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Understanding the Nature of Predatory Pricing in Large-Scale Market Economy with Genetic Algorithms*

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Abstract: In this paper the nature of predatory pricing is analyzed with genetic algorithms. It is found that, even under the same payoff structure, the results of the co-evolution of weak monopolists and entrants are sensitive to the representationof the decision-making process. Two representations are studied in this paper. One is the action-based representation and the other the strategy-based representation. The former is to represent a naive mind and the latter is to capture a sophisticated mind. For the action-based representation, the convergence results are easily obtained and predatory pricing is only temporary in all simulations. However, for the strategy-based representation, predatory pricing is not a rare phenomenon and its appearance is cyclical but not regular. Therefore, the snowball effect of a little craziness observed in the experimental game theory wins its support from this representation. Furthermore, the nature of predatory pricing has something to do with the evolution of the sophisticated rather than the naive minds.

Keywords: Chain-store game, Predatory pricing, Evolutionary game, Genetic algorithms, Co-evolutionary stability

1. INTRODUCTION AND MOTIVATION

Despite the famous price war between the two leading coffee manufactures Maxwell House and Folger which happened in the 1970s, many economists have been skeptical about the possibility of predatory pricing. Traditional models of firm behavior often conclude that price predation is not profitable. In the paper entitled "The Chain Store Paradox", Selten (1978) demonstrated that price wars are not supported in a straightforward game-theoretic model. In Selten's model, the chain store operates in N markets. In each of the N periods there is an entry threat in one of these markets. The potential entrant must choose whether to enter or stay out. Simultaneously, the chain store prepares a pricing response in case entry occurs, the choice being to acquiesce, matching the entrant's price, or to fight by undercutting. In the unique subgame perfect equilibrium, all potential competitors enter and the chain store behaves passively in all markets. However, intuition suggests that the chain store should seek early in the game to acquire a reputation for being "tough" toward early entrants in order to deter later entrants. This is the famous chain store paradox: despite a potentially large long-run payoff, the chain store is unable to build a reputation for toughness.

The chain store paradox is further confirmed by the study "In Search of Predatory Pricing" conducted by Issac and Smith (1985), in which they concluded: "We are unable to produce predatory pricing in a structural environment that, a priori, we thought was favorable to

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its emergence" (pp. 342). This opinion has been further popularized by textbooks. For example, in the book Modern Industrial Organization written by Carlton and Perloff (1990), the authors argued that "from the evidence cited earlier, it is still correct to regard price predation as a rare phenomenon" (pp. 411).

Economists, however, have gradually recognized that the chain store paradox is not robust with respect to small changes in the model. In particular, dramatically different results can emerge if there is imperfect information about the payoffs of the monopolists (the incumbents). For example, Kreps and Wilson (1982) studied a version of the chain-store game with two types of monopolists: the weak monopolists whose best response in a single-shot game is to play soft following entry, and the strong monopolists whose dominant strategy is to fight all entries. Suppose that the proportion of the strong monopolists is δ and the entrants apply Bayes' Theorem to revise their assessment of the probability that the monopolist is indeed a strong one, then it can be shown that, no matter how small δ is, the monopolist's optimal strategy, regardless of his actual payoffs, should exhibit such a behavior against its rivals in all, expect possibility the last few, in a long string of encounters. For the weak monopolist, the immediate cost of predation is a worthwhile investment to sustain or enhance its reputation, thereby deterring subsequent challenges. In other words, it is the uncertainly regarding what type of monopolist the incumbent is that is directly responsible for price wars.

This paper takes the assumption that entrants are uncertain about the monopolist's type. But, instead of Bayesian learning, this paper uses genetic algorithm learning to model the learning behavior of players. Modeling the adaptive behavior in evolutionary games by genetic algorithm learning is gaining popularity [See Axelord (1987), Marks (1994), Arifovic and Eaton (1995) and Arifovic (1995), and Chen, Duffy and Yeh (1996).]. The major advantage of applying this paradigm to games is that it enables us to relax stringent assumptions about bounded rationality and advances our understanding about the implication of bounded rationality for the solutions of games (See Sargent (1993) for details). Therefore, using GAs, we want to see whether the snowball effect of a little craziness--weak monopolists imitating strong monopolists, which in turn deters entry--could persistently exist in the game composed of GA-based adaptive players. In the next section, we will encode the chain-store game with two different representations, namely, the strategy-based representation and the action-based representation. We will then compare the search outcomes under different representations in the third section followed by concluding remarks.

