On the Consequences of "Following the Herd": Evidence from the Artificial Stock Market*

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Abstract ***In the context of agent-based artificial stock markets, we examine the significance of a validation operator when added to canonical genetic programming. Two kinds of traders are considered: one who is "prudent" and will experiment with a new idea before putting it into practice, and one who is "casual" and will take whatever suggested (follow the herd). We then used genetic programming to evolve a stock market composed of "causal" traders and a stock market composed of "prudent" traders. The artificial life of these two markets is summarized and compared by a few statistics considered important by financial econometrics. It is found that these two markets do exhibit some non-trivial difference in the size of speculative bubbles and price efficiency.***

Keywords: Genetic Programming, Artificial Stock Markets, Agent-Based Modeling, Following the Herd, Election Operator, Efficient Market Hypothesis

1 Motivation and Introduction

In this paper, two kinds of adaptive traders are studied within the context of the *artificial stock market*. The artificial stock market considered here is built upon the *standard asset pricing model* ([**?**]), and can be regarded as an *agent-based extension* of the standard model. Agents' (traders') adaptive behavior in this artificial market are modeled with genetic programming (**GP**). Two styles of genetic programming are employed. The first style is *canonical genetic programming* (**CGP**), which consists of three genetic operators: *reproduction*, *crossover* and *mutation*. The second style is to add to *canonical genetic programming* a *validation operator*, such as the *election operator* or the *elitist operator*. The second version of GP is called validation GP (**VGP**) in the paper.

These two styles of genetic programming may differ in their implication for traders' *degree of rationality*. For the former, traders are assumed to take whatever coming from the selection process without giving it a second thought or validating it, whereas for the latter, traders will not accept the a new idea until it has been validated. At first sight, it seems *obvious* that traders in the former case make their decisions more casually than the traders in the latter. However, since the *selection process* encapsulated in genetic programming is driven by the *survival-of-the-fittest principle*, the ideas suggested to traders are in fact of the select group and hence *by no means* random. Therefore, it may not be that clear *whether a validation operator can actually make any difference in such a context.*

This question may arouse economists' interest as well in that while there is no general agreement, many economists tend to believe

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that the prudent behavior of traders is indispensable for a certain desirable feature of the stock price, i.e., that the price is *stable* and around the *intrinsic value* of the stock. The casual behavior, often termed "*animal spirit*" or "*following the herd*" by economists, is usually regarded as the force that drives the price away from *the fundamental* with a wild fluctuation ([**?**]). *Bubbles* and *crashes* are usually condemned as a result from the so-called *noisy* traders. Therefore, for economists, our question posed above can be restated as follows. In a *competitive* market, i.e., a market operated according to the *survival-of-the-fittest principle*, would it be socially desirable if traders can be more prudent in the usual sense? Or, more precisely, would the price be more efficient, less volatile, and thus less deviating from the fundamental if traders are "asked" to be more prudent?

To answer this question, we simulated the artificial stock markets based on the two different styles of genetic programming, i.e., CGP and VGP. We then evaluated the price behavior of these two setups with modern financial econometrics ([**?**]). The evaluation was made to answer the following three questions.

- Is the price series generated from sophisticated traders more consistent with the fundamental value?
- Is the price series generated from sophisticated traders market less volatile?
- Is the price series generated from sophisticated traders more efficient in terms of the *efficient market hypothesis*?

The last question also concerns the emergence of *bubbles* and their *persistence*.

