Speculative Trades and Financial Regulations: Simulations Based on Genetic Programming *

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Abstract

By exploring a two-dimensional parameter space, this paper pindowns the area where speculative trades can contribute to the reduction of price volatility and are hence imperative for market efficiency. This area is delimited by a rather restrictive financial regulations imposed on an inherently unstable economy. Specifically, depending on the associated financial regulations, our GP-based simulations of cobweb markets show that speculative trades may reduce price volatility by 20% to 50% in an inherently unstable economy; on the other hand they may also increase price volatility by 300% to 3000%. This paper generalizes the earlier finding by Chen and Yeh (1997), which basically shows that in an inherently stable economy, speculative trades can only be destabilizing.

Key Words: Genetic Programming, Efficient Market Hypothesis, Speculative Trades, Short Selling, Volatility.

1 Motivation and Introduction

Let σ_x^2 be the variance of the price of an abstract commodity X, and assume that σ_x^2 can be decomposed into two parts, i.e., the *systematic* part σ_a^2 and the *non-systematic* part σ_b^2, or simply,

$$\sigma_x^2 = \sigma_a^2 + \sigma_b^2. \tag{1}$$

Based on Equation (1), the *efficient market hypothesis* (**EMH**) can be defined as follows: a market is said to be *efficient* if $\sigma_a^2 = 0$. In other words, if we consider σ_x^2 as a measure of *risk*, then the **EMH** is a hypothesis about the *minimum risk*. It says that when market is *efficient*, the market participants (consumers and producers) are actually exposed to the *minimum risk*. The argument which lends support to the **EMH** is the *classical theory of speculative trades*, which is built upon the *no-arbitrage condition*. By this condition, if σ_a^2 is greater than 0, then there must exist some underlying regularities of the price movement, e.g., the climate pattern. The speculators can then take the advantage of these regularities by trading on these patterns, e.g., buying a lot of goods in the rainy season and selling them in the dry season.

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This kind of trade will continue until all regularities are exploited, i.e., until $\sigma_a^2 = 0$. As a consequence, in a market where speculative trades are permitted,

$$\sigma_x^2 = \sigma_b^2. \tag{2}$$

Clearly, the σ_x^2 in Equation (2) is smaller than the σ_x^2 in Equation (1).

In other words, speculative trades can reduce price volatility by σ_a^2. The reduction of price volatility has significant implications for economic efficiency. Usually, when the price is steady and predictable, the decision to produce is more likely to be correct, and, as a result, larger *gains from trade* can be realized. Therefore, the main conclusion of the classical theory of speculative trades is that speculators function as *price stabilizers* and can enhance the economic welfare of market participants.

The reasoning process from Equation (1) to Equation (2) presented above has one important assumption, namely, that speculators themselves will not contribute to the increase in price volatility. In other words, even if speculators fail to bring down price volatility, there is no way that it can go up. Suppose that this assumption fails to hold, then Equation (2) must be modified by adding to it a positive term σ_c^2,

$$\sigma_x^2 = \sigma_b^2 + \sigma_c^2, \tag{3}$$

where σ_c^2 is trading noise brought by speculators. Given this modification, the classical theory of speculators can still sustain if and only if

$$\sigma_a^2 \geq \sigma_c^2. \tag{4}$$

Since the classical theory of speculative trades fails to take the factor σ_c^2 into account, it certainly cannot answer the question when Equation (4) can hold and, more importantly, when speculators can be *destructive*. Insufficient knowledge of Equation (4) has created a puzzle for economics students. In class, they are told that speculative trades are imperative for efficient market, while, walking on street, they are impressed by the fact that financial regulations are important for the healthy operation of financial markets. What is the foundation of financial regulations? Can these regulations be justified? How do we know that they are making markets efficient rather than inefficient?

Using *genetic programming* to simulate speculative trades, Chen and Yeh (1997) illustrated that the function of financial regulations is to control σ_c^2. Therefore, to some extent, financial regulations can contribute to the reduction of σ_x^2 given that speculative trades are permitted. The environment simulated by Chen and Yeh (1997) is a *multi-agent production economy* with *adaptive producers* as well as *adaptive speculators*. To see whether speculators are stabilizing or destabilizing the market, they used the CASE 1 in Chen and Yeh (1996) as the starting point and added speculators to it thereafter. In all the simulations, they had a consistent result: speculators are *destabilizing* rather than *stabilizing* the market. Furthermore, price volatility has a tendency to go up when the financial regulations are increasingly relaxed.

