Simulation and Study on Trading Strategies in Stock Market

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Abstract

This paper uses behavioral finance theory and computational experimental financial methods to build artificial stock market based on Netlogo. The artificial stock market is driven by events, and the market clearing mechanism and price formation mechanism are determined by the supply and demand relationship. There are two trading assets in the market, and there are several traders who randomly choose the four investment strategies.

The simulation analysis results show that the trend of the number of momentum traders is opposite to the change of the number of reverse traders, and the number of noise traders and rational traders is relatively stable. Herd behavior has a major impact on the number of noise traders. One of the reverse traders and the momentum trader can obtain significant excess returns, but at the same time it exhibits considerable volatility of returns, which means that investors are also exposed to a much greater risk.

1 An artificial stock market

1.1 Entities:

Multiple agents which are both prospective buyers and prospective sellers.

There are two separate stocks on the market, whose prices are driven by events.

1.2 Basic theory

Each agent will make a choice to buy or sell in each transaction and determines the number of stocks traded. At the beginning, each agent randomly selects their trading strategy and then adjusts the strategy based on their earnings over time.

The trading price of a stock is determined by the supply and demand relationship between the buyers and the sellers in the market. If the supply exceeds the demand, the corresponding stock price decreases; if the supply is less than demand, the price rises.

1.3 Model hypothesis

Assume that neither stock produces dividends;

Assume that trading stocks do not incur transaction costs;

Assuming no deposit system, so there is no linked mark-to-market system;

Assume that each stock can be short-selling with restrictions;

Assume that all agents in the market are divided into four categories.

1.4 Trading Strategy

1) Contrary Strategy:

Those who choose contrary strategy believe that the market will overreact, sorting stock returns over the past period, then buying stocks that have performed poorly in the past and selling stocks that performed well in the past.

2) Momentum Strategy:

Contrary to the contrary strategy, they believe that the price trend will continue, so they tend to buy stocks that perform well and sell stocks that perform poorly.

3) Rational Strategy:

Rational traders will independently evaluate two stocks based on the relationship between price and intrinsic value. They think that when the asset price is seriously overvalued, they will sell the assets. On the contrary, if the assets are undervalued, they will buy the assets.

4) Noise Traders:

Noise traders' judgments on the two stocks are also independent, but their judgment on the market is based on irrationality, and their investment decisions are determined by individual psychological bias, environmental forces (herd behavior), and random factors.

5) Update Strategy

Each agent has a certain amount of cash and stock at the beginning of the simulation. In the beginning, the cash and stock holdings for each trader are both zero.

> The trader's wealth is cash + stock holdings 1 * current price of stock 1
> + stock holdings 2 * current price of stock 2.

At the end of each transaction, check each trader's wealth. When the wealth is negative, indicating the trader's investment loss, then he has the motivation to change the investment strategy. The probability that the trader changes the investment strategy is set as the attribute (convert-rate), randomly converted to one of four investment strategies. This process can also be seen as a trader's learning, both traders who exit the market and traders who enter the market new.

2 Netlogo design of the artificial stock market

Netlogo's design is divided into three steps. First, establish the basic environment global variable of the simulation stock market, and then establish the patch attribute of different agents in the environment. Third, for some parameters that have a key influence on the stock price, the addition can be done according to the designer. The changed slider attribute is required, and finally the setup initialization setting and the programming of go are performed, and the result is drawn into a graph.

1） Gobal Variable

Table 1: Gobal Variable

Gobal Variable	Description
news-qualitative-meaning	The news of stock change on the market
intrinsic-value	The current intrinsic value of the stock, determined by news-qualitative-meaning
price	Current market price of stocks
price-%-variation-one	*return/price*
continuity	Compare the current trend of stocks in the previous period
return	*sum[stock_trade])/(sum[abs(stock_trade)]*
indicator-volatility-one	The absolute value of the income, showing the intensity of competition between the supply and demand
initial-price-adjustment-Contrarian	Adjustment of the basic period of the contrarian trader
initial-price-adjustment-Momentum	Adjustment of the basic period of momentum traders
initial-price	The stock price under the basic period

2）patch

In this simulation, we use different color patches to refer to the four types of traders. Blue represents a trader who chooses a rational strategy, Yellow represents a trader who chooses a reverse strategy, Green represents a trader who chooses a momentum trading strategy, and Red represents a noise trader.

Table 2: Patch Parameter

Patch Parameter	Description
private-message	Before the transaction, each trader will get information about the expected price rise or decrease of the stock.
Cash	The initial value is 0, then updated by the sell and buy of stocks.

stock-trade	Buy or sell a certain number of stocks
stock-hold	The accumulation of stock trading volume, the initial value is 0. When the value is negative, the trader has taken a short sale.
trade-direction	In the direction of the trade, if the trader decides to buy the stock as +1, the opposite is -1.

3）Slide Parameter

We can use the slider to set the parameters we think have a key influence on the stock price. The slider attribute can provide a certain range of variation and change the step size of these parameters, thus making the research on these key attributes more convenient. Researchers can adjust these parameters from time to time to observe market reactions and the status of traders.