2 Experimental Designs

The architecture of the artificial stock market is detailed in [**?**] and can be found on the website: http://econo.nccu.edu.tw/staff/csh/course/grad-mac/lec12/lec12.htm
Figure 1 depicts the market architecture of

Table 1: Parameters of the GP-Based Artificial Stock Market

The Stock Market	
Shares of the stock (H)	100
Initial Money supply (M_1)	100
Interest rate (r)	0.1
Stochastic Process (D_t)	$U(5.01, 14.99)$
Price adjustment function	$tanh$
Price adjustment (β_1)	10^{-5}
Price adjustment (β_2)	0.2×10^{-5}
Traders	
Number of Traders (N)	500
Degree of RRA (λ)	0.5
Criterion of fitness	Increment in wealth
Sample size of $\sigma^2_{t\|n_1}$ (n_1)	10
Evaluation cycle(n_2)	1
Sample size (n_3)	1
Search intensity (I^*)	1 (CGP), 5 (VGP)
($\theta_1, \theta_2, \theta_3$)	(0.5, 10^{-5}, 0.0133)
Genetic Programming	
Number of trees created by the full method	50
Number of trees created by the grow method	50
Function set	$\{+, -, Sin, Cos, Exp, Rlog, Abs, Sqrt\}$
Terminal set	$\{P_t, P_{t-1}, ..., P_{t-10}, P_{t-1}+D_{t-1}, ...,$
	$P_{t-10}+D_{t-10}\}$
Selection scheme	Tournament selection
Tournament size	2
Probability of creating a tree by reproduction	0.10
Probability of creating a tree by crossover	0.70
Probability of creating a tree by mutation	0.20
Probability of mutation	0.0033
Probability of leaf selection under crossover	0.5
Mutation scheme	Tree Mutation
Maximum depth of tree	17
Number of generations	20,000
Maximum number in the domain of Exp	1700
Criterion of fitness	Increment in Wealth
Sample Size (MAPE) (m_2)	1

single-population GP (**SGP**). The top of Figure 1 is the *market* as a single object, and the bottom is a *population of directly interacting heterogeneous agents.*

Traders will update their forecasting models with a prespecified schedule, say once for every n_2 trading days. The updating process of traders mainly consists of a sequence of two decisions. First, will she be dissatisfied with the forecasting model on which her current trading decisions are based, and search for a new one? Second, when should she stop searching? In the real world, the first decision is somehow *psychological* and has something to do with *peer pressure*. One way to model the influence of peer pressure is to suppose that each trader will examine how well she has performed over the last n_3 trading days, when compared with other traders. Suppose that traders are ranked by *the net change of wealth* over the last n_3 trading days. Let $W_{i,t}^{n_3}$ be this net change of wealth of trader i at time period t, i.e.,

$$\Delta W_{i,t}^{n_3} \equiv W_{i,t} - W_{i,t-n_3}, \tag{1}$$

and, let $R_{i,t}$ be her rank. Then, the probability that trader i will start a search at the end of period t is assumed to be determined by

$$p_{i,t} = \frac{R_{i,t}}{N}. \tag{2}$$

In addition to peer pressure, a trader may also decide to start a search out of a sense of *self-realization*. Let the growth rate of wealth over the last n_3 days be

$$\delta_{i,t}^{n_3} = \frac{W_{i,t} - W_{i,t-n_3}}{\mid W_{i,t-n_3} \mid}, \tag{3}$$

and let $q_{i,t}$ be the probability that trader i will start a search at the end of the tth trading day, then it is assumed that

$$q_{i,t} = \frac{1}{1 + exp^{\delta_{i,t}^{n_3}}}. \tag{4}$$

The searching process is driven by genetic programming. The new forecasting model is generated randomly from the collection of the existing models in the market at t, denoted by $GP_{i,t}$, by one of the following three genetic operators, reproduction, crossover and mutation, each with probability p_r, p_c, and p_m (Table 1). In the case of reproduction, we first randomly select two GP trees, say, $gp_{j,t}$ and $gp_{k,t}$. A *tournament selection* is then conducted based on the increment in wealth. The one with a higher increment, say $gp_{j,t}$, is selected and is denoted by $gp^r_{i,t}$. In the case of mutation, we follow the same procedure as reproduction except that $gp_{j,t}$ has a chance (probability of mutation) being further perturbed by *tree mutation*. Denote the result by $gp^m_{i,t}$. In the case of crossover, we first randomly select two pairs of trees, say $(gp_{j_1,t}, gp_{j_2,t})$ and $(gp_{k_1,t}, gp_{k_2,t})$. The tournament selection is applied separately to each pair, and the winners are chosen to be parents. The children, say (gp_1, gp_2), are born. One of them is randomly selected, and is denoted by $gp^c_{i,t}$.