While the role of financial regulations is explained in Chen and Yeh (1997), we can hardly see how speculators can contribute to price stability. The study was biased towards the side $\sigma_a^2 < \sigma_c^2$ and gave little attention to the other possibility: $\sigma_a^2 > \sigma_c^2$. However, as we shall see in this paper, this biased result, if any, is due to the design of the experiments, which set σ_a^2 initially too low and σ_c^2 too high.

The key variable used to control σ_a^2 is the *cobweb ratio*. The cobweb ratio was set to be 0.95 in Chen and Yeh (1997). This ratio will generate a *stable* cobweb model. As shown by Chen and Yeh (1996), in this stable case, σ_x^2, and hence σ_a^2, will converge to a number which is dependent on the *mutation rate*. Since normally the mutation rate is set to be a very small number, say, 0.0033, σ_a^2 can be small as well and, other things being equal, this setting makes Equation (4) more difficult to hold. On the other hand, the key variable which may affect σ_c^2 is the *financial depth* defined as the ratio of potential real speculative trades to the real output in the equilibrium. The financial depth is regularized by setting the upper limit for *short selling* $\underline{s}$ and the upper limit for the *inventory* $\bar{b}$. In Chen and Yeh (1997), it ranges from $\frac{1}{7}$ to $\frac{100}{7}$. This setting may be so high that Equation (4) can easily be violated.

Therefore, while Chen and Yeh (1997) showed when σ_c^2 can be greater than σ_a^2, the essence of this line of research is not to show that speculators are destabilizing. Rather, the belief underlying this line of research is that *markets without speculators cannot be efficient. On the other hand, markets with speculators can be even worse if appropriate financial regulations are absent.*

Table 1: Codes of Simulations

f.d. / c.r.	0.95	1.05	2.00	3
B.M.	A-0	B-0	C-0	D-0
0.005	A-1	B-1	C-1	D-1
0.01	A-2	B-2	C-2	D-2
0.1	A-3	B-3	C-3	D-3
1.0	A-4	B-4	C-4	D-4
10	A-5	B-5	C-5	D-5

The four numbers appearing in the **c.r.** row are four cobweb ratios. The four ratios are encoded by letters A, B, C, D in the ascending order. The five numbers in the **f.d.** column are the upper limit for short sells and inventory. These five limits are also encoded by numbers 1, 2, 3, 4, 5 in the ascending order. **B.M.** refers to the benchmark which is the case without speculators and is encoded by "0". For those cases with speculative trades, the duration for the short position is set to be 20. For details, see Chen and Yeh (1997a).

This paper modifies the environment simulated by Chen and Yeh (1997) in the following aspects. First of all, we are not just considering the stable cobweb model in which speculators can hardly find a role to play. Instead, by fine-tuning the cobweb ratio (**c.r.**), we simulate the economy from the stable case (**c.r.**=0.95), through fairly unstable ones (**c.r.**=1.05 and 2) and further to a highly unstable one (**c.r.**=3) (Table 1). Secondly, we also consider cases of more restrictive financial depth (**f.d.**). In particular, two cases which had not been explored in Chen and Yeh (1997), i.e., $(\underline{s}, \bar{b}) = (0.01, 0.01)$ and $(0.005, 0.005)$, are included (Table 1). As we shall see later, this parameter space is large enough to observe both the stabilizing and destabilizing function of speculators. Furthermore, by delimiting the space in which speculators are stabilizing or destabilizing, one can get a sketch of conditions under which Equation (4) holds or fails to hold. This is certainly an important step towards a general understanding about the nature of speculative trades and the meaning of financial regulations.

The rest of the paper is organized as follows. Section 2 briefly reviews the model. The design of simulations is given in Section 3, followed by the analysis of simulation results in Section 4.

2 The Analytical Framework

The analytical framework used in this paper is based on Muth (1961). Before adding the role of speculation to 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 (5):

$$c_{i,t} = xq_{i,t} + \frac{1}{2}ynq_{i,t}^2 \tag{5}$$

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:

$$\pi_{i,t}^e = P_{i,t}^e q_{i,t} - c_{i,t} \tag{6}$$

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

$$q_{i,t} = \frac{1}{yn}(P_{i,t}^e - x) \tag{7}$$

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:

$$P_t = A - B\sum_{i=1}^{n} q_{i,t} \tag{8}$$

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

$$\pi_{i,t} = P_t q_{i,t} - c_{i,t} \tag{9}$$

In a representative-agent model, it can be shown that the *rational expectations equilibrium price* (P^*) and *quantity* (Q^*) are (Chen and Yeh, 1996, p.449):

