac{P_{t-1}-P_{t-2}}{P_{t-2}} > r_2, \frac{q_{t-1}-q_{t-2}}{q_{t-2}} < -r_2$, then the price rises and the volume goes down, the price will fall.

If $\frac{P_{t-1}-P_{t-2}}{P_{t-2}} < -r_2, \frac{q_{t-1}-q_{t-2}}{q_{t-2}} < -r_2$, then the trading volume and price both fall down, the price will fall.

If $\frac{P_{t-1}-P_{t-2}}{P_{t-2}} < -r_2, \frac{q_{t-1}-q_{t-2}}{q_{t-2}} > r_2$, then the price goes down and volume goes up, the price will rise.

The initial value of r_2 will be randomly selected in the range within 2 percent and 5 percent, q_t is the volume in the t phase.

3) MACD

Moving average convergence and divergence (MACD) is developed from the double moving average lines which represents the computation of the difference between two exponential moving averages (EMAs) of stock closing prices. A crossing of the MACD line through zero happens when there is no difference between the fast and the slow EMS. A move from positive to negative is a signal to sell, on the contrary, a move from negative to positive is a signal to buy. A large scale of MACD indicates that a market change is about to take place.

DIF is the difference between short-term and long term exponential smoothing moving average of close price.

DEADifference Exponential Averageis the exponential smoothing moving average line of M-day. Usually, M is 9, 12 or 26.

If $DIF_{t-1} > 0$, the price will rise.

If $DIF_{t-1} < 0$, the price will fall.

If $DEA_{t-1} > 0$, the price will rise.

If $DEA_{t-1} < 0$, the price will fall.

If $MACD_{t-1} > 0$, the price will rise.

If $MACD_{t-1} < 0$, the price will fall.

Where, DIF_{t-1}= $MA_{12,t-1}$ C $MA_{26,t-1}$, $MACD_{t-1}$ = DIF_{t-1} - DEA_{t-1}, DEA_{t-1} is the 9-day moving average of DIF.

2.1.3. Other strategies

1) Disposition Effect

The disposition effect is an anomaly discovered in behavioral finance. It is assumed that the investors are willing to sell the revalued stocks while keep the devalued stocks, and the rules are as follows:

If $\frac{P_{t-1}-C_{t-1}}{C_{t-1}} > r_3$, the stock price will rise.

If $\frac{P_{t-1}-C_{t-1}}{C_{t-1}} < -r_3$, the stock price will fall.

Where C_{t-1} represents the investors holding cost in phase t-1, its initial value is about 10 percent of P_{t-1}. The initial value of r_3 is randomly selected in the range within 3 percent and 10 percent.

2) Herding behavior

Herding behavior means that an individual investors behavior is affected by other investors, and then he/she follows the public's thinking or behavior. It is also known as the ”bandwagon effect”. The rules are as follows.

If $\frac{buy-sell}{sell} > r_4$, then the supply is less than the demand, the price will rise.

If $\frac{buy-sell}{sell} < -r_4$, then supply is more than the demand, the price will fall.

Where, the initial value of r_4 is randomly selected in the range within 3 percent and 10 percent, the total amounts of sell and buy are set to be 2000 and 1850 respectively.

3) Chase sell

If $\frac{P_{t-1}-P_{t-2}}{P_{t-2}} > r_5$, the price will rise.

If $\frac{P_{t-1}-P_{t-2}}{P_{t-2}} < -r_5$, the price will fall.

If $P_{t-3} < P_{t-2} < P_{t-1}$, the price will rise.

If $P_{t-3} > P_{t-2} > P_{t-1}$, the price will fall.

The initial value of r_5 is randomly selected in the range within 3 percent and 10 percent.

4) Absolute execution strategy

Assuming that each investor has certain tolerance of risk, when the risk exceeds the tolerance, the investors will not hesitate to make the disposition. The model sets the absolute execution strategy as follows:

If $\frac{P_{t-1}-C_{t-1}}{C_{t-1}} > i_6$, then sell the stock

If $\frac{P_{t-1}-C_{t-1}}{C_{t-1}} < -i_6$, then buy the stock

The initial value of is randomly selected in the range within 20 percent and 30 percent.

