An Evolutionary Perspective on Strategic Group Emergence:
A Genetic Algorithm-Based Model

To be presented at the 1999 Academy Meeting

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July, 1999

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ABSTRACT

The literature on strategic groups has identified mobility barriers as the key to understanding strategic group phenomena. We develop a genetic algorithm-based model to examine conditions under which strategic groups emerge and stabilize over time. We find that mobility barriers, indeed, play an important role in isolating a high performing group of firms from the rest. Mobility barriers could be considered weapons for incumbents to safeguard their market territory against potential competitors, but these barriers say nothing about how firms survive against hostile environmental conditions such as fluctuations of demand, rapid technological changes, or the rapid saturation of the product market. Our model suggests that two extra mechanisms, intertemporal stability of payoffs and localization of competition, are as important as mobility barriers in understanding the emergence and stability of strategic groups.

INTRODUCTION

Since Hunt (1972) first coined the term, strategic groups, to point to the existence of heterogeneous activities within an industry, strategic group phenomena have garnered a great deal of attention in the strategy field. Fueled by Caves and Porter's (1977) seminal theoretical paper on mobility barriers, an empirical research program has emerged to explore the nature and existence of strategic groups in numerous industries.

Cursory observations of some industries appear to readily confirm the intuition about the strategic group phenomena. For example, in the U.S. pharmaceutical industry, a group of innovating firms have sought to survive by committing to R&D activities and selling novel drugs with above-normal prices, while a group of generic drug makers have produced imitative drugs with virtually no R&D and sold them at competitive prices. After World War II, this divergent structure was first observed (Comanor, 1963; Lee, 1998; Temin, 1980), and it has been maintained for almost half a century. Particularly striking in this industry are the longevity of top pharma giants and their high profitability in spite of the presence of pounding adversity in carrying out drug innovation (Kurdas, 1998).

Despite the concept's intuitive appeal, empirical studies have reported mixed findings and have encountered complexity in demonstrating the existence of stable intraindustry structure (Cool and Schendel, 1987), leaving room for critics to suggest an abandonment of the whole research program (Barney and Hoskisson, 1990). In an attempt to revitalize this stream of research, we offer an evolutionary perspective on strategic group behavior. Unlike a common approach, which has emphasized static aspects of a group structure, we focus on a competitive process that generates strategic groups by employing genetic algorithms (GAs, hereafter).

Most of conceptual work on strategic groups has been developed by intuition obtained from empirical observations in complex settings. Even mobility barrier (Caves and Porter, 1977), the most frequently cited concept, was not presented in an analytically rigorous manner. Indeed, it is very difficult, if not impossible, to develop a mathematical structure to study the strategic group phenomena, primarily because the complexity of strategic groups defies an employment of popular analytical tools in economics. To date, a few formal models exist to cast light on dynamics of strategic group behavior. The framework we consider in this paper permits us to fill a gap between conceptual theorizing and empirical modeling. With their reasonable costs and flexibility of modeling, the GA-based tools have the potential to sharpen insight into riddles of the strategic group phenomena.

To address how strategic groups emerge over time, we characterize an industry landscape by constructing a double-peaked payoff structure with asymmetric realized payoffs as shown in Figure 1. The horizontal axis represents the space for strategy, and the vertical axis represents the payoff for a corresponding strategy. The objective of a model firm is to search for an optimal payoff location without the knowledge of the landscape attributes *ex ante*. To make firms' search process harsher in the region around the higher peak, we characterize payoffs in this region to be stochastic as shown in Figure 2. The figure illustrates that firms adopting strategies around the lower peak enjoy deterministic realized payoffs, while firms adopting strategies around the higher peak realize either positive or zero payoffs depending on the result of the random draw. Intuitively, this payoff structure says that an activity associated with a lower peak is rewarded with certainty, whereas a higher performing action is rewarded with a high level of uncertainty. We impose all our model firms to start from activities around a lower peak, and then allow some firms to reshuffle their strategies to move beyond some neighborhood of this lower peak. Competition among model firms winnows on firms with inferior performance, and at the same time, both random shifts in strategy and imitation of better performer's strategy guide market evolution toward better and better payoff activities. The emergence of strategic groups is detected when a portion of firms successfully move to the higher peak location at the end of simulation.

Insert Figures 1 and 2 About Here

What mechanisms make this transition successful? If such a transition happens to be successful, why would firms in the lower peak not follow the firms in the higher peak? In line with Caves and Porter (1977), the results of our simulation show that mobility barriers associated with the higher-payoff activities tend to isolate high-performing firms from the rest of the population. This is no surprise.

But this mechanism says nothing about how this high-performing group arises and continues to survive in such a harsh condition. Mobility barriers may well be weapons for incumbents to safeguard their market territory against potential competitors, but not against hostile environmental conditions such as fluctuations of demand, rapid technological changes, or the rapid saturation of the product market (Teece, Pisano and Sheun, 1997). We find that high instability of payoffs associated with these sorts of environmental change is likely to hinder the maintenance of a group structure. The simulation illustrates and emphasizes that strategic group emergence hinges upon some sorts of intertemporal stability in payoffs.

Furthermore, in the current literature of strategic group, there has been no explicit consideration of how localization of selection pressures has effect on strategic group behavior, even though the concept of localized competition has been well incorporated in explaining organizational survival in ecological studies (Baum and Mezias, 1992; Baum and Singh, 1994a). By modeling this effect explicitly, we can avoid erroneously attributing this to the effect of mobility barriers. We find that unbridled competition among model firms over the entire strategy space is likely to hinder strategic group emergence, forcing the system to converge upon one of the two peaks. In our model, this convergence can be obtained when all firms are allowed to compete with one another and when competition winnows on the 10% of lowest performers every period. On the other hand, when we impose some restraint on competition such that only firms with similar strategic activities compete with each other, the industry evolution is more likely to show stable subpopulations around two local peaks. This means that strategic groups are more likely to emerge when selection pressures are more localized. In sum, our results suggest that intertemporal stability of payoffs and localized competition are as important as mobility barriers in understanding the emergence and stability of strategic groups.

This paper is organized as follows. In section 2, we characterize the strategic group phenomena. In section 3, we introduce genetic algorithms. Section 4 develops a dynamic model for strategic group emergence. Section 5 presents simulation results. Finally we discuss the implications of our findings about strategic group phenomena.

2. STRATEGIC GROUP PHENOMENA

2.1. Complexity of Strategic Group Research

For the past several decades, strategic group research has tried to address three main issues: (1) strategic group emergence, (2) performance difference between groups, and (3) stability of a group structure. The first issue, the process that generates strategic groups, has received relatively sparse attention in the field. Among the few studies on this issue, Caves and Porter's work (1977) is, perhaps, the first one to explain strategic group formation. They argued that initial random differences in firm preferences or the qualities of assets can lead firms to adopt differing strategies and to invest differently in mobility barriers. Later, Porter (1979) added exogenous causes such as technological changes as drivers of strategic group formation. In addition, empirical studies attributed the formation of a new strategic group to changes in competitive environments such as economic growth or decline (Mascarenhas, 1989), decline of demand growth (Olusoga, Mowka and Noble, 1995), changes in government regulation (Cool and Schendel, 1987; Galbraith, Merrill and Morgan, 1994), etc. However, these efforts have not resulted in formulation of a systematic theory about strategic group emergence.

Research on the other two main issues has been more active, drawing a great deal of attention from empiricists. In this stream of research, mobility barriers have been considered the key to sustain between-group performance difference as well as to stabilize a group structure. Yet, results of numerous empirical investigations on performance difference appear to be inconclusive and often conflicting (Cool and Schendel, 1987). For example, Dess and Davis (1984), Fiegenbaum and Thomas (1990), Mascarenhas and Aaker (1989), and McGee and Thomas (1986) found significant performance difference among strategic groups, while others did not (e.g., Cool and Schendel, 1987; Howell and Frazier, 1983; Lewis and Thomas, 1990).

