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A Joint Model of Macro Factors and Agent Based Structure

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***Abstract*—this paper made some modifications on traditional artificial stock market. It put forward traders' adaptive learning mechanism, enabling traders to enhance their adaptability to new stock environment by continuous learning. Furthermore, the paper started with external reasons and brought in macrocosmic analysis model, making the artificial stock market closer to the real one. At the same time, validating the characteristics of changes in stock prices, we found they meet EMH basically and the returns took on obvious heavy tail distributions. One stock was selected to be stimulated and forecasted in our artificial stock market, which gained satisfying results.**

***Index Terms*—Artificial stock market; forecast stimulation; heavy tail distributions; macroscopic model.**

I. INTRODUCTION

Financial market is generally recognized as a dynamic and nonlinear system. Many scholars have been trying to discover its internal mechanism and explain the principle of this market and the trader's behavior. At present, financial studies are divided into two main directions. One is based on Efficient Market Hypothesis (EMH). In this case, all information would be included in the changes of market prices immediately. Therefore, investors can hardly estimate stock's future movements through forecast. It's a wise choice to make judgments making full use of existing information. Different from some traditional theoretical model, some empirical evidence indicates that EMH is not always right. Upon that people put forward new theories to replace previous hypothesis, such as the Adaptive Market Hypothesis (AMH) [1] [2]. One of the main theoretical bases of AMH is principles of evolutionary biology. Presenter Andrew W. Lo, regards the whole financial market as an ecosystem, in which participants compete with each other by means of diverse strategies, in order to maximize the livability of their genetic material, which is profit in financial market. It avoids the limit of EMH by recognizing any strategy, only if it can enhance the livability. Fellows in the Santa Fe Institute (SFI) established an artificial stock market and simulated financial phenomena through recurring investors' behaviors and modes. Arthur and his companions [3] from SFI established the first Artificial stock market, which abandoned perfect rationality, linearity, general equilibrium and efficient market in traditional financial markets. Instead, the concepts of mperfect rationality, nonlinearity, disequilibrium and inefficient market, they introduced made the model closer to the real world. Other researchers from SFI perfected this artificial stock market later. Basic Model was introduced, which consisted three main parts, namely, market structure, trading mechanism and the main frame. They are illustrated briefly as follows: in the market structure, two kinds of investment vehicles are provided --stock and risk free bond, the amount of the former is limited while that of the latter is infinite; in the trading mechanism, market makers determine the clearing price of stocks and shares; in the the main frame, several bounded rational agents are endowed with the same amount of initial capital. These agents are generated with initial forecasted rules and trading strategies as well. When the simulation process starts, bad rules are eliminated and new rules are generated according to heredity arithmetic. Following research are aimed at making the three parts more practical based on this the main frame .In the part of market structure, Silvano Cocotte [4] increased the amount of investment vehicles. He established an artificial stock market involved several stocks and shares and analyzed their characteristics of time series. There seems no further emphasis in the aspect of perfection of market structure. His literature mainly focuses on the other two parts. In the trading mechanism, Audet compared two mechanisms—market maker and order-driven; Bottazzi [5] investigated aggregate auction and order-driven. Advantages and disadvantages of those mechanisms were not pointed out explicitly. As to the impact of price limits, Westerhoff's [6] result indicated that they have effects on both fluctuation and distortion of stock prices. Silvano Cincotti further discussed central market.

In the main frame, concerned with learning modes, Chen [7] modified the learning mechanisms of Agents in the artificial stock market. Chen had laterality on agents' social learning, adopted agent-based model and set up a trading school. These rules can be carried down from generation to generation. Chen Shuheng [8] also did corresponding work. He replaced individual learning with mutual social learning and discovered that under this mechanism, the return series are independent and identically-distributed series, which sustained EMH. More interestingly, Agents don't know whether the market is efficient or not, but the market would evolve to be efficient under the social learning mechanism. Moreover some scholars combine individual learning with social learning. For instance, Kendall [9] brought forward a way to evolve trading strategy by synthesize individual learning and social learning. Speaking of learning ability, Levy [10] found that when agents' path memory lengths are different, the prices and revenues of stocks show really authentic features. When the velocity of Agents' modification on forecasted rules is comparatively slow, the whole market would operate what EMH predicts—the fluctuations of prices

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reflect changes of values, no abnormal phenomenon and the volume is small. But when agents' speed of modifying their forecasted rules, the whole market will turn into a complex situation automatically: technical transaction and short-term bubbles will rise, with price of assets and statistic characteristics of volume taking on a GARCH effect in the real world.