2. REPRESENTATIONS OF THE CHAIN-STORE GAME

In this paper, GA is operated within two different representations of solutions. The first is to represent the solution as a strategy in the extensive form of a game, and the second is to represent the solution as a sequence of actions in the action space. For convenience purposes, we will call the first one the strategy-based GA and the second the action-based GA. To describe the coding of these two GAs, let us introduce the following notation. Let m denote the monopolist and e the entrant (In the next section, we shall further use M to denote strong monopolists and m is reserved for weak monopolists only.). As to actions, we shall use "0" to represent the action "fight" for the monopolist and "enter" for the entrant, and "1" to represent the action "match" for the monopolist and "out" for the entrant. Furthermore, let a^m_i and a^e_i be the action taken by the monopolist and the entrant in the ith period. a^m_i and $a^e_i \in A = \{0, 1\}$, $\forall i$. A strategy of the $i+1$-th period $S^p_{i+1} (p = m, e)$ is a function of the history of the actions taken by the opponent. More precisely,

$$S^m_{i+1}: \Omega^e_i \to A \tag{1}$$

$$S^e_{i+1}: \Omega^m_i \to A \tag{2}$$

where $\Omega^p_i = \{a^p_1, \dots, a^p_i \mid a_j \in A, j = 1, \dots, i\} (p = m, e)$. Since the cardinality of Ω^p_i is 2^i, a strategy $S^p_{i+1} (p = m, e)$ can be coded by a 2^i-bit binary string $s^p_1 \cdots s^p_{2^i}$ as follows:

$$S^m_{i+1}(a^e_1 \cdots a^e_i) = s^m_k, \text{ if } \sum_{j=0}^{i-1} a^e_{j+1} 2^j + 1 = k \tag{3}$$

$$S^e_{i+1}(a^m_1 \cdots a^m_i) = s^e_k, \text{ if } \sum_{j=0}^{i-1} a^m_{j+1} 2^j + 1 = k \tag{4}$$

For convenience, we shall slightly abuse the use of notations and henceforth simply let S^p_i be the binary string described as above. Given the binary strings $S^p_1, \dots, S^p_n (p = m, e)$, a n-period strategy σ^p_n can be coded by the concatenation of each period's strategy as follows.

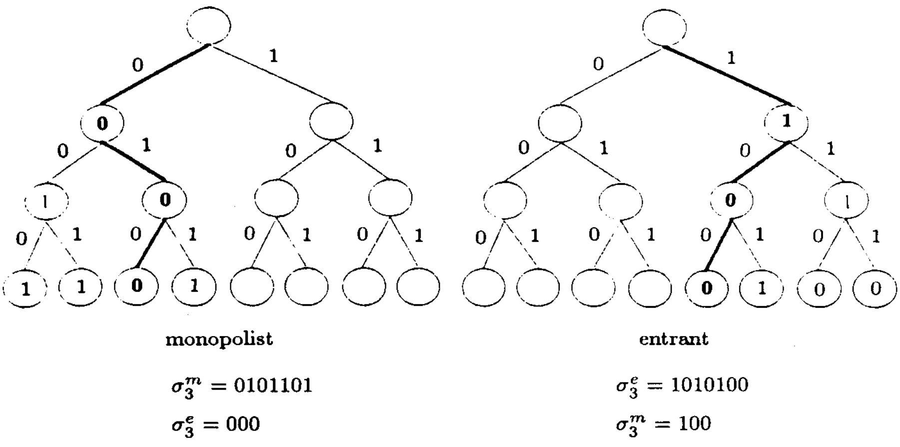


Fig. 1 Strategy-based and action-based representations

$$\sigma^p_n = S^p_1 \mid \cdots \mid S^p_n \tag{5}$$

For example, suppose in a three-period game ($n = 3$), $\sigma^m_3 = 0101101$ and $\sigma^e_3 = 1010100$, then based on the notations specified above, $S^m_1 = 0$, $S^m_2 = 10$, $S^m_3 = 1101$, and $S^e_1 = 1$, $S^e_2 = 010$, $S^e_3 = 0100$. Furthermore, $a^m_1 = 0$, $a^m_2 = 0$, $a^m_3 = 0$, $a^e_1 = 1$, $a^e_2 = 0$ and $a^e_3 = 0$. So, the sequence of actions taken by the monopolist is "001", and the sequence of actions taken by the entrant is "100". This can be easily seen in Fig. 1.