Once a trader decides to start a search, she has to make a decision when to stop searching. In the case of CGP, since there is no need for validation, it is basically a one-shot search. Traders will simply replace her original model by whatever is found, i.e.,

$$gp_{i,t+1} \equiv gp^*_{i,t}, \tag{5}$$

where, depending on which one applies, $*$ can be r, m or c. In the case of VGP, the trader will *validate* the newly-found model by using it to compete with $gp_{i,t}$ in terms of the increment in wealth. If it outperforms the old model, she will discard the old model, and put the new one into practice. Otherwise, she will start another search, and do it again and again until either she finds a better one or she continuously fails I^* times. The adaptation process described as above is also summarized in Flowchart 1.

3 Simulation Results

Based on the experimental design given above (Table 1), a single run with 20,000 generations was conducted for both CASE 1 (CGP) and CASE 2 (VGP). We then examine their performance differences in light of the questions posed above.

Table 2: Basic Statistics of the Return Series: CASE 1, "Casual" Traders (CGP)

T	$\overline{r}$	σ	SK	KU	JB	p
$\times$	10^{-3}	10^{-2}	1	1	10^3	1
1	1.08	1.6	4.87	39.39	118.31	0.00
2	-0.05	1.3	3.64	19.79	27.92	0.00
3	-0.02	1.2	3.16	14.10	13.61	0.00
4	0.05	1.2	3.11	14.17	13.63	0.00
5	0.00	1.2	3.26	15.56	16.71	0.00
6	0.07	1.2	3.26	15.19	15.94	0.00
7	-0.10	1.2	3.58	19.39	26.68	0.00
8	0.02	1.2	3.26	15.30	16.17	0.00
9	-0.04	1.2	3.31	15.44	16.56	0.00
10	0.07	1.1	3.05	13.20	11.78	0.00

"SK" refers to skewness, "KU" refers to kurtosis, "JB" the Jarqu-Bera test, and "p" the p value.

Table 3: Basic Statistics of the Return Series: CASE 2, "Sophisticated" Traders (VGP)

T	$\overline{r}$	σ	SK	KU	JB	p
$\times$	10^{-3}	10^{-2}	1	1	10^3	1
1	0.62	1.3	3.58	19.99	28.35	0.00
2	-0.05	1.3	4.57	32.52	79.61	0.00
3	0.11	1.3	3.74	19.62	27.70	0.00
4	-0.06	1.2	4.00	24.71	44.64	0.00
5	-0.18	1.3	4.72	34.01	87.61	0.00
6	0.19	1.3	4.20	26.65	52.53	0.00
7	-0.10	1.3	4.16	26.29	51.02	0.00
8	-0.03	1.2	4.25	29.78	65.83	0.00
9	0.05	1.3	4.80	42.86	140.09	0.00
10	-0.01	1.5	5.11	42.23	136.98	0.00

"SK" refers to skewness, "KU" refers to kurtosis, "JB" the Jarqu-Bera test, and "p" the p value.

First, is the price series generated from sophisticated traders (VGP) more consistent with the fundamental? The time series plot of the stock price is drawn in Figure 2 (CASE 1) and Figure 3 (CASE 2). Over this long horizon, P_t roughly fluctuates between 680 and 880 in CASE 1 and varies from 180 to 380, a much lower range, in CASE 2. Since the *intrinsic value* of the stock is 100, both cases seem to converge to a *bubble*. The size of the bubble in the case of causal traders (CASE 1) is indeed much larger than that in the case of "sophisticated traders" (CASE 2). Therefore, the answer for the first question is tentatively *yes*.

Nevertheless, the speculative bubble in both markets seems to have emerged as a sustainable one. Up to the end of these simulations, we see no tendency that the price will crash or that the price will move back to the fundamental value.[1] Of course, one may question whether 20,000-generation simulations are sufficient to draw any sound conclusion from. We are not sure about this, and we see no effective way to solve this problem except to run another simulation with a large number of generations, and this is an exercise for the future.

