TOWARD AN INTEGRATION OF SOCIAL LEARNING AND INDIVIDUAL LEARNING IN AGENT-BASED COMPUTATIONAL STOCK MARKETS: THE APPROACH BASED ON POPULATION GENETIC PROGRAMMING

Chia-Hsuan Yeh
Department of Information Management
Yuan Ze University
Taiwan

Shu-Heng Chen
Department of Economics
National Chengchi University
Taipei, Taiwan

Abstract:

Artificial stock markets has becomea fast-growing field in the past few years. The essence of this framework is the interaction between many heterogeneous agents. In order to model this *complex adaptive system*, the techniques of evolutionary computation have been employed. Chen and Yeh (2000) proposed a new architecture to construct the artificial stock market. This framework is composed of a single-population genetic programming (SGP) based adaptive agents and a *business school*.

However, one of the drawbacks of a SGP-based framework is that the traders can't work out new ideas by themselves. The only way is to consult researchers in the business school. In other works, traders only follow a kind of social learning, while the individual learning is totally missing. In order to model our traders more realistically, we employ a multi-population GP (MGP) based framework with the mechanism of a *school*. This extension is not only reasonable, but also has economic implications. How do the agents with different learning behavior influence the economy? Are the econometric properties of the simulation results based on MGP more like the phenomena found in the real stock market? In this paper, the comparison between SGP and MGP is studied from two sides. One is related to the micro-structure, traders' behavior and belief. The other to macro-properties, the econometric properties of time series.

Keywords: Evolutionary Computation, Genetic Programming, Agent-Based Modeling, Artificial Stock Market, Social Learning, Individual Learning

1. Introduction

In the past few years, the *artificial stock market* has been a hot topic in the fields of *agent based computational economics* and *finance*. The reason for this field growing fast is that it opens a broader view, so we can study basic problems in the financial market. For example, why are herd behavior, volatility clustering (*autoregressive conditional heteroskedasticity, ARCH*), *excess kurtosis* (*fat-tail distribution*), *bubbles* and *crashes*, *chaos*, and *unit roots* usually found in the financial markets? And, how do they happen? (See, for example, Lux (1995, 1997, 1998), Lux and Marchesi (1998), and LeBaron, Arthur and Palmer (1999)).The stock market is known as a *complex adaptive system*, the traditional techniques which have a top-down perspective can't serve this purpose. Therefore, the technique tends toward the *agent-based modeling* which is a *bottom-up* approach. Such idea is more appropriate and reasonable to model social or economic activities. Genetic algorithms, artificial neural net and genetic programming have been used to model this framework. The main difference between these approaches is twofold.

- representation
- social learning vs. individual learning

Different representation constitutes a different strategy space. Similarly, different styles of learning explain different kinds of human behavior. Both of them may induce different phenomena. Therefore, in order to obtain meaningful and reasonable results, employing the appropriate representation and learning behavior are the most important steps. In Lucas (1986),

> In general terms, we view or model an individual as a collection of decision rules (rules that dictate the action to be taken in given situations) and a set of preferences used to evaluate the outcomes arising from particular situation-action combinations. These decision rules are continuously under review and revision; new decision rules are tried and tested against experience, and rules that produce desirable outcomes supplant those that do not. (pp. 217)

From the viewpoint of representation, if a decision rule can *hopefully* be written and implemented as a computer program, and since every program in terms of its input-output structure can be understood as a function, and then a parse tree. This representation of a decision rule is exactly what genetic programming does. Consequently, the Lucasian adaptive economic agent can be modeled as:

- evolving a population of decision rules
- evolving a population of functions
- evolving a population of programs
- evolving a population of parse trees

Moreover, from the perspective of genetic programming, these decision rules can be reviewed and revised under the genetic operators (including reproduction, crossover and mutation). The performance of new decision rules are validated based on the fitness function. Selection is then conducted under the *survival-of-the-fittest principle* which approximates the concept of *rules producing desirable outcomes supplant those that do not.*

When we extend this idea to model a society of economic agents, a population of genetic programming is then employed. Each agent in this society is formed by a genetic programming. The action is determined by his own decision rules (strategies) and fitness function(s). The social and economic activities are the aggregate phenomena generated by these agents' interaction and coordination. This is the concept of multi-population genetic programming (MGP) which is distinguished from single-population genetic programming (SGP). In Vriend (2000), the implications of SGP/SGAs and MGP/MGAs are distinguished from *social* and *individual* learning. In other words, in social learning, agents learn from other agents' experience, whereas in individual learning, agents learn from their own experience and thinking. Therefore, what Lucas (1986) mentioned focuses on *individual learning*. Moreover, due to the criticisms given by Harrald (1998), he mentioned the traditional distinction between the *phenotype* and *genotype* in biology and doubted whether the adaptation could be directly operated on the genotype via the phenotype in social processes. In other words, it is not easy to justify why we can learn or know other agents' strategies (genotype) by means of their actions (phenotype). This further demonstrated the importance of multi-population GP/GAs (Arifovic (1995a, 1996), Miller (1996), Vila (1997), Arifovic, Bullard and Duffy (1997), Bullard and Duffy (1998a, 1998b, 1999), Staudinger (1998) are examples of SGA, while Andrews and Prager (1994), Chen and Yeh (1996, 1997a, 1997b, 1998), and Chen, Duffy and Yeh (1996) are examples of SGP. Examples of MGA can be found in Palmer et al. (1994), Tayler (1995), Arthur et al. (1997), Price (1997), Heymann, Pearzzo and Schuschny (1998)). However, there also exist problems in the MGP/MGAs modeling. The important phenomena found in economic activities, such as *following the herd* and *rumors dissemination* (or the style of social learning), are totally missing in the architecture of MGP/MGAs. Therefore, we need a new architecture to integrate both of the key features of *social learning* and *individual learning*.

In Chen and Yeh (2000), a new architecture was proposed to solve Harrald's criticism. The mechanism of "school" is introduced into the SGP framework. However, it is still a kind of social learning, the concept of a Lucasian adaptive economic agent is not captured. In this paper, we extend the previous research to a new architecture which is a multi-population GP framework with the mechanism of a school. It passes Harrald's criticism and integrates both social and individual learning. In this general framework, the psychological activities of each trader is also important. When does the trader intend to look for new strategies? When does he decide to do it by himself? This may influence the market dynamics.

In this primary study, we focus on the characteristics of multi-population GP with the mechanism of a school. Besides replicating the stylized facts, the issues related to the comparison between SGP-based and MGP-based simulations are also discussed. In Section 2, the analytical model of our artificial market is described. The experimental design is provided in Section 3. In Section 4, we analyze the simulation results and the concluding remarks are given in Section 5.

2. The Framework of the Artificial Stock Market

The basic framework of the artificial stock market considered in this paper is the standard asset pricing model employed in Grossman and Stiglitz (1980). The dynamics of the market are determined by an interaction of many heterogeneous agents. Each of them, based on his forecast of the future, maximizes his expected utility.

2.1. Description about Traders

For simplicity, we assume that all traders share the same *constant absolute risk aversion* (CARA) utility function,

$$U(W_{i,t}) = -exp(-\lambda W_{i,t}) \tag{1}$$

where $W_{i,t}$ is the wealth of trader i at time period t, and λ is the degree of relative risk aversion. Traders can accumulate their wealth by making investments. There are two assets available for traders to invest in. One is the riskless interest-bearing asset called *money*, and the other is the risky asset known as *stock*. In other words, at each period, each trader has two ways to keep his wealth, i.e.,

$$W_{i,t} = M_{i,t} + P_t h_{i,t} \tag{2}$$

where $M_{i,t}$ and $h_{i,t}$ denotes the money and shares of the stock held by trader i at time t. Given this portfolio ($M_{i,t}$, $h_{i,t}$), a trader's total wealth $W_{i,t+1}$ is thus

$$W_{i,t+1} = (1+r)M_{i,t} + h_{i,t}(P_{t+1} + D_{t+1}) \tag{3}$$

where is the price of the stock at time period t and is per-share *cash dividends* paid by the companies issuing the

P_t D_t

stocks. D_t can follow *a stochastic process* not known to traders. Given this wealth dynamics, the goal of each trader is to myopically maximize the one-period expected utility function,

$$E_{i,t}(U(W_{i,t+1})) = E(-exp(-\lambda W_{i,t+1}) \mid I_{i,t}) \quad (4)$$

subject to Equation (3), where $E_{i,t}(.)$ is trader i's conditional expectations of W_{t+1} given his information up to t (the information set $I_{i,t}$), and r is the riskless interest rate.

