

Competition and the Organizational Structure of Multi-Unit Firms*

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Abstract

A computational model of competing multi-unit firms, such as retail chains and multi-plant manufacturers, is developed in which unit managers and corporate staff continually search for better practices while consumers search among units to find a better match. The main objective of this research is to determine how the amount of discretion given to unit managers, as to how they run their units, influences the rate of innovation at the unit level and how this relationship depends on market structure.

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1 Introduction

What is the optimal degree of centralization within a firm? To what extent should lower level managers be given the authority to act independently of higher level management? In the case of a retail chain, this question takes the form of how much discretion corporate headquarters should give to store managers. Should a tightly-controlled set of operating procedures be mandated or should store managers be given considerable leeway with respect to running their stores?

Historically, different organizations chose different answers to these questions. A recent contrast is provided by two discount department stores, Wal-Mart and Ames:

[Sam] Walton [founder of Wal-Mart] valued change, experimentation, and constant improvement. But he didn't just preach these values, he instituted concrete *organizational* mechanisms to stimulate change and improvement. Using a concept called "A Store Within a Store," Walton gave department managers the authority and freedom to run each department as if it were their own business.

Whereas Walton concentrated on creating an organization that would evolve and change on its own, Ames leaders dictated all changes from above and detailed in a book the precise steps a store manager should take, leaving no room for initiative. [Collins and Porras (1994), pp. 36-7]

While anecdotes are many, little is understood about how exactly organizational structure influences the performance of a retail chain. Is there one organizational structure that is best? Or does it depend on a chain's environment? If so, what are the pertinent features of the environment and how do they influence the relative performance of different organizational structures? The objective of the line of research we have been pursuing is to provide some theoretical insight into these questions. The dimension of organizational performance that we focus on is the dynamic one alluded to in the description of Wal-Mart: the rate of improvement in store practices achieved through innovations and organizational learning.¹

Our model of a retail chain begins with the view that a store, at any given point in time, is characterized by its current operating practices or what Nelson and Winter (1982) would refer to as "routines." An innovation is viewed as a new way of running a store as represented by a new routine. A store's performance (profit) depends on how its current set of operating practices matches up with what is desired by its consumers. New ideas represent a new point in store practice space and associated with that new point is a level of profit. Store profit, being defined over this store practice space, then forms a landscape over which the store manager can search for better practices through hill-climbing. Markets are allowed to differ and, thus, the landscapes faced by different store managers can differ. Analogously, corporate headquarters searches over a landscape based upon chain profit.

¹For a similar comparison made between Sears, Roebuck and Montgomery Wards in the 1930s and 40s (where the former is more decentralized), see Worthy (1984). For a case study that examines the effect of the standardization of plants on innovation, see Adler and Cole (1993).

For this setting, we previously explored the case of a single chain (Chang and Harrington, 2000). To summarize our findings in that paper, a decentralized organizational structure outperforms a centralized one when stores' markets are sufficiently heterogeneous, consumers are not too sensitive to store practices, the horizon is sufficiently long, and the market environment is sufficiently stable. Otherwise, a superior profit path is achieved through centralization.

The objective of the current paper is to extend the model to allow for competing chains and investigate the interaction of market structure and organizational structure. The setting is now one in which each market is served by several chains. Consumers engage in search to find the store that best fits their needs. Chains compete in terms of their stores' practices. Each store develops new ideas on their own but also learn about new practices of other stores in their chain (via headquarters) and about the implemented practices of competing stores in their market. In this paper we compare the results for a single chain with when there are two competing chains and explore the effect of changing the frequency of consumer search and the degree of spillover of ideas across chains. Further work is underway to examine the model for various number of chains so as to better assess the effect of competition.

Overview of General Approach and Related Literature The conceptual framework employed in our research has two major components. First, innovation is viewed as an act of information creation that improves the organization's ability to satisfy the demands of its external market environment. Second, an organization is viewed as a collection of agents, each of whom is capable of generating new ideas. As such, the potential sources of innovative ideas are distributed among multiple agents, rather than concentrated at a single central authority. Together, these two views lead to the central thesis that the performance of a retail chain, as measured by its ability to respond to the external market environment, depends critically on the way it organizes the complex process of communicating and utilizing innovative ideas generated by multiple internal sources.

