Joint Conference of 1996 International Computer Symposium
December 19~21, Kaohsiung, Taiwan, R.O.C.

Genetic Programming Learning in the Cobweb Model with Speculators*

Shu-Heng Chen†, Chia-Hsuan Yeh‡, Wei-Chuan Chang⋆

Department of Economics
National Chengchi University
TEL: 886-2-9387308
FAX: 886-2-9390344
Taipei, Taiwan 11623
† E-mail: chchen@cc.nccu.edu.tw
‡ E-mail: g3258501@grad.cc.nccu.edu.tw
⋆ E-mail: g4258014@grad.cc.nccu.edu.tw

Abstract

The nature of speculators is studied with genetic programming. Speculators play an extremely controversial role in economic theory. While the positive aspects of speculators have been well formalized in the neo-classical economics framework, the potential negative aspects of speculators have not been treated equally well, in particular, the consequences of "speculating about the speculations of others". In spirit of the earlier works done by Arthur (1992) and Palmer et al. (1993), this paper models speculators with genetic programming (GP) in a production economy (Muthian Economy). Through genetic programming, we approximate the consequences of "speculating about the speculations of others", including the price volatility and the resulting welfare loss. Some of the patterns observed in our simulations are consistent with findings in experimental markets with human subjects. For example, we show that GP-based speculators can be noisy by nature. However, when appropriate financial regulations are imposed, GP-based speculators can also be more informative than noisy. On the other hand, our simulations results generally do not support the prediction based on rational expectations hypothesis.

Key Words: Genetic Programming, Speculators, No-Trade Theorem, Short Selling, Volatility.

1 Introduction

While it has been suspected for quite a long time that speculators can be *destructive* for the stability of markets, this property has not been successfully revealed from many formal models of speculators. On the contrary, it seems that, so long as we can model speculators in a more *adaptive* fashion, then they should function as *price stabilizers.* In other words, the only way we can observe the destructive side of speculators is to model them as ones *not too smart* or *too adaptive.*

For example, Even and Mishra (1996) found that, if all speculators are *trend speculators,* then speculation can help little to stabilize the price. Trend-based speculators look for trends that are at least *c* rounds long and place orders depending on whether the trend is up or down. Needless to say, speculators of this design are too simple to be adaptive. However, both Even and Mishra (1996) and Steiglitz, Honig and Cohen (1995) find that if *more adaptive* models of speculators are included, such as *Kalman-filtering speculators* and *poll speculators*, speculators could indeed significantly improve the economy. In the case of Even and Mishra (1996), they find that, while the volatility was over three times the mean price without speculators and with trend speculators, with any of other adaptive speculators the volatility dropped to less than 2% of the mean price.

This dramatic reduction in volatility has significant implications for economic efficiency. Usually, when the price is steady and predictable, the decision to produce, to farm, or to mine is more likely to be correct, and, as a result, larger *gains from trade* can be realized. Therefore, if speculators can indeed function as price stabilizers, then public policies should allow more room for speculation rather than restrict or prohibit it. In fact, the view shared by many neo-classical economists is that speculation will be *stabilizing* and not *destabilizing* in any given market that is exposed to *regular recurring disturbances.* So, in principle, it is desirable to have public policies allowing for speculation in these markets.

However, identifying whether recurring disturbances are *regular* may encounter some technical difficulties, in particular, when the nature of disturbances is not exogenously given but endogenously generated. In the literature, this difficult issue belongs to the

*Research support from NSC grant No.84-2415-H-004-001-1 is gratefully acknowledged. This paper is an abbreviated version of Chen, Yeh and Chang (1996).

field *econometrics of bounded rationality* or *econometrics of self-referential systems.* In these systems, the final outcome of the market will crucially depend on the beliefs held by market participants, and disturbances can be endogenously generated if speculators *believe* that there are disturbances and *react* accordingly. One of the most interesting experiments that illustrate this property is Smith, Suchanek and Williams (1988), which can be regarded as the experimental counterpart of Tirole's *no-trade theorem* (Tirole, 1982).

In the laboratory markets of Smith, Suchanek and Williams (1988), the exogenously recurring disturbances are *regular*; nevertheless, speculators did not *stabilize* the market. In fact, they did exactly the opposite. The view shared by many Keynesian economists is that speculative behavior can lead to *price destabilization* with an adverse influence on economic stability. From their viewpoints, speculators succeed not because they can predict the future course of the underlying *non-speculative factors* in the market better than general producers and consumers but because *they can forecast correctly the degree of foresight of other speculators.* As Keynes (1936) stated, "We have reached the third degree [in the stock market] where we devote our intelligence to anticipating what average opinion expects average opinion to be." (Keynes, 1936, p.156). While bringing this aspect of speculators' behavior into modeling is imperative for a better understanding of the consequences of speculation, it has been ignored in many existing models of speculation, in particular, models with only one agent, i.e., the *representative agent.*

Clearly, in the representative-agent setup, there is no need to speculate on other speculators. Therefore, in the models of this sort, no matter how well speculators can cope with exogenous disturbances, the intelligence to speculate about other speculators' opinions is simply useless. Thus, representative-agent models are not appropriate to capture the behavior of speculating about other speculators' opinions.