Table 3: Slide Parameter

Slide Parameter	Description
scale-of-foundamentalists	Total number of traders on the artificial stock market
correct-rate	The probability that a trader receives a private-message that correctly reflects news-qualitative-meaning before each transaction begins.
Convert-rate	The probability that a trader will convert a strategy in the event of a loss.
Affect-rate	The proportion of noise traders affected by personal factors and herding effects.
limitation-of-short-selling	Short selling restrictions in the artificial stock market
base-term	Observing the variables of the basic period

4) Netlogo Model Building

(1) Initialize the program *'set up'*

Step 1: Initialize market environment parameters and trader holding assets

Step 2: Determine the investment strategy of patches in the market based on (scale-of-fundamentalists),

First let all the patches to 'blue', which means rational traders,

Then make each patch produce random from 0 to (scale-of-fundamentalists),

- If the random number is 0, the color of the patch changes to 'yellow' (contrary trade);
- If the random number is 1, the color of the patch changes to 'green' (momentum trader);
- If the random number is 2, the color of the patch changes to 'red' (noise trader);
- If the random number is other, the color of the patch is still 'blue' (rational traders).

(2) Main program *'go'*

<u>**Step1: Update the stock news *'news-arrival-one'* and *'news-arrival-two'***</u>

Firstly, independently judge the market development direction of two stocks: introduce a random number with a standard normal distribution,

- If the random number is greater than 0, then the information for this period of the stock is positive, the stock price will rise, and the ***'news-qualitative-meaning'*** is +1,

  Price = intrinsic-value + random (0-1).
- If the random number is less than 0, then the information for this period of the stock is negative, the stock price will fall, so the '***news-qualitative-meaning*** 'is -1,

  Price=intrinsic-value - random(0-1)

Secondly, determine if the trader can get the correct information: randomly generate a floating point number from 0 to 1, and compare it to the initially set ***'correct-rate'***.

- If the random value is less than correct-rate, then the trader is considered to be able to correctly obtain the '***news-qualitative-meaning*** ' information on the market;
- If the random number is greater than correct-rate, then the trader is not able to correctly obtain the '***news-qualitative-meaning*** ' information on the market.

Thirdly, determine the market news that each trader ultimately receives. If the trader believes that the market will rise in the future, the ***'private-message'*** is +1, otherwise the ***'private-message'*** is -1.

Step 2: Traders execute trades according to different strategies 'patches-decision'

First of all, ***'stock-trade-one', 'stock-trade-two', 'trade-direction-one', and 'trade-direction-two'*** are initialized to zero.

Then, according to the different investment strategies of different traders, the classification design is carried out.

- When the trader chooses Contrarian Strategy: first set ***'base-term'*** and determine ***'initial-price-one-Contrarian', 'initial-price-two-Contrarian'***,

  If the yield of stock 1 is greater than that of stock 2, the trader will buy stock 2 and then sell stock 1.

Yield = (Price – initial_price_Contrarian)/initial_price_Contrarian.

- When the trader chooses Momentum Strategy, the trader's strategy is exactly the opposite of the reverse trader. They buy stocks with higher yields and sell stocks with lower yields.

Yield = (Price – initial_price_* Momentum)/initial_price_* Momentum*.*

- When the trader is a noise trader, the decision includes the other trader's decision around him, his own judgment on the market, and the random interference factor subject to the standard normal distribution. The impact weights of personal judgment and herd effect are ***affect-rate*** and ***1-affect-rate***.

  If the calculation result is greater than 0, the stock is bought; if it is less than 0, the stock is sold. In this model, if the noise trader's expectations are the same as the market's trend, the noise trader will feel confident, so his '***affect-rate'*** will increase.

Decision = affect_rate * sum[trade_direction_one]of neighbors + (1 – affect_rate) * private_message_one +(random_normal 0-1)

- When the trader is a rational trader. If the trader judges that the intrinsic value of the stock is greater than the market price of the stock, he will issue the buy stock; and if the trader judges that the intrinsic value of the stock is less than the market price of the stock, he will issue the stock.

Finally update all stocks' stock holdings '***stock-hold'***, which is the cumulative value of stock trading.

Step 3: market-clearing

$$\text{return} = \frac{\Sigma\, Stock\_trade}{\Sigma\, |Stock\_trade|}$$

$$\text{price\_variation} = \frac{return}{price}$$

$$\text{price}_{new} = \text{price} + \text{return}$$

$$continuity \times return \begin{cases} < 0 \Rightarrow continuity = \dfrac{return}{|return|} \\ > 0 \Rightarrow continuity = \dfrac{return}{|return|} \times |continuity + 1| \end{cases}$$

Step 4: update-strategy

- If wealth < 0, the trader has an investment loss and would change his trading strategy randomly.
- If wealth > 0, the trader continues to use the same strategy.

Step 5: Observing the volatility of investment behavior

indicator-volatility=abs (return),

Used to indicate the competition of traders in the market.