It is well known that under $CARA$ utility and Gaussian distribution for forecasts, trader i's desire demand, $h^*_{i,t+1}$ for holding shares in a risky asset is linear in the expected *excess return*:

$$h^*_{i,t} = \frac{E_{i,t}(P_{t+1}+D_{t+1})-(1+r)P_t}{\lambda \sigma^2_{i,t}}, \quad (5)$$

where $\sigma^2_{i,t}$ is the conditional variance of ($P_{t+1}+D_{t+1}$) given $I_{i,t}$.

The key point in the agent-based artificial stock market is the formation of $E_{i,t}(.)$. In this paper, the expectation is modeled by genetic programming. The details are described in the next section.

2.2. The Mechanism of Price Determination

Given $h^*_{i,t}$, the market mechanism is described as follows. Let $b_{i,t}$ be the number of shares trader i would like to submit a bid to buy at period t, and let p_M be the number of shares trader i would like to offer to sell at period t. It is clear that

$$b_{i,t} = \begin{cases} h^*_{i,t} - h_{i,t-1}, & h^*_{i,t} \geq h_{i,t-1}, \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

and

$$o_{i,t} = \begin{cases} h_{i,t-1} - h^*_{i,t}, & h^*_{i,t} < h_{i,t-1}, \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

Furthermore, let

$$B_t = \sum_{i=1}^{N} b_{i,t} \quad (8)$$

and

$$O_t = \sum_{i=1}^{N} o_{i,t} \quad (9)$$

be the totals of the bids and offers for the stock at time t, where N is the number of traders. Following Palmer et al. (1994), we use the following simple rationing scheme (this simple rationing scheme is chosen mainly to ease the burden of intensive computation. A realistic alternative is to introduce the double auction price mechanism.):

(10)

$$h_{i,t} = \begin{cases} h_{i,t-1} + b_{i,t} - o_{i,t}, & \text{if } B_t = O_t, \\ h_{i,t-1} + \frac{O_t}{B_t} b_{i,t} - o_{i,t}, & \text{if } B_t > O_t, \\ h_{i,t-1} + b_{i,t} - \frac{B_t}{O_t} o_{i,t}, & \text{if } B_t < O_t. \end{cases}$$

All these cases can be subsumed into

$$h_{i,t} = h_{i,t-1} + \frac{V_t}{B_t} b_{i,t} - \frac{V_t}{O_t} o_{i,t} \tag{11}$$

where $V_t \equiv \min(B_t, O_t)$ is the volume of trade in the stock.

Based on Palmer et al.'s *rationing scheme*, we can have a very simple price adjustment scheme, based solely on the *excess demand* $B_t - O_t$:

$$P_{t+1} = P_t(1 + \beta(B_t - O_t)) \tag{12}$$

where β is a function of the difference between B_t and O_t. β can be interpreted as speed of adjustment of prices. One of the β functions we consider is:

$$\beta(B_t - O_t) = \begin{cases} tanh(\beta_1(B_t - O_t)) & \text{if } B_t \geq O_t, \\ tanh(\beta_2(B_t - O_t)) & \text{if } B_t < O_t \end{cases} \tag{13}$$

where $tanh$ is the *hyperbolic tangent function*:

$$tanh(x) \equiv \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{14}$$

The price adjustment process introduced above implicitly assumes that the total number of shares of the stock circulated in the market is fixed, i.e.,

$$H_t = \sum_i h_{i,t} = H. \tag{15}$$

In addition, we assume that dividends and interests are all paid by cash, so

$$M_{t+1} = \sum_i M_{i,t+1} = M_t(1 + r) + H_t D_{t+1}. \tag{16}$$

2.3. Formation of Adaptive Traders

As to the formation of traders' expectations, $E_{i,t}(P_{t+1} + D_{t+1})$, we assume the following functional form for $E_{i,t}(.)$.

$$E_{i,t}(P_{t+1}+D_{t+1}) = \begin{cases} (P_t + D_t)(1 + \theta_1 f_{i,t} * 10^{-4}), & \text{if } -10000.0 \leq f_{i,t} \leq 10000.0, \\ (P_t + D_t)(1 + \theta_1), & \text{if } f_{i,t} > 10000.0, \\ (P_t + D_t)(1 - \theta_1), & \text{if } f_{i,t} < -10000.0 \end{cases} \tag{17}$$

The population of (i=1,..., N) is formed by genetic programming. That means, that the value of is decoded from its

$f_{i,t}$ $f_{i,t}$

GP tree $gp_{i,t}$. According to the martingale hypothesis, the trader holds martingale belief if $E_{i,t}(P_{t+1}+D_{t+1})=P_t+D_t$. Therefore, the *cardinality* of set $\{i \mid E_{i,t}(P_{t+1}+D_{t+1})-(P_t+D_t)=0\}$, denoted by $N_{1,t}$, gives us the information about *how well the efficient market hypothesis is accepted among traders*.

As to the subjective risk equation, we modified the equation originally used by Arthur et al. (1997).

$$\sigma^2_{i,t}=(1-\theta_2)\sigma^2_{t-1|n_1}+\theta_2[(P_t+D_t-E_{i,t-1}(P_t+D_t))^2]. \tag{18}$$

where

$$\sigma^2_{t-1|n_1}=\frac{\sum_{j=0}^{n_1-1}[P_{t-j}-\overline{P}_{t|n_1}]^2}{n_1-1} \tag{19}$$

and

$$\overline{P}_{t|n_1}=\frac{\sum_{j=0}^{n_1-1}P_{t-j}}{n_1} \tag{20}$$

In other words, $\sigma^2_{t-1|n_1}$ is simply the *historical volatility* based on the past n_1 observations.

2.4. Single-Population Based Business School

In the SGP architecture, the business school serves as a faculty of researchers. Traders can consult with them when they face peer pressure or the loss of large sums of money. However, the researchers and traders may have a different focus. Traders care about the models or strategies which are helpful for making money. While the researchers may pay attention to the accuracy of forecasting, for example, *mean absolute percentage error* (MAPE). Therefore, the business school considered here can be viewed as a collection of forecasting models. Then, the single-population GP can be applied to model its evolution.

Each researcher (forecasting model) is represented by a GP parse tree. The school will be evaluated with a prespecified schedule, say once for every m_1 trading days. At the evaluation date t, the business school will generate a group of new forecasting models in order to fit (or survive in) the new situation. Each forecasting model $gp_{i,t-1}$ at period $t-1$ will be examined by a *new model* which is generated from the same business school at period $t-1$ by one of the following four genetic operators, reproduction, crossover, mutation, and immigration, each with probability p_r, p_c, p_m, and p_I (Table 1). The tournament selection is applied in the procedures of four genetic operators as follows:

- Reproduction:
  Two forecasting models (GP trees) are randomly selected from GP_{t-1}. The one with lower MAPE over the last m_2 days' forecasts is chosen as the *new model*.
- Mutation:
  Two forecasting models are randomly selected from GP_{t-1}. The one with lower MAPE over the last m_2 days' forecasts is chosen as the candidate with the probability of p_M (In Table 1, the probability is 0.3) being mutated. No matter if the candidate is mutated or not, that one (the new one if it is mutated) is chosen as the *new model*.

Crossover:
Two pairs of forecasting models are randomly chosen, say ($gp_{j_1,t-1}$, $gp_{j_2,t-1}$) and ($gp_{k_1,t-1}$, $gp_{k_2,t-1}$). The one with lower MAPE in each pairs is chosen as the *parent*. One of the two children which is born by the crossover of their parents is randomly chosen as the *new model*.

- Immigration:
  A forecasting model is randomly created as the *new model*. This operator is used to approximate the concept of *imagination*.

Therefore, each forecasting model at period $t-1$is compared with the new model generated by one of the three genetic operators based on the criterion of MAPE. The lower one is selected as the new forecasting model for the next period (generation).