Therefore, to have an informative model of speculators, the *production side* of the economy should be included explicitly. While Even and Mishra (1996) did introduce producers into their model, they did not endow their producers with the capability to learn. If producers themselves are not able to learn and stabilize the exogenous disturbances, then it is not surprising that the only possibility to stabilize the price is to add adaptive speculators. However, by doing this, we are implicitly assuming that speculators are smarter than producers. In this paper, we shall study the function of speculators in a *production economy* simultaneously with *adaptive producers* in a *mutliagent setup.*

The rest of this paper is organized and briefly described as follows. The model used in this paper is Muth (1961). The details and the justification for the use of this model is given in Section 2. The modeling technique for the adaptive behavior of both producers and speculators is *genetic programming.* Over the last few years, genetic programming has been successfully shown to be a powerful technology to modeling the adaptive behavior observed in the laboratory with human subjects[1]. In Section 3, we discuss how to design genetic programming to serve this purpose. The GP-based mutliagent adaptive economy was simulated and the simulation results along with some analyses are summarized in Section 4, followed by the concluding remarks on some limitations of this paper and future directions for research.

2 The Analytical Framework

The analytical framework used in this paper is based on Muth (1961). There are several reasons why Muth's model is chosen for this research. First, since there is a production side in Muth's model, it enables us to analyze the possible impact of speculators on the fundamentals of the economy. Second, the Muthian economy without speculators under multiagent setup has been studied computationally (Arifovic, 1994; Chen and Yeh 1996) and experimentally (Wellford, 1989) in the past. Its properties are well-known: the adaptive multiagent system has a self-stabilizing feature and has a tendency to converge to *rational expectation equilibrium.* Therefore, we can use this system as a *benchmark* for making comparison with the Muthian economy *with speculators.*

2.1 Model without Speculators

Before adding the role of speculation to the Muth's model, let's briefly review the multiagent system proposed by Chen and Yeh (1996). Consider a competitive market composed of n firms which produce the same goods by employing the same technology and which face the same cost function described in Equation (1):

$$c_{i,t} = xq_{i,t} + \frac{1}{2}ynq_{i,t}^2 \tag{1}$$

where $q_{i,t}$ is the quantity supplied by firm i at time t, and x and y are the parameters of the cost function.

Given $P_{i,t}^e$ and the cost function $c_{i,t}$, the expected profit of firm i at time t can be expressed as follows:

$$\pi_{i,t}^e = P_{i,t}^e q_{i,t} - c_{i,t} \tag{2}$$

Given $P_{i,t}^e$, $q_{i,t}$ is chosen at the level such that $\pi_{i,t}^e$ can be maximized and, according to the first order condition, is given by

$$q_{i,t} = \frac{1}{yn}(P_{i,t}^e - x) \tag{3}$$

Once $q_{i,t}$ is decided, the aggregate supply of the goods at time t is fixed and P_t, which sets demand equal to supply, is determined by the demand function:

$$P_t = A - B\sum_{i=1}^{n} q_{i,t} \tag{4}$$

Given P_t, the actual profit of firm i at time t is :

$$\pi_{i,t} = P_t q_{i,t} - c_{i,t} \tag{5}$$

[1]For a survey article, the interested reader is referred to Chen (1996).

In a representative-agent model, firms are assumed to have identical expectations and hence identical production, i.e. $P^e_{i,t}=P^e_t$ and $q_{i,t} = q_t$ for all i. In this case, Equation (4) can be rewritten as follows:

$$\begin{aligned} P_t &= A - Bnq_t \\ &= A - B\frac{1}{y}(P^e_t - x) \end{aligned} \quad (6)$$

If we further assume that the expectations are realized, then Equation (6) can be rewritten as Equation (7):

$$P_t = A - B\frac{1}{y}(P_t - x) \quad (7)$$

The only expectation that can be realized can be found by solving Equation (7) directly, i.e.,

$$P^*_t = \frac{Ay + Bx}{B + y} \quad (8)$$

Given P^*_t, we can find that

$$Q^*_t = \frac{A - x}{B + y} \quad (9)$$

Since (8) (9) are time invariant, we shall use P^* and Q^* to denote this steady state. P^* and Q^* are the *fundamentals* of the Muthian economy. Arifovic (1994) and Chen and Yeh (1996) found that, without speculators, the long-run behavior of the adaptive multiagent system could be predicted by these fundamentals.