2.2. The Application of Strategy Set

For any strategy, it has the similar determine statement:

$$\text{if condition}_{\mathrm{j}_{t-1}} \text{ then } \left(\lambda_{\mathrm{i,j}}, \mathrm{w}_{\mathrm{i,j}}, \psi_{\mathrm{i,j}}\right)$$

Where, $\psi_{\mathrm{i,j}} \in \{0,1\}$, meaning whether the strategy is activated. If the historical information matches the condition of strategy, then the strategy is motivated, $\psi_{i,j}$ =1, otherwise, $\psi_{i,j}$ =0. $\lambda_{\mathrm{i,j}} \in [-1,1]$, meaning the investors estimation for the price. If $\lambda_{\mathrm{i,j}} \in [-1,0]$, the price will rise; if $\lambda_{\mathrm{i,j}} \in (0,1]$, the price will fall; if $\lambda_{i,j}$ =0 the price is unchanged. $W_{i,j}$ represents the strategys weight in the strategy set.

When more than one policy is activated, the investors will make the prediction based on the following steps:

(1) Determine the price trend by $a_{i,t-1}$. If $a_{i,t-1} > 0$, the investors think that the price will go up, if $a_{i,t-1} < 0$, the investors think that the price will go down. Where

$$a_{i,t-1}, b_{i,t-1} = \frac{\sum_{j=1}^{n} \lambda_{i,j} \cdot w_{i,j} \cdot \psi_{i,j}}{\sum_{j=1}^{n} w_{i,j} \cdot \psi_{i,j}}$$

(2) Find out the motivated strategies which have different trend with the predicted value in step 1, setting $\psi_{i,j}$ =0.

(3) Calculate $a_{i,t-1}$, and make prediction of the price. The expected value is $\mathrm{E_i}(\mathrm{P_t}) = (1+\mathrm{b}_{\mathrm{i},t-1})\mathrm{P}_{t-1}$

2.3. Investment Decision

After making forecast for the next period, the investors will make the trading if the transaction is profitable and achieve their profit requirement; otherwise, they might maintain the status quo.

$$\begin{cases} \frac{E_i(P_t)-P_{t-1}}{P_{t-1}} > r_f[1+(1-\eta_i)]+f, & buy \\ \frac{E_i(P_t)-P_{t-1}}{P_{t-1}} = r_f[1+(1-\eta_i)]+f, & unchanged \\ \frac{E_i(P_t)-P_{t-1}}{P_{t-1}} < r_f[1+(1-\eta_i)]+f, & sell \end{cases}$$

As for the offer price, many empirical studies show that new order flow is generally concentrated on the current highest bid and the minimum selling price around in the limit order book, and will not deviate too far (Zeng, 2007) [15]. Assuming the distance between the buy order and highest bid is $\mathrm{L_{s,i}}(\mathrm{t}) \bullet \theta$ and distance between sell order and minimum selling price is $\mathrm{L_{b,i}}(\mathrm{t}) \bullet \theta$, where θ is the tick size, the detailed rules are as follows:

$$\begin{cases} S_i(t) = S_{\min} + L_{s,i}(t) \cdot \theta \\ B_i(t) = B_{\max} + L_{b,i}(t) \cdot \theta \end{cases}$$

Where, S_i(t) is the asking price and B_i(t) is the bidding price, S_{min} and B_{max} are the minimum selling price and the highest bidding price in the order book, respectively. $L_{s,i}$(t) and $L_{b,i}$(t) are randomly selected from the normal distribution within 0 and 50.

Short sell is forbidden in this model, so the trading volume is limited by the maximum trading volume of traders and is influenced by their own preferences. The formula is as follows:

$$\begin{cases} X_i(t) = N(u, \xi_{i,t}) \\ u = \frac{(X_{i,t})_{\max}}{4}(1-\eta_i) \\ \xi_{i,t} = 0.3u \end{cases}$$

Where, $(\mathrm{X_{i,t}})_{\max} = \mathrm{I}_{\mathrm{i},t-1}/\mathrm{E_i}(\mathrm{P_t})$, representing the maximum buying amount; $(\mathrm{X_{i,t}})_{\min} = \mathrm{Q}_{\mathrm{i},t-1}$, representing the minimum selling amount. $I_{i,t-1}$ is the cash preservation from last phase, $Q_{i,t-1}$ is the stock preservation from last phase.