Table 1: Parameters of the Stock Market (I)

The Stock Market	
Shares of the stock (H)	100
Initial money supply (M_1)	100
Interest rate (r)	0.1
Stochastic process (D_t)	Uniform distribution, U(5.01,14.99)
Price adjustment function	$tanh$
Price adjustment (β_1)	0.2 $\times 10^{-4}$
Price adjustment (β_2)	0.2 $\times 10^{-4}$
Parameters of Genetic Programming	
Function set	$\{+,-,\times,\%,Sin,Cos,Exp,Rlog,Abs,Sqrt\}$
Terminal set	$\{P_t,P_{t-1},\cdots,P_{t-10},P_t+D_t,\cdots,P_{t-10}+D_{t-10}\}$
Selection scheme	Tournament selection
Tournament size	2
Probability of creating a tree by reproduction (p_r)	0.10
Probability of creating a tree by immigration (p_I)	0.20
Probability of creating a tree by crossover p_c	0.35
Probability of creating a tree by mutation p_m	0.35
Probability of mutation	0.3
Probability of leaf selection under crossover	0.5
Mutation scheme	Tree mutation
Replacement scheme	(1+1) Strategy
Maximum depth of tree	17
Maximum number in the domain of Exp	1700

Number of generations	10000

Table 2: Parameters of the Stock Market (II)	
Business School	
Number of faculty members (F)	500
Criterion of fitness (Faculty members)	MAPE
Evaluation cycle (m_1)	20
Sample Size (MAPE) (m_2)	10
Search intensity in Business School (I_s^*)	5
Traders	
Number of traders (N)	100
Number of ideas for each trader	20
Degree of RRA (λ)	0.5
Criterion of fitness (Traders)	Increments in wealth (Income)
Sample size of $\sigma^2_{t\|n_1}$ (n_1)	10
Evaluation cycle(n_2)	1
Sample size (n_3)	10
Initial probability of consulting business school ($p^{sm}_{i,t}$)	0.5
Search intensity by Trader itself (I_h^*)	5
θ_1	0.5
θ_2	0.0133

2.5. The Interaction between Traders' Behavior and Business School

The main distinction between SGP and MGP is in the formation of traders' behavior. In the architecture of MGP, we allow the traders to think about how to react to the environment by themselves. Therefore, at the evaluation date t, each trader has to make a decision. Should he change his mind (the strategy used in the previous period)? If the answer is yes, where should he consult? the business school or himself.

The way we use to model this psychological activity can be summarized as the following procedure. First, whether each trader changes his mind or not depends on his net change of wealth over the last n_2 days compared with other traders. Let $R_{i,t}$ be his rank and $\Delta W^{n_2}_{i,t}$ be this net change of wealth of trader i at time period t, i.e.,

$$\Delta W^{n_2}_{i,t} \equiv W_{i,t} - W_{i,t-n_2}, \tag{21}$$

Then, the probability for the trader i changing his mind at period t is determined by

$$p_{i,t} = \frac{R_{i,t}}{N}. \tag{22}$$

Equation (22) means that the trader with higher rank faces a higher peer pressure. Hence, he has higher motivation to change his mind. Second, in addition to the peer pressure, each trader also cares about his own satisfaction. That means, traders intend to improve their growth rate of income. Let the growth of income over the last n_2 days be

$$\delta_{i,t}^{n_2} = \frac{\Delta W_{i,t}^{n_2} - \Delta W_{i,t-n_2}^{n_2}}{\mid \Delta W_{i,t-n_2}^{n_2} \mid}, \tag{23}$$

and let $q_{i,t}$ be the probability that trader i will look for new strategies at the end of the tth period, assume that it is determined by

$$q_{i,t} = \frac{1}{1+exp^{\delta_{i,t}^{n_2}}}. \tag{24}$$

Therefore, the traders that make great (less) progress have a lower (higher) probability of changing their mind.

Based on the description above, we know the probability ($r_{i,t}$) that trader i decides to change his mind.

$$r_{i,t} = p_{i,t} + (1-p_{i,t})q_{i,t} = \frac{R_{i,t}}{N} + \frac{N-R_{i,t}}{N}\frac{1}{1+exp^{\delta_{i,t}^{k}}} \tag{25}$$

However, we have not yet mentioned how a trader comes up with a new idea. In order to model this process, we have introduced a probability measure to describe this psychological activity. Let $p_{i,t}^{sm}$ be the probability that trader i would like to look for new ideas from the business school. On the other hand, the probability that trader i decides to work out new ideas by himself is $1-p_{i,t}^{sm}$. This probability is determined by

$$p_{i,t}^{sm} = \begin{cases} p_{i,t-n_2}^{sm} - (r_{i,t} - r_{i,t-n_2})p_{i,t-1}^{sm}, & \text{if} \quad r_{i,t} - r_{i,t-n_2} \geq 0, \quad \text{Case1}, \\ p_{i,t-n_2}^{sm} - (r_{i,t} - r_{i,t-n_2})(1-p_{i,t-1}^{sm}), & \text{if} \quad r_{i,t} - r_{i,t-n_2} < 0, \quad \text{Case1}, \\ p_{i,t-n_2}^{sm} + (r_{i,t} - r_{i,t-n_2})(1-p_{i,t-1}^{sm}), & \text{if} \quad r_{i,t} - r_{i,t-n_2} \geq 0, \quad \text{Case2}, \\ p_{i,t-n_2}^{sm} + (r_{i,t} - r_{i,t-n_2})p_{i,t-1}^{sm}, & \text{if} \quad r_{i,t} - r_{i,t-n_2} < 0, \quad \text{Case2}, \\ p_{i,t-n_2}^{sm}, & \text{Case3}. \end{cases} \tag{26}$$

where Case1 means that trader i looked for a new idea from the business school at period $t-n_2$, Case2 means that trader

i made a new idea by himself at period $t - n_2$, and Case3 means that trader i didn't change his mind at period $t - n_2$.

The idea of Equation (26) is very straightforward. If a trader has a high motivation to change his mind, then he will think about whether the result is due to the wrong decision, for example, consulted researchers in the business school, made in the $t - n_2$ th period or not. Therefore, he is prone to reduce his confidence in the business school.

Once a trader decides to go to a business school, he has to consult one researcher at the school randomly (or pick up one forecasting model at the school randomly). Then, he compares the new idea with his old one used in the previous period based on the criterion of MAPE by means of calculating the stock price and dividends over the last n_3 trading days. If the new idea outperforms his old idea, he will adopt the new one. Otherwise, he will look for a new one at the school once again until either he succeeds or he fails for I_s^* times. Of course, it is very possible that the trader decides to work out a new idea by himself. The new idea is also generated by four genetic operators which have happened in his mind. He has to compare the new idea with the old one based on the net change of wealth over the last n_2 trading days (Of course, the new idea doesn't really have be used. We can assume that the trader used the new idea since n_2 trading days before, then calculate its performance over these n_2 trading days). If the new one outperforms the old one, he will adopt it. Otherwise, he will think about it once again until he succeeds or he fails for I_h^* times.

3. Experimental Designs

In this paper, we consider three different scenarios, Market A, B and C. The difference between these markets are shown in Table 3. Market A is the SGP based market. It is compared with Market B in which traders work out new ideas by themselves rather than consulting with researchers. The difference between these frameworks provides the effects of prediction accuracy oriented and profit oriented agents. Market C is a more realistic one. The agents can adapt themselves to modify the confidence between the school and themselves. This design coincides with a part of human psychological activity.

Table 3: The Market Structure

Market	Architecture	Probability of consulting business school
A	SGP with business school	1.0
B	MGP with business school	0.0
C	MGP with business school	Adaptive adjustment, Equation (26)

Based on the different designs, simulations are conducted according to the parameters shown in Table 1 and 2. In Market B and C, each trader has twenty ideas in his mind. These ideas also evolve from generation to generation. In Table 4, the important variables related to the traders and market are summarized. These are helpful for us to go one step further to analyze our simulation results. For example, the number of martingale believers ($N_{1,t}$) tell us how many traders hold martingale beliefs at period t. The time series {$N_{1,t}$} also provides us with the information about how the market dynamics interact with the traders' belief. We are also interested in how well the traders "live" in the market. Do they change their mind usually? Do they benefit from the business school or their own minds? These subjects can be refereed to ($N_{2,t}$, $N_{4,t}$) and ($N_{3,t}$, $N_{5,t}$). $f_{i,t}$ and $\kappa_{i,t}$ are the complexity measures of traders' strategies in terms of a GP-tree. How the complexity of traders' strategies coevolve with market dynamics is also an important issue. Of course, the typical phenomena found in the financial markets are also analyzed. For example, is {P_t} normal or stationary? Is return series ({R_t}) independently and identically distributed? Or, is {R_t} nonlinearly dependent? Does {R_t} have the property of GARCH...., and so on.