2.2 Model with Speculators

To extend the model (Equations (1)-(9)) with speculation, the behavior of speculators has to be specified first. Suppose we let $I_{j,t}$ represent the inventory of the jth speculator at the end of the tth period, then the profit to be realized is

$$\pi_{j,t} = I_{j,t}(P_{t+1} - P_t). \quad (10)$$

Of course, the actual profit $\pi_{j,t}$ is unknown at the moment when the inventory plan is conducted; therefore, like producers, speculators tend to set the inventory up to the level where speculators' expected utility $Eu_{j,t}$ or expected profits $E\pi_{j,t}$ can be maximized. Maximizing $Eu_{j,t}$ and $E\pi_{j,t}$ can be two quite different objectives. Generally speaking, the former will take speculators' risk attitude into account but the latter will not. Speculators in the latter setup may act too aggressively. For example, when speculators expect the price to go up in the next period, they can tend to demand an infinite amount of stocks if there are no financial constraints. In finance, to avoid such unrealistic behavior, the usual assumption is that speculators are *risk averse*. Under this assumption, speculators not only consider the first moment of price into account but also take the second moment of price (the volatility of price) into account. Therefore, we shall follow Muth (1961) to assume that the objective function for speculators is to maximize the expected utility rather than the expected profit.

Without assuming any specific form of utility function, what Muth (1961) did was to approximate the general utility function by taking the second-order Taylor's series expansion about the origin:

$$u_{j,t} \approx \phi(\pi_t) = \phi(0) + \phi'(0)\pi_{j,t} + \frac{1}{2}\phi''(0)\pi^2_{jt} \quad (11)$$

Based on Equation (11), the approximated utility depends on the moments of the probability distribution of π_t, i.e.,

$$Eu_{j,t} \approx \phi(0) + \phi'(0)E\pi_{j,t} + \frac{1}{2}\phi''(0)E\pi^2_{j,t} \quad (12)$$

It can be shown that the first two moments are:

$$E\pi_{j,t} = I_{j,t}(P^e_{j,t+1} - P_t) \quad (13)$$

$$E\pi^2_{j,t} = I^2_{j,t}[\sigma^2_{t,1} + (P^e_{j,t+1} - P_t)^2] \quad (14)$$

where $\sigma^2_{t,1}$ is the conditional variance $var(P_{t+1} \mid \Omega_t)$ and Ω_t is the σ-algebra generated by $P_t, P_{t-1}, \ldots$.

Replacing the first and the second moment of Equation (12) by Equations (13) and (14) respectively, we can rewrite the expected utility function as follows.

$$\begin{aligned} Eu_{j,t} &\approx \phi(0) + \phi'(0)I_{j,t}(P^e_{j,t+1} - P_t) \\ &+\frac{1}{2}\phi''(0)I^2_{j,t}[\sigma^2_{t,1} + (P^e_{j,t+1} - P_t)^2] \end{aligned} \quad (15)$$

The optimal position of the inventory can then be derived approximately by solving the first order condition,

$$\begin{aligned} \frac{dEu_{j,t}}{dI_{j,t}} &= \phi'(0)(P^e_{j,t+1} - P_t) + \phi''(0)I_{j,t}[\sigma^2_{t,1} \\ &+(P^e_{j,t+1} - P_t)^2] = 0, \end{aligned}$$

and the optimal position of the inventory $I^*_{j,t}$ is given by

$$I^*_{j,t} = -\frac{\phi'(0)(P^e_{j,t+1} - P_t)}{\phi''(0)I_{j,t}[\sigma^2_{t,1} + (P^e_{j,t+1} - P_t)^2]}. \quad (16)$$

By letting $\alpha = -\frac{\phi'(0)}{\phi''(0)\sigma^2_{t,1}}$ and the square of the expected price change be small relative to variance[2], Equation (16) can be written more precisely as follows.

$$I_{j,t} = \alpha(P^e_{j,t+1} - P_t) \quad (17)$$

Equation (17) explicitly shows that speculators' optimal decision about the level of inventory depends

[2] This assumption is reasonable because the original expansion of the utility function is valid only for small changes.

on their expectations of the price in the next period, i.e., $P^e_{j,t+1}$.

If the market is composed exclusively of n producers, the market equilibrium condition derived from Equations (3) and (4) is:

$$\frac{A}{B} - \frac{1}{B}P_t = \sum_{i=1}^{n} \frac{1}{yn}(P^e_{i,t} - x) \quad (18)$$

Now, if the market is composed of n producers and m speculators, Equation (18) is no longer the equilibrium condition. Instead, the equilibrium condition with the inventory is given in Equation (19),

$$\frac{A}{B} - \frac{1}{B}P_t + \sum_{j=1}^{m} \alpha(P^e_{j,t+1} - P_t) = \sum_{i=1}^{n} \frac{1}{yn}(P^e_{i,t} - x) + \sum_{j=1}^{m} \alpha(P^e_{j,t} - P_{t-1}). \quad (19)$$