That there exists a crucial linkage between the optimal organizational structure and the external environmental contingencies has long been recognized by organizational theorists (Lawrence and Lorsch, 1967; Mintzberg, 1979; Burton and Obel, 1995; Baligh, Burton, and Obel, 1996). This linkage has also been applied to understanding strategy implementation in diversified multi-unit business firms (Govindarajan, 1986, 1988; Morrison and Roth, 1993) as well as to studying the impact of information technology (IT) on the coordination structure of multi-market organizations (Anand and Mendelson, 1997; Nault, 1998). Our work contributes to this literature by explicitly modelling the innovation process through which an organization responds to various aspects of its environment. Given our view of innovation as the process of information creation and communication, our work is also related to Radner (1993) and Van Zandt (1998) which look at how the allocation of computational tasks within a hierarchy affects the efficiency of organizational information processing. Similar issues are addressed in Jehiel (1999) in the context of team theory (Marschak and Radner, 1972), in which the central question is how the decentralized information in a team should be organized and communicated so as to improve the efficiency

of the decision making. Another related body of work addresses the issue of intra-organizational screening of new information, where agents at different organizational levels may have conflicting opinions about the value of some information (Sah and Stiglitz, 1986; Chang and Harrington, 1998).

One of the major environmental contingencies in our model that affects the optimality of an organizational form is the heterogeneity in the markets that various stores serve. Given that the generation of information is distributed and the initial ownership of the new knowledge is private, the heterogeneity in external environments faced by the agents naturally introduces the potential for conflicting interests and, thus, the agency problem (Holmström, 1979, 1982; Rotemberg and Saloner, 1993; Baiman *et al.*, 1995; Aghion and Tirole, 1997; Chang and Harrington, 1999; Rotemberg, 1999). By assuming a fixed stream of new ideas, our work bypasses the issue of incentives in generating innovations and instead focuses on the design of organization for effective communication and utilization of available information. Nevertheless, it will be shown later that the relative effectiveness of a given organizational form is very much affected by the conflict of interests among agents.

We model innovation as the dynamic process by which a piece of information utilized in a given period further influences the creation, communication, and utilization of future innovation. This process is extensively researched in the body of literature commonly referred to as “organizational learning.”² Of particular relevance are organizational learning models that encompass boundedly rational agents experimenting with new ideas and making piecewise improvements (Cohen, 1981; Levinthal and March, 1981; Nelson and Winter, 1982). While our research belongs to this literature that models organizational learning as adaptive search, the exact search mechanism we utilize is distinct. In our model, innovation is modelled as random search carried out in a finite fixed space of ideas. This particular approach is rooted in the concept of a fitness landscape, defined in a multidimensional space in which each attribute of an organization (retail chain or a store in our model) is represented by a dimension of the space and a final dimension indicating the performance (profitability) of the organization. An adaptation by an organization is then represented by movement on the landscape toward a location reflecting higher fitness value. In the context of population genetics, Kauffman (1993) demonstrated that the topography of the fitness landscape is determined by the degree of interdependence of the fitness contribution of the various attributes of an organism. Taking the Darwinian perspective from organizational ecology, Levinthal (1997) uses this connection in the context of organizational attributes to examine the effectiveness of organizational adaptation at the population level. Both Carley and Svoboda (1996) and Carley and Lee (1998) also utilize the search-over-rugged-landscape perspective in modelling organizational restructuring as adaptive search for better organizational design given a group of learning agents.³ Our work is an extension in this body of literature in

²Recent works representative of this category can be found in Cohen and Sproull (1996).

³The same perspective is used by Kauffman *et al.* (1998) and Auerswald *et al.* (1999) in modeling technological innovation. Kollman *et al.* (1998) offer another context for its application: they examine how institutional structure influences the efficacy of search for better solutions within the context of federal systems using states as policy laboratories.

that our model investigates the impact of internal structure on the effectiveness of organizational search on the rugged landscape, where the ruggedness arises from the complementarity among various dimensions of store operations.

2 A Computational Model of a Retail Chain

A retail chain is modelled as a corporate headquarters (HQ) and a set of stores. There are L chains and M geographically distinct markets. $\Delta_j \subseteq \{1, 2, \dots, M\}$ denotes the set of markets served by chain j and $\Phi_h \subseteq \{1, 2, \dots, L\}$ denotes the set of chains serving market h . The operations of chain j 's store in market h in period t is fully described by an N -dimensional vector, $z^{j,h}(t) \equiv (z_1^{j,h}(t), \dots, z_N^{j,h}(t)) \in \{1, \dots, R\}^N$, where $z_k^{j,h}(t)$ is the practice for the k th dimension of store operations. There are then R feasible practices for each dimension. The store operations of chain j is represented by an element of $\{1, \dots, R\}^{N|\Delta_j|}$.

2.1 Consumer Preferences and Market Demand

Each market has a fixed set of 992 consumers with each consumer being defined by a vector of ideal store practices which is referred to as a consumer's type. The consumer types populating a market is constructed in the following manner. A consumer's type is a random draw from a distribution which is parameterized by his "seed" which is an element of a proper subset of $\{1, \dots, R\}$. If a consumer's seed is s then his type is a random draw from $\{s - E, \dots, s + E\}^N \subset \{1, \dots, R\}^N$ according to a uniform distribution where E is a parameter. The seeds for the 992 consumers in market h are distributed according to a triangular density function over $\{S_h - G, \dots, S_h + G\} \subset \{1, \dots, R\}$.⁴ In the simulations, $R = 100$, $G = 25$, and $S_h \in \{40, 42, \dots, 60\}$. This construction of the distribution of consumer types is performed independently for each market. By this specification, markets differ according to the single parameter S_h and heterogeneity between markets h' and h'' can be measured by $|S_{h'} - S_{h''}|$.