Table 4: Time Series Generated from the Artificial Stock Market:

Aggregate Variables	
Stock price	P_t
Trading volumes	V_t
Totals of the bids	B_t
Totals of the offers	O_t
# of martingale believers	$N_{1,t}$
# of traders registered to the business school	$N_{2,t}$
# of traders with successful search in the business school	$N_{3,t}$
# of traders registered to themselves	$N_{4,t}$
# of traders with successful thinking	$N_{5,t}$
Individual Trader	
Forecasts	$f_{i,t}$
Subjective risks	$\sigma_{i,t}$
Bid to buy	$b_{i,t}$
Offer to sell	p_M
Wealth	$W_{i,t}$
Income	$\Delta W^1_{i,t}$
Rank of profit-earning performance	$R_{i,t}$
Complexity (depth of $f_{i,t}$)	$f_{i,t}$
Complexity (# of nodes of $f_{i,t}$)	$\kappa_{i,t}$

4.1. Macro-properties

As to the properties of time series, whether this artificial stock market can replicate the stylized facts found in the financial markets or not is the first question the researchers working in this field will face.

1. Are stock prices and stock returns normally distributed?
2. Does the price series have a unit root?
3. Are stock returns independently and identically distributed?

The time series of the stock price in the last 9000 periods for each market is drawn in Figure 1, 2 and 3 respectively, we ignore the first 1000 periods for adjustment. In these figures, the range of price fluctuation in Market B is higher than that in Market A and C. However, the homogeneous rational expectations equilibrium price under full information is

$$P_f = \frac{1}{r}(\overline{d} - \lambda\sigma^2 h) \tag{27}$$

where r is interest rate, $\overline{d}$ is the average of dividends, σ^2 is the variance of dividends series and h is the average of shares of the stock for each trader. Therefore, the fundamental price (P_f) in these markets is 58.375. It implies that the market composed of profit oriented traders tends to overestimate the *intrinsic value* of the stock.

Figure 1 : Time Series Plot of the Stock Price (Market A)

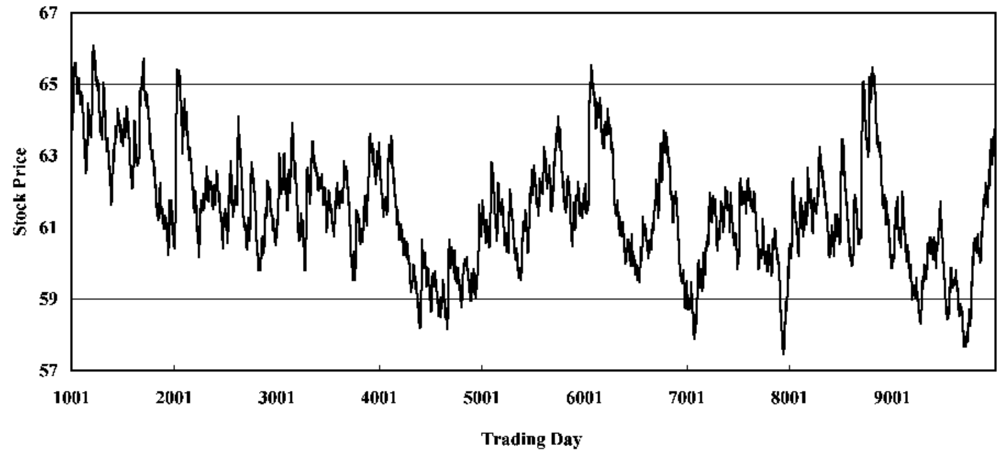


Figure 2 : Time Series Plot of the Stock Price (Market B)

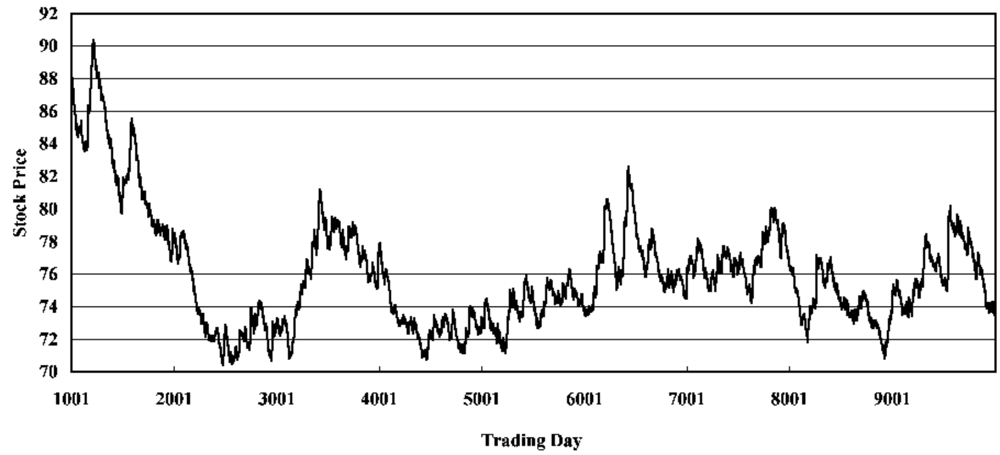
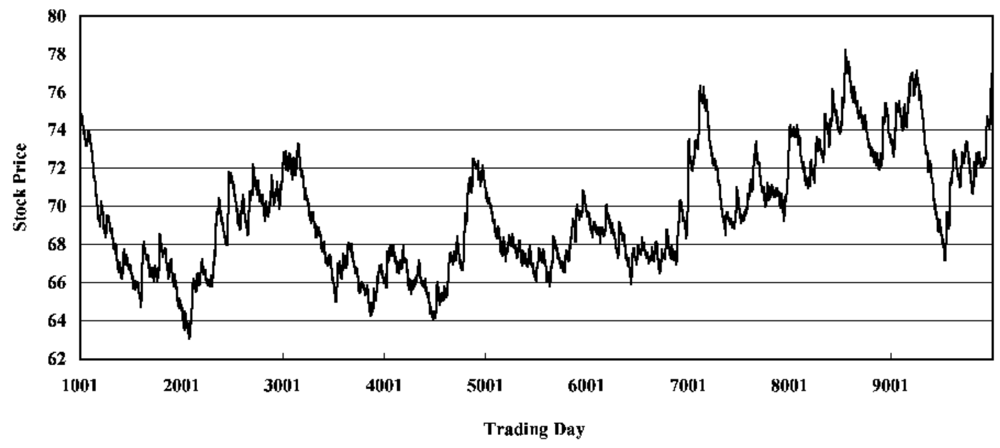


Figure 3 : Time Series Plot of the Stock Price (Market C)



The Stock return is derived by

$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{28}$$

Figure 4, 5, and 6 are the time series plots of the stock return, the basic statistics of the time series of stock price and return are given in Tables 5 and 6. According to the Jarqu-Bera normality test, neither the stock price nor the return follows normal distribution. Moreover, the leptokurtosis of the stock return also confirms the fat tail phenomenon usually found in the financial data. In Table 7, the result of the Dickey-Fuller test shows that there exists a unit root in the price series for each market except the first subperiod of Market A and the second subperiod of Market C based on 99% significance level.

Table 5: Basic Statistics of the Artificial Stock Price Series

Periods	$\overline{P}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
Market A						
1-1000	78.327	13.622	0.692	2.200	106.543	0.000
1001-2000	63.395	1.357	-0.354	2.312	40.648	0.000
2001-3000	61.915	1.180	0.917	3.636	157.216	0.000
3001-4000	61.861	0.888	-0.331	2.725	21.493	0.000
4001-5000	60.108	1.181	0.927	3.232	145.782	0.000
5001-6000	61.608	0.896	0.132	2.951	3.027	0.220
6001-7000	61.781	1.633	0.356	2.035	59.891	0.000
7001-8000	60.455	1.156	-0.521	2.493	55.985	0.000
8001-9000	61.874	1.345	0.902	3.066	135.894	0.000
9001-10000	60.107	1.285	0.461	2.999	35.509	0.000
Market B						
Periods	$\overline{P}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
1-1000	108.093	12.686	-0.451	1.650	109.829	0.000
1001-2000	82.783	3.343	0.232	2.110	41.934	0.000
2001-3000	73.328	2.196	1.075	3.077	193.047	0.000
3001-4000	76.482	2.449	-0.572	2.382	70.552	0.000
4001-5000	72.997	1.330	1.273	5.006	437.919	0.000
5001-6000	74.010	1.124	-0.481	2.604	45.196	0.000
6001-7000	76.872	2.054	0.659	2.813	73.986	0.000
7001-8000	76.979	1.258	0.429	2.765	33.023	0.000
8001-9000	74.165	1.437	0.134	2.422	16.917	0.000
9001-10000	76.186	1.726	0.278	2.009	53.777	0.000
Market C						
Periods	$\overline{P}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
1-1000	95.378	12.084	-0.435	1.738	97.920	0.000
1001-2000	68.124	2.558	1.192	3.467	245.969	0.000
2001-3000	68.608	2.415	-0.676	2.251	99.674	0.000
3001-4000	68.139	2.498	0.592	2.058	95.352	0.000
4001-5000	67.384	2.232	0.929	2.813	145.415	0.000