This concludes the construction of our model. As has been shown in Arifovic (1994) and Chen and Yeh (1996), prices in this multiagent system *without* speculators can be predicted in the long run by *rational-expectations equilibrium price* P^*. If this result can be extended to the case with speculators, then what we can expect is that, eventually, all speculators will leave the market and all speculative trade will disappear. In other words,

$$\lim_{t\to\infty} \Delta I_{j,t} \to 0, \quad \forall j = 1, ..., m, \quad (20)$$

where $\Delta I_{j,t} = I_{j,t} - I_{j,t-1}$. This is because when $P_t = P^*$, $\forall t \geq t^*$, the price differential no longer exists after the period t^*, and henceforth there would be no incentive for speculation. So, under the hypothesis of rational expectations, *speculators should not be destabilizing.* However, the weakness of this argument is already revealed in Smith, et al. (1988), namely, *disclosing the objective value of an asset alone is not sufficient to rule out speculative trade.* As a matter of fact, introducing speculators into markets may generate more complex types of equilibria. As Arthur (1992) had concluded, "We find no evidence that market behavior ever settles down; the population of predictors *continually coevolves.*" (p. 24).

3 Population Learning via Genetic Programming

Since the GP-based algorithm for producers is the same as that of Chen and Yeh (1996), we only describe the GP-based algorithm for speculators. Unlike its application to modeling producers' adaptive behavior, genetic programming is applied to modeling the *inventory policy* $I_{j,t}$ of speculators rather than their price expectations $P^e_{j,t}$. However, since the inventory policy is a function of price expectations and price expectations are formed based on the history of prices, $I_{j,t}$ can be written as a function of the past prices, namely,

$$I_{j,t} = I_{j,t}(P_{t-1}, P_{t-2}, ...,). \quad (21)$$

In the following, genetic programming will be applied to model the adaptation of the function form of $I_{j,t}$. Let GP^s_t, a population of LISP trees, represent a collection of speculators' inventory policies $I_{j,t}$. A speculator j, $j = 1, ..., m$, makes a decision about its inventory at time t using a tree, $I_{j,t}$ ($I_{j,t} \in GP^s_t$), a *parse tree* written over the *function set* and *terminal set* which are given in Table 1. In this paper, all simulations conducted are based on the terminal set which includes the ephemeral random floating-point constant R ranging over the interval [-9.99,9.99] and the prices lagged up to h periods, i.e., P_{t-1},..., P_{t-h}. Therefore, the inventory-policy functions that speculators may use are the linear and nonlinear functions of P_{t-1},..., P_{t-h}, $I_{j,t}(P_{t-1}, ..., P_{t-h})$. The parameter h determines speculators' ability to recall the past. To endow speculators with the capability to learn not to be myopic, h must be set large enough. In this paper, h is set to be 10.

The decoding of a parse tree $I_{j,t}$ gives the policy function used by speculator j at time period t, i.e., $I_{j,t}(\Omega_{t-1})$ where Ω_{t-1} is the information of the past prices up to P_{t-1}. Evaluating $I_{j,t}(\Omega_{t-1})$ at the realization of Ω_{t-1} will give us the inventory of speculator j at time t, i.e., $I_{j,t}$. Without any further restrictions, the range of $I_{j,t}$ is $(-\infty, \infty)$. The case $I_{j,t} < 0$ is called *short selling* in finance. In this paper, short selling is permitted for speculators subjected to the corresponding requirement for the *short covering*. More precisely, we allow the speculator to sell short but to be constrained by a maximum amount $\underline{s}$. When the speculator sell shorts up to $\underline{s}$, he is no longer allowed to sell short any more; instead, he has to recover shorts. Also, the *short position* cannot be kept for more than D days. In other words, if $I_{j,t}$ is negative for $t = T-1, T-2, ..., T-D$, then speculator j is forced to recover shorts at time T.

In addition to the lower bound of $I_{j,t}$, we also set an upper bound of $I_{j,t}$, $\overline{b}$. The lower bound and upper bound of $I_{j,t}$ correspond to some of the financial regulations observed in the real world. The purpose of these financial regulations is to prohibit excessive speculative trade which might possibly destabilize the economy. Therefore, the setting of $\overline{s}$ and $\underline{b}$ enables us to evaluate the significance of these financial regulations to speculative trade. Of course, in the stationary rational expectations equilibrium, these regulations play absolutely no role because, eventually, speculative trade will disappear automatically.

The *raw fitness* of a parse tree $I_{j,t}$ is determined by the value of the speculator's payoffs earned at the end of time $t+1$ based on the equation

$$\pi_{j,t} = I_{j,t}(P_{t+1} - P_t) - \omega I_{j,t}, \quad (22)$$

where ω is the unit cost of the inventory. Physically, ω can be the unit price paid for renting the space to store the commodity. Financially, ω can be the interests paid for the loan to buy the commodity.