$$P_t^* = \frac{Ay + Bx}{B + y}, \tag{10}$$

$$Q_t^* = \frac{A - x}{B + y} \tag{11}$$

To extend the model (Equations (5)-(11)) 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

$$\pi_{j,t} = I_{j,t}(P_{t+1} - P_t). \tag{12}$$

Of course, the actual profit $\pi_{j,t}$ is unknown at the moment when the inventory plan is carried out; therefore, like producers, speculators tend to set the inventory up to the level where speculators' expected utility $Eu_{j,t}$ or expected profit $E\pi_{j,t}$ can be maximized. 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:

$$u_{j,t} \approx \phi(\pi_t) = \phi(0) + \phi^{'}(0)\pi_{j,t} + \frac{1}{2}\phi^{''}(0)\pi_{jt}^2 \tag{13}$$

Based on Equation (13), the approximate utility depends on the moments of the probability distribution of π_t, i.e.,

$$Eu_{j,t} \approx \phi(0) + \phi^{'}(0)E\pi_{j,t} + \frac{1}{2}\phi^{''}(0)E\pi_{j,t}^2 \tag{14}$$

Solving the first and the second moment of Equation (14), we can rewrite the expected utility function as follows.

$$Eu_{j,t} \approx \phi(0) + \phi^{'}(0)I_{j,t}(P_{j,t+1}^e - P_t) + \frac{1}{2}\phi^{''}(0)I_{j,t}^2[\sigma_{t,1}^2 + (P_{j,t+1}^e - P_t)^2], \tag{15}$$

where $\sigma_{t,1}^2$ is the conditional variance $var(P_{t+1} \mid \Omega_t)$ and Ω_t is the σ-algebra generated by $P_t, P_{t-1}, \ldots$. The optimal position of the inventory can then be derived approximately by solving the first order condition and the optimal position of the inventory $I_{j,t}^*$ is given by

$$I_{j,t} = \alpha(P_{j,t+1}^e - P_t), \tag{16}$$

where $\alpha = -\frac{\phi^{'}(0)}{\phi^{''}(0)\sigma_{t,1}^2}$. Equation (12) explicitly shows that speculators' optimal decision about the level of inventory depends on their expectations of the price in the next period, i.e., $P_{j,t+1}^e$.

Now, if the market is composed of n producers and m speculators, the equilibrium condition is given in Equation (17),

$$\frac{A}{B} - \frac{1}{B}P_t + \sum_{j=1}^{m} \alpha(P_{j,t+1}^e - P_t) = \sum_{i=1}^{n} \frac{1}{yn}(P_{i,t}^e - x) + \sum_{j=1}^{m} \alpha(P_{j,t}^e - P_{t-1}). \tag{17}$$

This concludes the construction of our model.

Table 2: 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	$\{P_{t-1}, P_{t-2}, \cdots, P_{t-10}, R\}$
Number of trees created by reproduction	30 (P), 10 (S)
Number of trees created by crossover	210 (P), 70 (S)
Number of trees created by mutation	60 (P), 20 (S)
Probability of mutation	0.2
Maximum depth of tree	17
Probability of leaf selection under crossover	0.5
Number of generations	1000
Maximum number in the domain of Exp	1700
Criterion of fitness	Profit

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

3 Simulation Design

The modeling technique for the adaptive behavior of both producers and speculators in the market is *genetic programming*. The GP-based algorithm for producers can be found in Chen and Yeh (1996), and the GP-based algorithm for speculators can be found in Chen and Yeh (1997). All the control parameters for the Muthian economy are given in Table 2. Due to the space limit, we will not repeat the details here. However, we do want to emphasize that the *selection scheme* employed in this paper is *tournament selection* instead of the *proportionate selection* (*roulette-wheel selection*).

The *selection scheme* is an important operator in genetic programming. When applying genetic programming to *optimization*, the user must notice that different selection schemes may have different implications for the fitness value, selection intensity, selection variance, and loss of diversity. By the same token, when genetic programming is applied to *simulating the evolution and learning of the economic system*, we have to keep in mind that different schemes may have different economic implications. From the viewpoint of matching processes, Chen and Yeh (1997a) argued that what proportionate selection simulates is the evolution of a *centralized* network economy and that what tournament selection does is the evolution of a *decentralized* network economy. They also pointed out that to simulate the adaptive behavior of "*speculating about of others' speculations*", tournament selection seems to be more appropriate. Therefore, this paper, unlike previous studies, choose *tournament selection* as the selection scheme[1]

Given the GP-based adaptive producers and speculators, we simulate all the economies as indicated in Table 1. From CASE x.1 to CASE x.5 ($x = A, B, C, D$), the financial regulations on $\overline{b}$ and $\underline{s}$ are gradually relaxed from 0.005 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 potential speculative trades to Q^* is relaxed from $\frac{1}{140}$ to $\frac{100}{7}$. The larger the $\overline{b}$ and the $\underline{s}$, the higher the possible proportion of "*non-productive activities*" to the economy.