(3) *'do-plot'*

In this simulation, we focus on the degree of deviation of price from intrinsic value over time, the change in the returns of various traders, and the impact of different factors on the survival of traders. Therefore, the horizontal axis is time, and the vertical axis represents the variable we are interested in. For specific graphic variables and attributes, please see the following table:

Table 4 : graphic variables and attributes

Graphic Space Name	Graph Name	Graphic Space Name	Graph Name
Total	number-of-ContrarianTraders	intrinsic-value-one	intrinsic-value-one
	number-of-MomentumTraders	price-one	price-one
	number-of-NoiseTraders	intrinsic-value-two	intrinsic-value-two
stock-trade-one	trade-of-contrariantraders	price-two	price-two
	trade-of-momentumtraders	return	return-one
	trade-of-noisetraders		return-two
stock-trade-two	trade-of-contrariantraders	volatility	indicator-volatility-one
	trade-of-momentumtraders		indicator-volatility-two
	trade-of-noisetraders	wealth-of-contrariantraders	wealth-of-contrariantraders
stock-hold-one	hold-of-contrariantraders		wealth-of-rationaltraders
	hold-of-cmomentumtraders	wealth-of-momentumtraders	wealth-of-momentumtraders
	hold-of-noisetraders		wealth-of-rationaltraders
stock-hold-two	hold-of-contrariantraders	wealth-of-noisetraders	wealth-of-noisetraders
	hold-of-cmomentumtraders		wealth-of-rationaltraders
	hold-of-noisetraders		

3 The result of simulation

We obtain the following result when we simulate 1120 times of experiment. The color yellow, green, red and blue represent contrarian traders, momentum traders, noise traders and rational traders respectively.