To avoid a negative fitness value, each raw fitness value is then adjusted to produce an *adjusted fitness* measure $\mu_{j,t}$ and is given as follows.

$$\mu_{j,t} = \pi_{j,t} + \beta \quad if \ \pi_{j,t} \geq -\beta,$$
$$= 0 \quad if \ \pi_{j,t} < -\beta. \quad (23)$$

By doing this, we are assuming that the policy function $I_{j,t}$ ($j = 1, 2, ...m$) which makes speculators lose more than \$ β will be automatically deleted in the following genetic operations. The choice of "β" is due to the following consideration. Since at the early stage of the evolution, speculators have very limited knowledge about the market, their expectations are sort of random guessing and, as a result, it is very likely that most of them would lose money. If we only consider speculators with positive payoffs, then the selection process can easily be dominated by those few speculators who luckily earn positive payoffs at the initial stage. The similar consideration can also be found in Chen and Yeh (1996) and Chen, Duffy and Yeh (1996).

Each such adjusted fitness value $\mu_{j,t}$ is then normalized. The *normalized fitness* value $p_{j,t}$ is given in Equation (24).

$$p_{j,t} = \frac{\mu_{j,t}}{\sum_{j=1}^{n} \mu_{j,t}} \quad (24)$$

It is clear that normalized fitness is a *probability measure*. Moreover, $p_{j,t}$ is greater for a better parse tree $I_{j,t}$. Once $p_{j,t}$ is determined, GP^s_{t+1} is generated from GP^s_t by three primary genetic operators, i.e., *reproduction, crossover*, and *mutation*. All the control parameters for the Muthian economy are given in Table 1.

Given the GP-based adaptive producers and speculators, our computer simulations were implemented by using the *stable case* with the *cobweb ratio 0.95*, i.e., CASE 1 in Chen and Yeh (1996), with different financial regulations on the *long* and *short positions*, which are characterized by parameters D, $\overline{b}$ and $\underline{s}$ (See Table 2).

From CASE 1 to CASE 4, the financial regulations on $\overline{b}$ and $\underline{s}$ are gradually relaxed from 0.1 to 10. Since the equilibrium quantity Q^* is 70 and there are one hundred speculators in the market, these settings imply that the proportion of speculative trade to Q^* is relaxed from $\frac{1}{7}$ to $\frac{100}{7}$. CASE 5 and and CASE 6 consider the situation with no upper limit on the long position. CASE 5 is to be compared with CASE 1, and CASE 6 with CASE 4. The larger the $\overline{b}$ and the $\underline{s}$, the higher the possible proportion of "*non-productive activities*" to the economy. The question under a long debate in economics is whether these seemingly non-productive activities can be *productive*. More precisely, can these speculative activities lead to a stable economy? To answer this question, we shall compare the economic performance of these six cases with the *benchmark* which has the same fundamental parameters but has no speculators.

4 Results of Simulations

Simulations were conducted for Cases 1 to 6 and the benchmark in accordance with Tables 1 and 2.

Table 1: Tableau of GP-Based Adaptation

number of producers	300
number of speculators	100
number of trees created by the full method	30 (P), 10 (S)
number of trees created by the grow method	30 (P), 10 (S)
Function set	$\{+, -, Sin, Cos\}$
Terminal set	$\{P_{t-1}, P_{t-2}, ..., P_{t-5}, R\}$
number of trees created by reproduction	30 (P), 10 (S)
number of trees created by crossover	210 (P), 70 (S)
The number of trees created by mutation	60 (P), 20 (S)
The probability of mutation	0.2
The maximum depth of tree	17
The probability of leaf selection under crossover	0.5
The number of generations	1000
The maximum number in the domain of Exp	1700
Criterion of fitness	Profits
β	-10 (P), -50 (S)

"P" stands for the producers and "S" stands for the speculators. The number of trees created by full method or grow method are the number of trees initialized in Generation 0 under depth of tree is 2, 3, 4, 5, and 6. For details, see Koza (1992).

For each case, we ran five simulations and each simulation was conducted for one thousand periods (generations). Basic statistics such as average prices and standard deviations for all cases are given in Table 3. The results of our simulations are described as follows.

Let us consider the benchmark first. The benchmark is the CASE 1 in Chen and Yeh (1996). Since this case is a *stable cobweb model*, the performance of the benchmark is essentially the same as that of the CASE 1 in Chen and Yeh (1996), while their control parameters are slightly different. In fact, in this paper, to stimulate possible room for speculation, the mutation rate is set to be 0.2, while the same parameter is set to be 0.0033 in Chen and Yeh (1996). However, in terms of $\delta_{P,b}$ (Table 3), this higher mutation rate has negligible effect on the stability of the economy[3].