5001-6000	67.993	1.176	0.671	2.598	81.920	0.000
6001-7000	68.139	0.931	0.497	3.292	44.805	0.000
7001-8000	71.386	1.850	0.856	3.030	122.231	0.000
8001-9000	73.899	1.524	0.394	2.855	26.759	0.000
9001-10000	72.785	2.353	-0.239	2.479	20.811	0.000

Table 6: Basic Statistics of the Artificial Stock Return Series

Market A						
Periods	$\bar{r}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
1-1000	-0.000334	0.002317	3.285	18.637	11987.340	0.000
1001-2000	-0.000059	0.001681	1.118	5.572	484.201	0.000
2001-3000	0.000012	0.001765	1.167	5.453	478.198	0.000
3001-4000	0.000031	0.001692	0.891	4.381	212.057	0.000
4001-5000	-0.000022	0.001652	1.028	4.881	323.840	0.000
5001-6000	-0.000014	0.001635	0.728	3.365	94.037	0.000
6001-7000	-0.000039	0.001653	1.495	10.351	2624.689	0.000
7001-8000	0.000019	0.001627	0.890	4.498	225.542	0.000
8001-9000	-0.000006	0.001846	2.006	12.640	4543.108	0.000
9001-10000	0.000056	0.001567	0.418	2.545	37.777	0.000
Market B						
Periods	$\bar{r}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
1-1000	-0.000020	0.002738	2.283	8.642	2195.468	0.000
1001-2000	-0.000115	0.001555	1.308	7.179	1012.972	0.000
2001-3000	-0.000070	0.001479	0.868	3.959	164.160	0.000
3001-4000	0.000063	0.001601	1.019	5.090	355.131	0.000
4001-5000	-0.000061	0.001404	0.556	2.728	54.607	0.000
5001-6000	0.000005	0.001504	0.844	3.664	137.171	0.000
6001-7000	0.000032	0.001638	1.074	4.932	347.946	0.000
7001-8000	0.000005	0.001541	0.814	3.891	143.645	0.000
8001-9000	-0.000025	0.001470	0.950	5.776	471.729	0.000
9001-10000	-0.000008	0.001642	2.076	15.744	7486.346	0.000
Market C						
Periods	$\bar{r}$	σ	Skewness	Kurtosis	Jarqu-Bera	p-value
1-1000	-0.000176	0.002498	2.356	10.604	3334.458	0.000
1001-2000	-0.000148	0.001514	1.115	6.842	822.669	0.000
2001-3000	0.000105	0.001710	1.116	5.578	484.671	0.000
3001-4000	-0.000087	0.001489	0.635	3.135	68.111	0.000
4001-5000	0.000071	0.001570	0.669	3.427	82.344	0.000
5001-6000	-0.000018	0.001497	0.730	3.544	101.359	0.000
6001-7000	0.000039	0.001636	1.990	15.699	7379.999	0.000

7001-8000	0.000016	0.001587	1.045	5.452	432.728	0.000
8001-9000	-0.000001	0.001622	1.370	7.217	1054.134	0.000
9001-10000	0.000042	0.001677	1.284	6.277	722.641	0.000

Table 7: Unit Root Test

	Market A	**Market B**	**Market C**
Periods	DF of P_t	DF of P_t	DF of P_t
1-1000	-3.743	-0.205	-1.629
1001-2000	-1.102	-2.378	-3.287
2001-3000	0.139	-1.641	1.907
3001-4000	0.556	1.176	-1.993
4001-5000	-0.452	-1.490	1.412
5001-6000	-0.070	0.119	-0.387
6001-7000	-0.775	0.592	0.773
7001-8000	0.399	-0.019	0.194
8001-9000	-0.163	-0.550	-0.163
9001-10000	1.145	-0.205	0.787

The MacKinnon critical values for rejection of hypothesis of a unit root at 99% (95%) significance level is -2.5668 (-1.9395).

As to the third question, it is related to the classical version of *efficient market hypothesis*. Technically speaking, the market is efficient if there exist no linear and nonlinear structures in the return series. Here, we employ the procedure proposed by Chen, Lux and Marchesi (1999). First, the Rissanen's predictive stochastic complexity (**PSC**) is used to filter the linear signal. Once the linear signal is filtered, if there is any structure left in the residual, it must be nonlinear. Therefore, the most frequently used nonlinear test, **BDS test**, is then applied to the residual series. However, there are two parameters needed to be chosen. One is the distance parameter (ϵ standard deviations), and the other is the *embedding dimension* (DIM). Here, the result of the BDS test is performed under $\epsilon = 1$ and DIM=2, 3, 4, 5. In Table 8, we found that there exists a linear structure in the three markets, while the R^2 is very low. Moreover, most periods fail to reject the nonexistence of a nonlinear signal. However, it is well known in econometrics that nonlinearity could be found in the second moment. The (G)ARCH family of time series is designed to capture this behavior, which is the phenomenon of volatility clustering. Therefore, we carried out the Lagrange multiplier test for the presence of ARCH effects. If the null hypothesis of the ARCH effect is rejected, we will further identify the GARCH structure according to Bayesian Information Criterion (BIC). The test results are exhibited in Table 9. Clearly, the presence of GARCH effects seems to be very robust compared with the BDS test.

Table 8: PSC Filtering and BDS Test

Market A						
Periods	(p,q), (R^2)	DIM=2	DIM=3	DIM=4	DIM=5	Reject
1-1000	(1,0) (0.084)	2.763	3.355	3.573	3.801	Yes
1001-2000	(1,2) (0.095)	1.170	1.536	1.657	1.732	No
2001-3000	(1,2) (0.130)	1.446	1.503	1.545	1.537	No
3001-4000	(1,0) (0.046)	0.983	1.267	1.522	1.634	No
4001-5000	(2,0) (0.069)	1.314	1.588	1.696	1.709	No
5001-6000	(0,3) (0.051)	0.876	1.318	1.522	1.618	No

6001-7000	(1,0) (0.066)	0.804	0.863	0.959	1.000	No
7001-8000	(0,2) (0.072)	1.254	1.393	1.425	1.392	No
8001-9000	(1,2) (0.148)	1.156	1.209	1.267	1.342	No
9001-10000	(1,0) (0.017)	0.822	0.955	1.098	1.245	No
Market B						
Periods	(p,q), (R^2)	DIM=2	DIM=3	DIM=4	DIM=5	Reject
1-1000	(1,0) (0.120)	2.631	2.950	3.164	3.472	Yes
1001-2000	(3,3) (0.086)	0.910	1.215	1.292	1.361	No
2001-3000	(1,0) (0.029)	1.436	1.382	1.465	1.517	No
3001-4000	(1,2) (0.079)	0.992	1.185	1.262	1.248	No
4001-5000	(0,0) (0.000)	1.028	1.154	1.229	1.275	No
5001-6000	(2,2) (0.048)	1.465	1.476	1.532	1.544	No
6001-7000	(2,2) (0.086)	1.217	1.568	1.670	1.674	No
7001-8000	(1,0) (0.036)	0.993	1.141	1.259	1.346	No
8001-9000	(1,0) (0.048)	0.777	0.794	0.835	0.798	No
9001-10000	(2,2) (0.083)	1.003	1.238	1.438	1.546	No
Market C						
Periods	(p,q), (R^2)	DIM=2	DIM=3	DIM=4	DIM=5	Reject
1-1000	(1,2) (0.172)	3.198	3.851	4.487	5.187	Yes
1001-2000	(1,0) (0.043)	0.831	1.056	1.160	1.175	No
2001-3000	(0,2) (0.081)	1.679	2.057	2.273	2.336	Yes
3001-4000	(2,2) (0.037)	0.993	1.261	1.242	1.188	No
4001-5000	(3,2) (0.053)	1.157	1.210	1.183	1.155	No
5001-6000	(4,0) (0.033)	0.850	0.984	1.084	1.078	No
6001-7000	(1,0) (0.056)	0.767	0.884	1.002	1.017	No
7001-8000	(1,0) (0.060)	1.452	1.545	1.572	1.598	No
8001-9000	(1,0) (0.056)	1.591	1.694	1.693	1.603	No
9001-10000	(3,3) (0.108)	0.928	1.148	1.323	1.417	No

The BDS test statistic is asymptotically normal with mean 0 and standard deviation 1. The significance level of the test is set at 0.95.