Figure : The intrinsic value of stock one

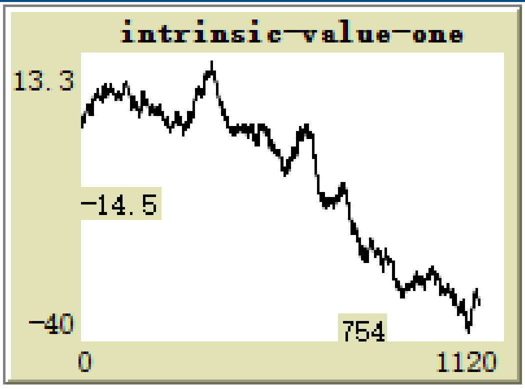


Figure : The market price of stock one

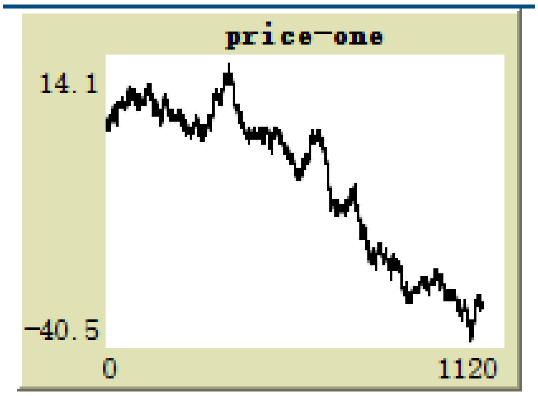


Figure : The intrinsic value of stock two

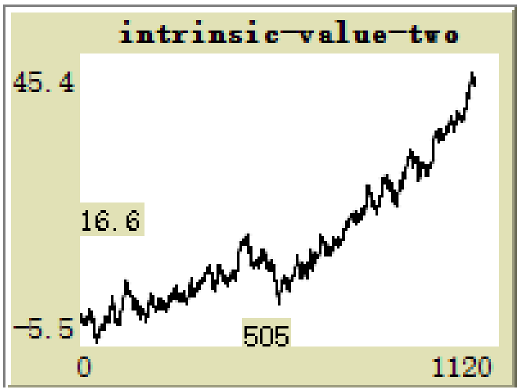


Figure : The market price of stock two

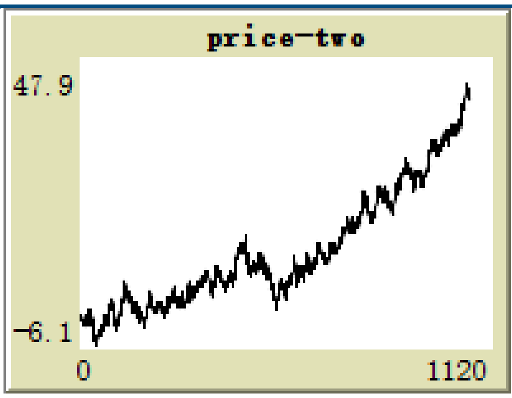


Figure : The number of hold for stock one

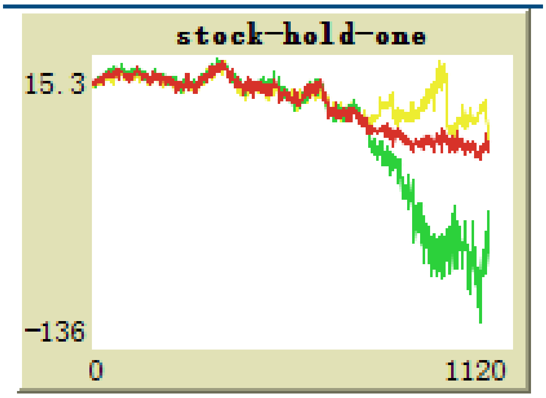


Figure : The number of hold for stock two

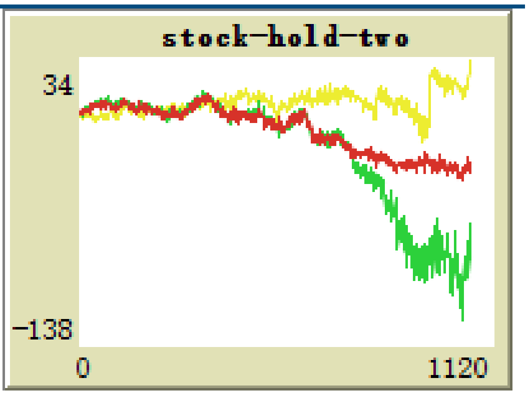
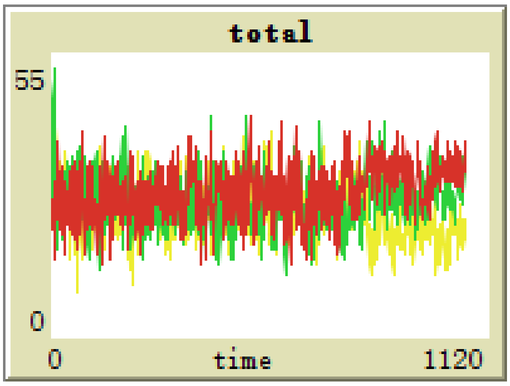


Figure : The number of not noise traders

Figure : The return of market



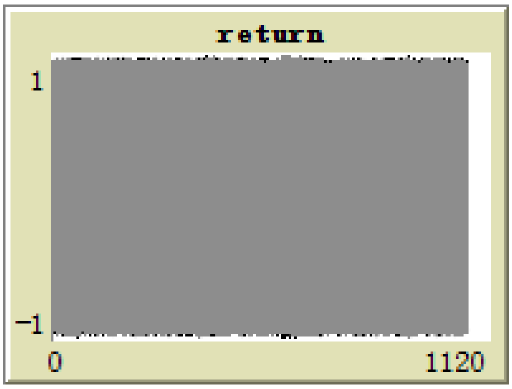


Figure : The volatility of market

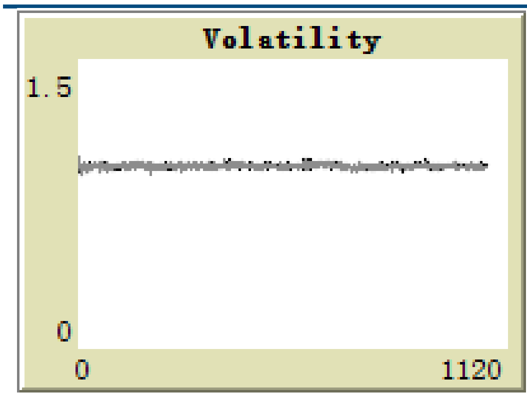


Figure : The wealth of noise and rational traders

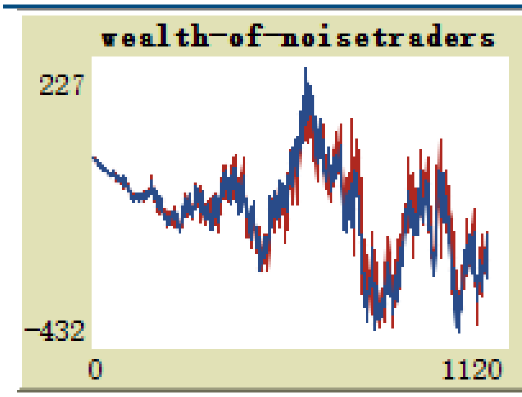


Figure : The wealth of contrarian and rational traders

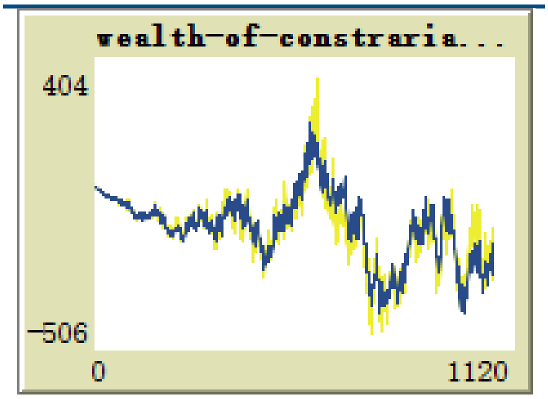
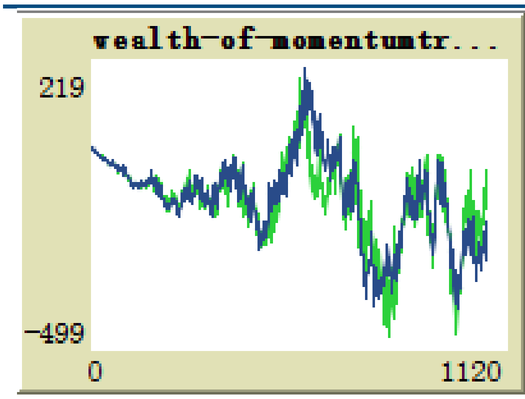


Figure : The wealth of momentum and rational traders



4 The analysis of simulation result

4.1 The relationship between the market price and intrinsic value

4.1.1 The causal relationship between market price and intrinsic value

According to the result of Netlogo platform, we apply Eviews statistic method to test whether stock market price have causal effects on intrinsic value. The null hypothesis is that the stock market price is the reason that cause the change of intrinsic value and the intrinsic value resulting in the variety of market price.