In terms of coding, the action-based GA is much simpler. It is just the n-bit binary string $a^p_1 \cdots a^p_n (p = m, e)$, denoted by α^p_n, as we have already seen in the example above.

The reason why we study the chain-store game under different representations is as follows. We know that the search efficiency induced by GA is not independent of the representation of the search space. In some cases, the poor performance of the search is attributed to the poor representation of the search space and it is thought that there are some bad representations which should be avoided. However, in some cases, a representation which is poor in terms of computation efficiency might be natural from the perspective of human reasoning.

For instance, consider the two representations of the chain-store game given above. One might argue that the action-based GA is an efficient representation because the code length of the action-based GA grows linearly in terms of the number of the periods of the game, while that of the strategy-based GA grows with the exponential rate of 2. If the game is played for 8 periods, the code length of a strategy under the action-based GA is only 8 as opposed to 255 under the a strategy-based GA. Alternatively speaking, the cardinality of the search space for the former is only 2^8, while it is 2^{255} for the latter. Therefore, the search space represented by the strategy-based GA might not be parsimonious enough and might cause some problems such as slow convergence to the optimum. Nevertheless, the strategy-based GA is natural in the sense that it represents a complete strategy which is composed of contingency plans and is very much like human reasoning. By contrast, we cannot see how players actually reason from the action-based GA.

Table 1 Structure of payoffs

		Payoffs (in Francs)		
Entrant	Monopolist	Entrant	Weak Monopolist	Strong Monopolist
IN	Fight	80	70	160
	Match	150	160	70
OUT	No Choice	95	300	300

3. THE PAYOFF FUNCTION OF THE CHAIN-STORE GAME

The chain-store game in this paper will be based on the version studied by Jung et al. (1994). In this game, the market is composed of two types of monopolists: the weak and the strong. They are distinguished by the payoffs of their actions to the entrant threat (see Table 1). For the strong monopolists, fighting with the entrant will earn them a higher payoff ($ 160) than matching ($ 70). However, for the weak monopolists, the opposite is true.

In each generation of game, there are equal numbers of monopolists and potential entrants, who are randomly paired, i. e., one monopolist to one entrant (See Table 2). The players of the same pair then play against each other in n consecutive periods. The payoff for each player in each π_i is computed based on Table 1. The payoff for each player and his associated strategy σ_n^p is computed as $\pi = \sum_{i=1}^{n} \pi_i$. π will then be used as the fitness value of the binary string of σ_n^p (See Table 2.), and the σ_n^p are updated using the basic GA operators whose control parameters are given in Table 2. The reproduction operator makes copies of individual binary string (strategies) and places them in the mating pool. The crossover operates on the pairs of randomly selected binary strings (strategies) from the mating pool. The mutation operator randomly changes the value of a position within a binary string (a strategy). Given the updated set of binary strings, the algorithm proceeds to the next cycle for another generation of chain-store games.

While this application of GAs is quite standard, the distinguishing feature of this application is that there is no optimal strategy for either weak monopolists or potential entrants in an absolute sense. This is due to the fact that the payoff of each strategy is not unique and it crucially depends on the opponent it plays against. For example, the payoff of σ_3^m = 0101101 is \$ 440 if its opponent strategy σ_3^e is 1010100; however it is \$ 530 if its opponent strategy σ_3^e is 0001111. Therefore, in this application of GAs, σ_n^m will co-evolve with σ_n^e. Given this co-evolutionary process, we can study whether a stable co-strategy ($\sigma_n^{m,*}$, $\sigma_n^{e,*}$) will emerge. The analysis within this framework extends the study of Kreps and Wilson (1982) based on the Bayesian learning scheme. The problem with the Bayesian learning scheme is its limitation to deal with crazy or cut-throat strategies because basically it assumes that players are rational. But, whether irrational behavior as a strategy can be completely eliminated from this evolutionary process is an unsettled issue (e. g. Jung et al., 1994). As we shall see later, the simulations based on the GA learning scheme enable us to tackle part of this issue.