Table 9: GARCH Modeling

Periods	**Market A**	**Market B**	**Market C**
1-1000	(1,1)	(2,2)	(1,2)
1001-2000	(1,1)	(1,2)	(1,1)
2001-3000	(0,1)	(1,1)	(1,1)
3001-4000	(1,1)	(1,1)	(1,1)
4001-5000	(1,1)	(1,1)	(1,1)
5001-6000	(1,1)	(0,1)	(0,1)

6001-7000	(1,1)	(1,1)	(1,1)
7001-8000	(1,1)	(1,1)	(1,1)
8001-9000	(1,1)	(0,1)	(0,1)
9001-10000	(0,1)	(1,1)	(1,1)

4.2. Micro-structure

Based on the result described above, there doesn't exist too much of a difference between the three markets. However, it doesn't imply anything about the micro-structure. We are interested in how the traders behave in the three markets. The basic questions proposed in the previous research (Chen and Yeh, 2000) would help us to examine this issue. Are they *martingale believers*? Do they search for new ideas intensively? What kind of strategies do the traders employ?...., and so on.

In Table 10, it is evidenced that, on average, the martingale belief doesn't survive in the traders' mind. The time series plot of the number of martingale believers for each market is also given in Figure 7, 8 and 9 respectively. In the 10000 periods, there are no more than eight traders holding martingale beliefs in any period. Now, we may interested in what the traders actually do if they don't believe in the martingale hypothesis. In Table 11 and 12, we can get an impression of the traders' search and thinking activities. In each market, there is about 90% of traders trying to change their ideas which means that the price dynamics are not easily captured. However, the inside information in each market is different. In Market A, the traders follow the ideas from the business school which is prediction accuracy oriented. There is about 50% of traders who registered to the business school that benefit from their search. Clearly, search is useful. It also implies that the *useful forecasting models* change over time. There is no robust forecasting model in this environment. On the other hand, the business school updates knowledge every 20 periods. As time goes on, these models are gradually out-of-date before the knowledge is updated once again. In this situation, even though the traders are very adaptive in the sense that they modify strategies at each period, they can only reuse the *old* ideas. Therefore, the chance of their benefitting from the business school gets less. It is also exhibited in the decrease in the average number of traders with successful searches on the h day after the business school has updated the information (See Table13).

In Market B, the traders' actions purely follow profit maximization and they renew their ideas at each period. It induces a different phenomenon. On average, there are about 17 traders (except first subperiod) who benefit from their own thinking. The average of the ratio of traders with successful thinking is also lower. The reason for this is as follows. First, the traders' action is to myopically maximize the one-period expected utility and they evaluate the ideas too frequently (at each period). It makes the strategies have a lower chance of survival. Second, the traders' ideas in their minds also evolve at each period. Therefore, even though each trader has 20 ideas, these ideas easily tend to evolve similar structures (How to design the evolution of traders' minds is an important issue. It will influence the traders' adaptability. We may only evolve the realized strategies and keep the other strategies unchanged, or the synthesis of both methods. Of course, this problem is not easy to solve. It is left for future research). It explains the low ratio of traders with successful thinking.

In the beginning of the simulation of Market C, there exist both types of traders, prediction accuracy and profit oriented traders. Due to both criteria coevolving in this market, it makes it more difficult for the traders to capture the price dynamics and make a profit. Therefore, more traders tend to change their strategies (See the final column in Table 11), and the number of traders getting useful ideas gradually decreases (See the final column in Table 12). The interesting thing is that the traders' behavior tends to be profit oriented.As market dynamics get dominated by them, so the number of profit oriented traders with successful thinking increases. This makes it more difficult for the prediction accuracy oriented traders to survive. There are two possible reasons to explain this phenomenon.

- Profit oriented traders find it easier to survive.
- Profit oriented traders are more adaptive compared to the researchers in the business school.

In order to test the hypotheses, we can set the equal evaluation cycle for the traders and the business school ($m_1 = n_2$), for example, 20. The second conjecture is related to the influence of speculators who care about short-term profits and investors who focus on long-term profits. These problems will be discussed in future research.

Table 10: Average Number of Martingale Believers ($\overline{N}_1$)

Periods	Market A	Market B	Market C
1-1000	0.323	0.812	0.501

1001-2000	0.191	0.547	0.437
2001-3000	0.133	0.625	0.552
3001-4000	0.229	0.617	0.411
4001-5000	0.224	0.715	0.460
5001-6000	0.148	0.519	0.443
6001-7000	0.191	0.583	0.523
7001-8000	0.206	0.487	0.535
8001-9000	0.112	0.562	0.493
9001-10000	0.090	0.653	0.616

Table 11: Average Number of Traders Registered to the Business School and to Themselves

	Market A	Market B	Market C		
Periods	$\overline{N_5}$	$\overline{N_5}$	$\overline{N_5}$	$\overline{N_5}$	$\overline{N_2+N_4}$
1-1000	88.762	87.196	47.280	45.452	92.732
1001-2000	88.956	87.400	40.054	53.035	93.089
2001-3000	88.877	87.282	36.092	56.763	92.855
3001-4000	88.756	87.310	30.314	62.666	92.980
4001-5000	88.689	87.258	26.297	66.627	92.924
5001-6000	88.814	87.247	22.560	70.390	92.950
6001-7000	88.859	87.088	20.106	72.809	92.915
7001-8000	88.982	87.432	16.052	76.799	92.851
8001-9000	88.915	87.465	14.264	78.799	93.063
9001-10000	88.884	87.312	10.546	82.429	92.975

Table 12: Average Number of Traders with Successful Search and thinking

	Market A	Market B	Market C		
Periods	$\overline{N_5}$	$\overline{N_5}$	$\overline{N_5}$	$\overline{N_5}$	$\overline{N_3+N_5}$
1-1000	43.048 (0.484)	28.285 (0.324)	28.987 (0.610)	15.677 (0.351)	44.664 (0.481)
1001-2000	44.066 (0.495)	17.455 (0.199)	23.501 (0.587)	10.656 (0.201)	34.157 (0.366)
2001-3000	42.588 (0.478)	17.826 (0.204)	21.140 (0.585)	11.417 (0.201)	32.557 (0.350)
3001-4000	44.776 (0.504)	17.470 (0.200)	18.874 (0.621)	12.598 (0.200)	31.472 (0.338)
4001-5000	43.284 (0.487)	17.357 (0.198)	15.657 (0.597)	13.361 (0.200)	29.018 (0.312)
5001-6000	42.664 (0.479)	17.322 (0.198)	13.511 (0.597)	14.234 (0.202)	27.745 (0.298)
6001-7000	45.340 (0.510)	17.428 (0.200)	12.052 (0.599)	14.574 (0.200)	26.626 (0.286)
7001-8000	42.439 (0.476)	17.497 (0.200)	9.733 (0.606)	15.305 (0.199)	25.038 (0.269)
8001-9000	42.650 (0.479)	17.460 (0.199)	8.571 (0.600)	15.887 (0.201)	24.458 (0.262)

9001-10000	45.490 (0.511)	17.337 (0.198)	6.112 (0.582)	16.589 (0.201)	22.701 (0.244)

The values shown in parentheses is the average of the ratio of traders with successful search and thinking.