Figure : The Granger Causality test of stock one

Pairwise Granger Causality Tests
Date: 03/18/19 Time: 20:48
Sample: 1 907
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
PRICE_ONE does not Granger Cause INTRINSIC_VALUE_ONE	905	1.23829	0.2904
INTRINSIC_VALUE_ONE does not Granger Cause PRICE_ONE		117.978	3.E-46

Figure : The Granger Causality test of stock two

Pairwise Granger Causality Tests
Date: 03/18/19 Time: 20:54
Sample: 1 907
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
PRICE_TWO does not Granger Cause INTRINSIC_VALUE_TWO	905	0.22916	0.7952
INTRINSIC_VALUE_TWO does not Granger Cause PRICE_TWO		129.240	5.E-50

Under the 0.05 significant level, the probability of intrinsic value of two stocks influence the market value all less than 0.05, thus we can reject null hypothesis and conclude that the intrinsic value will affect the market value for both stocks. However, the probability of market price of two stocks influence the intrinsic value all larger than 0.05, thus we cannot reject null hypothesis and conclude that the market price cannot affect the intrinsic value for both stocks.

4.1.2 The Stationarity test of price series

The stationarity of time series means that the statistical properties such as mean, variance and autocorrelation will not change with time. In this part, we test the stationarity of market price series by estimating ADF. The market series can be considered as time series. The null hypothesis is that the market price series has a unit root (means the market prices series is not stationary). For the two stocks, the probability of ADF test both larger than 0.05, we cannot reject the null hypothesis and conclude that the two stocks market price series are not stationary. Then we test the first difference of two stocks market price series and find that the first difference of two stocks market price series are stationary. We can summary that the market price series which is simulated by Netlogo is in line with operating method of the actual stock market.

Figure : The ADF test of stock 1 market price

Figure : The ADF test of first difference of stock 1 market price

Augmented Dickey-Fuller Unit Root Test on PRICE_ONE

Null Hypothesis: PRICE_ONE has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.035719	0.2709
Test critical values:	1% level	-2.567517	
	5% level	-1.941173	
	10% level	-1.616464	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRICE_ONE)
Method: Least Squares
Date: 03/18/19 Time: 21:20
Sample (adjusted): 2 907
Included observations: 906 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PRICE_ONE(-1)	-0.002456	0.002371	-1.035719	0.3006

R-squared	0.001157	Mean dependent var	0.004829
Adjusted R-squared	0.001157	S.D. dependent var	0.926357
S.E. of regression	0.925821	Akaike info criterion	2.684831
Sum squared resid	775.7155	Schwarz criterion	2.690139
Log likelihood	-1215.228	Hannan-Quinn criter.	2.686858
Durbin-Watson stat	2.609998		

Augmented Dickey-Fuller Unit Root Test on D(PRICE_ONE)

Null Hypothesis: D(PRICE_ONE) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-41.33701	0.0000
Test critical values:	1% level	-2.567520	
	5% level	-1.941173	
	10% level	-1.616464	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRICE_ONE,2)
Method: Least Squares
Date: 03/18/19 Time: 21:21
Sample (adjusted): 3 907
Included observations: 905 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(PRICE_ONE(-1))	-1.308069	0.031644	-41.33701	0.0000

R-squared	0.654004	Mean dependent var	-5.68E-05
Adjusted R-squared	0.654004	S.D. dependent var	1.498375
S.E. of regression	0.881365	Akaike info criterion	2.586415
Sum squared resid	702.2315	Schwarz criterion	2.591728
Log likelihood	-1169.353	Hannan-Quinn criter.	2.588444
Durbin-Watson stat	2.091519		

Figure : The ADF test of stock 2 market price

Figure : The ADF test of first difference of stock 2 market price

Augmented Dickey-Fuller Unit Root Test on PRICE_TWO

Null Hypothesis: PRICE_TWO has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.033024	0.6716
Test critical values:	1% level	-2.567517	
	5% level	-1.941173	
	10% level	-1.616464	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRICE_TWO)
Method: Least Squares
Date: 03/18/19 Time: 21:16
Sample (adjusted): 2 907
Included observations: 906 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PRICE_TWO(-1)	-5.66E-05	0.001714	-0.033024	0.9737

R-squared	-0.000983	Mean dependent var	-0.028959
Adjusted R-squared	-0.000983	S.D. dependent var	0.923516
S.E. of regression	0.923970	Akaike info criterion	2.680828
Sum squared resid	772.6163	Schwarz criterion	2.686136
Log likelihood	-1213.415	Hannan-Quinn criter.	2.682855
Durbin-Watson stat	2.626687		

Augmented Dickey-Fuller Unit Root Test on D(PRICE_TWO)

Null Hypothesis: D(PRICE_TWO) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-41.64781	0.0000
Test critical values:	1% level	-2.567520	
	5% level	-1.941173	
	10% level	-1.616464	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRICE_TWO,2)
Method: Least Squares
Date: 03/18/19 Time: 21:18
Sample (adjusted): 3 907
Included observations: 905 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(PRICE_TWO(-1))	-1.314831	0.031570	-41.64781	0.0000