Table 2 The parameters of the GA-based chain store games

periods of a single play (n)	8
number of the strong monopolists	33
number of the weak monopolists	67
number of potential eatrants	100
chromosomes (action-based coding)	α_n^p
chromosomes (strategy-based coding)	σ_n^p
reproduction technique	Roulette Wheel Selection
crossover technique	One-Point Crossover
crossover rate	0.8
mutation rate	0.0001
evalution function	Tatal Payoffs (π)
number of generations (GA cycles)	50000

4. THE RESULTS OF THE SIMULATIONS

4.1 The Action Based GA

As specified by Table 2, five simulations were conducted for the action-based GA. The results of the simulations show that while price wars can happen, they can persistently exist only between strong monopolists and entrants. Predatory pricing, defined as weak monopolists fighting entrants, is not evolutionarily stable in our simulations. To see this, the proportion of strong and weak monopolists who choose the action "fight" is shown in Table 3(a) and 3(b) separately, and the proportion of entrants who choose the action "in" is shown in Table 3(c). In Table 3(a), the actions chosen by almost all strong monopolists converge to " α_8^M = 00000000 " very quickly. Also, in Table 3(b), they all converge to " α_8^m = 11111111" for almost all weak monopolists. As to the entrants, we can see that the ratio of "in" is about 90 . The reason for this ratio can be explained as follows. Suppose all the strong monopolists choose to fight and the weak monopolists choose to match in all periods, then the expected payoff of the action "in" is \$ 127 per period and is higher than the payoff of the action "off".

which is \$ 95. Therefore, on the average, the temptation for the action "in" is stronger. However, since 1/3 of the monopolists are strong, 1/3 of the action α_8^e = 00000000 will earn the worst total payoff (\$ 640) and this leaves room for other actions to survive. In fact, based on the statistics of these five simulations, the action "00000000" dominates 40 % - 45 % of all the surviving actions for entrants. We can further increase this ratio by decreasing the number of strong monopolists and increasing the number of weak monopolists. Roughly speaking, the co-evolutionary processes which we obtain from these simulations are as follows.

Table 3(a) The ratio of "fight": strong monopolists

Gen \ *n*	1	2	3	4	5	6	7	8
0	0.42	0.58	0.55	0.39	0.42	0.64	0.67	0.30
50	1.00	1.00	1.00	1.00	0.18	1.00	0.52	1.00
100	1.00	1.00	1.00	1.00	1.00	1.00	0.24	1.00
150	1.00	1.00	1.00	1.00	1.00	1.00	0.03	1.00
200	1.00	1.00	1.00	1.00	1.00	1.00	0.24	1.00
250	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00
300	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00
350	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
400	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
450	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
500	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 3(b) The ratio of "fight": weak monopolists

Gen \ *n*	1	2	3	4	5	6	7	8
0	0.51	0.58	0.54	0.42	0.52	0.60	0.63	0.55
50	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
100	0.00	0.00	0.01	0.00	0.00	0.00	0.96	0.00
150	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.00
200	0.00	0.00	0.00	0.01	0.00	0.00	0.94	0.00
250	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00
300	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.00
350	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
400	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
450	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
500	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00

Co-evolutionary equilibrium: Selten's case

$$\alpha_{8,t}^{M} \xrightarrow{} (1) \qquad \alpha_8^{M,*} = 00000000$$
$$\alpha_{8,t}^{m} \xrightarrow{} (1) \qquad \alpha_8^{m,*} = 11111111$$
$$\alpha_{8,t}^{e} \xrightarrow{} (0.4) \qquad \alpha_8^{e,*} = 00000000$$

where " $\xrightarrow{} (p)$ " means converging with probability p.

The equilibrium of predatory pricing can be considered another interesting result of coadaptation. In general, we can characterize this kind of equilibrium as follows.