Furthermore, there has been no agreement on what the stability of a group structure implies. For example, Amel and Rhoades (1988), and Wiggins and Ruefli (1995) argued that the stability of group structure could confirm the existence of strategic groups, while Cool and Schendel (1987), Mascarenhas (1989), McGee, Thomas and Pruett (1995) challenged this view by pinpointing a complex possibility that changes in a group structure could happen with environmental changes or firm initiatives.

Despite the accumulation of numerous empirical studies and conceptual work, success of this research program appears to be mixed at best in answering the question of the genesis and existence of strategic groups (Hatten and Hatten, 1987). Piling-up of empirical studies has been adding more complexity to the issue than clarifying it, primarily because empiricists are severely limited in their ability to control unwanted external variances. This has led extreme critics to even propose an abandonment of the entire stream of strategic group research (Barney and Hoskisson, 1990). Nevertheless, one thing that both proponents and skeptics agree to is that the field needs a solid theory, which can cast light on the issue in a dynamic setting. Apparently, any of these limitations would be sufficient grounds to push research in different directions.

2.2. The Evolutionary Framework

We offer an evolutionary framework as a new way of thinking about the strategic group phenomena. Within this framework, it is rather obvious to answer the question about what is strategic about strategic group. Here, strategy is meant to be a solution (or an activity vector in the multidimensional activity space or a gene composition in the genotype space) to a survival problem, and strategic groups, or stable subpopulations, should be associated with multiple strategic choices amenable to survival. The main emphasis in this framework is not on whether multiple subpopulations exist in all industries in a static sense, but on what mechanisms give rise to the emergence of these subpopulations in dynamic settings. We now consider four relevant features for strategic group emergence. They are multipeaked payoff function, mobility barriers, intertemporal stability of payoff, and localized competition.

Multipeaked Payoff Function

Existence of strategic groups implies that more than one strategic choice can be viable in an industry and that some choice could be better than others. In a modeling term, this is equivalent to a multipeaked payoff function where there are more than a single local peak. This is in a direct contrast with the neoclassical competitive market, where the one best solution exists and where the assumption of global quasi-concavity guarantees that firms won't be trapped on an inferior local peak. When this assumption characterizes a payoff function or landscape, it is meaningless to talk about strategic groups. It is not surprising why neoclassical economists have not worried about intraindustry heterogeneity.

Mobility Barriers

Given a multipeaked payoff function, a fundamental problem naturally arises in a study of strategic group emergence: if some firms happen to find a better payoff location, why would others in lower payoff location not follow these first movers? Obviously, if the entire population eventually makes a transition to a better payoff location, it would be meaningless to talk about strategic groups. The relevant issue is what hinders this possibility when strategic groups are observed in an industry.

Caves and Porter (1977) addressed this question by offering a mechanism, what they called mobility barriers. In search of better payoff possibilities, firms may adopt different strategies. When one of these attempts leads higher performance, other firms are tempted to imitate it. Caves and Porter (1977) argued that because mobility barriers tend to inhibit this imitative behavior, first movers can sustain high performance.

In characterizing mobility barriers, they mentioned two elements: (1) structural barriers and (2) conduct-based barriers. The first element may encompass many structural properties, but we pay attention only to the baseline uncertainty of payoff in adopting a high-performing activity. For example, if a firm that used to produce generic products attempts to engage in innovation, it will be exposed to a higher level of uncertainty. Concerning this point, Caves and Porter (1977: 243) argued:

> The cost of making the entry decision is sunk, and many other costs of entering will have limited salvage value. Each item in our list is uncertain in its value or effect and contributes to determining the overall variance of expected returns and the chances of ruin following entry."

The higher the level of uncertainty, the higher structural barrier. The basic idea here is that the higher performing strategic action is much harder to obtain because stochastic errors tend to confuse firms in search of better-performing strategic activities. Even when they find a right activity for a high expected return, its realization in the short run may be often associated with disappointing results. Or, firms may have to just wait for returns to realize for a long while due to the lagged nature of payoff (Lee and Harrison, 1998). These characteristics are not uncommon in risky businesses like innovation where commitment is required over nontrivial periods of time (Caves, 1984).

The second element is related to firms' proactive actions to erect a barrier. This is particularly relevant to early movers who found a high-performing strategic choice. In order not to share such high return with potential entrants, they may attempt to erect a barrier by increasing scale of production capacity, R&D, marketing, etc. Then, those firms that are tempted to imitate the first movers may have difficulty matching them. The argument is quite plausible and intuitively appealing. Are these two types of mobility barriers necessary for the genesis of strategic groups? The framework we consider here permits us to check this intuition dynamically as well as to examine other fundamental issues in strategic group research.

Intertemporal Stability of Payoff

Mobility barriers may well protect incumbents in a lucrative segment by serving as weapons against potential entrants. However, the business of survival is not a one-shot event, but a going concern over time. Mobility barriers do not say anything about how firms can defend themselves against hostile nature. Suppose that some firms become high performers by changing their strategic choice as Caves and Porter envisioned. Unless this choice continues to yield high performance, high performers may not be sustained, and then multiple strategic groups cannot be observed. There are good reasons why such stability may not be guaranteed over time. For example, survival of firms in the semiconductor industry has been at the mercy of highly cyclical nature of industry demand, which is known as the silicon cycle. Furthermore, firms that continuously succeed in innovations can enjoy lucrative payoffs over time not because they effectively protect the market territory for their old products, but because they can generate new products before returns from old ones decline substantially. This means that a payoff from one-time success is time-bound. Teece et al. (1997) argued that strategy research has drawn little attention to such dynamic aspect of firm survival that requires some sort of intertemporal stability in payoff structure.

In risky business like innovation, such intertemporal stability of payoff is often established by a positive feedback loop between success probability and return. That is, winners are more likely to continue to do well because success brings a substantial revenue stream over several years to let them further seek new technological opportunities. Positive feedback of this sort tends to stabilize winners' payoffs over time. Nelson and Winter (1982) numerically demonstrated that this mechanism indeed operates. Also this is empirically observed in the study of the history of the aircraft industry (Phillips, 1966) and the history of the U.S. pharmaceutical industry (Lee, 1998). Especially in the pharmaceutical industry, it has been argued that pharma giants have their ability to survive costly failures (e.g., Carr, 1998; Kurdas, 1998). We believe that this quality is not any less important than mobility barriers in understanding the stability of strategic groups. Surprisingly, no one has yet addressed this issue in strategic group research. Thus, in our model, we build this mechanism into a payoff structure to confirm our intuition.

Localized Competition

The multi-peaked payoff function is a prerequisite for modeling strategic group phenomena. Would, then, selection on a multi-peaked payoff function automatically give rise to strategic group formation? To illustrate this point, we consider two extreme idealistic conditions. For simplicity, we assume that the market allows for a constant number of firms to survive. First, suppose that competition is unrestrained. That is, competition winnows on any low performers regardless of their strategic differences (i.e., competition is happening on the entire horizontal axis in Figure 1). Here the strategic choice of each firm influences the survival chance of any other firms in the entire space. A computer simulation in Figure 3 illustrates that a group structure does not emerge. Note that the payoff is deterministic and mobility barriers are absent in this illustrative simulation. Here the bar chart represents the percentage of firms in the higher-peak region, and at the end of a simulation run, 100% of firms move to the higher-peak region. As high-performing firms begin to survive on the high-performance terrain, they tend to quickly replace the lower performers in the left. If time is sufficiently long, selection will force the system to converge on the highest peak as shown here.

Insert Figure 3 About Here.