E controls the degree of correlation in a consumer's preference; that is, the degree to which preferring particular values for one dimension imply that similar values tend to be preferred for other dimensions. If $E = 0$ then a consumer's ideal vector of store practices is an element of $\{(1, \dots, 1), \dots, (R, \dots, R)\}$ so that consumers assign the same ideal value to all dimensions. More generally, the lower is E , the greater is the correlation across dimensions. A reason for such a correlation is the presence of a few consumer traits - such as income, parents' traits, education - which influence preferences over a large set of dimensions. For example, people with higher income may incur greater search costs (due to their higher value of time) so they would prefer everyday low prices with fewer sales (which avoids having to spend time searching for sales), fewer product lines and larger inventories (reducing the chances of being out-of-stock of a product and thus creating the need for another trip to the store), and more attentive though more aggressive sales personnel (which might speed up

⁴The distribution over consumer seeds for a market is non-stochastic. The 992 seeds approximate a triangular density function.

the time spent buying) as might be achieved by having sales personnel work on commission.

While a more complete specification of consumer preferences is provided in the Appendix, we describe here the basic properties essential to the analysis. Consumer decision making with respect to which store to buy from and how much to buy from that store is assumed to depend only on the distance between the consumer's ideal store practices and the actual practices of stores. We use Euclidean distance which takes the form $\sqrt{\sum_{k=1}^N (z_k - w_k)^2}$ for a consumer of type $\underline{w} \equiv (w_1, \dots, w_N)$ and a store with practices $\underline{z} \equiv (z_1, \dots, z_N)$. A consumer ranks stores according to this metric. Furthermore, it is assumed that the number of units demand by a consumer equals

$$\left[A - \sqrt{\sum_{k=1}^N (z_k - w_k)^2} \right]^\sigma \quad (1)$$

so that it is decreasing in this distance; where $\sigma > 1$ and $A \geq \sqrt{N(R-1)^2} + 1$ so that $\left[A - \sqrt{\sum_{k=1}^N (z_k - w_k)^2} \right] > 1$ for all $(\underline{w}, \underline{z})$.

2.2 Consumer Search

Market h is served by the chains in Φ_h and thus each consumer has $|\Phi_h|$ stores from which to choose. In any time period, a consumer shops from exactly one store but, as will be described below, he can change stores over time. As stated above, consumers rank stores according to the distance between his preferences and store practices. Thus, a consumer of type \underline{w} prefers a store with practices \underline{z}' to a store with practices \underline{z}'' if and only if (iff):

$$\sqrt{\sum_{k=1}^N (z'_k - w_k)^2} < \sqrt{\sum_{k=1}^N (z''_k - w_k)^2}. \quad (2)$$

A consumer enters each period with a “favorite store” which is the store he currently most prefers. Associated with a favorite store is the consumer's perception of the distance between the store and the consumer. Suppose chain j 's store in market h is the favorite store of a consumer in market h . Furthermore, suppose the consumer last visited that store in period t' (why it might not have been the previous period will be made clear momentarily). The consumer's perception of the distance between the store and the consumer is specified to be $\sqrt{\sum_{k=1}^N (z_k^{j,h}(t) - w_k)^2}$ where $\underline{z}^{j,h}(t)$ is this store's set of practices as of period t .

Search proceeds as follows. In each period, a consumer buys from his favorite store with probability $1 - Q$. In that event, his favorite store remains unchanged though the perceived distance from that store is updated to reflect the current practices of the store. With probability Q , he engages in search which involves randomly selecting a store from the set of all stores in his market (excluding his favorite store) and then buying from that store. At the end of the period, the consumer compares the distance

for the store just visited with the distance assigned to his favorite store. If the former is larger then the consumer does not change his favorite store (nor the distance assigned to it).⁵ If the former is smaller then the consumer changes his favorite store to the store just visited and assigns to that store a distance based on the store's current practices. The random variable determining whether a consumer searches or not is assumed *iid* across consumers and across time. Note that if $Q = \frac{|\Phi_h|-1}{|\Phi_h|}$ then a consumer has no loyalty as the *ex ante* probability of buying from a store is the same across all stores and thus is independent of a consumer's past experiences. It is then reasonable to assume $Q \in \left[0, \frac{|\Phi_h|-1}{|\Phi_h|}\right]$ where $Q = 0$ is absolute loyalty as no experimentation occurs.