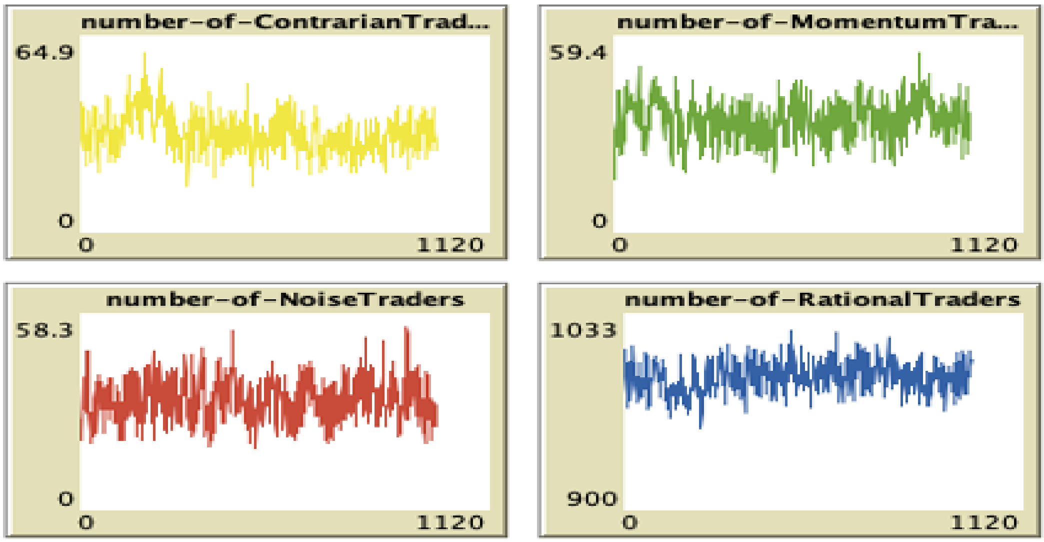
R-squared	0.657386	Mean dependent var	5.48E-05
Adjusted R-squared	0.657386	S.D. dependent var	1.498353
S.E. of regression	0.877034	Akaike info criterion	2.576563
Sum squared resid	695.3469	Schwarz criterion	2.581876
Log likelihood	-1164.895	Hannan-Quinn criter.	2.578592
Durbin-Watson stat	2.076859		

4.2 Analysis of market status of traders

4.2.1 The general conclusions about the state of stock market

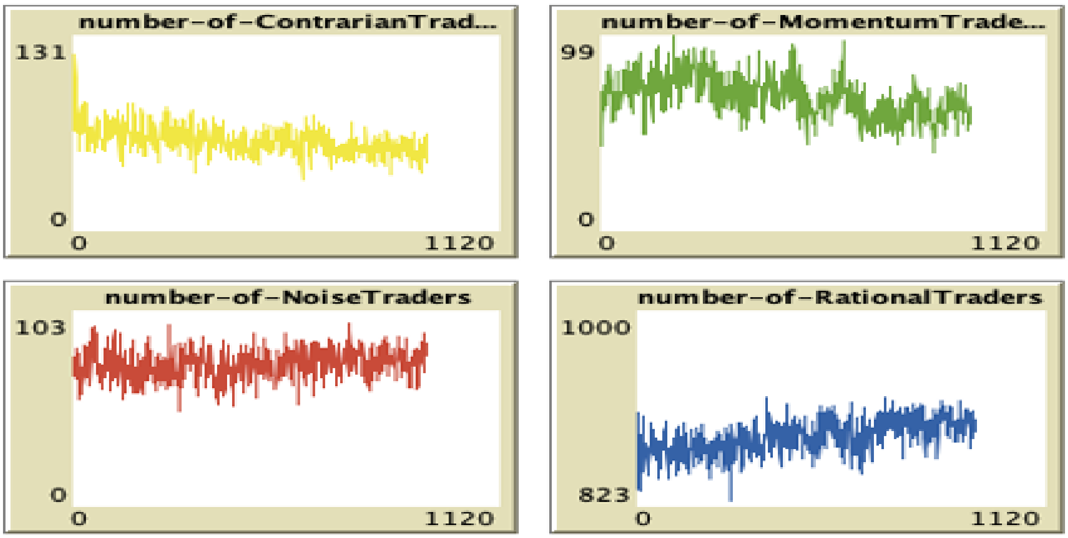
Firstly, we set the basic parameters of simulation market as following: the scale of fundamentalists equals to 32, the correct rate equals to 0.5, the affect rate equals to 0.27, the limitation of short selling equals to 150 and the base term contrarian and base term momentum all are 1. The result of the simulation platform is presented in the following figures.