LeBaron etc [11] investigated into the characteristics of time series of prices in the artificial stock market. His conclusions were similar to that of Arthur's, that is, the market varies when agents are at different evolution rates, and the artificial stock market duplicates some characteristics of what the real world possesses. Meanwhile, referring to Beltratti [12]'s studies, he used artificial neural network; classify learning system, etc. to delineate Agents' intelligence. Thomas h. Noe [13] Applies the concepts in the artificial stock market to creativity of corporation's investment decision. However, this paper mainly discussed the stimulation of traders' financial behaviors under microcosmic conditions. His neglect of macrocosmic factors' effects on investors' decisions was a big defect of this model, so we take macrocosmic factors as main variables into consideration. We observed some basic features in the Adaptive Stock Market, such as the modality of the curve of stock values, the changes of stock prices, the yields. Finally one stock was selected to be stimulated and forecasted in our artificial stock market, which gained satisfying results.

II. Modeling

There are two tradable assets in the market. One is risk free bond, paying for a fixed interest rate r in each time period; the other is risky stocks, paying for dividends, which meets the following autoregressive process:

$$d_t = (1-\rho-\rho^2)\overline{d} + \rho d_{t-1} + \rho^2 d_{t-2} + \mu_t \tag{1}$$

In this equation, ρ is a real number between (0,1), $\overline{d}$ is the basic dividend of stock, μ_t submits to the normal distribution: $\mu_t \sim (0,\tau)$

As for traders in the market, assuming that they possess the same Risk Aversion Preference Function:

$$U(W_{i,t+1}) = -e^{-\lambda W_{i,t+1}} \tag{2}$$

In this equation, the coefficient λ stands for hedging extent, $W_{i,t+1}$ stands for the expectation of wealth in the next period. Whether the investors choose to trade stocks depends on their expectations of revenues stocks can bring with. This can be expressed as:

$$W_{i,t+1} = x_{i,t}(p_{t+1} + d_{t+1}) + (1+r_f)(W_{i,t} - p_t x_{i,t}) \tag{3}$$

In this equation, $x_{i,t}$ stands for the stock holdings of institution i at the moment of t. Assume that the return of share prices and dividends obey normal distribution. Thus when expected revenues and losses are in equilibrium, the investor's optimum stock holding is:

$$\widehat{x_{i,t}} = \frac{E_{i,t}[p_{t+1} + d_{t+1}] - p_t(1+r)}{\lambda\sigma^2_{t,p+d}} \tag{4}$$

$E_{i,t}[p_{t+1} + d_{t+1}]$ Stands for institution i's expectation of future stock prices and dividends at the moment of t. $\sigma^2_{t,p+d}$ is the standard deviation of time series of stock prices and dividends. In each period, unwitting trader's modification of volume reflects his modification of difference between real prices and expected prices.

A. .Pricing：

Now we define $b_{i,t}$ and $O_{i,t}$ as the amount of stocks that institution i is willing to buy and sell at the time of t respectively.

$$b_{i,t} = \begin{cases} x_{i,t} - x_{i,t-1}, x_{i,t} \ge x_{i,t-1} \\ 0, otherwise \end{cases} \tag{5}$$

$$O_{i,t} = \begin{cases} x_{i,t-1} - \widehat{x_{i,t}}, \widehat{x_{i,t}} \le x_{i,t-1} \\ 0, otherwise \end{cases} \tag{6}$$

Therefore, at the moment of t, the buying orders of all institutions sum up to $B_t = \sum_{i=1}^{N} b_{i,t}$ and the total selling orders amounts to $O_t = \sum_{i=1}^{N} O_{i,t}$. The holdings of stocks are defined as:

$$x_{i,t} = \begin{cases} x_{i,t-1} + b_{i,t} - o_{i,t}, if, B_t = O_t \\ x_{i,t-1} + (O_t / B_t) b_{i,t} - o_{i,t}, if, B_t > O_t \\ x_{i,t-1} + b_{i,t} - (B_t / O_t) o_{i,t}, if, B_t < O_t \end{cases} \tag{7}$$

The modification of prices is defined as:

$$P_{t+1} = P_t(1 + \beta(B_t - O_t)) \tag{8}$$

$$\beta(B_t - O_t) = \begin{cases} \tanh(\beta_1(B_t - O_t)), if, B_t \ge 0, \\ \tanh(\beta_2(B_t - O_t)), if, B_t < 0 \end{cases} \tag{9}$$

In the above formula, *tanh* represents Hyperbolic Tangent Function. We assume that all dividends and bonuses are paid in cash, and then we come to an equation:

$$M_{t+1} = \sum_i M_{i,t+1} = M_t(1+r) + H_t D_{t+1} \tag{10}$$

B. Traders' Strategy Selection and Learning Process

In our model, the expression of expected future stock prices and dividends is:

$$E_{i,t}(P_{t+1} + D_{t+1}) = (P_t + D_t)(1 + \theta_1 \tanh(\theta_2 \cdot f_{i,t})) \tag{11}$$

Where θ_1 、θ_2 are undetermined parameters, $f_{i,t}$ is the adaptation factor of prices and expected future stock prices and dividends.