Now consider another ideal situation where competition happens only within some local space. In other words, firms with similar strategies compete with one another more intensely than firms with dissimilar strategies do. The essence of localized competition is that the more firms resemble one another, the lower their individual payoff will be. A simulation result shown in Figure 4 indicates that two groups of firms emerge over time. As the bar chart indicates, the percentage of firms in the higher-peak region increases at the beginning and becomes stable around some point below 100%. That is, the market is divided into two groups of firms. Note that the larger number of firms (roughly 70%) are in the higher-peak region, because the mechanism of mobility barrier is absent in this ideal case. This happens primarily because as more firms move to the higher-peak region, the industry payoff will be shared by more firms, and the average firm performance goes down up to the point where it equals the average firm performance in the lower-peak region. Obviously, this kind of equality in average performance between strategic groups is unrealistic due to the presence of mobility barriers in most cases.

Insert Figure 4 About Here.

The upshot is that market selection on a multipeaked payoff function is likely to form a group structure when the localized competition feature is present. The result is consistent with Hawley (1950). He argued that the localized competition between like entities for finite resources eventually leads to differentiation of entities. Some ecological studies (Baum and Mezias, 1992; Baum and Singh, 1994a, 1994b; Hannan and Freeman, 1977; Hawley, 1950) have used the concept of localized competition in explaining the differentiation of firms, firm failure, and founding.

Also, this feature is implicitly assumed in the concept of strategic groups, implying that not all firms in an industry engage in unbridled head-to-head competition among one another in the entire space. That is, the more similar activities two firms take, the more intense competition is between the two. For example, Caves and Porter's (1977) notion of conduct-based barrier explicitly assumes that as far as first movers make it hard for other firms to follow them, the supranormal return does not have to be shared with entire firms in an industry.

However, we emphasize that the localized competition feature is distinct from the mechanism of mobility barrier, which simply capitalizes on this feature to localize crowding to a specific niche. Unless one models two distinct mechanisms explicitly, he or she may possibly misattribute the effect of one to the other. In GAs, localized competition was first operationalized by Goldberg and Richardson (1987), using their modeling term "sharing." They used this operational concept to treat a special optimization problem in GAs.

We apply this sharing concept to model strategic group emergence. Firms in some neighborhood of the activity space compete for the same scarce resources. Given some fixed demand or resources, an increase in the number of firms within the neighborhood means increased competition, which in turn results in degradation of the payoffs of all firms in this neighborhood. On the other hand, when two firms maintain some remote distance from each other, the payoff degradation will be smaller or nil. The process of localized competition discourages crowding of firms around a specific strategic choice and is likely to generate strategic groups.

All of the four factors described above look relevant to the emergence of strategic groups. Are they all in fact important in the genesis of strategic groups? In Section Four, we develop a dynamic model to experiment with each of these factors. Before doing this, we briefly introduce the basic idea of GAs.

3. Genetic Algorithms

One may wonder why we adopt GAs to examine the strategic group phenomena. As typical in our field, researchers can directly examine real dynamic systems as they are. Yet, because of enormous complexity involved in them, direct encounter with them is often more confusing than clarifying the issues of researchers' interest. An alternative strategy is to build a computational model and to gain insight from observing its behavior in a controlled setting. Such controllability and manageability are a virtue of computational tools like cellular automata or GAs. This virtue has made them become popular with the rise of science of complexity. In this vein, Holland's (1998: 17) argument is illuminating:

> Computer-based models present the modeler with a rigorous challenge. The claims of verbally described models are often established by rhetoric. What appear to be equally strong arguments often back competing claims for the same model... The same can sometimes be said of traditional mathematical models, where even the most rigorous mathematical proofs skip "obvious" steps. It is impossible to skip steps in a computer program.

Although GAs have been primarily applied to optimization problems, it can be used in understanding the behavior of diverse complex adaptive systems such as the ecosystem or the market economy (Holland, 1975; Mitchell, 1996). For example, Axelroad (1997) used this tool to understand the complex behavior of a game theoretic model. In the field of organization science, Bruderer and Singh (1996) applied the GA to study organizational learning. Of special interest to us are the concepts of niche and species, which have been used in some GAs to address multi-modal problems (Goldberg and Richardson, 1987; Deb and Goldberg, 1989). Since strategic group emergence shares some analytical similarities with the problem of speciation, we can benefit from this particular application of GAs.

What, then, are genetic algorithms? They are a class of robust and efficient search methods based on the concept of biological evolution in nature (Holland, 1975; Goldberg, 1989). The basic elements of GAs are population, the Darwinian notion of selection, and genetic operators. A population, likened to a population of living organisms, consists of individuals or solutions. Since this study explores strategic group phenomena, we use the term "firms" instead of individuals. Each firm is typically represented in the form of bit strings, likened to genes in a living organism. The bit strings can represent many different firm characteristics: it can represent organizational structure, strategies, or the amount of R&D investment. Each firm is evaluated based on a fitness function, or a performance criterion. Then, the selection mechanism removes less fit (or poorly performing) firms from the population at each generation (i.e., survival of the fittest).

Another important elements are genetic operators: crossover and mutation. The genetic operators specify how new bit strings are generated from old ones. In crossover, two bit strings (parents) mate with each other and generate their offspring by combining some components of their bit strings. In the market evolution, the inheritance of some attributes from parents to offspring runs parallel with the fact that imitators tend to benchmark leading firms and copy some of their attributes. Here firms with a higher fitness value have higher chances to be selected as parents. Mutation modifies one or more bit string values of a firm in generating offspring, selected at random. The mutation is analogous to a major strategic change in the market evolution.

A typical GA works as follows: (1) it begins by randomly generating an initial population; (2) during each iteration, called a *generation*, firms in the population are evaluated by a fitness function; (3) parents are selected based on their fitness and paired to produce new firms, called *offspring*; (4) a new generation is formed by selecting firms based on their fitness so as to keep the population size constant; (5) the GA terminates when a prespecified stopping conditions are satisfied, typically some number of generations.

4. Model

We assume that the payoff function for model firms is characterized by two asymmetric peaks as shown in Figure 1. Here, the vertical axis represents industry payoff (e.g., the total amount of profit opportunity in each niche) and the horizontal axis represents strategic choice or activity. This is a sort of idealization of an industry landscape where two strategic activities are associated with two local peaks.

We assume that a firm's strategic choice x takes on a real value between 0 and 1. For modeling purpose, this number is encoded as a 10-bit string, where each bit takes on a value of 0 or 1. For example, 1000000001 represents 0.5015. The value can be any decision variable that affects the competitive posture of a firm. What the value can represent depends on the characteristics of an industry. For instance, it can be an R&D expenditure in the pharmaceutical industry, where R&D investment shapes firm competitiveness as well as intraindustry heterogeneity in performance (Porter, 1979). Alternatively, this value can be considered as a budget allocation ratio in a two-dimensional unit simplex. For example, 0.7 means that a firm allocates 70% of its budget into R&D investment for new product development and 30% into production of known products. Or, each bit can represent one organizational element and thus a 10-bit string can indicate how 10 organizational elements are configured.

Our GA begins by randomly generating an initial population of 50 firms between 0 and 0.5 (Note that the entire activity space ranges from 0 to 1). We deliberately set up such a relatively homogeneous condition merely to provide a clearer view of our mechanisms. Then, some firms are allowed to explore a new region of the activity space in an attempt to increase their performance. This type of exploratory, or entrepreneurial activity, is analogous to mutation in biological evolution. As is the case in biological evolution, not all new strategic choices are associated with higher payoffs.

During each generation, firms in the population are evaluated using a fitness function (described below). After evaluating the fitness, or performance, of each firm in the population, parents are selected and paired to produce a specified number of offspring. Offspring in GAs are essentially competitors to their parents since GAs select out some portion of least fit strings. Since parents and their offspring share some similarities in solutions, offspring can be considered as imitators whereas parents are considered as target firms to be benchmarked and imitated. The better a firm performs, the more likely it will be imitated by others. In the language of GAs, this intuition is captured in the following selection rule: A probability for any firm to become a parent in the next generation is proportional to its fitness.