Now, given the benchmark, we would like to investigate the difference between the economy with speculators (CASEs 1-6) and that without them (the benchmark), in particular, the impact of speculators on the stability of the economy. In addition, the design of CASEs 1-4 allows us to inquire simultaneously, to what extent, the financial regulations could play an important role in determining the function of speculators. From Table 3, we can see that the deviation of the average price $\overline{P_b}$ from P^* is significantly larger

[3]This is the self-stabilizing feature which was also observed in Chen and Yeh (1996).

Table 2: Parameter Values of the Muthian Economy

Set	D	$\bar{b}$	$\underline{s}$
CASE 1	20	0.1	0.1
CASE 2	20	2	2
CASE 3	20	6	6
CASE 4	20	10	10
CASE 5	20	∞	0.1
CASE 6	20	∞	10

In all of these cases, $A = 2.184$, $B = 0.0152$, $x = 0$, $y = 0.016$, $\frac{B}{y} = 0.95$, $\omega = 0.1$ and $P^* = 1.12$. These parameters are called the fundamental parameters of the Muthian economy. The "Benchmark" is the case with the same fundamental parameters, but without any speculators.

than the benchmark. For example, for the worst case, the absolute percentage deviation of CASEs 2 to 4 all exceeds 10%. This ratio is only 0.02% for the benchmark. On the other hand, the volatility of the economy with speculators is significantly higher compared with the one without speculators. The average of the volatility ($\overline{\delta_{P,b}}$) over five simulations is 0.16718, 0.45796, 0.42718 for CASE 2, 3, 4 respectively, while it is only 0.0024 for the benchmark. Therefore, *speculators are destabilizing.* The difference in the volatility of price of some cases are also directly reflected in Figures 1.1-1.3.

Nevertheless, there is one interesting exception, i.e., CASE 1. For CASE 1, if we consider $\delta_{P,a}$ only, then the average volatility is only 0.04728; compared with the one in the benchmark, it is much lower. In fact, in all five simulations, the volatility obtained in CASE 1 is uniformly smaller than that of the benchmark. This is quite an interesting phenomenon because it tells us *when* and *how* speculation can be stabilizing. *It is in the early stage of evolution that speculators can help stabilize the economy if "appropriate" speculative trade is allowed.* Roughly speaking, this is the picture of speculators which neo-classical economists have in mind (Borna and Lowry, 1987).

In addition to the four cases discussed above, CASE 5 is identical to CASE 1 except that it does not set the upper limit $\bar{b}$, and CASE 6 is related to CASE 4 in the same way. Simulating these two cases enables us to see the function of the existence of the upper limit $\bar{b}$. From Table 3, we can see that this deregulation can have an dramatic impact on CASE 1, but it has little effect on CASE 2. This finding may be generalized a lithe bit, namely, *when regulations on $\underline{s}$ and $\bar{b}$ are loose enough, further relaxation might have little impact.* In other words, we conduct that the damage that speculators can possible made may have its limit. Up to a point, the impact of speculators on the stability of the economy can be insensitive to the further changes of institutional parameters.

Table 3: Results of the Simulations of GP: CASE 1-6 and Benchmark

Simulation CASE		1	2	3	4	5
B	$\overline{P_a}$	1.1195	1.1195	1.1258	1.1318	1.1185
	$\delta_{P,a}$	0.0543	0.1337	0.1036	0.0880	0.1290
B	$\overline{P_b}$	1.1199	1.1203	1.1200	1.1203	1.1198
	$\delta_{P,b}$	0.0026	0.0034	0.0019	0.0019	0.0035
1	$\overline{P_a}$	1.1267	1.3197	1.1360	1.1322	1.1247
	$\delta_{P,a}$	0.0463	0.0579	0.0483	0.0398	0.0441
1	$\overline{P_b}$	1.1200	1.1222	1.1287	1.1275	1.1216
	$\delta_{P,b}$	0.0259	0.0280	0.0300	0.0298	0.0257
2	$\overline{P_a}$	1.1293	1.1319	1.1539	1.1256	1.2726
	$\delta_{P,a}$	0.1942	0.1514	0.2004	0.1208	0.2366
2	$\overline{P_b}$	1.1280	1.1246	1.1205	1.1182	1.2958
	$\delta_{P,b}$	0.1522	0.1268	0.2071	0.1222	0.2276
3	$\overline{P_a}$	1.2299	1.1816	1.2639	1.1445	1.1476
	$\delta_{P,a}$	0.7540	0.4371	0.5537	0.2660	0.4540
3	$\overline{P_b}$	1.2331	1.1556	1.2388	1.1212	1.1234
	$\delta_{P,b}$	0.7802	0.4730	0.3899	0.2344	0.4123
4	$\overline{P_a}$	1.1387	1.1324	1.2598	1.1544	1.1863
	$\delta_{P,a}$	0.2643	0.3924	0.7501	0.3824	0.4564
4	$\overline{P_b}$	1.1213	1.1208	1.2452	1.1274	1.1826
	$\delta_{P,b}$	0.3039	0.3410	0.6166	0.4188	0.4286
5	$\overline{P_a}$	1.1630	1.1297	1.1467	1.1603	1.1411
	$\delta_{P,a}$	0.3547	0.3252	0.2831	0.2906	0.2832
5	$\overline{P_b}$	1.1362	1.1214	1.1213	1.1337	1.1259
	$\delta_{P,b}$	0.4442	0.4019	0.2311	0.2401	0.3031
6	$\overline{P_a}$	1.1743	1.1729	1.1995	1.1406	1.1433
	$\delta_{P,a}$	0.4296	0.5720	0.4233	0.2045	0.4594
6	$\overline{P_b}$	1.1375	1.1175	1.1623	1.1244	1.1274
	$\delta_{P,b}$	0.4398	0.4356	0.4547	0.1406	0.4922