Co-evolutionary equilibrium: Predatory pricing

$$\alpha_{8,t}^{M} \to (1) \quad \alpha_{8}^{M,*} = 00000000$$
$$\alpha_{8,t}^{m} \to (p_1) \quad \alpha_{8}^{m,*} = 00000000$$
$$\alpha_{8,t}^{e} \to (p_2) \quad \alpha_{8}^{e,*} = 11111111$$

Table 3(c) The ratio of "In": entrants

Gen \ n	1	2	3	4	5	6	7	8
0	0.49	0.44	0.53	0.42	0.46	0.52	0.43	0.51
50	0.79	0.87	0.98	1.00	1.00	0.99	0.01	0.98
100	0.92	0.89	0.94	0.96	0.97	0.96	0.06	0.98
150	0.92	0.90	0.91	0.93	0.96	0.93	0.02	0.93
200	0.90	0.92	0.88	0.92	0.96	0.95	0.07	0.96
250	0.89	0.89	0.89	0.91	0.93	0.94	0,06	0.96
300	0.90	0.89	0.91	0.93	0.92	0.94	0.13	0.88
350	1.00	0.96	0.94	0.97	0.97	0.89	0.97	0.87
400	0.94	0.88	0.93	0.95	0.93	0.90	0.95	0.86
450	0.93	0.90	0.88	0.94	0.94	0.92	0.93	0.85
500	0.92	0.89	0.88	0.92	0.93	0.89	0.93	0.86

Table 4 The snowball effect of a little craziness: simulation 4-4

Gen	250	300	350	400	450	500
p_1	0.91	0.73	0.72	0.57	0.49	0.64
p_2	0.98	0.97	0.96	0.94	0.94	0.94

where p_1 has a positive relation with p_2. One of the extreme cases is that $p_1 = 1$ and $p_2 = 1$, and the small p_1 coupled with high p_2 is corresponding to the snowball effect of a little craziness termed by Jung et al. (1994). This kind of phenomenon only happened three times in our simulations. In Table 4, we exhibit the results of p_1 and p_2 for period 4 of simulation 4. Only in these few periods did weak monopolists successfully scare away entrants. For the rest of the periods, however, the entrants were able to detect the camouflage of the fox under the lion's skin.

One conjecture for the unlikelihood of the predatory pricing equilibrium is that, compared with Selten's co-evolutionary equilibrium, the predatory pricing equilibrium has a much smaller basin of attraction. One might suggest that the payoff structure is responsible for this asymmetry. However, as we shall see in the next subsection, representation itself might be a real key factor.

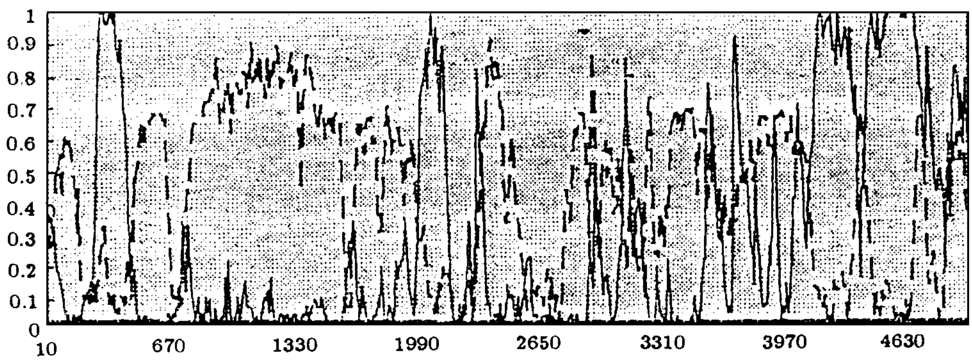
4.2 The Strategy-Based GA

For the strong monopolists, "fight to the end" ("00000000") is still the dominating strategy. A more careful analysis reveals that while predatory pricing can never disappear, real large-scale price wars do not happen very often. To see this, Fig. 2(a) to 5(h) plot the ratios of the weak monopolists and potential entrants who take action "0" at the sixth stage of the game.