2.4. Investors Learning Mechanism

The investors learning ability is mainly reflected on the constant correction of trading strategy. At the end of each phase, the weight will be adjusted according to the accuracy of forecasting.

$$w_{i,j,t} = w_{i,j,t-1} \pm \left(1 - \left|\frac{E(P_t) - P_t}{P_t}\right|\right) \cdot \gamma$$

Where, $w_{i,j,t}$ is the weight in the strategy set at t moment; γ is a learning rate which is usually selected within 0 and 0.3.

The traders decision in learning depends on the result from self assessment. The traders assessment is calculated from the traders rate of profit based on each traders score in terms of peer pressure from other traders. In other words, this score shows the performance of one trader compared to the others. The final assessment for the traders is then normalized into the range of [0,1]. Depending on the assessment, a trader may choose to:

If a traders assessment is 1, and the trader is not using a strategy drawn from the pool, then he/she will copy the strategy into the central pool, and go into the next trading using the same strategy.

If a traders assessment is 1.0, and the trader is using a strategy copied from the pool, it is not necessary to do it again, just update the strategy and go into the next trading using the same strategy.

If a traders assessment is less than 0.9, the trader has a probability of 50 percent to copy a strategy from pool, which means the trader will discard whatever strategy is used, and select a better trading strategy from the pool and go into the next trading with this copied strategy. Or, with a probability of 50 percent, the trader will decide to discard whatever strategy being used, and select another set of indicators as inputs.

If the assessment is between 0.9 and 1, the trader is satisfied with the performance and continues to use the strategy.

A number of experiments with different threshold values were carried out to study the situation when a trader should be allowed to make the strategy.

3. Process of Simulation and Initial Parameters Setting

A trader that wants to make an offer to sell or to buy at a specific price sends a limit order to the order book, where it is visible for all the other traders. If a market participant wants to buy or sell right away, he or she can place an order instead. This order has no price limit, but is

Table 1: Initial parameters setting for simulation

Investors	institutional(s)	i ndividual(s)		
Quantity	4	1 000		
Initial Money	[5E+6,10E+6]	[1.0E+4,10.0E+4]		
Initial Stock	[2E+5, 8E+5]	[500,5000]		
Risk aversion η	r andom number N(0.2,0.1)			
λ (bullish)	[30%,10%]			
λ (bearish)	[-10%,-30%]			
Weight of Investors	100%	40%	30%	30%
Fundamental analysis	45%			35%
Technical analysis	45%	100%		45%
Other strategies	10%		100%	20%

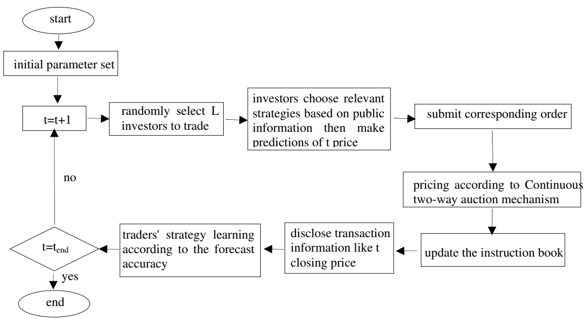

Figure 2: Simulation process of artificial stock market

matched with a suitable offer in the order book so that a trade will take place. The order book is sorted, so that the buy order offering the highest upper price limit, the best buy, will be the one that is matched with the first incoming market sell order. Equally, an incoming market buy order will be matched with the best ask, that is the lowest price that a seller is asking for. If a market order requests a greater volume of shares than is offered by the best-priced limit order, the trade will also encompass limit orders deeper into the order book, with perhaps another price. If several limit orders offer the same price, the earliest one will be matched before the later ones. This sorting principle is called price-time priority.

The model makes the following assumption about the initial parameters for the investors listed in Table 1.

After the initial parameters are set up, the simulation clock will move forward in a discrete which is shown in Figure 2. In cycle t, the system randomly picks up L investors to trade. When the transaction is finished, the market will disclose the information of close price and traded volume, giving a chance to refresh the strategies. Meanwhile, the system will also clear the instruction book and the simulation clock will move forward to t+1 cycle.