$\overline{P_a}$ = the average of P_t of a simulation (from Generation 1 to 1000).
$\overline{P_b}$ = the average of P_t of a simulation (from Generation 501 to 1000).
$\delta_{P,a}$ = standard deviation about the P_a of a simulation (from Generation 1 to 1000).
$\delta_{P,b}$ = standard deviation about the P_b of a simulation (from Generation 501 to 1000).

Table 4: The Rate of Improvement in terms of Volatility

Simulation CASE	1	2	3	4	5
B	0.0163	0.0247	0.0236	0.0178	0.0213
1	0.5594	0.4836	0.6211	0.7487	0.5828
2	0.7837	0.8375	1.0344	1.0116	0.9620
3	1.0348	1.0821	0.7042	0.8812	0.9081
4	1.1498	0.8690	0.8220	1.0952	0.9391
5	1.2523	1.2359	0.8163	0.8262	1.0703
6	1.0237	0.7615	1.0742	0.6875	1.0714

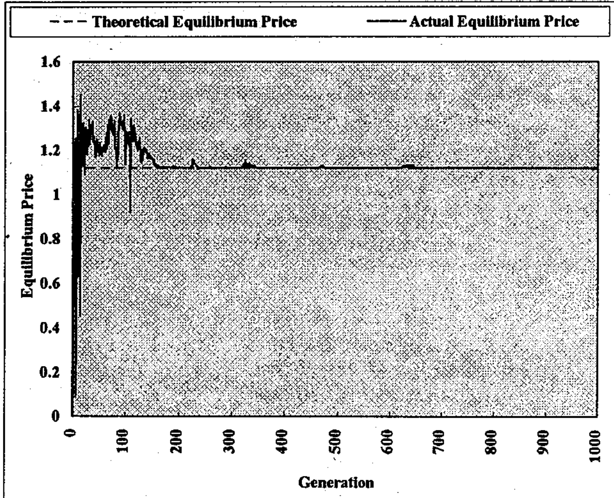

Figure 1.1 : Equilibrium Price in Each Generation (Benchmark-1)

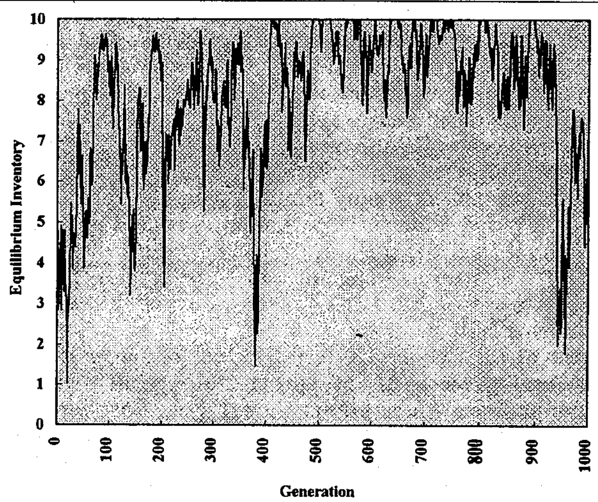

Figure 2.1 : Equilibrium Inventory in Each Generation (Case 1-4)

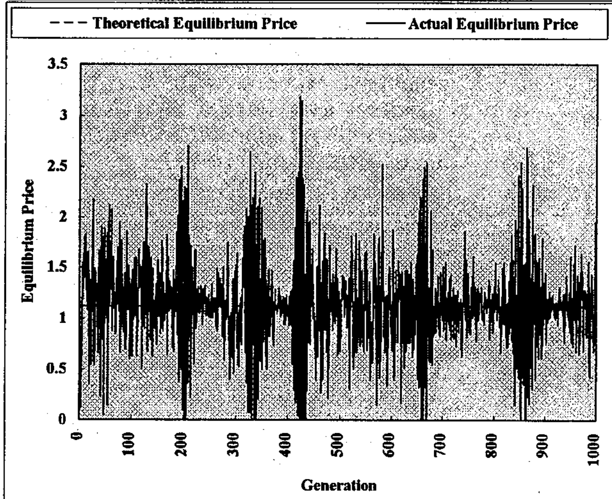

Figure 1.2 : Equilibrium Price in Each Generation in Each Generation (Case 3-5)