In producing offspring, two genetic operators—crossover and mutation—are applied. Crossover can be thought of either as a change in firm strategies by combining strategies of previously successful firms or as a founding of a new firm that recombines strategies of previously successful firms (Bruderer and Singh, 1996). It operates on two firms (parents) at a time and generates offspring or an imitator by combining attributes from both parents. We used uniform crossover, in which the imitator inherits a value for each gene position from one or the other parent with probability .5 (i.e., randomly). Mutation independently modifies one or more gene values of a firm. As described before, mutation is considered an abrupt or exploratory strategic change in our case. We used the mutation probability of 0.005. In other words, the probability of value changes in any bit is .05 ($.005 \times 10$ bits).

A new generation is formed by removing lowest performing firms (i.e., those with lowest fitness values) from the population and by adding offspring. Our GA removes and adds 10% of the population during each generation. Finally, our GA terminates when 2000 generations is reached.

In our GA models, we manipulate four parameters: structural barrier, conduct-based barrier, intertemporal stability of payoff function, and localized competition.

Structural and Conduct-based Barriers

As described before, mobility barriers are decomposed into structural and conduct-based barriers. For the structural one, we only consider uncertainty of payoffs associated with strategic change. In our standard model, we assume that the lower-performing activity is associated with relatively more frequent payoff or lower risk. On the other hand, a higher performing activity is associated with higher risk. For simplicity, we specified a payoff function such that the first half of the region [0, 0.5) is deterministic and that the second half [0.5, 1] is stochastic. Then, we characterize a stochastic payoff such that a draw of strategic choice can result in either zero payoff or a positive payoff. This simplifying assumption captures the essence of a payoff structure in industries where a risk-averse group and a risk-taking group can coexist. We use p_f to denote success probabilities for first movers at the time of entering high payoff location. The smaller the value of p_f, the higher the level of the structural barrier.

The second component of mobility barrier is the conduct-based barrier. Caves and Porter (1977) argued that first movers can erect a barrier by increasing a scale of production capacity, marketing intensity, or R&D intensity. Since these attempts can lower success probability of late movers in entering an attractive segment of the market, we can operationalize the conduct-based barrier as follows. Let p_n be the late entrants' success probability. When p_n is lower than p_f, there exists a conduct-based barrier. Then, the larger difference between p_f and p_n, the higher the level of the conduct-based barrier. Define n_b as a threshold of conduct-based barriers being established. For instance, if n_b is 5, the success probability of firms that enter the niche with higher payoff is p_f until there are 5 firms in the niche. On the other hand, we assume that there are neither structural nor conduct-based barriers to entry in the case of lower payoff location. This reflects the concept of asymmetrical mobility barriers in the literature (e.g., Hatten and Hatten, 1987; Oster, 1982).

Intertemporal Stability of Payoff Function

As described in Section 2, it is usually the case that success confers further success (Nelson and Winter, 1982). The positive feedback of this sort tends to stabilize winners' payoffs over time. For example, when one shot payoff from the success of innovation is huge enough to support the firm's R&D expenditure for a long time, or patent protection is long enough, the payoff function can be thought of as very stable. For simplicity, firms located in a lower payoff region receive nonzero payoffs over time as long as they are alive, while firms in a higher payoff region may receive zero payoff depending on the result of random draw even though their previous payoffs are positive. In our model, p_i represents the intertemporal stability of the payoff function. p_i of 0.95, for instance, means that once a firm is successful at a particular generation, its success probability at the next generation is 95%. In the lower peak region, p_i is set to 1.00.

All the landscape characteristics described above can be formally represented as follows:

$$y = \text{sine}(3\pi\ x) + 3x \qquad \text{if } 0 \leq x < 0.5,$$

$$= \text{sine}(3\pi\ x) + 3x \qquad \text{if } 0.5 \leq x \leq 1 \text{ and } r > p,$$

$$= 0 \qquad \text{if } 0.5 \leq x \leq 1 \text{ and } r \leq p,$$

where $r \sim$ Uniform(0,1) and p is a success probability. Now, p is described by the three probabilities described above as follows:

$$p = p_f \quad \text{if } age = 0 \text{ and } n_p \leq n_b$$

$$= p_n \quad \text{if } age = 0 \text{ and } n_p > n_b$$

$$= p_t \quad \text{if } age > 0$$

where age is the number of generations for which a firm has survived, n_b is a threshold of conduct-based barriers, and n_p is the number of firms in the higher payoff location. When $p = p_f = p_n = p_t = 1$, the landscape is completely deterministic.

Localized Competition

As described in Section 2, localized competition forms niche-like and species-like subdivision of the environment and population. In nature, different species do not directly compete with one another. Instead they exploit separate niches in which other organisms have little interest or advantages. Similarly, the intensity of competition between two subpopulations is positively associated with their similarity (Baum and Mezias, 1992; Baum and Singh, 1994a, 1994b; Hannan and Freeman, 1977; Hawley, 1950). Such a phenomenon can be modeled by using the operational concept of sharing in GAs (Goldberg and Richardson, 1987; Deb and Goldberg, 1989). In sharing, instead of allowing a full measure of payoff for each firm, it is forced to share its payoff with its neighbors. Goldberg and Richardson (1987:

41) noted: "These sharing functions help mitigate unbridled head-to-head competition between widely disparate points in a search space."

In our GA, the fitness function is defined as follows:

$$f_i = y_i / m_i,$$

where f_i is performance, y_i is the payoff, and m_i is the niche count for firm i. m_i is defined as follows:

$$m_i = \sum_{j=1}^{N} sh(d_{ij}),$$

where N is the population size, $d_{ij} = | x_i - x_j |$ is the distance between firms i and j, and $sh(d_{ij})$ is the sharing function. $sh(d_{ij})$ is defined as follows:

$$sh(d) = 1 - (d / \sigma_{share})^{\alpha} \quad \text{if } d < \sigma_{share}$$

$$= 0, \qquad \text{otherwise.}$$

Here, σ_{share} determines the range of neighborhood and α is an arbitrary parameter value for the power law sharing function. All the firms within the neighborhood σ_{share} share a focal firm's payoff. For instance, σ_{share} of 0.10 indicates that all the firms located within the distance of 0.10 from the focal firm are its neighbors. The smaller the value of σ_{share}, the more localized the competition. In our experiments, we choose 0.10, 0.25, 0.50, 0.75, and 1.00 for σ_{share} as shown in Figure 5. Figure 6 illustrates the behavior of power law sharing function for selected values of α, given that σ_{share} is set to 0.50. We use α of 0.5. A model with α of positive infinity and σ_{share} of 1.00 in this research setting will produce identical results with a regular GA model in the absence of sharing.

Insert Figures 5 and 6 About Here

5. Results

As mentioned before, our standard model includes all of the four parameters: conduct-based barrier, structural barrier, intertemporal stability of payoff, and localized competition. Again note that the first three stochastic parameters operate only for the higher-payoff region to characterize the difficulty in surviving there. On the other hand, such harsh conditions are completely absent in the lower-payoff region. Figure 7 shows a typical simulation result of our standard model, when parameter values for α, σ_{share}, p_i, p_f, and p_n are set to 0.50, 0.50, 0.96, 0.10, and 0.01 respectively. The figure illustrates the emergence of two groups after 2000 generations. Of the total of 50 firms, 11 percent are located near the higher peak, while the remainders are around the lower peak. The average fitness (or performance) of the firms near the higher peak is much higher than that of the firms around the lower peak.

Insert Figure 7 About Here

We conducted experiments, one at a time, by varying each of the four parameters in the standard model: conduct-based barrier, structural barrier, intertemporal stability of payoff, and localized competition. Each experiment is carried out with fifty simulation runs to generate quasi-asymptotic outcomes.