Table 13: Average Number of Traders with Successful Search on the h day after the Business School Has Updated the Information

	Market A	Market B	Market C	
h	$\overline{N}_{3,h}$	$\overline{N}_{5,h}$	$\overline{N}_{3,h}$	$\overline{N}_{5,h}$
1	49.622 (0.560)	18.76 (0.215)	17.450 (0.664)	13.798 (0.214)
2	46.322 (0.522)	18.78 (0.216)	17.202 (0.650)	13.988 (0.216)
3	45.516 (0.512)	19.07 (0.217)	16.802 (0.637)	14.108 (0.218)
4	44.876 (0.504)	18.78 (0.215)	16.348 (0.623)	13.856 (0.213)
5	44.314 (0.498)	18.64 (0.213)	15.918 (0.601)	14.072 (0.215)
6	43.464 (0.489)	18.39 (0.210)	16.070 (0.611)	13.912 (0.213)
7	43.646 (0.491)	18.36 (0.209)	15.990 (0.609)	14.160 (0.217)
8	44.214 (0.496)	18.28 (0.209)	15.812 (0.602)	13.940 (0.213)
9	42.672 (0.481)	18.08 (0.207)	15.312 (0.578)	14.276 (0.222)
10	43.152 (0.485)	18.44 (0.211)	15.436 (0.580)	14.098 (0.216)
11	41.934 (0.471)	18.50 (0.211)	15.248 (0.584)	14.166 (0.217)
12	41.820 (0.470)	18.49 (0.211)	15.382 (0.578)	13.904 (0.213)
13	41.948 (0.472)	18.27 (0.209)	15.038 (0.569)	14.230 (0.219)
14	42.562 (0.479)	18.42 (0.210)	15.210 (0.577)	13.718 (0.211)
15	43.636 (0.488)	18.73 (0.214)	15.522 (0.582)	13.830 (0.213)
16	42.996 (0.482)	18.47 (0.210)	14.942 (0.572)	14.244 (0.219)
17	42.656 (0.480)	18.58 (0.212)	15.398 (0.583)	13.918 (0.213)
18	43.118 (0.484)	19.21 (0.220)	15.546 (0.588)	13.944 (0.212)
19	42.304 (0.476)	18.45 (0.211)	15.764 (0.597)	14.210 (0.219)
20	41.918 (0.471)	18.09 (0.207)	15.886 (0.587)	14.224 (0.219)

The values shown in parentheses are the ratios of traders with successful search on the h day after business school has updated the information.

The information about the complexity of evolving strategies also confirms the differences between these markets. The results are exhibited in Table 14. Figure 10-12, 13-15 are the time series plots of the complexity of evolving strategies in terms of the depth and nodes of GP trees respectively. In the business school, the strategies try to trace the price dynamics in the past 10 periods (m_2) over time. Therefore, they tend to become more complex in order to fit the nonlinear structure. On the other hand, as mentioned above, the traders' action in Market B is to myopically maximize the one-period expected utility. Therefore, it is not necessary to evolve complex structures. Moreover, the ideas are renewed at each period, which further makes the strategies have less of a chance of getting complicated. In Market C, due to the increase in the proportion of profit oriented traders, the complexity of the strategies decreases gradually.

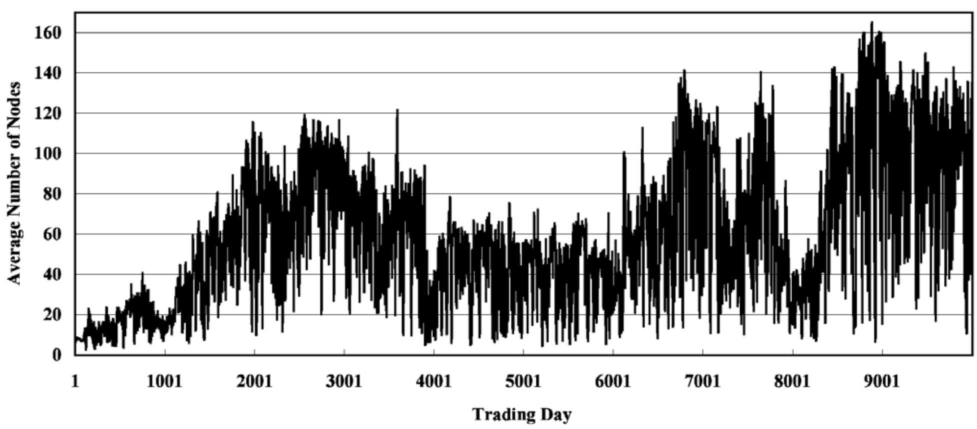


Figure 13 : Trader's Complexity : The Average of the Number of Nodes of GP-Trees (Market A)

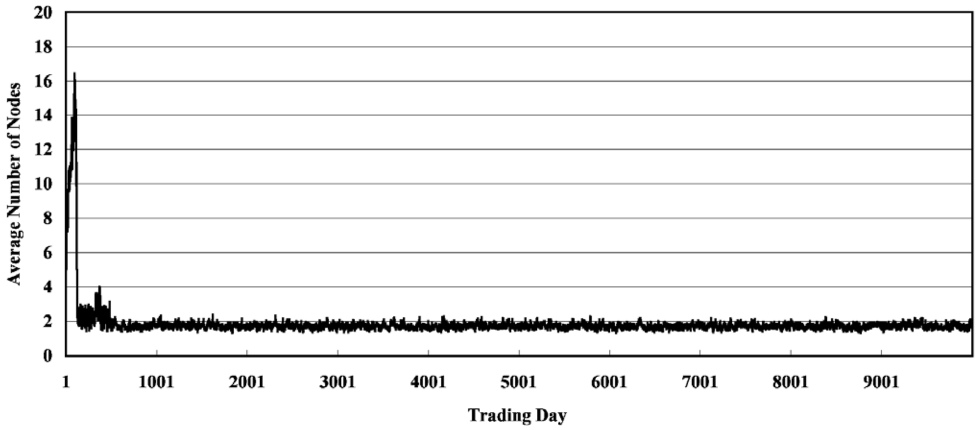


Figure 14 : Trader's Complexity : The Average of the Number of Nodes of GP-Trees (Market B)

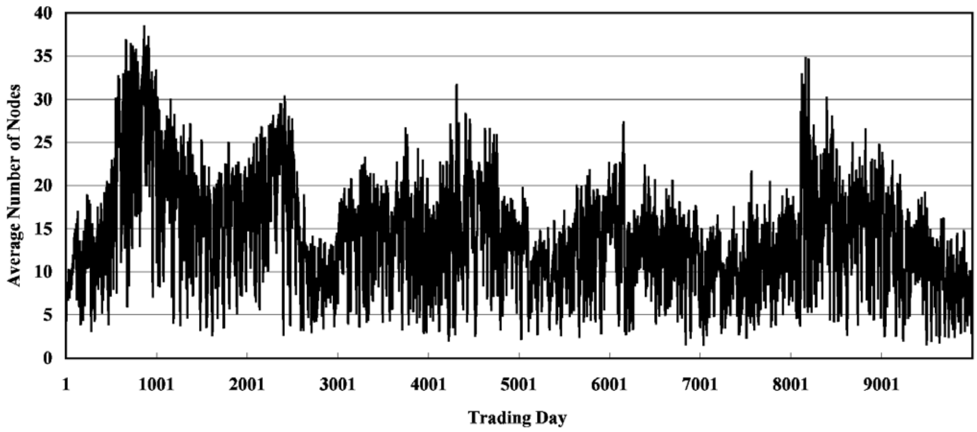


Figure 15 : Trader's Complexity : The Average of the Number of Nodes of GP-Trees (Market C)

Table 14: Complexity of Evolving Strategies

	Market A		Market B		Market C	
Periods	$\bar{k}$	$\bar{\kappa}$	$\bar{k}$	$\bar{\kappa}$	$\bar{k}$	$\bar{\kappa}$

1-1000	6.493	15.454	2.056	3.073	6.725	18.389
1001-2000	10.636	45.340	1.507	1.741	6.926	12.878
2001-3000	12.948	76.731	1.493	1.726	6.408	12.280
3001-4000	11.832	60.339	1.505	1.726	5.045	14.305
4001-5000	11.378	43.411	1.437	1.731	4.992	14.590
5001-6000	11.252	40.831	1.499	1.532	4.514	41.631
6001-7000	12.014	66.418	1.584	1.697	4.144	12.614
7001-8000	11.735	60.898	1.497	1.723	3.702	10.190
6001-9000	11.752	74.461	1.494	1.718	3.950	15.930
9001-10000	13.853	100.877	1.493	1.732	3.256	10.648

$\bar{k}$ and $\bar{\kappa}$ are the average of k_t and κ_t taken over each period.

5. Concluding Remarks

In the primary research, we built an environment composed of multi-population genetic programming based traders. Besides replicating the stylized facts, the comparison between SGP-based and MGP-based simulations was also discussed. From the marco-phenomena point of view, we don't get too much of a difference, while in the micro-structure we do. The difference may come from:

- the different oriented traders: profit and prediction accuracy,
- the different learning styles,
- the different evaluation cycles,
- the evolution of the traders' minds.

These factors co-influence our integrated framework, Market C. Even though Market C is gradually dominated by the profit oriented traders, and hence, the traders follow individual learning. However, this result can not be attributed to the superiority of individual leaning over social learning. Because we employed a very special architecture: a profit oriented individual learning and a prediction accuracy oriented social learning. In order to focus on the influence of different learning styles, we can use only one fitness criterion, profit or prediction accuracy based learning.