Considering the current stock environment, the parameters are set up as follows: Risk-free interest rate r_f=0.03, price limit τ=0.1, tick unit θ=0.01, the proportion of trading cost f=0.005, phases of historical data h=120, number of traders in each phase L=100.

The investors are consisted of institutional sector and individual sector. The individual investors still dominate in quantity, but their financial strength is no longer evident. According to annual report of China Securities Registration and Settlement Statistics 2008, the institutional investors held the market value of 54.62 percent.The difference between these two types of investors is mainly in that institutional investors have advantages in scale economics, information processing and relatively fixed investment philosophy and decision-making style. The investigation from Zhang (2010) suggests that 60 percent of the investors rely on their own independent analysis of investment decisions [9], while the remaining 40 percent rely on insider information, media, and expertise, etc. When making a decision, up to 35 percent investors use technical analysis. Meanwhile, more than 30 percent investors make an irrational strategy such as herding behavior.

4. Simulation Experiment

A random walk is the fundamental assumption in modeling for financial time series. It is a stepwise movement, where each step is taken in a randomly chosen direction. An example of a random walk is an individual moving sideways on a straight line, taking steps either to the left or to the right, with equal probability. Brownian motion is the continuous equivalent to a random walk, and has always been of interest when looking at financial data since the price curve emerging from a financial market actually follows a random walk. If the step size of a random walk is diminished and tends toward zero, the walk will approach a Brownian motion.

A central moment is the variance of the random variable, which measures how dispersed the possible values are around the mean. The normalized central moment is also known as the skewness. A kurtosis indicates the peakedness of a distribution, and is defined so that the kurtosis of a normal distribution will be zero. A positive kurtosis means a sharper and higher peak than the normal distribution, and also fatter tails. The variance of such leptokurtic distributions is more due to infrequent extreme deviations than to frequent moderate deviations. The leptokurtic distributions are of much interest in the analysis of financial time series, since price changes are not normally distributed, but have a positive kurtosis. This is disturbing for investors because the fat tails of distributions means that the investment is of high risk.

Through the simulation experiment, the time series of price and return rate are shown in Figure 3 and Figure 4. It is observed that the price and return both have obviously fluctuations. Meanwhile, the return series has the skewness and kurtosis of 6.280 and 0.053; the

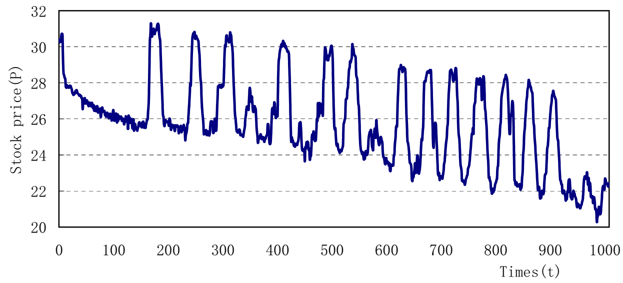

Figure 3: The time series of simulated stock price

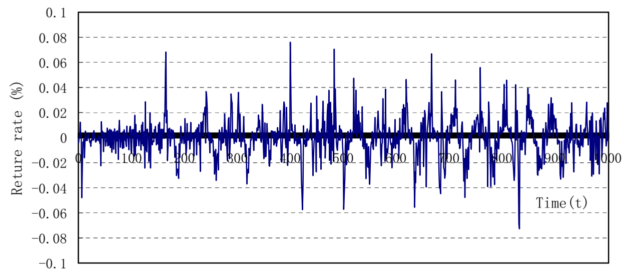

Figure 4: The time series of simulated return rate

sequence has a significant high-peak and fat-tail feature, and skewed to the right. These features coincide with the status quo of Chinas Shanghai and Shenzhen stock market. On the basis of above model, this article focuses on the input variables and analyzes the relationships between the stock market. The input variables include transaction cost, risk-free interest, investor formation, tick size, price limit system.

4.1. titleTransaction Cost, Risk-free Interest Rate and Trading Volume

It is well known that the increase in transaction cost or risk-free interest rate will lead to the increased opportunity cost of investing in stocks while the other conditions keep unchanged, thus the investors willingness to invest in stock market will decrease. This is verified from the simulation results shown in Figure 5 and Figure 6.