Table 1 reports the results of variation in conduct-based barrier (p_n). Here, p_i and p_f represent intertemporal stability of payoff and structural barrier respectively. The difference between p_f and p_n indicates the height of conduct-based barrier. The outcomes of experiments are presented in the last five columns. Two criteria are applied to detect whether strategic groups emerge after 2000 iterations. The first criterion is whether at least one firm with a positive fitness value is located around each peak after 2,000 generations. The results shown in the column of "% of SG Emergence" indicate what percent of 50 simulation runs result in the emergence of strategic groups. The other criterion in the column of "% of Firms in High Peak" represents what percent of the population belongs to the group in the neighborhood of the higher peak, when the strategic groups emerge. When two strategic groups emerge, we estimate the average fitness values (or performance) for firms around the lower and the higher peaks. Their differences and their t-values are listed in the last column.

The results of the experiment with p_n show that the higher the level of barrier, the lower the chance for strategic group emergence as well as the percentage of firms near the higher peak. The results imply that the first movers' barrier-erecting activity does reduce the number of firms near the higher peak by lowering late movers' chance of successful entry. That, in turn, increases the performance of firms near higher peak as shown in the corresponding values in the seventh column. The decrease in the percentage of strategic group emergence above results from the fact that even the successful first movers may not continue to survive in the later generation and that the decrease in the success probability of late movers.

Insert Table 1 About Here

The second major variation in Table 2 examines the effect of structural barrier, namely the uncertainty of exploring unknown strategic choices. If we vary the value of p_f only, conduct-based barrier – the difference between the success probability of first movers and that of late entrants – is also changing. Therefore we can not isolate the effect of structural barrier from that of conduct-based barrier. To isolate the effect of conduct-based barrier, we also vary p_n by two ways. First, we set the value of p_n as proportional to p_f. Second, we set the value of p_n to have the same distance from the value of p_f. See the results of variation in values of p_f. The basic idea behind manipulating this variable is that the lower the value of p_f, the higher the level of structural barrier. The results show that the harder it is to explore a better-performing activity as operationalized in decreasing success probabilities, the smaller the chance for strategic group emergence is, and the smaller the number of firms in the neighborhood of the higher peak is. Again, the level of performance for the high performing group is negatively correlated with the number of firms near the higher peak. All of these results should not be surprising to those who are familiar with the strategic group literature.

Insert Table 2 About Here

Now, let us take a look at the effects of intertemporal stability of payoff. See the results shown in Table 3, where each value of p_t represents the chance of obtaining the same payoff at the next generation. The results appear to be very sensitive to small changes in p_t. As this value drops by a small increment, the chance of strategic group emergence as well as the average number of firms near the higher peak gets smaller rapidly. Although this is not operationalized as a part of mobility barriers, its effect is quite similar to that of mobility barriers.

Insert Table 3 About Here

To illustrate the unusual effect of intertemporal stability of payoff, we take an extreme case, which is shown in the last row of Table 3. When p_t is set to 1, the difference in the average performance between the low- and the high-performing groups becomes statistically insignificant. This is somewhat surprising since the two types of mobility barriers described above are still in operation. To further examine why this might happen, we traced the evolution of strategic group behavior over time as shown in Figure 8. Since the payoff for the higher peak region is guaranteed over time when any firm correctly discovers it, one can consider this as a relatively benign condition. Over time, the number of firms near the higher peak increases, resulting in overcrowding. This in turn reduces the average level of performance. This result is neither obvious nor explicitly discussed in the literature when researchers talk about mobility barriers.

Insert Figure 8 About Here

Finally, we varied the conditions for localized competition. The results are shown in Table 4. Note that the smaller the value of σ_{share} is, the more localized competition is. The results indicate that two strategic groups are more likely to emerge when competition is more localized. The extreme case is when σ_{share} is 1.0 and α is positive infinity. In this case, the competition is not localized at all (i.e., no sharing). As we remove the localized competition mechanism from the standard model, the chance for strategic group emergence drops from 46% to 18%. Given the presence of the two types of mobility barriers, removing the effect of localized competition from the standard model results in a major change in outcomes.

Insert Table 4 About Here

Figures 9 and 10 illustrate why strategic groups are unlikely to emerge when the localized competition is absent. At the end of 2000 generations, all the model firms converge upon one of the two local peaks. Where the system will end up depends on chance events. This is equivalent to what Arthur (1994) called path-dependence. In any case, this is a typical outcome when the localized competition effect is removed.

Insert Figures 9 and 10 About Here

6. Discussion and Conclusions

We examined conditions under which strategic groups emerge out of random strategic choices when selection, in conjunction with innovation (mutation) and imitation (crossover), guides market evolution toward higher and higher performing activities. Given the landscape characterized by a double-peaked payoff structure and by the high uncertainty of obtaining reward in the region around the higher peak, the emergence of a group structure is detected when a portion of firms successfully move to the higher peak location at the end of a simulation run. Our simulation experiments established the importance of three mechanisms that can influence strategic group behavior: (1) mobility barriers, (2) stability of payoff, and (3) localized competition. We now return to the major issues in strategic group research and discuss them with our findings about the three mechanisms.

Emergence and Stability of Strategic Groups

To address the emergence and stability of a group structure, existing studies have used initial differences in preferences and qualities of assets (Caves and Porter, 1977), various enactment of environments (Fombrun and Zajac, 1987), and changes in competitive environments. These studies have primarily sought to explain why firm heterogeneity in strategy might arise. Once a group structure emerges, on the other hand, mobility barriers have been conceived to be the key to stabilize this structure (Caves and Porter, 1977).

GA-based models imply that adopting different strategies is indeed necessary for strategic group emergence. In our model, without the mutation operator, model firms cannot move beyond the neighborhood of the lower-performing region. However, such adoption of different strategic activities is not a sufficient condition for strategic group emergence. At least, some of these choices should be able to survive from selection pressures in the market. So, what is missing in the literature is an explicit consideration of a selection process although some scholars alluded it (Cool and Schendel, 1987).

The viability of strategic choices in our model depends on several mechanisms. One of those is localized competition, which serves to mitigate unrestrained head-to-head competition among firms with diverse strategic choices. In particular, we impose the condition such that competition degrades only the payoffs of firms that share strategic similarity with one another. Such restraint on competition, or localization of competition, is shown to be essential in the emergence of strategic groups. Without this restraint, market evolution forces unbridled competition among all firms regardless of their strategic difference, guiding the market to converge upon one of the two local peaks, where all the model firms become homogeneous in their strategy. Our findings suggest that strategic group research can benefit from drawing upon the notions of niche and localized competition (Baum and Mezias, 1992; Baum and Singh, 1994a, 1994b; Hannan and Freeman, 1977; Hawley, 1950).

In the strategic group literature, mobility barriers have been considered the main mechanism to stabilize a group structure when it happens to emerge (e.g., Caves and Porter, 1977). Our findings do suggest that this mechanism deters the mobility of the lower-performing group to the higher-performing activity region. However, this mechanism does not say much about how incumbents in the higher peak can continue to survive. Even though some firms may choose a right activity by chance and enjoy a high payoff once, instability of a payoff structure can easily eliminate these firms in the next several rounds as they quickly run out of luck. Such instability may be caused by fluctuations in demand or a quick market saturation of leading products. Unless there are some dynamic mechanisms to allow winners to persist, strategic groups are unlikely to be sustained. Positive feedback inherent in Schumpeterian dynamics could be an example of such mechanism. In Schumpeterian dynamics, winners are more likely to innovate and thereby to escape from such instability since the revenue stream from one-shot success carries forward and allows them to seek new technological opportunities more aggressively. This, in turn, tends to breed further success in the future. Over time, winners become resilient to inherent risk in innovation (Lee, 1998). Our study shows that stability of strategic groups is sensitive to intertemporal stability of a payoff structure.

Performance

In the strategic group literature, mobility barriers are conceived essential to sustain performance difference between strategic groups (Caves and Porter, 1977; McGee and Thomas, 1986). Indeed, we found that performance difference is more likely to be pronounced when mobility barriers are high, confirming the above intuition. Yet, a rare anomaly arises when we imposed perfect stability (i.e, $p_i = 1$) of a payoff in the higher-payoff region. Intuitively this condition means that once a firm becomes a winner, its survival is continuously guaranteed. In this benign environment, between-group performance difference is not shown to be significant despite the presence of both structural and conduct-based barriers. As shown in Figure 8, performance difference does arise at the early stage of the industry evolution but disappears as more firms keep entering. The basic message is that mobility barriers cannot deter entry in the long run when one-shot winners can continue to do well.

