Modeling Speculators with Genetic Programming*

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Abstract. 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.

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

1 Motivation and Literature Review

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

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that, so long as we can model speculators in a more *adaptive* fashion, then they should function as *price stabilizers*. For example, Even and Mishra (1996) found that, if all speculators are *trend speculators*, then speculation can help little to stabilize the price. However, Even and Mishra (1996) 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.

The dramatic reduction in 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, 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 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).

Roughly speaking, no-trade theorem is an *impossibility theorem*. It says that, if there is no private information about the asset and there are only rational-expectations traders, then there will be no gains of trade, and hence, no trade. *If there is trade, it must be speculative.* What Smith, Suchanek and Williams did was design such a laboratory market and investigate the possibility of the speculative trade. 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*. 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.

Arthur (1992) and Palmer et al. (1993), to our best knowledge, are the first few papers to illustrate how the aspect of speculating about the speculations of others can be possibly modeled with the help of *multiagent systems*, i.e., systems composed of heterogeneous speculators. The idea proposed by Arthur is, in effect, Holland's *classifier system.* This line of research has been taken further by Marengo and Tordjman (1996). Marego and Tordjman (1996) used *classifier systems* with *reinforcement learning* in the modeling of speculators. They generated some very promising features, such as the *persistently high trading volume* and *price bubbles followed by crashes.* While these simulations results along with the experimental results of Smith, Suchanek and Williams (1988) can lend support to the destabilizing feature of speculators, all these models are *purely* speculative in the sense that the *fundamentals* of the economy are simply missing.

In this paper, we shall study the function of speculators in a *production economy* simultaneously with *adaptive producers* in a *multiagent setup.* The paper distinguish itself from the literature reviewed above in one of the following three aspects. First, it is not a representative-agent model. Second, it is not a pure speculative economy. Last, it allows for the adaptation of producers. These three distinguishing features enable us to stand in a better position to study speculators from Keynes' perspective.

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.* In Section 3, we discuss how to design genetic programming to serve this purpose. The GP-based multiagent 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. Therefore, we can use this system as a *benchmark* for making comparison with the Muthian economy *with 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 $P^e_{i,t}$ and the cost function $c_{i,t}$, the expected profit of firm i at time t can be expressed as follows:

$$\pi^e_{i,t} = P^e_{i,t} q_{i,t} - c_{i,t} \tag{2}$$

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

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

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 :

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

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

$$P^*_t = \frac{Ay + Bx}{B + y}, \tag{6}$$

$$Q^*_t = \frac{A - x}{B + y} \tag{7}$$

To extend the model (Equations (1)-(7)) 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

$$\pi_{j,t} = I_{j,t}(P_{t+1} - P_t). \tag{8}$$

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. 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:

$$u_{j,t} \approx \phi(\pi_t) = \phi(0) + \phi'(0)\pi_{j,t} + \frac{1}{2}\phi''(0)\pi^2_{jt} \tag{9}$$

Based on Equation (9), the approximated utility depends on the moments of the probability distribution of π_t, i.e.,

$$Eu_{j,t} \approx \phi(0) + \phi^{'}(0)E\pi_{j,t} + \frac{1}{2}\phi^{''}(0)E\pi_{j,t}^2 \quad (10)$$

Solving the first and the second moment of Equation (10), we can rewrite the expected utility function as follows.

$$Eu_{j,t} \approx \phi(0) + \phi^{'}(0)I_{j,t}(P_{j,t+1}^e - P_t) + \frac{1}{2}\phi^{''}(0)I_{j,t}^2[\sigma_{t,1}^2 + (P_{j,t+1}^e - P_t)^2] \quad (11)$$

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

$$I_{j,t} = \alpha(P_{j,t+1}^e - P_t), \quad (12)$$

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 (13),

$$\frac{A}{B} - \frac{1}{B}P_t + \sum_{j=1}^{m}\alpha(P_{j,t+1}^e - P_t) = \sum_{i=1}^{n}\frac{1}{yn}(P_{i,t}^e - x) + \sum_{j=1}^{m}\alpha(P_{j,t}^e - P_{t-1}). \quad (13)$$

This concludes the construction of our model.

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 $P_{j,t}^e$. 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,[2]

$$I_{j,t} = I_{j,t}(P_{t-1}, P_{t-2}, \cdots,). \quad (14)$$

In the following, genetic programming will be applied to model the adaptation of the function form of $I_{j,t}$. Let GP_t^s, 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, $I_{j,t}$ ($I_{j,t} \in GP_t^s$), a *parse tree* written over the *function set* and *terminal set* which are given in

[2] See the full paper for the detailed discussion of the use of this general function from.

Table 1. 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 addition to the lower bound of $I_{j,t}$, we also set an upper bound of $I_{j,t}$, $\bar{b}$.

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 (8). 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.

$$\begin{aligned} \mu_{j,t} &= \pi_{j,t} + \beta \quad & if \;\; \pi_{j,t} \geq -\beta, \\ &= 0 & if \;\; \pi_{j,t} < -\beta. \end{aligned} \tag{15}$$

The choice of "β" is due to the similar consideration 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 (16).

$$p_{j,t} = \frac{\mu_{j,t}}{\sum_{j=1}^{n} \mu_{j,t}} \tag{16}$$

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, $\bar{b}$ and $\underline{s}$ (See Table 2).

From CASE 1 to CASE 4, the financial regulations on $\bar{b}$ 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 $\frac{100}{7}$. The larger the $\bar{b}$ and the $\underline{s}$, the higher the possible proportion of "*non-productive activities*" to the economy.