We explain further by putting forward the equation:

$$\sigma^2_{i,t} = (1-\theta_3)\sigma^2_{t-1|n1} + \theta_3[(P_t + D_t - E_{i,t}(P_t + D_t))^2] \tag{12}$$

Where $\sigma^2_{i,t}$ means n_1 days variance since the time of t-1, which is determined by the difference between intraday prices and dividends and traders' expected prices and dividends. θ_3 Is a parameter determining formulary distribution.

Different institutions have different trading strategies, which are determined by their various former expectations. In the first instance, our presupposition of institutions' expectations of strategy pricing is:

$E[P_t] = \sum_{i=1}^{n} \mu_k P_k$, where μ is a random variable and $E[\sum_{i=k}^{n} \mu_k P_k] = P_{t-1}$. Different institutions have their own trading strategy, so they propose a method to choose diverse of μ sequence, resulting distinct forecast criterion to the future. Therefore, we measure their forecast error using the following formula:

$$MPE = \frac{1}{n}\sum_{i=k}^{n} \left| \frac{P_t - E[P_t]}{P_t} \right| \tag{13}$$

Here $E[P_t]$ stands for different institutions' future expected prices, so we can establish a μ sequence according to those institutions' trading strategy. Then GA's selection process is denoted as follows, using Heredity Arithmetic (Holland):

BEGIN

Randomly create initial population $E[P_k]$

WHILE NOT stopping condition DO

t:=t+1

Evaluation of $E[P_{t-1}]$

Selection from $E[P_{t-1}]$ and Reproduction into $E[P_t]$

Mutation on $E[P_t]$

END

END

We use sequence μ to generate the corresponding MPT_i of each institution, get its reciprocal to generate the corresponding binary numerical value. Their probability of being selected by the next generation can be expressed as:

$$\Pi_i = \frac{f_i}{\sum_{j=k}^{N} MPE_i} \tag{14}$$

Through this selection process, we eliminate 10% strategies each time. Naturally, the remaining 90% strategies can go into the next circulation. At the same time, new strategies will be generated by crossing-over at random. One original investing strategy will be selected by each investor from all institutions' strategies, together with a μ sequence. This is investors' forecast about future investment. At the end of period one, we will come up with a ranking of them according to their income. Laggards have to give up their primary strategies and choose new ones. Here, they select appropriate strategies from those of institutions to make preparations for the next round of investment plan.

Here, we adopt annealing as the algorithm of how investors choose institutions:

BEGIN

Calculate MAPE ($f_{i,t}$)

I=1

Randomly select a $gp_{i,t}$ (~ [1, 50])

Calculate MAPE ($gp_{i,t}$)

If MAPE ($gp_{i,t}$)>MAPE ($f_{i,t}$) go to step (10)

I=I+1

If I=5 go to step (3)

$f_{i+1,t} = f_{i,t}$

Go to Step (11)

$f_{i+1,t} < gp_{i,t}$

END

Through simulated annealing, traders get new trading strategies and begin to operate using these new ones. They then generate new expectations about future stock prices and make modifications to their deals. The whole market's supply and demand equilibrium ratio determines the next period's intending prices and both institutions and investors will perfect their strategies. Market-makers will price new stock prices according to new supply and demand relations; institutions will adjust their strategies; traders will decide whether to choose new strategies and then evolve all through this process.

III. .MACRO FACTOR

Stock prices would adjust correspondingly when macroeconomic conditions take changes. For instance, contractionary fiscal policy has inhibiting effects on the economy, which is bad news to the stock market; while slack fiscal policy tend to stimulate the economy and is a good news. Also, monetary policy and the specific trade's development will influence investors' expectations.

Macrocosmic factors can be classified in general as: fiscal policy, monetary policy and economic growth. These can be detailed later. We must fully understand these factors' starting time, duration and incidence, so we divided them into short-term and long-term. We assume in our model that if some macrocosmic factors are effective in the long run, its results will impenetrate all along the simulation process; if some macrocosmic factors are effective in the short run, the duration of this event will be enacted to the average circulating length in R/S analysis method.

$$A_m = A \times e^{-a(t-1)} \tag{15}$$

Here A is the initial value, α is attenuation coefficient. When t=1is just the present time, A_m equals A. Thus the Macro Economy-parameter attenuation function is $A_m = A \times e^{-0.3(t-1)}$.