2.3 Store and Chain Profit

Define $\Gamma_i^{j,h}(t)$ to be the set of consumers that are shopping at chain j 's store in market h in period t . $\Gamma_i^{j,h}(t)$ is comprised of: i) those consumers who have chain j 's store as their favorite store in period t and chose not to experiment; and ii) those consumers who experimented and chose chain j 's store. The store's period t profit is specified to be

$$\pi\left(\underline{z}^{i,h}(t), \Gamma_i^{j,h}(t)\right) \equiv \sum_{i \in \Gamma_i^{j,h}(t)} \left[A - \sqrt{\sum_{k=1}^N (z_k^{j,h}(t) - w_k^i)^2} \right]^\sigma. \quad (3)$$

This is the sum of consumers' demands where per unit profit is normalized to one.

As a chain's profit is the simple sum of stores' profits, chain j 's profit is:

$$\sum_{h \in \Delta_j} \sum_{i \in \Gamma_i^{j,h}(t)} \left[A - \sqrt{\sum_{k=1}^N (z_k^{j,h}(t) - w_k^i)^2} \right]^\sigma. \quad (4)$$

The state variables for chain j 's store in market h are its practices, $(z_1^{j,h}(t), \dots, z_N^{j,h}(t))$, the set of customers for whom this store is their favorite store, and the distances those consumers assign to this store. We will refer to these consumers as a store's set of loyal customers. The equation of motion on this set is crucial. Consumers who had this store as their favorite store and experimented and found something better will no longer be a loyal customer. Consumers who were not loyal as of period t but tried this store in period t and found their practices preferable to the perceived practices of their favorite store will become a loyal customer.

3 Structure of the Landscape

A store's landscape can be thoroughly characterized by evaluating the profit function (3) for all practices. To get a feel for this landscape, let us consider two- and three-

⁵Thus, a consumer expects a store to maintain the same practices. While a consumer should expect a store's practices to change, it seems reasonable to assume it is a Martingale. Further assuming it is a degenerate distribution makes the analysis easier.

dimensional store practice spaces, $N \in \{2, 3\}$ with $R = 100$, $G = 25$, $\sigma = 3$, and a market seed of 50. Each replication uses a fresh set of consumer types drawn from $\{50 - E, \dots, 50 + E\}^N$.⁶ The results are in Table 1 which reports the number of local optima for various values of N and E .

The key property to note is that there are multiple local optima, except when the correlation in consumer preferences is sufficiently low. We believe that this ruggedness in the landscape plays an important role in the analysis. What it means is that stores with similar (or even identical) markets can end up with very different practices as a result of targeting different optima.

4 Modelling of Innovation

In each period, each store generates one idea. An idea is represented by a dimension and a value assigned to that dimension and thus is an element of $\{1, \dots, N\} \times \{1, \dots, R\}$. We create an idea by randomly selecting a dimension from $\{1, \dots, N\}$ and assigning to it a randomly selected element from $\{1, \dots, R\}$. If this idea is adopted by a store then the store's practice in the specified dimension is changed to the new value. As an example, consider $N = 5$ and $R = 100$ and suppose current store practices are (25, 56, 71, 33, 89). If idea (3, 95) is adopted then store practices are (25, 56, 95, 33, 89). If this idea is implemented by another store currently employing (11, 29, 54, 49, 65), its new practices are (11, 29, 95, 49, 65).⁷

In each period, the ideas generated by stores are considered for adoption sequentially with the order being randomly determined. We consider two organizational forms. In the decentralized organization, store managers have the authority to implement ideas. In the centralized organization, the authority rests with HQ.⁸ Furthermore, as will be made evident, we assume that HQ does not have the detailed information of stores' markets so that it either mandates a practice throughout the chain or not. Hence, we associate a uniformity of practice with centralization.

Consider the decentralized organization. In any period, a store manager has a non-empty set of ideas to consider which come from several sources. First, a store manager generates one idea each period. Second, the store manager observes each idea adopted by another store in the same market in the previous period with probability Q_S . Third, the store receives, via HQ, the ideas adopted by other stores in its chain in

⁶To derive the set of local optima, one must calculate store profit for R^N store practice vectors. Given $R = 100$, this is a computationally intensive exercise except when N is small. Alternatively, there are methods for estimating the number of local optima and these do not involve exhaustively searching the space. Such methods will be deployed in characterizing the landscape for higher values of N .

⁷We are limiting our attention to one-dimensional ideas. Multi-dimensional ideas were considered in Chang and Harrington (2000) and, at least for the questions considered, qualitative results were not found to be sensitive to the dimensionality of ideas.