The complexity shown above may partially explain why we do not have consistent, uniform support from empirical studies for the differential performance hypothesis (Cool and Schendel, 1987). Our model is very simple compared to reality, but even the simple model generates such complex behavior: existence of performance difference depends not only on the degree of mobility barriers but also other factors such as stability of payoff and the stage of industry evolution. Then, it may be rather naïve to expect consistent support for intraindustry heterogeneity in performance across diverse industries where complexity is likely to be much more pronounced.

In conclusion, our study established the systematic basis for considering mobility barriers in the context where a selection process constantly exerts an influence on firm survival. Mobility barriers are shown to play a substantial role in maintaining performance difference between groups when a group structure emerges. However, the findings of this study suggest that mobility barriers alone are not sufficient for the emergence and stability of strategic groups as many researchers have argued. Equally essential mechanisms in playing the latter role are restraint on competition and stability of industry payoff. Yet, to our knowledge, no one has attempted to conceptualize these mechanisms explicitly and to show their precise implications in dynamic settings. We argue that the field can benefit from pushing research in the direction we explored.

Obviously, our model is a sort of idealization, which is remote from any real industry situation. Because of its controllability and simplicity, we can gain some insight into conceivable strategic group behavior. Yet, the very simple features leave many caveats and limitations, which point to directions for future research. In particular, we assumed that the industry landscape do not change over time. In reality, changes in industry landscape are more a rule than an exception. Future research can examine the effect of regulatory changes or technological breakthrough on strategic group behavior. This type of research can generate very important policy implications and provide insights in understanding dynamics of strategic group changes (Cool and Schendel, 1987).

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Table 1. Variation in Conduct-based Barriers

P_i	P_f	P_n	% of SG Emergence	% of Firms in High Peak	Average Fitness: Low Peak	Average Fitness: High Peak	Average Fitness: Difference (t)
0.96	0.10	**0.005**	50.0%	6.0%	0.045	0.651	0.606 (8.02**)
		0.01	46.0%	6.5%	0.046	0.673	0.627 (8.57**)
		0.02	60.0%	8.0%	0.047	0.522	0.475 (5.37**)
		0.03	70.0%	7.6%	0.046	0.543	0.497 (5.95**)
		0.04	62.0%	9.5%	0.048	0.526	0.478 (5.43**)
		0.05	68.0%	10.3%	0.048	0.470	0.422 (5.61**)
		0.06	90.0%	12.6%	0.049	0.448	0.399 (4.64**)
		0.07	88.0%	12.8%	0.049	0.434	0.385 (6.13**)
		0.08	88.0%	15.5%	0.051	0.384	0.333 (4.92**)
		0.09	96.0%	18.7%	0.053	0.336	0.283 (4.38**)
		0.10	94.0%	21.9%	0.055	0.320	0.265 (3.99**)

Table 2. Variation in Structural Barriers

P_i	P_f	P_n	% of SG Emergence	% of Firms in High Peak	Average Fitness: Low Peak	Average Fitness: High Peak	Average Fitness: Difference (t)
0.96	**0.01**	**0.001**	2.0%	2.2%	0.043	2.025	1.982 (2363.53**)
	0.05	**0.005**	40.0%	5.3%	0.045	0.600	0.555 (7.69**)
	0.10	**0.010**	46.0%	6.5%	0.046	0.673	0.627 (8.57**)
	0.15	**0.015**	92.0%	9.4%	0.047	0.524	0.477 (6.89**)
	0.20	**0.020**	90.0%	9.8%	0.048	0.477	0.429 (5.33**)
	0.30	**0.030**	98.0%	11.4%	0.049	0.477	0.429 (6.00**)
	0.40	**0.040**	100.0%	12.5%	0.050	0.449	0.399 (5.98**)
	0.50	**0.050**	100.0%	12.5%	0.049	0.461	0.412 (5.96**)
0.96	**0.10**	**0.01**	46.0%	6.5%	0.046	0.673	0.627 (8.57**)
	0.15	**0.06**	90.0%	11.9%	0.049	0.435	0.385 (5.49**)
	0.20	**0.11**	100.0%	23.4%	0.056	0.322	0.266 (4.73**)
	0.30	**0.21**	100.0%	48.4%	0.082	0.193	0.111 (2.62**)
	0.40	**0.31**	100.0%	62.3%	0.107	0.168	0.061 (2.40**)
	0.50	**0.41**	100.0%	68.0%	0.126	0.158	0.032 (1.51)

Note: : standard model

Localized competition: Both α and σ_{share} are set to 0.50 in all models.

p_i : intertemporal stability of payoff function of firms around a high payoff location.

p_f : success probability of first movers at the time of entering a high payoff location.

p_n : success probability of late entrants at the time of entering a high payoff location.

t: t-statistics; * α = 0.05, ** α = 0.01

Table 3. Variation in Intertemporal Stability

P_i	P_f	P_n	% of SG Emergence	% of Firms in High Peak	Average Fitness		
					Low Peak	High Peak	Difference (t)
0.90			6.0%	5.2%	0.046	0.558	0.512 (11.09**)
0.91			16.0%	3.3%	0.045	0.936	0.891 (6.43**)
0.92			14.0%	3.8%	0.044	0.828	0.784 (18.75**)
0.93			22.0%	5.7%	0.045	0.679	0.643 (7.45**)
0.94			20.0%	3.1%	0.044	0.800	0.756 (8.88**)
0.95	0.10	0.01	28.0%	4.6%	0.045	0.748	0.703 (8.22**)
0.96			**46.0%**	**6.5%**	**0.046**	**0.673**	**0.627 (8.57**)**
0.97			70.0%	6.4%	0.046	0.559	0.513 (6.53**)
0.98			92.0%	8.0%	0.047	0.584	0.537 (5.64**)
0.99			100.0%	11.3%	0.049	0.494	0.445 (5.57**)
1.00			100.0%	63.6%	0.111	0.141	0.030 (1.15)

Note: : standard model

Localized competition: Both α and σ_{share} are set to 0.50 in all models.

p_i : intertemporal stability of payoff function of firms around a high payoff location.

p_f : success probability of first movers at the time of entering a high payoff location.

p_n : success probability of late entrants at the time of entering a high payoff location.

t: t-statistics; * $\alpha = 0.05$, ** $\alpha = 0.01$

Table 4. Variation in Localized Competition

Sharing		% of SG Emergence	% of Firms in High Peak	Average Fitness		
σ_{share}	α			Low Peak	High Peak	Difference (t)
0.10	0.5	82.0%	8.1%	0.158	1.198	1.040 (5.19**)
0.25	0.5	70.0%	7.4%	0.072	0.858	0.787 (6.12**)
0.50	**0.5**	**46.0%**	**6.5%**	**0.046**	**0.673**	**0.627 (8.57**)**
0.75	0.5	38.0%	4.9%	0.040	0.295	0.255 (2.94**)
1.00	0.5	34.0%	4.2%	0.038	0.170	0.132 (11.10**)
1.00	$+\infty$	18.0%	3.7%	0.031	0.055	0.024 (15.30**)

Note: : standard model

p_i, p_f, and p_n are set to 0.96, 0.10, and 0.01 respectively in all models.

p_i : intertemporal stability of payoff function of firms around a high payoff location.

p_f : success probability of first movers at the time of entering a high payoff location.

p_n : success probability of late entrants at the time of entering a high payoff location.

t: t-statistics; * $\alpha = 0.05$, ** $\alpha = 0.01$

Figure 1. Industry Landscape: Bimodal Payoff Function (y = sine($3\pi\ x$) + $3x$)