Second, is the price series generated from sophisticated traders less volatile? Statistically speaking, this question is about *distribution* and *moments*. Given the price series, the return series is derived as usual,

$$r_t = \ln(P_t) - \ln(P_{t-1}) = p_t - p_{t-1}. \quad (6)$$

Figures 4 and 5 give a *histogram* (empirical distribution) of the stock returns, and Tables 2 and 3 give the basic statistics of these return series. From these two tables, the null hypothesis that these series are *normal* are rejected by the Jarqu-Bera statistics in all periods as it is also noticeably demonstrated in Figures 4 and 5.

The excess kurtosis (the so-called *fat-tail property*) is striking in both cases. Put another way, the probability of the occurrence of a large return is higher than what the normal distribution predicts. One of the usual explanations for the fat-tail property is that traders' reactions to news are *highly positively correlated*. What is interesting is that sophisticated traders (CASE 2) lead to a high degree of this co-movement (a fatter tail). This result is not unexpected since traders in CASE 2 search more intensively than traders in CASE 1, and thus the former have a higher chance to converge to the same forecastor than the latter. In addition, the standard deviation (usually known as *risk*) is quite stable around 0.012

[1] [?] argued that bubbles may have a positive effect on the market provided they are *sustainable*.

and 0.013 in both cases. In other words, the fluctuation of the price is not affected by the degree of traders' sophistication. (Figures 1 and 2).

Third, is the price series generated from sophisticated traders more efficient in terms of the efficient market hypothesis? We first tested whether the price series has a *unit root*. The standard tool to test for the presence of a unit root is the celebrated Augmented Dickey-Fuller (ADF) test ([**?**]). The ADF test consists of running a regression of the first difference of the log prices series against the series lagged once, lagged difference terms, and optionally, a drift and a time trend.

$$\Delta p_t = \beta_1 p_{t-1} + \sum_{i=1}^{4} \beta_{i+1} \Delta p_{t-i} + \beta_6 + \beta_7 t \quad (7)$$

The null hypothesis is that β_1 is zero, i.e., $p_t(\ln(P_t))$ contains a unit root. If β_1 is significantly different from zero then the null hypothesis is rejected.

As can be seen from Table 4, for CASE 1, from the total number of 10 subperiods only the first subperiod failed to reject the presence of a unit root, while, for CASE 2, six of the ten subperiods failed to reject. Therefore, the financial time series generated by casual traders is in effect *stationary*, whereas the one generated by sophisticated traders is *non-stationary*.

Next, we followed the procedure of [**?**]. This procedure is composed of two steps, namely, *PSC filtering* and *BDS testing*. We first applied Rissanen's predictive stochastic complexity (**PSC**) to filter the linear process. The fourth and the fifth columns of Table 4 give us the $ARMA(p,q)$ process extracted from the return series $\{r_t\}$. Some of these series are *linearly independent* ($p = 0, q = 0$), and others are either AR(1) or MA(1). Higher order of linear dependence does not exist in any of these series.

Once the linear signals are filtered out, any signals left in the residual series must be *nonlinear*. Therefore, one of the most frequently used statistic, the BDS test ([**?**]), is applied to the residuals from the PSC filter. There are two parameters required to conduct the BDS test. One is the distance parameter (ϵ standard deviations), and the other is the *embedding dimension* (DIM). The qualitative result is found not sensitive to our choice of these two parameters; hence we only report the result with $\epsilon = 1$ and $DIM = 5$. The result is given in Table 5. Since the BDS test is asymptotically normal, it is quite easy to have an eyeball check on the results.