Moreover, as the opportunity cost increases, the variance of trading cost which is a proportion to the investment shows a downward trend in Table 2, reflecting a decreasing volatility, resulting in investors more cautious investment attitude. This is difficult to be testified by empirical analysis because of the interaction between transaction cost and risk-free interest rate or other factors. The artificial stock market can compensate for the deficiency of traditional mathematical models and show a superiority of controllability and repeatability.

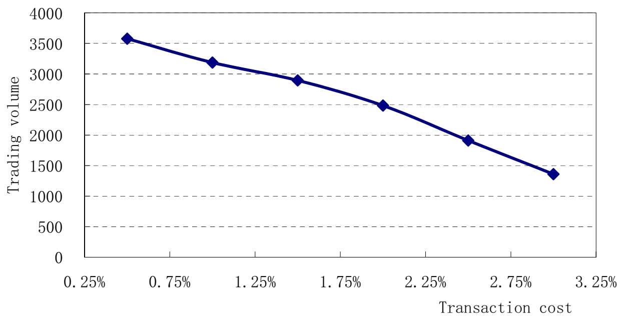

Figure 5: Relationship between transaction cost and volume

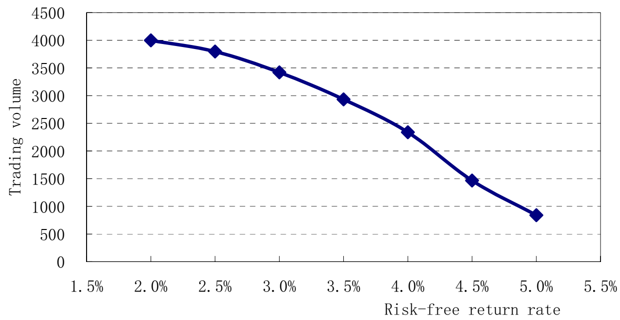

Figure 6: Relationship between risk-free interest and volume

Table 2: Variance changed with the trading cost

Transaction cost(f)	Variance(10^{-6})	Kurtosis	Skewness
0.0%	6.17	4.77	1.30
0.5%	6.75	9.71	1.72
1.0%	5.89	8.89	1.87
1.5%	4.27	6.20	1.37
2.0%	3.34	2.99	1.09
2.5%	2.89	8.71	2.15
3.0%	2.12	9.87	2.55

4.2. Volatility Influenced by Investors

Institutional investors play an important role in the capital markets. It has increased rapidly both in number and in proportion since China stock market starts to unconventionally develop institutional investors in 2001. However, institutional investors with large-scale development are accompanied by a question: what has the institutional investors brought about to China's capital market in the end? Whether it keeps the market stable or increases the market volatility?

The answer is testified in this study by changing the investors proportion. As shown in Figure 7, the relationship between investors proportion and the volatility of return varies in different phases. When the proportion of institutional investor is less than 90 percent, it can mitigate the increase in stock market volatility, but

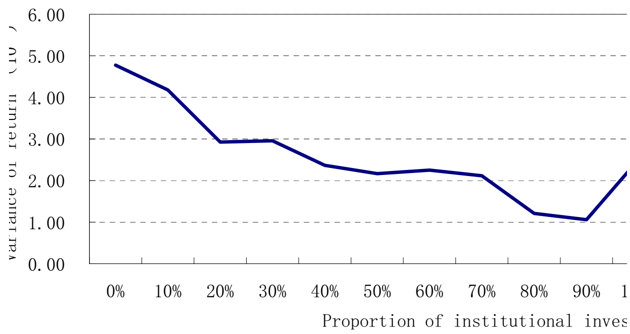

Figure 7: Variance of return vs. institutional investor proportion

the stabilizing effect is not the same at different stages. When the ratio increased from 10 percent to 20 percent, the stabilizing effect is obvious; in other stages, only a small increase in institutional investors can reduce the magnitude of stock market volatility. This is mainly due to the fact that institutional investors are more rational compared to the individual investors, so they offset the increase in the number of non-rational behavior of individual investors to stabilize the stock market. However, this stabilization requires a "quantitative to qualitative" change process. When the proportion exceeds 90 percent, this stabilizing effect no longer exists; on the contrary, the institutional investors are exacerbated by the rise in the proportion of stock market instability. At this stage, the irrational behavior of institutional investors and large volume of transaction is also easy to highlight the stock market fluctuation.