4 Simulation Results

Simulations were conducted for all cases, including the benchmark, in accordance with Tables 1 and 2. For each case, we ran five simulations and each simulation was conducted for one thousand periods (generations).

[1] For the design of tournament selection, the interested reader is referred to Chen and Yeh (1997a).

Table 3: Relative Volatility (q):

f.d. (j) / **c.r.** (i)	0.95 (A)	1.05 (B)	2.00 (C)	3 (D)
B.M.	1	1	1	1
0.005 (1)	0.9408	0.9353	0.8760	0.4860
0.01 (2)	0.9934	0.9529	0.4791	1.2611
0.1 (3)	1.1447	1.1882	1.1552	0.7953
1.0 (4)	5.4079	6.4118	3.7406	3.5769
10 (5)	36.4013	47.2824	34.6648	31.5030

Here, volatility is estimated by averaging the standard deviations of the five simulations in each case. The standard deviations are estimated based on the last five hundred observations, i.e., $\{P_t\}_{t=501}^{1000}$.

Basic statistics such as average prices and standard deviations for all cases can be found in Chen and Yeh (1997b). In Figures 1-8, some selected samples are depicted. To see the impact of speculative trades on price volatility under different financial depths, we define *relative volatility* $q_{i,j}$ as

$$q_{i,j} = \frac{\widehat{\sigma_{x,ij}}}{\widehat{\sigma_{x,i0}}}, \tag{18}$$

where $i = A, ..., D$, $j = 1, ..., 5$. "$\widehat{\ }$" means "the estimated", and the result is exhibited in Table 3.

By the definition given above, $q < 1$ indicates that the market experiences a reduction in price volatility, and $q > 1$ means that the market experiences an increase in volatility. From Table 3, we have two interesting observations. First, speculative trades can contribute to the reduction of volatility only if the corresponding financial regulations are *appropriately* imposed. For example, in our simulations, $q > 1$ when **f.d.** ≥ 1. Second, speculative trades can contribute to the reduction of volatility more significantly if the market is inherently unstable (high **c.r.**). For example, in CASEs C and D, depending on the associated financial regulations, 20% to 50% of volatility can be reduced.

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Figure 1 : Equilibrium Price in Each Generation (CASE A5-5)

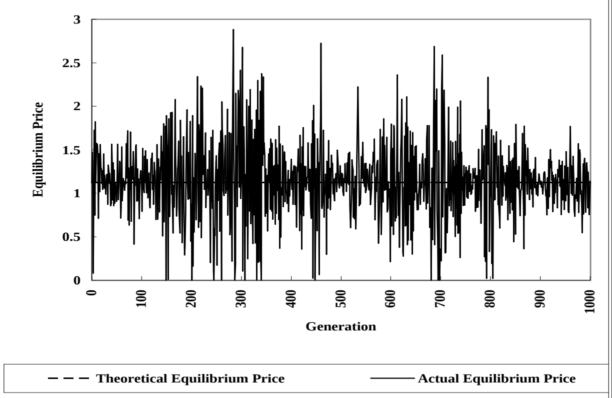

Figure 2 : Equilibrium Price in Each Generation (CASE B1-4)

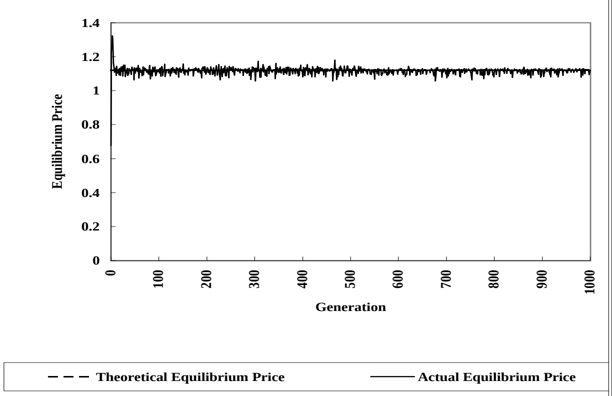

Figure 3 : Equilibrium Price in Each Generation (CASE C1-3)