⁸For the one-chain model in Chang and Harrington (2000), we considered simulations with a richer set of organizational forms defined by $\Omega \subseteq \{1, \dots, N\}$ where Ω is the set of dimensions controlled by HQ. The optimal structure was, almost always, either full centralization, $|\Omega| = N$, or full decentralization, $|\Omega| = 0$. To save on computational time, we have focused our attention on those two structures.

the previous period. Fourth, HQ observes each idea adopted by another chain in the previous period with probability Q_H and those ideas are passed along to the stores. A store manager sequentially evaluates all these ideas and adopts an idea if it raises current store profit.⁹ In evaluating ideas, a store uses its current base of consumers, $\Gamma_i^{j,h}(t)$. This is motivated by the view that an idea may be temporarily adopted to see how well it performs. A new practice that increases the profit from existing consumers does so because it meets their needs better which then makes them more likely to make this store their favorite store.

For the sake of clarity, let us provide a more formal presentation of this adoption rule for when chain j 's store in market h has two ideas to consider in period t . The store enters the period with practices $(z_1^{j,h}(t), \dots, z_N^{j,h}(t))$. Recall that an idea, generically denoted (x, y) , is an element of $\{1, \dots, N\} \times \{1, \dots, R\}$. Let $(\underline{z}', (x, y))$ denote the vector $\underline{z}' \in \{1, \dots, R\}^N$ but with the x^{th} element replaced with value y . Randomly denumerate the two ideas and let (x_i, y_i) be the i^{th} idea. The adoption rule is as follows.

- If

$$\pi\left(\left(\underline{z}^{i,h}(t), (x_1, y_1)\right), \Gamma_i^{j,h}(t)\right) > \pi\left(\underline{z}^{i,h}(t), \Gamma_i^{j,h}(t)\right)$$

then adopt (x_1, y_1) .

- If (x_1, y_1) is adopted and

$$\pi\left(\left(\left(\underline{z}^{i,h}(t), (x_1, y_1)\right), (x_2, y_2)\right), \Gamma_i^{j,h}(t)\right) > \pi\left(\left(\underline{z}^{i,h}(t), (x_1, y_1)\right), \Gamma_i^{j,h}(t)\right)$$

then adopt (x_2, y_2) .

- If (x_1, y_1) is not adopted and

$$\pi\left(\left(\underline{z}^{i,h}(t), (x_2, y_2)\right), \Gamma_i^{j,h}(t)\right) > \pi\left(\underline{z}^{i,h}(t), \Gamma_i^{j,h}(t)\right)$$

then adopt (x_2, y_2) .

Now consider a centralized organization. In any period, a store manager generates an idea and considers whether, if adopted, it would raise store profit. If so, the idea is passed up to HQ. If not, the idea is discarded.¹⁰ In any period, HQ then receives ideas from several sources. First, those ideas that its stores generated and passed up.

⁹Thus, a store manager engages in myopic hill-climbing. An alternative formulation would be to allow her to consider all possible combinations of new ideas and to adopt the one that yields the highest current profit. We do not think this would change our results. If the rate of new ideas is such that a store manager rarely evaluates more than one idea per period then there is clearly no difference.

¹⁰The motivation for discarding it is that it takes some (small) time and effort by the store manager to communicate an idea and that it is not optimal for her to do so unless she thinks it will benefit her own store. Any individual is faced with many ideas - certainly many more than can be given attention - and engages in a screening process to determine which ideas are worth thinking carefully about.

Second, a store in the chain may observe ideas adopted by other stores in the same market in the previous period. Each of those ideas are observed with probability Q_S . If the store likes the idea (that is, its adoption would raise the store’s profit) then it passes the idea up to HQ. Third, HQ observes each idea adopted by another chain in the previous period with probability Q_H . With this set of ideas, HQ sequentially evaluates them in a myopic manner; mandating a practice throughout the chain if doing so raises chain profit and otherwise discarding the idea. In evaluating ideas, HQ uses a measure of profit based on the current set of consumers at its stores.

Implicit in these adoption rules are certain assumptions about what agents know about their environment. We do not suppose that they have complete information about the landscape though we do imagine that they have some information and, furthermore, that they can experiment so as to get a reasonable estimate of store (or chain) profit from the adoption of an idea. Rather than model this process of experimentation, which would further complicate our analysis by introducing additional noise, we implicitly assume it is done instantly and costlessly. It is also implicitly assumed that store managers have better information about their local markets than HQ. This rationalizes why a store manager can determine the suitability of a particular practice for her market while HQ is incapable of making such a detailed judgment. However, HQ is assumed to have information about the distribution of stores’ environments (that is, how many markets of a particular type that the chain serves) - which allows it to calculate chain profit - but not about which store faces which environment - so that it cannot perform the same fine-tuning that store managers can.