Table 4: Unit Root Test and PSC Filtering

T	DF Test		PSC(p,q)	
	CASE 1	CASE 2	CASE 1	CASE 2
1	−3.372*	−4.566	(0,0)	(1,0)
2	−8.315	−3.355*	(1,0)	(1,0)
3	−5.871	−3.132*	(0,1)	(1,0)
4	−5.669	−4.073	(0,0)	(0,0)
5	−6.513	−4.242	(0,0)	(0,0)
6	−7.627	−3.008*	(0,0)	(1,0)
7	−4.601	−3.458	(0,0)	(0,0)
8	−7.068	−2.459*	(0,1)	(1,0)
9	−6.741	−3.054*	(1,0)	(1,0)
10	−4.506	−2.602*	(0,1)	(1,0)

The MacKinnon critical values for rejection of hypothesis of a unit root at 95% significance level is -3.4146.

Based on Table 5 the null hypothesis that the filtered returns are IID (identically and independently distributed) is significantly rejected in all the subperiods. The result suggests the existence of *nonlinear* dependence in both cases. Furthermore, from the test statistics, the filtered returns of CASE 2 seem to be *less nonlinearly dependent* and hence *more random* than those of CASE 1. Therefore, in terms of nonlinear dependence, the price series generated by sophisticated traders is more efficient than the one generated by causal traders.

So far, we have examined our simulated time series with a test for non-linear dependence. However, it is well known that most of the non-linearity in financial data seems to be contained in their second moment. The voluminous (G)ARCH (Generalized AutoRegressive Conditional Heteroskedasticity) literature is the outcome of the attempt to capture by appropriate time series models the regularities

Table 5: BDS Test and GARCH Modeling

T	BDS TEST		GARCH Modeling	
	CASE 1	CASE 2	CASE 1	CASE 2
1	4.05	4.92	(1,1)	(1,2)
2	6.61	4.57	(0,1)	(1,2)
3	6.77	4.85	(1,1)	(1,1)
4	5.36	3.95	(0,1)	•
5	4.90	3.96	(1,1)	•
6	4.84	4.16	(1,1)	(1,1)
7	5.08	4.17	(0,1)	•
8	6.76	4.75	(1,1)	(1,2)
9	6.77	4.22	(0,1)	(1,2)
10	7.02	4.41	(1,1)	(1,2)

The test statistic is asymptotically normal with mean 0 and standard deviation 1. The significance level of the test is set at 0.95. The (p,q) within each bracket refers to the model GARCH(p,q), while • means that there is no ARCH effect.

in the behavior of volatility. In order to proceed further, we carried out the Lagrange multiplier test for the presence of ARCH effects. A detailed description of ARCH and GARCH as well as an associated SAS program to run the test is available from the website:
http://econo.nccu.edu.tw/ai/staff/csh/course/finaecon/lec6/lec6.htm
If the ARCH effect is rejected, we will further identify the GARCH structure of the series by using the Bayesian Information Criterion (BIC). The results are exhibited in Table 5. Clearly, the *ARCH effect* is quite ubiquitous. Out of the 20 series, there are only 3 series without the ARCH effect.

4 Conclusions

In our simulations, we find that the market composed of casual traders did perform differently from the market composed of sophisticated traders. Their difference is conspicuously reflected in the size of *speculative bubbles* and *price efficiency*, but there is no discernible difference in *risk*. In sum, *the validation operator has its independent role, and may not be waived from canonical genetic programming.*