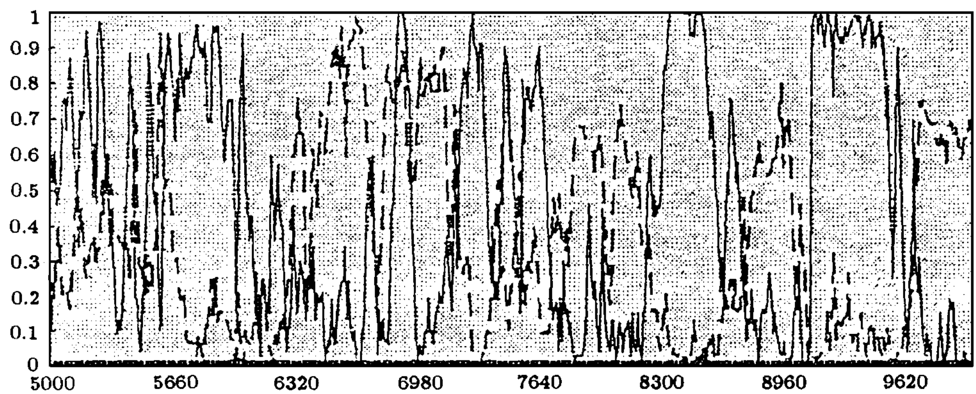
The interesting thing to notice about these figures is that these two ratios tend to move in opposite directions. Most of the time when the ratio for the weak monopolists is high, the ratio for the potential entrants is low and vice versa. Since predatory pricing can happen only when the weak monopolist who would like to fight meets the potential entrants who would like to join the market, the inverse relation between these two ratios seem to suggest that, most of the time, predatory pricing can only happen in a very limited number of markets.

5. CONCLUDING REMARKS

Predatory pricing as adaptive behavior is analyzed in this paper with genetic algorithms using different representations. It is shown that predatory pricing as a strategy can hardly survive in an action-based representation but can easily survive in the strategy-based representation and that the snowball effect of a little craziness can win support from this latter representation. While from the viewpoint of computation, the action-like reasoning more closely and enhances our understanding of the unstability of co-evolution when the complexity of decision making increases. The findings of this paper are consistent with what we have learned from evolutionary game theory in the sense that the result of the game depend on the complexity constraints assigned to the players. In this paper, the action-based GA is analogous to a thought process with high complexity. It remains to be investigated how the complexity of the thought process evolves.



(a)



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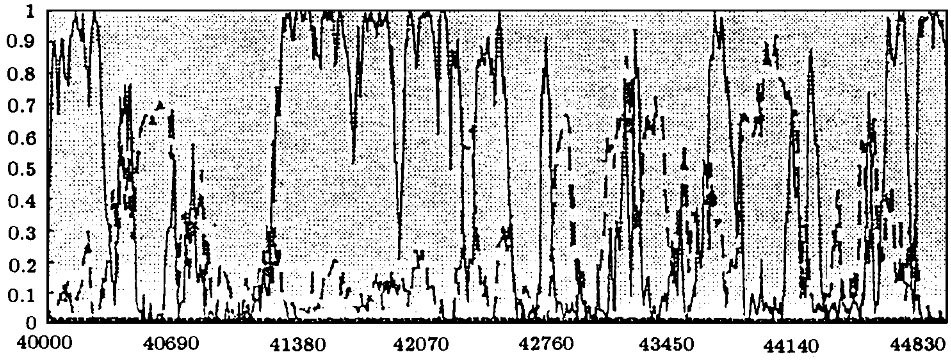
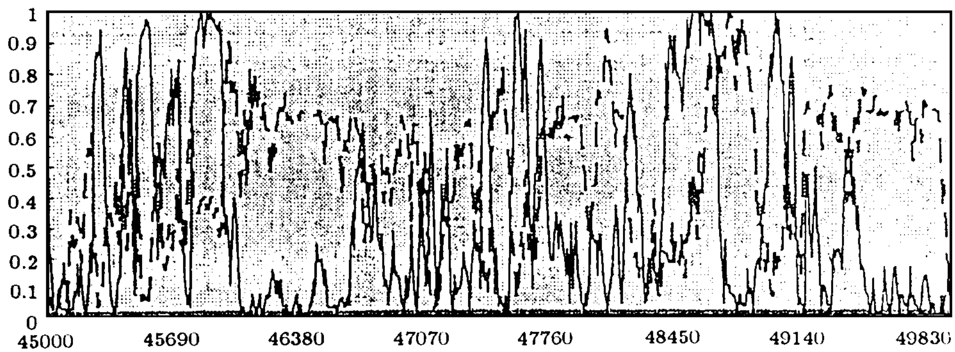


(i)



(j)

Fig. 2 The radio of the players who take the action "0" in the sixth stage.
(— weak monopolists; -- potential entrants)

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