Q_S and Q_H are inter-chain spillover parameters as they measure the extent to which ideas adopted by a chain are observed by competing chains. Note that we have assumed that intra-chain spillover is perfect as HQ observes the adopted idea of one of its stores with probability one. Thus, we should interpret Q_S and Q_H as measuring the rate of inter-chain spillover *relative* to the rate of intra-chain spillover. Another key parameter worth noting is Q , the rate of consumer search. Q will affect the rate of convergence though exactly how is unclear. As $Q \rightarrow 0$, so that consumer search slows down, one would expect the system to converge slower since it takes a longer time for consumers to find the best store for them. On the other hand, convergence would seem to be faster when $Q = 0$ than when $Q > 0$ as there is no movement in consumers. Also note that $Q = 0$ and $Q = \frac{|\Phi_h|-1}{|\Phi_h|}$ may yield similar results. In both cases, stores face a stationary distribution on customers though it is degenerate when $Q = 0$ and is non-degenerate when $Q = \frac{|\Phi_h|-1}{|\Phi_h|}$.

5 Simulation Design

Thus far, simulations have been performed for when each chain serves all markets, $\Delta_j = \{1, \dots, M\} \forall j$. For each set of parameter values, the computational experiment consists of X replications of the innovation procedure. Each replication involves a randomly drawn vector of consumer types for each market, a set of initial store practices (which are the same for all stores within a chain but are *iid* across chains),

and *TLM* ideas, as each store generates one idea per period and there are M stores per chain and L chains. T is the number of periods. We've set $T = 1000$ as it appears to be of sufficient length for the profit paths to have settled down, at least for moderate parameter values. The last remaining element of the initial conditions are the initial values for consumers' state variables. In period 0, consumers are randomly assigned to stores and buy from the store with which they are matched. That store, and the associated distance, is specified to be the consumer's favorite store for the first period of the simulation.

For each replication, the profit path was calculated when the chain is centralized and when it is decentralized.¹¹ Let $v_C^{t,i}(O)$ denote the profit of a centralized chain in period t for replication i , when the other chain has organizational structure O . Similarly define $v_D^{t,i}(O)$ for when the chain is instead decentralized. One of the measures we will report is the time series on $\left(\frac{1}{X}\right) \sum_{i=1}^X \left[v_C^{t,i}(O) - v_D^{t,i}(O) \right]$ where X is the number of replications. Next define

$$V_C^i(O; T) \equiv \sum_{t=1}^T \left(\frac{1}{T} \right) v_C^{t,i}(O); \quad V_D^i(O; T) \equiv \sum_{t=1}^T \left(\frac{1}{T} \right) v_D^{t,i}(O)$$

as average chain profit over the first T periods for a centralized and decentralized chain, respectively. Defining $\delta^i(T; O) \equiv V_C^i(O; T) - V_D^i(O; T)$, we can construct the following test statistic:

$$Z = \frac{\bar{\delta}(O; T)}{\frac{\sqrt{\left(\frac{1}{X}\right) \sum_{i=1}^X (\delta^i(O; T))^2 - (\bar{\delta}(O; T))^2}}{\sqrt{X}}}$$

where

$$\bar{\delta}(O; T) \equiv V_C(O; T) - V_D(O; T) \equiv \left(\frac{1}{X} \right) \sum_{i=1}^X V_C^i(O; T) - \left(\frac{1}{X} \right) \sum_{i=1}^X V_D^i(O; T).$$

This will be reported for $T \in \{500, 1000\}$.

The simulations have been run for when there are three markets ($M = 3$). Recalling that market h is defined by S^h , it is assumed that $(S^1, S^2, S^3) = (50 - \alpha, 50, 50 + \alpha)$ where $\alpha \in \{0, 2, \dots, 10\}$ so that α measures the degree of inter-market heterogeneity. In expectation, markets are identical when $\alpha = 0$. The following additional parameter values are assumed: $\sigma = 3$, $R = 100$, $E = 2$, $N = 20$, $G = 25$, and $X = 400$. All stores are endowed with a set of practices from $\{1, \dots, 100\}$ ²⁰. The simulation programs were written in C++ and compiled with Microsoft Visual C++.¹²

¹¹In calculating the performance of both organizational forms using the same initial practices and the same sequence of ideas, we are able to control for two sources of randomness.

¹²The pseudo code is in the Appendix and the source code is available upon request from Myong Chang.

6 The Case of One Chain

Prior to exploring competition among chains, it is useful to have some understanding of the role of organizational structure in the case of a single chain. As this was examined in detail in Chang and Harrington (2000), only some limited results are reported here.¹³ Note that, with one chain, the search and spillover parameters, (Q, Q_S, Q_H) , are irrelevant.

On the basis of average chain profit over the first T periods (with that average profit being averaged over the 400 replications), Table 2-A reports the optimal organizational structure for various degrees of inter-market heterogeneity. Table 2-B reports the difference in average profit between the centralized and decentralized structures. The number in parenthesis below an entry is the value for the test statistic Z where 1.645 is the value for a one-sided 5% test and 2.326 is for a one-sided 1% test.

Property 1: Centralization outperforms when markets are sufficiently similar and the horizon is sufficiently short.