As regards the initial value A, each specific factor should have a different A. In order to simplify, we suppose A equals 0.1 when all short run factors brings good news and A equals -0.1 when all short run factors brings bad news; A_m equals

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0.001 when all long run factors brings good news and A_m equals -0.001 when all long run factors brings bad news.

The coefficients of Trade Analysis are similar to those of Macroeconomic Analysis and we can adopt the Time Effective Analysis alike:

$$A_m = A \times e^{-0.3(t-1)} \tag{16}$$

Consequently, the coefficient of Corporate Analysis is:

$$A_c = 0.001 \times \frac{3-n}{2} \tag{17}$$

Where n is the ranking of P/E ratio in its trade.

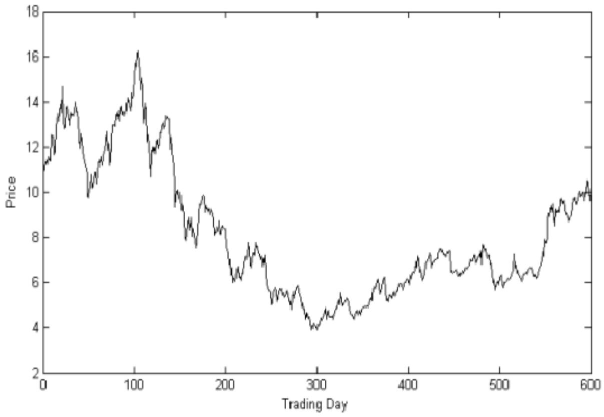
We modify on traders' previous expectation function $E(P_t + d_t)$:

$$E(P_{t+1}+d_{t+1})=(P_t+D_t)(1+\theta_1\tanh(\theta_2\cdot f_{i,t}))+(P_t+d_t)(A_m+A_{tr}+A_c) \tag{18}$$

As can be seen from the above equation, the event's time effects become those affecting the stock values and dividends in the future, which make the changes of traders' investing strategies, depend not only on previous stock prices changes but also on macroeconomic events. In the later repeated trading process, new stock prices and trading strategies will be matched.

IV. Simulation And Demonstration Of The Model

We assume that the amount of institutions' strategies is 50, 2000 investors participate in this investment. After 600 times' circulation, the curve of changes of stock prices is illustrated in CHART 1:

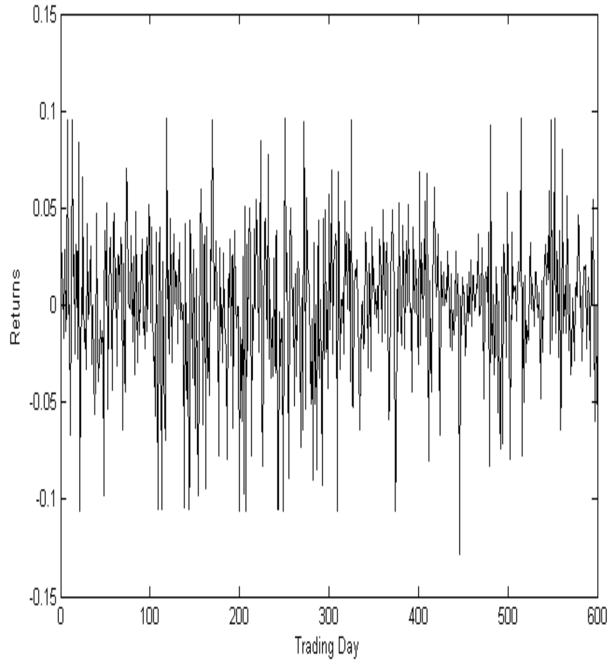


It can be seen that the initial stock price's deviations from the zenith and the nadir are almost the same, both at around 6 RMB When the trend of price has become evident, traders in the agent-based stock market altered their strategies, which elevated the stock price from the lowest point. As a whole, the stock price fluctuated up or down around its value, which conforms the EMH.