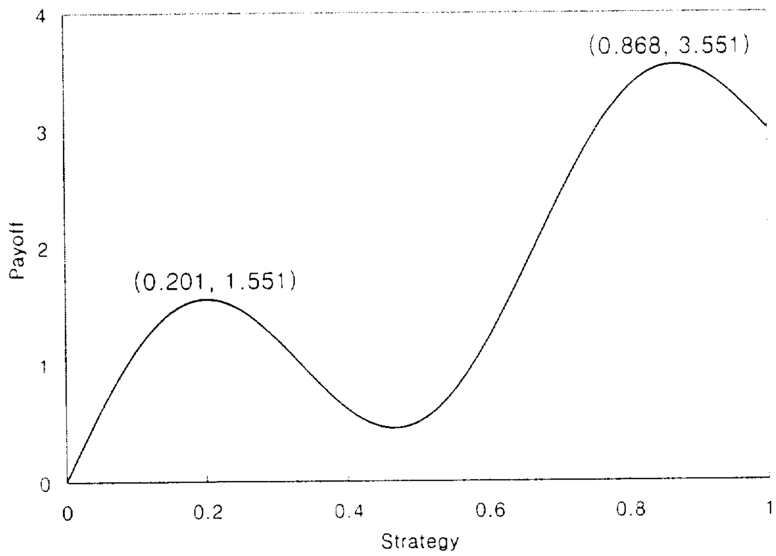

Figure 2. Realized Payoff (n=200, p = 0.1 when x > 0.5)

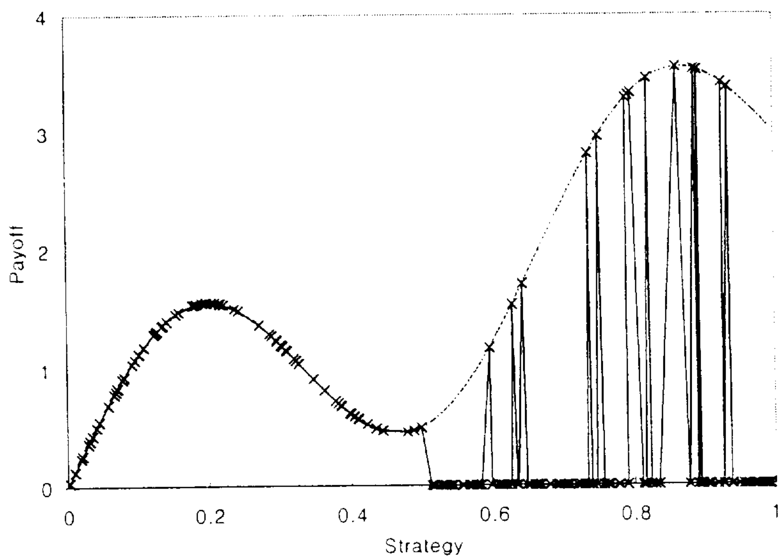

Figure 3. Evolution of Strategic Groups and Their Performance

(Without sharing, $P_i = 1.0$, $P_f = 1.0$, $P_n = 1.0$)

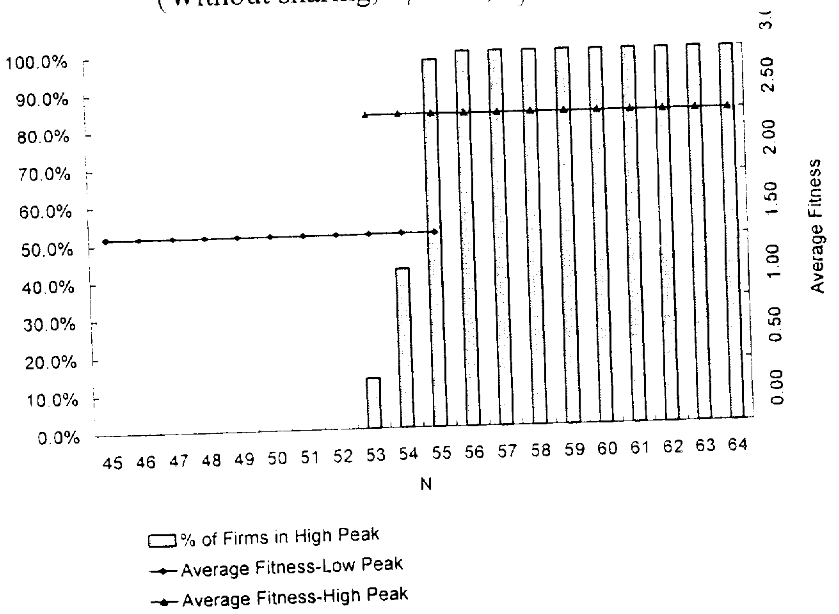

Figure 4. Evolution of Strategic Groups and Their Performance

(With sharing, $P_i = 1.0$, $P_f = 1.0$, $P_n = 1.0$)