Given that markets are heterogeneous, the benefit of decentralization is clear - it allows each store manager to tailor practices to the local market. How then does a centralized structure outperform? Our analysis revealed there is an implicit cost to decentralization. As stores tailor their practices to their markets in a decentralized chain, their practices drift farther apart. As a result, a new practice adopted by one store is increasingly unlikely to be compatible with the current practices of other stores. In essence, stores come to target distinct consumer types (i.e., different local optima) and what works for one type of consumer doesn't tend to work for another type of consumer. Inter-store learning is then less under decentralization and this is detrimental to the rate of improvement in store practices. The virtue of a centralized structure is that it enhances inter-store learning by keeping stores close in store practice space so that they are targeting similar consumers. With these two countervailing effects, a centralized structure outperforms as long as markets are not too different.

Figure 1 shows the differential in chain profit between a centralized and a decentralized organization over time (that is, profit under centralization in period t minus profit under decentralization in period t , averaged across all replications).¹⁴ As shown, the centralized structure is superior in the early periods, which is when learning is most active. That superiority dissipates over time as stores in the decentralized chain eventually come to identify desirable (and distinct) local optima and independently converge to them. While mutual learning is less under decentralization, the ultimate superiority of its global optimum favors decentralization in the

¹³In that paper, it was assumed that $N = 10$ and $E = 0$. Also, there were 1000 consumers whose types approximated a triangular density function. For purposes of comparability with the case of multiple chains, the results reported here are for when each of 992 consumers, whose seeds approximate a triangular density function, becomes a buyer with probability .5. Hence, on average, there are 496 consumers.

¹⁴Note that $L = 1$ is equivalent to the case of $L = 2$ and $Q = 0$ in that no consumer search means that each store has a permanently loyal set of consumers.

long run.¹⁵ However, if one allows for consumer preferences to change stochastically so that there is continual change in the environment, centralization outperforms in the long-run as well (that is, the steady state) when markets are not too different.¹⁶

7 The Case of Two Competing Chains

In this section, we consider the case of two competing chains, $L = 2$, so as to begin to explore what new relationships emerge in the presence of competition.¹⁷ Both chains have stores in the same three markets. The market seeds are symmetric around 50 with $(S^1, S^2, S^3) = (50 - \alpha, 50, 50 + \alpha)$ and $\alpha \in \{0, 2, \dots, 10\}$. Q is the probability that a consumer searches in each period and $Q \in \{0, .01, .03, .05, .1, .2, .3\}$. Note that $Q = .3$ is a very high rate of consumer search as it implies that, on average, 30% of all consumers are searching each period. Since, when $Q = 0$, consumers are not searching then each consumer permanently buys from the store to which he is initially assigned. Hence, the case of no consumer search is equivalent to the case of a single chain. The preliminary runs reported in this paper assume no spillover: $(Q_S, Q_H) = (0, 0)$. The assumptions on other parameter values are as previously specified unless stated otherwise.

7.1 Equilibrium Organizational Structures

On the basis of average chain profit, Table 3 reports the equilibrium organizational structures. These results were generated as follows. For each replication (which is a set of consumer types, a set of initial practices, and a sequence of ideas), we calculated the path of chain profit under decentralization and under centralization. After replicating 400 times, the profit in each period was averaged across replications. This gave us a time-series for average chain profit under each organizational form. Profit was then averaged over the first T periods and this was used as entries in a 2×2 payoff matrix for the game in which chains simultaneously (and once and for all) select organizational forms. For this game, the set of Nash equilibria was derived. An entry in Table 3 is the set of equilibrium market structures where CC denotes that there is a unique equilibrium with two centralized structures, DD is that there is a unique equilibrium with two decentralized structures, and CD is that there are two asymmetric equilibria.¹⁸

¹⁵In Chang and Harrington (2000), we show that an idea is more likely to be valuable to all stores under centralization so that mutual learning is indeed higher. Note that it does not have to be true that mutual learning is higher under centralization. The degree of mutual learning depends not only on the similarity in stores' current positions - which is constrained to be identical in the centralized chain - but also on the similarity in their market environments.

¹⁶See Chang and Harrington (2000).

¹⁷The next version of this paper should include results for higher values of L so that we can examine the effect of the degree of competition.

¹⁸So as to save on computational time and given symmetry, we ran three of the four configurations: both chains are centralized, chain 1 is centralized and chain 2 is decentralized, and both chains are decentralized. Let $W_i(O_1, O_2)$ denote the average profit to chain i given organizational structures, (O_1, O_2) . Given symmetry, CC is an equilibrium iff $W_2(C, C) \geq W_2(C, D)$. DD is an equilibrium

We find that an equilibrium always exists and, except for when asymmetric equilibria exist, there is a unique equilibrium.¹⁹ Asymmetric equilibria occur at the interface of a region in which CC is an equilibrium with when DD is an equilibrium. For example, consider $Q = .03$ and $T = 1000$. When $\alpha \leq 6$ both firms are centralized and when $\alpha = 10$ both firms are decentralized. However, at $\alpha = 8$, equilibrium involves one firm being centralized and the other being decentralized.