TABLE 1 Presents The Changes Of Stock Prices In Per Hundred Days And The Data Analysis:

Period	Price Time Series					
	$\bar{p}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
1-100	12.4524	1.2525	-0.2612	2.0489	4.906221	0
101-200	10.6519	2.3567	0.6428	2.2951	8.956881	0
201-300	5.9142	1.0257	-0.0651	2.0941	3.490029	0
301-400	5.1623	0.5615	0.2071	2.0011	4.872345	0
401-500	6.7953	0.4459	-0.2521	2.2954	3.127828	0
501-600	7.9185	1.5289	0.0747	1.3101	11.99201	0

CHART 2 Shows The Fluctuations of Stock Prices



As can be seen from CHART 2, the return rate of stock we define the return is Logarithmic rate of return ($ret_t = \ln(p_t) - \ln(p_{t-\tau})$, $\tau = 1$)took on an obvious characteristic of heavy tail distributions.

TABLE 2 :Shows The Results Of Data Analysis Of Stock Returns:

Period	Income Return Time Series					
	$\bar{p}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
1-100	0.003837	0.001308	-0.14438	0.780167	-20.1845	0
101-200	-0.00731	0.00192	-0.49888	0.03077	-32.5867	0
201-300	-0.00601	0.002179	-0.30412	-0.26633	-42.9123	0
301-400	0.00356	0.001189	-0.61048	1.238431	-6.71824	0
401-500	0.000639	0.001096	-0.79466	2.642341	9.991647	0
501-600	0.003873	0.001022	0.277959	1.575453	-7.16788	0

From each period's Jarqu-Bera Inspection, we can see that neither price nor return met normal distribution. P-value illuminated the return curve was markedly skewed

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distributed. And we get a significantly skewed distribution results. which conforms that in the real market.

A. Forecast Based on Agent-based Stock Market

Shanghai Pudong Development Bank (SPD Bank) is selected as our example. We choose the quotation of Shanghai Stock Exchange A Share SPD Bank(600000)as our time series, between Aug. 1st 2008 and Jan. 1st 2010. The macrocosmic parameters are set as follows:

Suppose the time of short term effects is 40days and α=0.3. We set 10 days to the duration of trading strategy, so every 11th day A Share stock market will revise the valuation. This will affect investors' behaviors. The Fitting curve of the two is shown in Chart 3:

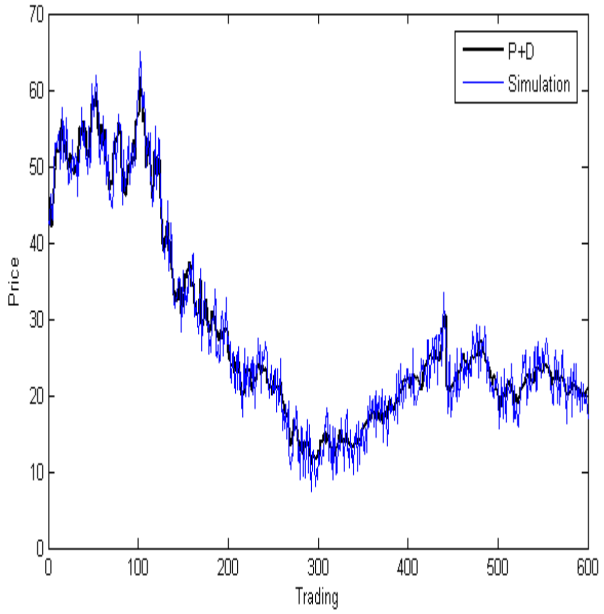

TABLE 3 SHOW THE ERROR OF THE MODEL

	Error Estimate of Artificial Stock Market					
	MSE	Maximum	Minimum	Skewness	Kurtosis	Stand Deviation
Stand Deviation	5.4	3.99	0	-0.09993	-1.18701	2.55

The market's fitting curve is consistent with overall stock prices because our 10 days' valuation revision period is relatively short. It is obvious that agent-based market's forecasts of unilateral falling and unilateral rising are comparatively accurate: the biggest error of ten days' quotation is 3.99 and the smallest error is 0. Also, the MSE value is relatively small once the stock price takes an evident fluctuating trend. When the stock has a visible unilateral trend, the convergence value of forecasted price is in evidence, with the minimum number at zero, standard deviation at 2.55 yuan. This means the average value error of stock is about 2.55 yuan and the range of changes of stock price is relatively stable. Overall, the agent-based market forecast is effective.

V. SUMMARY

This paper generalized status quo and previous researches on agent-based stock market. It brought in macrocosmic analysis model as an important instrument based on investors' self-adaptive adjustment. We validated some characteristics the real market possesses and did some creative experiments by this artificial stock market. Indeed, the experiment had some flaws. Firstly, the macrocosmic analysis model did not discuss the extent of macrocosmic influence. Instead, it focused on the time factors. Besides, only one stock was calculated but several stocks' mutual linkages, etc. All these needs to be studied further so that we can capture the operating mechanism and characteristics of the stock market better.

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