Figure : The result of initial state



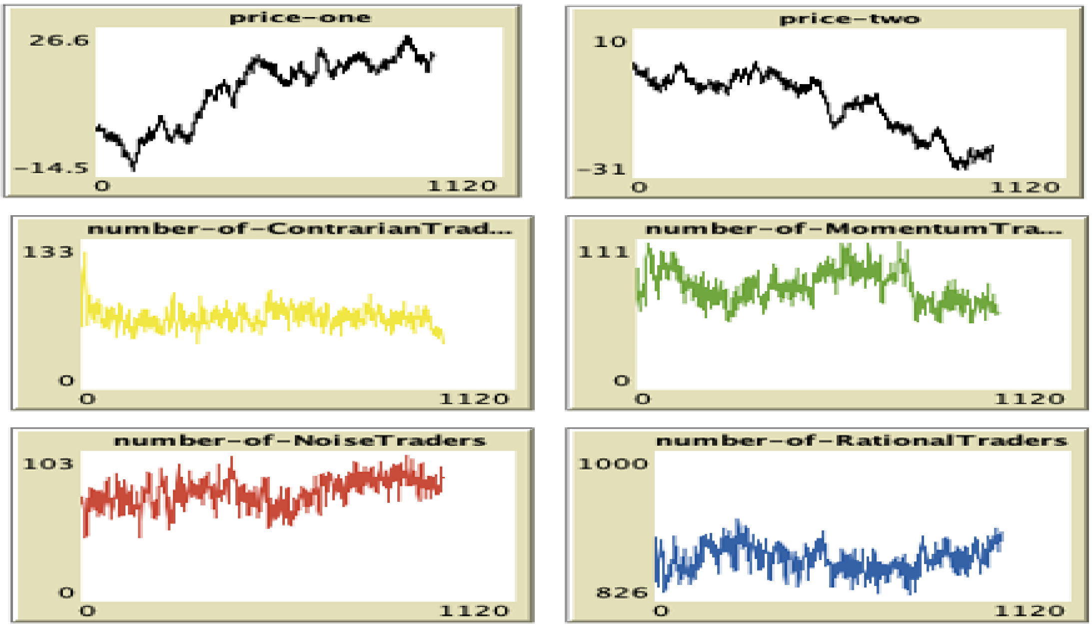
It can be seen from the observation that the number of momentum traders and reverse traders has the largest volatility, followed by the number of noise traders. The fundamental reason is that momentum traders and reverse momentum traders are most sensitive to the change of market price, so the volatility is the most obvious. Furthermore, there are opposite tendency for the change of contrarian traders and momentum traders in result. The tendency appears obvious when we alter the scale of fundamentalists to 15.

Figure : The result after change state



We assume that there are two types of financial assets in the market, so that the execution of a trader's strategy depends not only on the change of one stock, but also on the performance of multiple assets, which closer to the actual market. For the extreme cases (one stock price rises sharply and the other falls sharply), The experimental results we obtained are shown in the following figure. The volatility trend of contrarian traders and momentum traders is opposite in extreme cases, which is same with the real stock market.

Figure : The result of extreme case



4.2.2 The influence of the choice of base period on the trading state

We set the base term contrarian and base term momentum is both 1 firstly and change base term contrarian to 3 after 1000 times experiments. The contrarian traders and momentum traders have the largest fluctuations and have a clear trend in the opposite direction. Similarly, the result is same when base term contrarian remains unchanged while base term momentum is altered. Thus we can conclude that the choice of observing base period has no influence on the strategic choice and learning of investors.

Figure : The intrinsic value of stock one

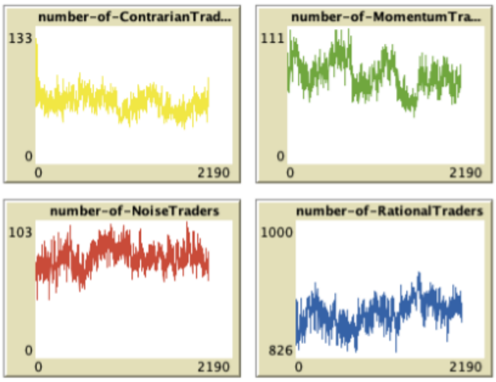
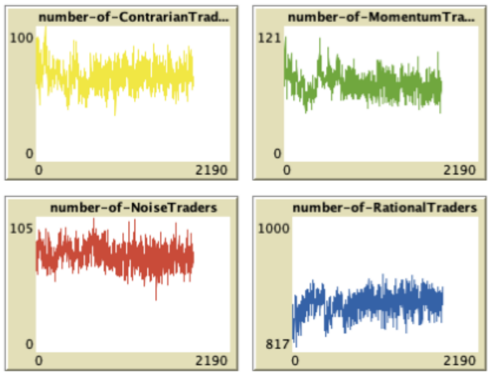