4.3. The Volatility and Liquidity Influenced by Tick Size and Price Limit

The standard deviation of return is used to measure the volatility, and the circulating velocity is used to measure the liquidity of the market. The circulating velocity L (t) is calculated as follows.

$$L(t) = \frac{N(t)}{[LM(t-1)+LM(t)]/2}$$

Where N(t) is the transaction volume in cycle t, LM(t) is the circulating market equity at the end of cycle t.

According to financial market microstructure theory, the trading mechanism is the endogenous variable for price formation and the main factor of market performance. However, the traditional empirical methods fail to strip out the impact of individual factors. The artificial stock market will compensate for this shortage and draw a more specific conclusion.

Table 3: Experiment results by changing tick size

Tick size (θ)	0.01	0.02	0.03	0.05
Std. of yields(10^{-2})	1.59	2.58	3.32	4.11
Effective bid-ask spread (10^{-2})	1.47	2.85	4.16	5.77
Circulation speed (10^{-3})	1.1	1.17	1.19	1.13

Table 4: Experimental results by changing price limit

Price limit range(τ)	10%	15%	20%	No limit
Std. of yields(10^{-2})	4	5.3	5.8	8.5
Circulation speed (10^{-3})	1.69	1.73	1.7	1.63

4.3.1. Tick Size

The stock market has practiced unified tick size ρ=0.01 *yuan* since the rule established. This trading mechanism has no problem when the change of stock price is small. However, with the increasing amount of high price stock, the change step becomes larger and larger, scholars like Liu and Han (2007) suggested that it is necessary to set different tick size according to different share prices [11]. To find out whether the suggestion is reasonable, this study conducts the simulation with fixed initial share price which is set about 30 *yuan*, and then the tick size ρ is changed at 0.01, 0.02, 0.03, and 0.05. The results are listed in Table 3.

As the tick size increases, the variation amplitude of stock price becomes larger but the concentration degree reduces, so that it increases the market volatility. The effective bid-ask spread moves in line with tick size, and the circulating velocity reaches the highest when the tick size is 0.03 *yuan*. It is also found that increasing tick size from 0.01 to 0.03 *yuan* is helpful to increase the liquidity. Concretely speaking, when θ changes from 0.01 to 0.03, the target price keeps unchanged although the bid-ask spread becomes larger, so that the investors may reduce the scope of offer and the cost of stock transaction negotiations. This can increases the limit order transaction protection of investors, thus improving the market liquidity. When θ is increased to 0.05, the effective bid-ask spread is too large, and the larger transaction cost will dampen investor transactions to reduce market liquidity.

4.3.2. Price Limit

In order to reduce the stock market bubble and stabilize the market, regulatory commission has taken a price limit system whereby 10 percent of the price limits. However, whether the price limit can achieve the policy objective has been controversial. Supporters argue that price limit for the over-reaction to market provides a cooling-off period which will reduce market volatility; while opponents argued that the implementation of price limit has hindered the price discovery process and does not play the role of price stability. In response to this controversy, the model conducts a simulation by setting different price limit with the percentage of 10, 15, 20 and unrestricted.

It can be seen in Table 4 that, along with the strengthening of price limits, the price volatility is reduced, indicating the price limit system indeed played a buffer role. This is mainly due to the use of ”chase sell” strategy for a larger proportion of non-rational investors in artificial stock market, and price limit system provides investors time to calm down and do a more rational decision-making, thereby reducing the excessive market volatility.

As for the liquidity, with the liberalization of price limit, the circulating velocity tends to increase at the beginning and then decrease. When price limit changes from 10 percent to 15 percent, price limit system is conducive to the dissemination of information and reduces information asymmetry, thus contributing to the market price discovery, improving the liquidity of stock market. When the price restriction is removed, because the model did not consider the interference of outside information policy, each decline in share price rose 20 percent to touch the lower limit and its stabilizing effect on stock prices is not obvious, so the market liquidity decreases.