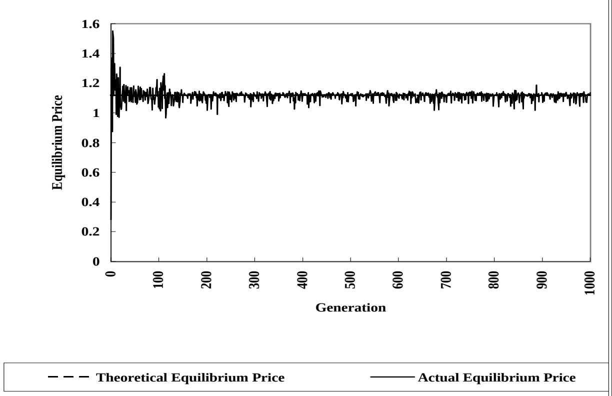

Figure 4 : Equilibrium Price in Each Generation (CASE D3-5)

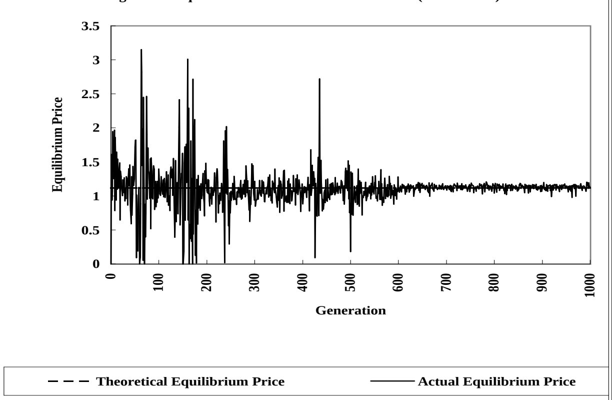

Figure 5 : Inventory in Each Generation (CASE A5-5)

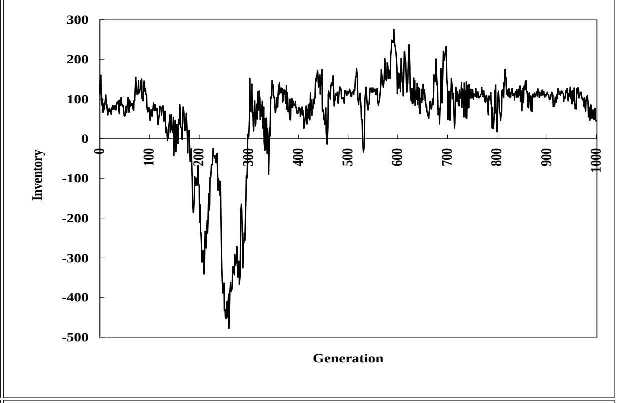

Figure 6 : Inventory in Each Generation (CASE B1-4)

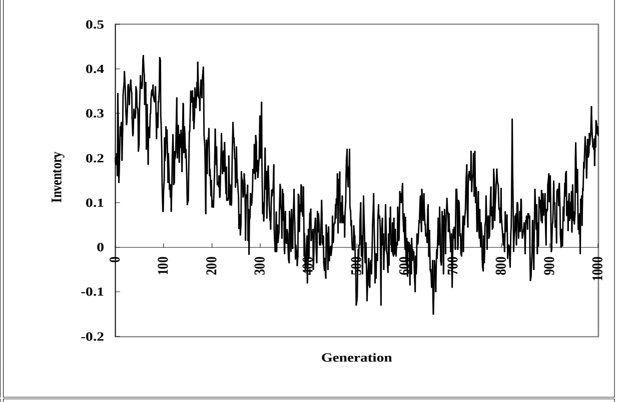

Figure 7 : Inventory in Each Generation (CASE C1-3)

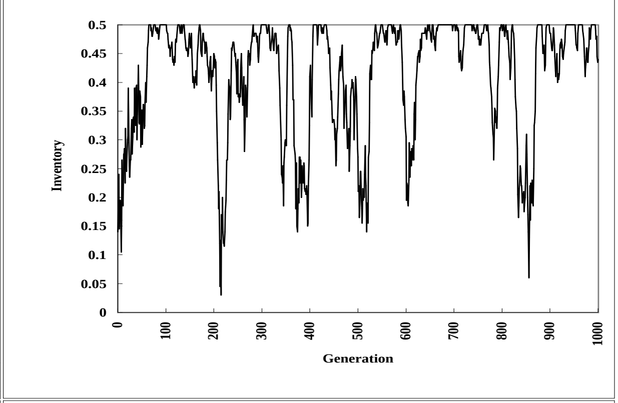

Figure 8 : Inventory in Each Generation (CASE D3-5)