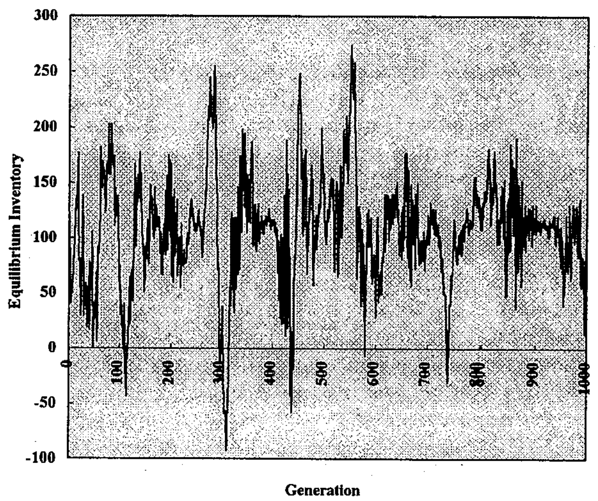

Figure 2.2 : Equilibrium Inventory in Each Generation (Case 3-5)

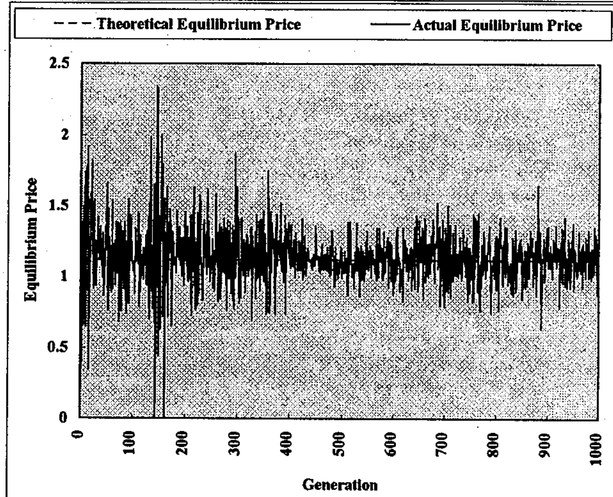

Figure 1.3 : Equilibrium Price in Each Generation in Each Generation (Case 6-4)

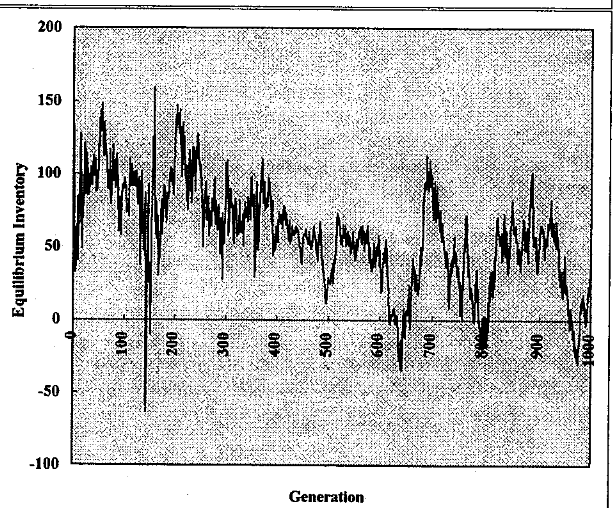

Figure 2.3 : Equilibrium Inventory in Each Generation (Case 6-4)

5 Concluding Remarks

This paper is in great contrast to Chen and Yeh (1996). This contrast evidences that speculators can be destabilizing. In economics literature, this result is consistent with the experimental results observed in Smith et al. (1988) and with the simulation results in Palmer et al. (1993). However, unlike these two studies, the economy simulated in this paper is not purely speculative. With appropriate financial regulations which subject speculative trade to serious financial constraints, speculators may actually help stabilize the economy. Still, there are some questions which remain to be answered.

First of all, while the *secret nature* of speculators can be uncovered by genetic programming, the underlying difficulties which hinder the GP-based producers from coordinating well with the GP-based speculators have not been fully explored. Why is the self-stabilizing feature of the GP-based producers gone when speculators enter the markets? If speculators are destabilizing, what accounts for such a property? This is also the fundamental issue raised, but left unsolved, in Smith et al. (1988). We do not know more about this except the following *search-theoretic conjecture* motivated by genetic programming.

This conjecture is to relate the *infinite regress* problem to the *size of the search space*. "Speculating about the speculations of others" in economics is known as an infinite regress problem. This problem may induce a rather large search space and create a coordination problem. But *constraints*, including technological constraints and financial regulations, play a crucial role in reducing the size of the search space. That may explain why financial regulations help stabilize the economy[4]. However, the formal relation between the size of the search space and the coordination failure requires further studies.

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