Constraints in the model are never turned off. Some of these constraints are in fact due to trading mechanisms and independent of the chosen implementation. The functioning of the order book makes sure that a trader who wants to buy does not trade with any seller, but only with the one offering the best price. Although certain traders might follow what the other traders has done, most of them will probably do not change the order book right away.

5. Conclusion

The artificial stock market model provides a brand new method to analyze the stock market. The benchmark forms a key test for the market. The agent-based simulation gives a solution to understand why it is not converging in some instances, then how much can be discerned about the out of equilibrium structure, and learning dynamics of the market.

This study presents a computer simulation of the stock market based on the input variables which include transaction cost, risk-free interest, type of investors, tick size, and price limit system. The simulation has the advantage to overcome the problem of traditional empirical models that can not deal with more variables effectively. The simulation results show that the increase in transaction cost or risk-free interest will lead to increased opportunity cost of investing in stocks, thus reducing investor's willingness to buy stocks which declines the trading volume. The irrational behavior of institutional investors and large trade volume is also easy to increase the stock market fluctuations. An appropriate increase in the tick size and price limit system will help to relax the liquidity, but will increase to some extent, the volatility of the market. This requires the regulatory commission to fully weigh the volatility and liquidity in policy making.

Acknowledgement

This paper is supported by National Natural Science Foundation of China (project grant number: 70971009).

References

[1] J. P. Bouchaud, J. Mezard and M. Potters, Statistical Properties of Stock Order Books: Empirical Results and Models, Quantitative Finance **2**, 251-256 (2002).
[2] S. Kim Seok-Hun and K. Im, Business Model Characterization by Analyzing Business Model components of Patent Data, Applied Mathematics and Information Sciences **6**, 303-309(2012).
[3] M. Potters and J.P. Bouchaud, More Statistical Properties of Order Books and Price Impact, Physica A: Statistical Mechanics and its Applications **324**, 133-140 (2003).
[4] X. Zhao, A. He, J. Wu, A Mathematical Characterization of System Design and Modeling, Applied Mathematics and Information Sciences **6**, 345-356 (2012).
[5] R. Lucas, Rational Choice: the Contrast between Economics and Psychology, Adaptive Behavior and Economic Theory **1**, 217-242 (1986).
[6] J. Holland, J. Miller, Artificial Adaptive Agents, American Economic Review **81**, 365-370(1991).
[7] W. B. Arthur, J. Holland, B. LeBaron, R. Palmer. and P. Talyer, Asset Pricing under Endogenous Expectations in an Artificial Stock Market, The Economy as an Evolving Complex System **1**, 15-44 (1997).
[8] B. LeBaron, A Builders Guide to Agent based Financial Markets, Quantitative Finance **1**, 254-261 (2001).
[9] W. Zhang, W. Liu, Q. Wang, B. Liu, The Modeling for the Complexity of Capital Market: Agent-Based Computational Experiment Finance, Modern Finance and Economics **23**, 3-7 (2003).
[10] B. Gao, H. Dai, H. Xuan, An Agent-based Stock Market Simulation Model, Systems Engineering Theory Methodology Applications **6**, 19-23 (2005).
[11] W. Liu, L. Han, Simulation of Investors by Multi-Agent Artificial Stock Market Model, J. of Management **4**, 40-46 (2007).
[12] D. Liu, Z. Wang, H. Sun, H. Zhang, Simulation of Stock Prices Behavior Based on Agent, Computer Engineering **19**, 172-174 (2004).
[13] L. Sun and M. Lv, Simulation Research of Stock Market price, J. of Nanjing Audit University **4**, 20-25 (2007).
[14] T. Yu, Agent-based Modeling of Stock Market and its Complex Dynamics, Complex Systems and Complexity Science **21**, 43-51 (2007).
[15] H. Zeng and D. Shen, Simulation Research of Multi-agent Based Stock Market, J. of Computer Simulation **15**, 185-18 (2005).

Jinchuan Ke got master degree in Computer Science and PH.D degree in System Engineering from University of Alaska Fairbanks. Dr. Ke is currently a professor in the School of Economics and Management, Beijing Jiaotong University. His research area covers Information System, Financial Engineering, Risk management, Knowledge Management, and so on.