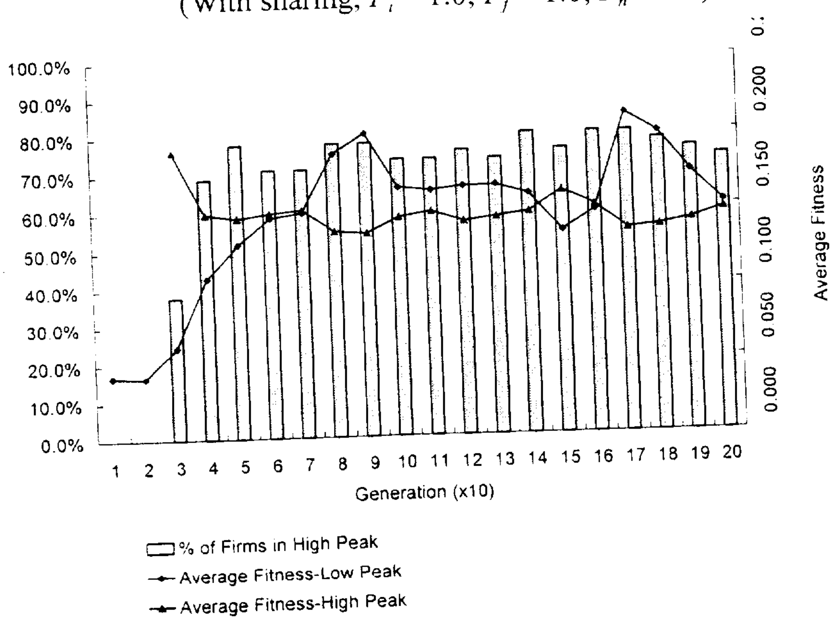

Figure 5. Power Law Sharing Functions: α =0.5 with Selected Values of σ_{share}

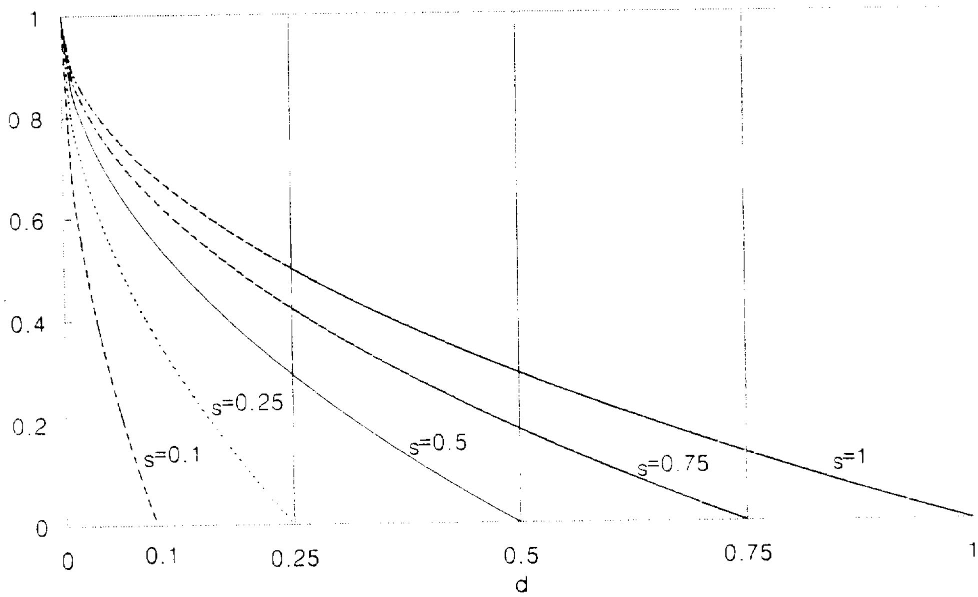

Figure 6. Power Law Sharing Functions: σ_{share} =0.5 with Selected Values of α

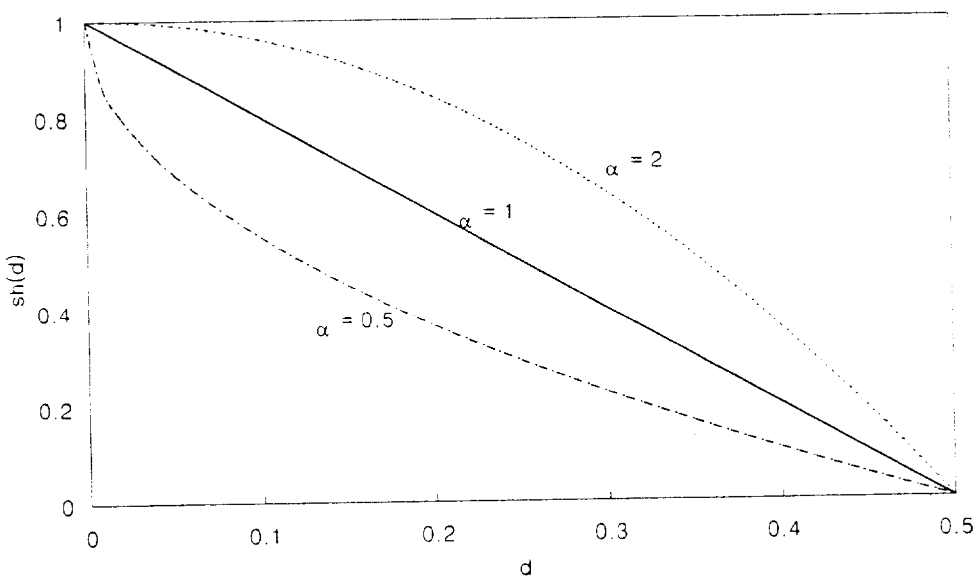

Figure 7. A Typical Simulation Result of the Standard Model

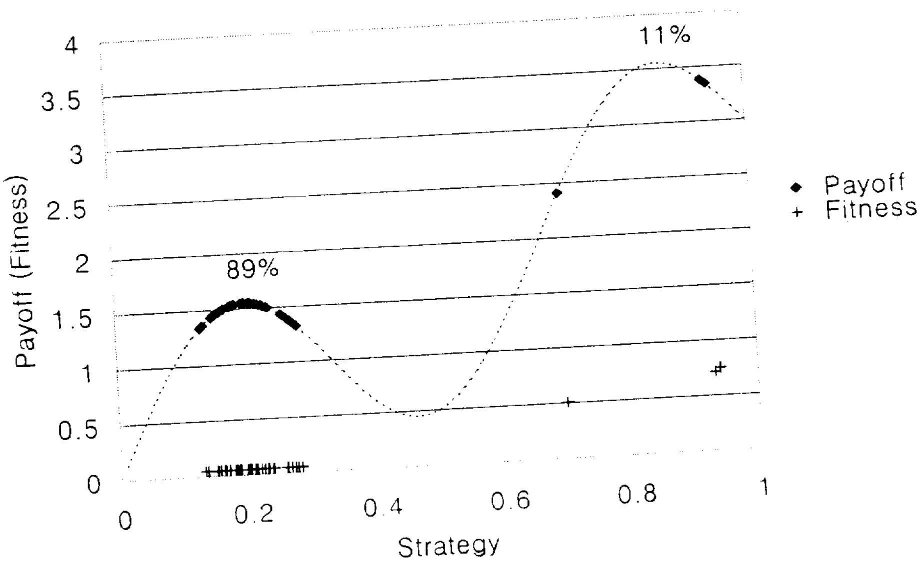

Figure 8. Evolution of Strategic Groups and Their Performance

(With sharing, $P_i = 1.0$, $P_f = 0.10$, $P_n = 0.01$)

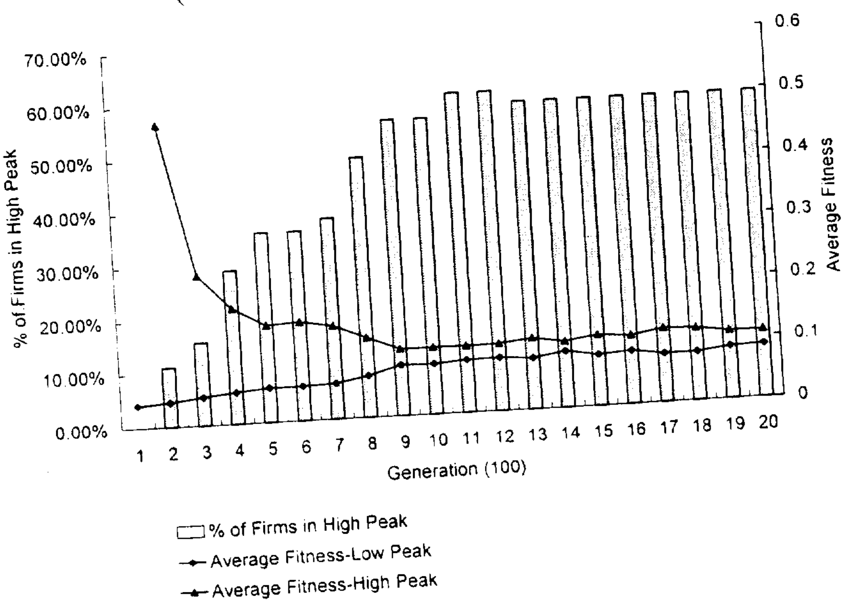

Figure 9. A Simulation Result without Sharing: Convergence to A Lower Peak

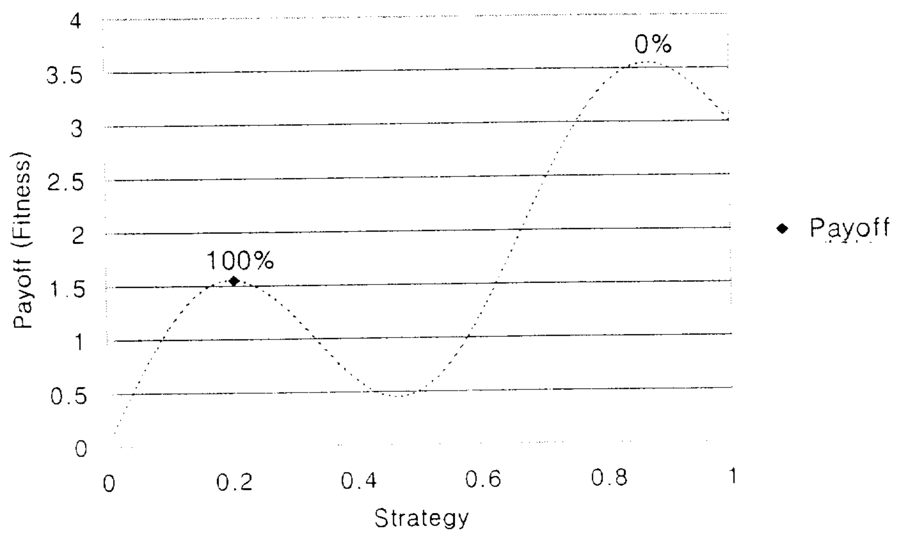

Figure 10. A Simulation Result without Sharing: Convergence to A Higher Peak