Although we haven't clear answers about the degree of influence for each item described above, we propose the above four directions for future studies. These may help us better understand the functions of these four factors, and therefore, build up a more reliable framework which integrates both social and individual learning, and in which the agent's behavior will serve as the prototype of an economic agent.

6. Bibliography

1

Andrews, M. and R. Prager (1994), "Genetic Programming for the Acquisition of Double Auction Market Strategies," in K. E. Kinnear (1994) (eds.), *Advances in Genetic Programming*, Vol. 1, MIT Press. pp. 355-965.

2

Arifovic, J. (1995a), "Genetic Algorithms and Inflationary Economies," *Journal of Monetary Economics*, Vol. 66, No. 1, pp. 219-243.

3

Arifovic, J. (1996), "The Behavior of the Exchange Rate in the Genetic Algorithm and Experimental Economies," *Journal of Political Economy*, Vol. 104, No. 3, pp. 510-545.

4

Arifovic, J., J. Bullard and J. Duffy (1997), "The Transition From Stagnation to Growth: An Adaptive Learning Approach," *Journal of Economic Growth*, Vol. 2, No. 2, pp. 285-284.

5

Arthur, W. B., J. H. Holland, B. LeBaron, R. Palmer, and P. Taylor (1997), "Asset pricing Under Endogenous Expectations in an Artificial Stock Market," in *The Economy as an Evolving Complex Systwm*, Vol. II, W. B. Arthur, S. Durlauf, and D. Lanl (eds.), Santa Fe Institute Studies in the Sciences of Complexity, Proceedings Volume XXVII, Reading, MA: Addison-Wesley. pp. 15-44.

6

Bullard, J. atd J. Duffy (1998a), "A Model of Learning and Emulation with Artificial Adaptive Agents," *Journal of Economic Dynamics and Control*, Vol. 22, No. 2, pp. 179-207.

7

Bullard, J. and J. Duffy (1995b), "Learning and the Stability of Cycles," *Macroeconomic Dynamics*, Vol. 2, pp. 22-58.

8

Bullard, J. and J. Duffy (1999), "Using Genetic Algorithms to Model the Evolution of Heterogeneous Beliefs," *Computational Economics*, Vol. 13, pp. 41-60.

9

Chen, S.-H., and C.-H. Yeh (1996), "Genetic Programming Learning and the Cobweb Model," in P. Angeline (ed.) *Advances in Genetic Programming*, Vol. 2, Chapter 22, MIT Press, Cambridge, MA. 1996, pp. 443-466.

10

Chen, S.-H., J. Duffy, and C.-H. Yeh (1996), "Genetic Programming in the Coordination Game with a Chaotic Best-Response Function," in P. Angeline, T. Back, and D. Fogel (eds.) *Evolutionary Programming V: Proceedings of the Fifth Annual Conference on Evolutionary Programming*, MIT Press, Cambridge, MA, 1996, pp. 277-286.

11

Chen, S.-H., and C.-H. Yeh (1997a), "Modeling Speculators with Genetic Programming," in P. Angeline, R. G. Reynolds, J. R. McDonnell, and R. Eberhart (eds.), *Evolutionary Programming VI*, **Lecture Notes in Computer Science**, Vol. 1213, Berlin: Springer-Verlag. 1997. pp. 137-147.

12

Chen, S.-H., and C.-H. Yeh (1997b), "Speculative Trades and Financial Regulations: Simulations Based on Genetic Programming," *Proceedings of the IEEE/IAFE 1997 Computational Intelligence for Financial Engineering* (**CIFEr'97**), New York City, U.S.A., March 24-25, 1997. IEEE Press, pp. 123-129.

13

Chen, S.-H., and C.-H. Yeh (1998), "Genetic Programming in the Overlapping Generations Model: An Illustration with Dynamics of the Inflation Rate," in V. W. Porto, N. Saravanan, D. Waagen and A. E. Eiben (eds.), *Evolutionary Programming VII*, **Lecture Notes in Computer Science**, Vol. 1447, Berlin: Springer-Verlag. 1998, pp. 829-838.

14

Chen, S.-H., and C.-H. Yeh (2000), "Evolving Traders and the Business School with Genetic Programming: A New Architecture of the Agent-Based Artificial Stock Market," *Journal of Economic Dynamics and Control*, Vol. 25, Issue 3-4, 2001. pp. 363-393.

15

Chen, S.-H., T. Lux and M. Marchesi (1999), "Testing for Non-Linear Structure in an Artificial Financial Market," *Journal of Economic Behavior and Organization*, forthcoming.

16

Grossman, S. J. and J. Stiglitz (1980), "On the Impossibility of Informationally Efficiency Markets," *American Economic Review*, 70, pp. 393-408.

17

Harrald, P. (1998), "Economics and Evolution," the panel paper given at the *Seventh International Conference on Evolutionary Programming*, March 25-27, San Diego, U.S.A.

18

Heymann, D., R. P. J., Pearzzo and A. Schuschny (1998), "Learning and Contagion Effects in Transitions Between Regimes: Some Schematic Multi-Agents Models," *Journal of Management and Economics*, Vol. 2, No. 2.

19

Holland, J. H., and J. H. Miller (1991), "Artificial Adaptive Agents in Economic Theory," *American Economic Review*, Vol. 81, No. 2, Papers and Proceedings, pp. 365-370.

20

LeBaron, B., W. B. Arthur, and R. Palmer (1999), "Time Series Properties of an Artificial Stock Market," *Journal of Economic Dynamics and Control*, Vol. 23, pp. 1487-1516.

21

Lucas, R. E. (1986), "Adaptive Behavior and Economic Theory," in Hogarth, R. M. and M. W. Reder (eds.), *Rational Choice: The Contrast between Economics and Psychology*, University of Chicago Press, pp. 217-242.

22

Lux, T. (1995), "Herd Behavior, Bubbles and Crashes," *Economic Journal*, Vol. 105, No. 431, pp. 881-896.

23

Lux, T. (1997), "Time Variation of Second Moments from a Noise Trader/Infection Model," *Journal of Economic Dynamics and Control*, Vol. 22, pp. 1-38.

24

Lux, T. (1998), "The Socio-Economic Dynamics of Speculative Markets: Interacting Agents, Chaos, and the Fat Tails of Return Distribution," *Journal of Economic Behavior and Organization* 33, pp. 143-165.

25

Lux, T. and M. Marchesi (1999), "Scaling and Criticality in a Stochastic Multi-Agent Model of a Financial Market," *Nature*, Vol. 397, pp. 498-500.

26

Miller, J. (1996), "The Coevolution of Automata in the Repeated Prisoner's Dilemma," *Journal of Economic Behavior and Organization*, Vol. 29, No. 1, pp. 87-112.

27

Palmer, R. G., W. B. Arthur, J. H. Holland, B. LeBaron, and P. Tayler (1994), "Artificial Economic Life: A Simple Model of a Stockmarket," *Physica D*, 75, pp. 264-274.

28

Price, T. C. (1997), "Using Co-Evolutionary Programming to Simulate Strategic Behavior in Markets," *Journal of Evolutionary Economics*, Vol. 7, No. 3, pp. 219-254.

29

Staudinger, S. (1998), "Money as Medium of Exchange: An Analysis with Genetic Algorithms," in *Proceedings of Conference on Computation in Economics, Finance, and Engineering*, June 29-July 1, University of Cambridge.

30

Tayler, P. (1995), "Modeling Artificial Stocks Markets Using Genetic Algorithms," in S. Goonatilake and P. Treleaven (eds.), *Intelligent Systems for Finance and Business*, pp.271-288.

31

Tesfatsion, L. (1996), "How Economists Can Get Alife," in B. Arthur, S. Durlauf and D. Lane (eds.), *The Economy as an Evolving Complex Systems II,* Santa Fe Institute in the Science of Complexity, Vol. XXVII, Addison-Wesley, Reading, MA, pp. 533-564.

32

Vila, X. (1997), "Adaptive Artificial Agents Play a Finitely Repeated Discrete Principal-Agent Game," in R. Conte, R. Hegselmann, and P. Terna (eds.), *Simulating Social Phenomena*, **Lecture Notes in Economics and Mathematical Systems**, Springer, pp.437-456.

33

Vriend, N. (2000), "An Illustration of the Essential Difference between Individual and Social Learning, and Its Consequence for Computational Analysis," *Journal of Economic Dynamics and Control*, Vol. 24, Issue 1, pp. 1-19.

7. About this document ...

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