4 Results of Simulations

4.1 Volatility

Simulations were conducted for Cases 1 to 4 and the benchmark in accordance with Tables 1 and 2. For each case, we ran five simulations and each simulation

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	$\{P_{t-1}, P_{t-2}, \cdots, P_{t-10}, R\}$
number of trees created by reproduction	30 (P), 10 (S)
number of trees created by crossover	210 (P), 70 (S)
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).

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.

Given the benchmark, we would like to investigate the difference between the economy with speculators (CASEs 1-4) 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 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.*

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.*

Table 2. Parameter Values of the Muthian Economy

Set	D	$\bar{b}$	$\underline{s}$
CASE 1	$U[0,20]$	0.1	0.1
CASE 2	$U[0,20]$	2	2
CASE 3	$U[0,20]$	6	6
CASE 4	$U[0,20]$	10	10

In all of these cases, $A = 2.184$, $B = 0.0152$, $x = 0$, $y = 0.016$, $\frac{B}{y} = 0.95$, and $P^* = 1.12$. $U[0,20]$ is the random variable with the uniform distribution over $[0,20]$. 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.

4.2 Welfare Analysis

As we mentioned earlier, the consequences of high volatility in price may make both producers and consumers suffer. In this section, we would like to figure out exactly how bad the economy will suffer because of speculative trade. On producers' side, we use *producers' surplus* as an indicator. More precisely, we divided producers' surplus of each generation achieved in each simulation by *producers' surplus* obtained from the static cobweb model, i.e., 37.24. This ratio called λ was further averaged over the last 500 periods and is presented in Table 4.

From Table 4, we can see that after 500-period adaptation, producers in the benchmark earn almost all of what they can possibly earn ($\lambda = 0.9992$). The high profits shared by all producers come from the *stable price* (The volatility, on average, is only 0.0024). However, when this stability is taken away by speculative trade, the realized profits shared by all producers are dramatically reduced.

On consumers' side, we consider the risk to which consumers were exposed. In economics, in the normal case, consumers are assumed to be the *risk averser*. So, if the goods consumed are supplied in a very volatile manner, consumers will suffer. Let $Q_{D,t}$ be the quantity of goods consumed by *consumers* in each period. From the series $\{Q_{D,t}\}_{t=501}^{1000}$, the *mean* ($\overline{Q_D}$) and the *standard deviation* δ_{Q_D} are derived. Based on economic theory, consumers' welfare depends not only on $\overline{Q_D}$ but also on δ_{Q_D}. Usually, the higher the $\overline{Q_D}$ and the lower the δ_{Q_D}, the better off the consumers. Table 5 presents these statistics of all cases.

To see what these numbers mean, recall that $Q^* = 70$. While in almost all cases the quantity actually supplied is very close to 70, the difference in volatility among these cases is pretty significant. In the benchmark, consumers consume the right amount ($\theta = 69.994$) with negligible risk ($\eta = 0.175$). However, when

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

Simulation		1	2	3	4	5
CASE						
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

$\overline{P_a}$ = 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).

financial regulations are getting loose, η starts to pick up and it can reach 25 or more, which already exceeds $\frac{1}{3}$ of $\overline{Q_D}$. *Therefore, the introduction of speculative trade to the economy not only costs producers their potential profits, but also exposes consumers to an extremely risky environment.* However, this welfare loss can be reduced significantly if appropriate financial regulations are imposed.

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

Table 4. Welfare Analysis: Producers

Simulation	1	2	3	4	5	$\overline{\lambda}$
CASE B	0.9988	0.9988	0.9993	0.9998	0.9989	0.9992
1	0.9023	0.8825	0.8966	0.9133	0.9068	0.9004
2	0.8744	0.9130	0.8752	0.8635	0.8927	0.8839
3	0.5575	0.7713	0.8611	0.8506	0.7758	0.7674
4	0.8422	0.7862	0.7736	0.8250	0.8174	0.8089

$\overline{\lambda}$ is the average of the relative realized producers' surplus over the last 500 periods.

Table 5. Welfare Analysis: Consumers

Simulation		1	2	3	4	5	θ
CASE							η
B	$\overline{Q_D}$	70.005	69.978	69.997	69.977	70.013	69.994
	δ_{Q_D}	0.169	0.223	0.126	0.125	0.232	0.175
1	$\overline{Q_D}$	69.997	69.850	69.426	69.502	69.890	69.733
	δ_{Q_D}	1.704	1.846	1.973	1.962	1.691	1.835
2	$\overline{Q_D}$	69.471	69.695	69.966	70.112	58.432	67.535
	δ_{Q_D}	10.013	8.348	13.627	8.041	14.977	11.001
3	$\overline{Q_D}$	65.973	68.187	62.418	69.916	70.150	67.329
	δ_{Q_D}	44.813	29.568	24.954	15.424	25.970	28.146
4	$\overline{Q_D}$	69.926	69.942	64.086	69.804	66.623	68.076
	δ_{Q_D}	19.937	22.438	34.331	26.680	25.183	25.714

θ is the average of the $\overline{Q_D}$ over the five simulations, and η is the average of the δ_{Q_D}.

economy simulated in this paper is not purely speculative; therefore, a welfare analysis can be meaningfully conducted in this framework. In fact, in this paper, the impact of speculative trade on the welfare loss of consumers and producers is quantified. Through this quantification, the significance of financial regulations is lucidly seen. 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.

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. However, the formal relation between the size of the search space and the coordination failure requires further studies.

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