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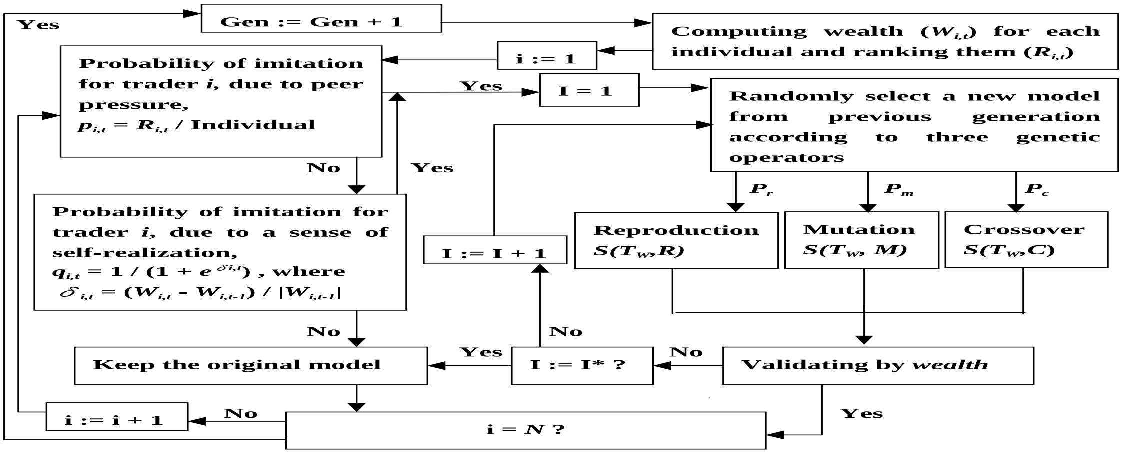

N : Number of traders
$S(T_W,i)$: Selection procedure according to tournament selection with criterion of $W_{i,t}$ based on *i* (genetic operator)

Flowchart 1 : Traders' Search Process by Imitation

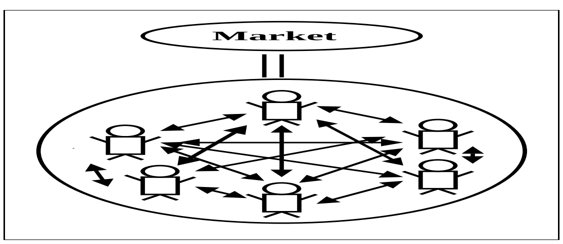

Figure 1 : The Market Architecture Represented by Single-Population GP (SGP)

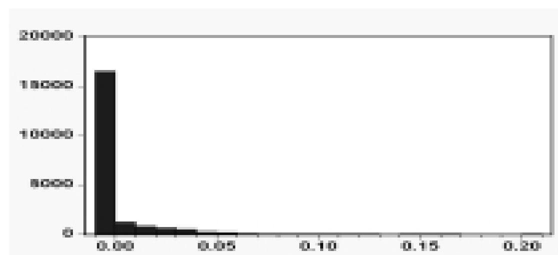

Figure 4 : The Histogram of Stock Returns (CASE 1)

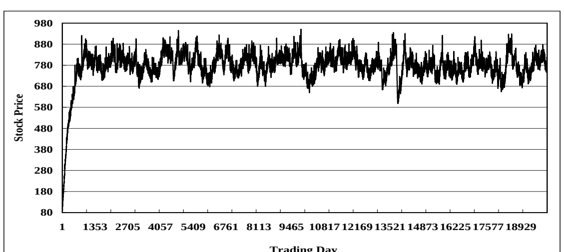

Figure 2 : Time Series Plot of the Stock Price

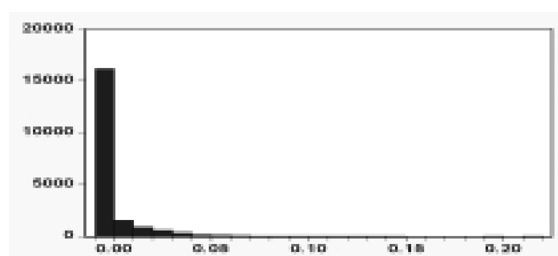

Figure 5 : The Histogram of Stock Returns (CASE 2)

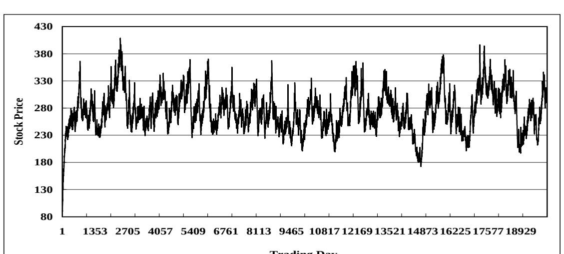

Figure 3 : Time Series Plot of the Stock Price