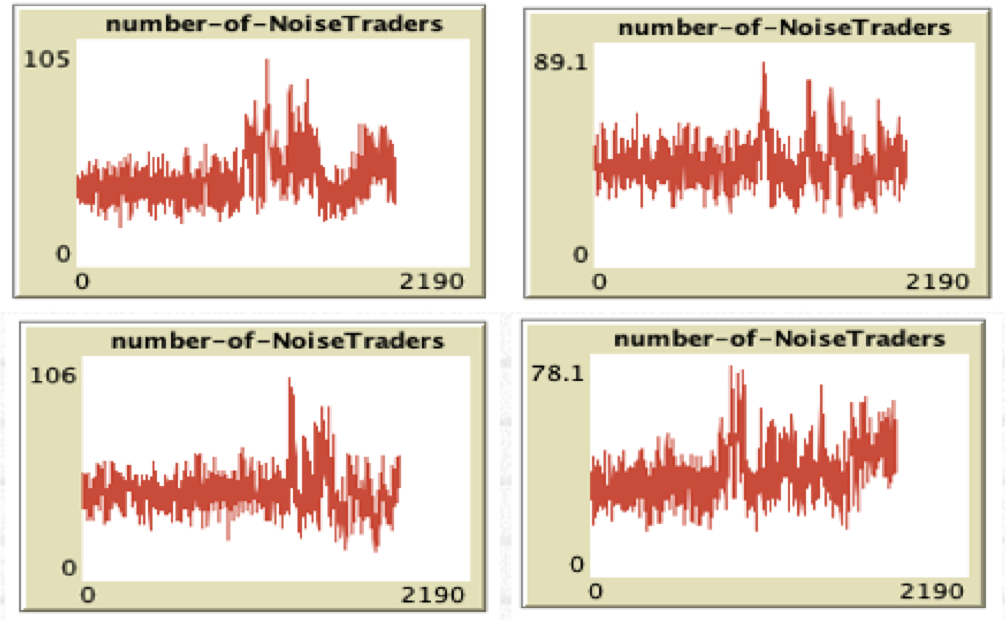
Figure : The market price of stock one



4.2.3 The influence of noise affect-rate on transaction status

Affect-rate represents the proportion of noise traders' investment decision execution affected by individual factors and herd factors, meanwhile, we have designed noise traders to increase and decrease this weight through expected feedback from the market. At the beginning, we select affect-rate is 0.8, which means individual factors greater influence the investors' decision than herb factors. Then, we change the affect-rate to 0.2 after 1000 transactions and the herb factors effect was dominant. We find that noise traders' quantity volatility increases significantly after several tests, which indicates that herding factors are the main reason for the fluctuation of noise population.

Figure : The result after change state



The transaction volume of the two stocks also changes significant when affect-rate alter. Many tests show that the transaction volume of two stocks fluctuate between positive and negative 0.8 when the affect-rate is 0.8, while the trading volume decreases rapidly and fluctuate between positive and negative 0.6, which is also the result of the herd effect.

4.3 The analysis of traders' benefit

The investors have different responses to the rise and fall of stock prices due to investors adopt different investment strategies. Therefore, we analyze the returns of various investors based on the different trends of the two stocks. We divide the trends of two stocks into four cases.

Figure : Case 1 both stocks rise

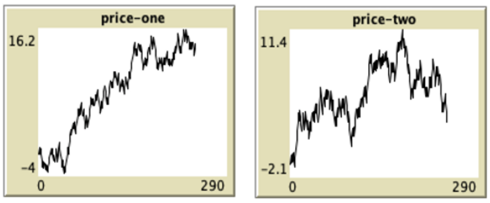


Figure : Case 2 one stock rise the other fall

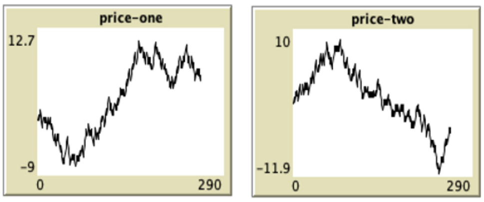
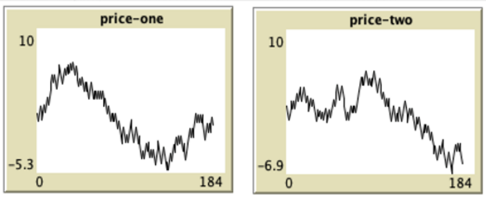


Figure : Case 3 both stocks fall



Traders	factors	Case 1	Case 2	Case 3
Contrarian Trader	Average income	10.98	128.46	134.53
	Standard deviation	22.73	189.63	190.72
	Biggest gains	139.82	1102.98	1104.82
	Minimum income	-62.32	-203.47	-211.98

	Kurtosis	6.62	4.18	4.92
	Skewness	2.32	1.84	1.89
Momentum trader	Average income	2042.43	9.73	8.42
	Standard deviation	2422.67	20.87	21.37
	Biggest gains	9124.25	143.25	142.65
	Minimum income	-19.72	-32.53	-32.15
	Kurtosis	-0.65	8.23	8.1
	Skewness	0.94	2.61	2.74
Noise trader	Average income	125.82	61.98	63.72
	Standard deviation	88.73	34.85	34.17
	Biggest gains	346.72	139.92	140.82
	Minimum income	-0.76	0.26	0.01
	Kurtosis	-1.73	-0.72	-0.83
	Skewness	0.63	-0.38	-0.41
Rational trader	Average income	27.73	16.82	19.73
	Standard deviation	42.84	21.98	20.71
	Biggest gains	209.73	96.63	95.02
	Minimum income	-4.92	-4.82	-3.91
	Kurtosis	3.64	2.54	2.43
	Skewness	2.17	1.52	134.53

For momentum and contrarian trading strategies, the higher yield and higher volatility. And noise traders with stable excess returns and low volatility is a good choice of investment strategies. The rational trader represents the general strategy of the market, and less return is the best choice for the conservative investment risk aversion.

5. Conclusion

We conduct simulation analysis on the investment strategies and returns of irrational traders in the stock market, and draw the following conclusions based on the simulation results:

Firstly, In the simulated market, the quantity variation trend of momentum traders is opposite to that of reverse traders, especially in the case of small market size. The number of noise traders and rational traders is relatively stable and will not be driven out of the market. When the trade goes on long enough, one side of the momentum trader and the other side of the contrarian trader is completely shut out of the market.

Secondly, Herding behavior has a significant impact on the number of noise traders. When the influence factor of herding increases, the number of noise traders begins to show obvious fluctuations, and herding behavior also has a significant impact on stock trading.

Finally, one of the contrarian and momentum traders can earn significant excess returns. They also have high volatility in earnings, which means investors take on a lot more risk. The fact that noise traders consistently outperform rational traders and have insignificant volatility also confirms that noise traders are not driven out of the market.

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