Property 2: Generally, a unique equilibrium exists and it involves symmetric organizational forms.

In that it is quite possible that the differences in average profit across organizational forms that are used to produce Table 3 are the product of noise, we test for statistical significance in Tables 4 and 5. These tables report the difference in average profit between the centralized and decentralized structures, $V_C(O) - V_D(O)$, depending on the organizational form of the other firm and various parameters. The number in parenthesis below an entry is the value for the test statistic Z where 1.645 is the value for a one-sided 5% test and 2.326 is for a one-sided 1% test. Generally, the differential performance between organizational forms is highly statistically significant.

In contrasting the case of one and two chains, let us compare the case of no consumer search among stores ($Q = 0$) with when consumers search among competing stores and engage in comparison shopping ($Q > 0$). Examining Table 3, we find that centralization is more frequently the optimal organizational structure when there is competition, at least for moderate values for Q . When competition is absent ($Q = 0$), firms choose to be centralized only when $\alpha \leq 2$ for $T = 500$ and $\alpha = 0$ for $T = 1000$.²⁰ When consumer engage in search among the stores, so that chains are competing for consumers, centralization occurs for all $\alpha \leq 6$, at least when $Q \leq .2$. The result is even more striking if one examines the time series for the profit differential between centralized and decentralized chains. In Figure 1, which is the case of no competition, decentralization begins to yield higher profit sometime before period 200. In contrast, Figures 2-7 show that when markets are not too different and consumer search is not too great, centralization can yield higher profit even in period 1000.

Property 3: For moderate levels of consumer search, the relative performance of centralization is enhanced when there is competition.

This result runs counter to our initial intuition which was that the presence of a decentralized competing chain would accentuate the cost of centralization. The benefit of centralization is that it improves mutual learning but at the cost of some stores not having practices well-suited to their market's consumers. A competing

iff $W_1(D, D) \geq W_1(C, D)$. CD is an equilibrium iff $W_1(C, D) \geq W_1(D, D)$ and $W_2(C, D) \geq W_2(C, C)$.

¹⁹We also calculated a chain's expected average profit if it assigned equal probability to the other chain being decentralized and centralized. The results are very similar to what is in Table 3.

²⁰Note that this is the same as in Table 2A which is not coincidental as $L = 1$ is equivalent to $L = 2$ and $Q = 0$.

decentralized chain would seem to be able to take advantage of that constraint and successfully grab a big share of the market. Obviously, there is something more going on here and it must be related to how consumers are sorting themselves. One may find that though the stores of a centralized chain may not get a large share of the market (when the other chain is decentralized), they may do a very good job of satisfying the needs of a small segment of the market. For example, suppose a centralized chain results in all of its stores having practices that are generally less than 48. This commonality in practices allows them to engage in a lot of mutual learning and thus do a good job of satisfying consumers whose ideal preferences are less than 48. While they lose the rest of the market to the decentralized chain (which may be quite large if most consumers prefer values higher than 48), they get a lot of demand per capita out of the consumers that they do serve. At this point, this explanation is speculative. We need to examine what is happening to the set of consumers served by a chain and the demand per capita from those consumers.

7.2 Inter-Market Heterogeneity and Time-Series Properties

When there is one chain, a more diverse set of markets very clearly enhances the relative performance of decentralization. One comes to a similar conclusion for the case of two chains when examining the equilibrium configurations. It is an equilibrium for both chains to be centralized when markets are sufficiently similar and it is an equilibrium for both chains to be decentralized when markets are sufficiently different. However, more is going on than is revealed by what is happening with equilibrium structures and this is revealed in Tables 4 and 5. When $\alpha \geq 6$, the differential in average profit between the centralized and decentralized forms does indeed decline with α so that decentralization does relatively better as markets are made more distinct. However, when α is raised from 0 to 2 and from 2 to 4, the contrary is true - the difference in average profit between centralization and decentralization rises. This property holds across a variety of values for consumer search and organizational forms for the competing chain. It clearly runs counter to the intuition coming from the single-chain model and requires further investigation.

Property 4: When markets are sufficiently similar, the relative performance of centralization is enhanced as markets become more diverse. When markets are sufficiently different, the relative performance of decentralization is enhanced as markets become more diverse.

A more striking difference between the case of one and two chains is observed for the time-series on the profit differential. With one chain, centralization yielded higher profit in the early periods and this profit difference steadily declines and becomes negative well within the time horizon of 1000 periods. This is shown in Figure 1 where the profit differential jumps up to some positive level²¹ and falls monotonically. It typically becomes negative before period 100. Turning to Figures 2-7, the time-series

²¹It appears as if it starts at a positive level but actually it starts at zero and then becomes positive in the first period.

for when there are two chains is quite different. First, it is noisier because of the randomness associated with consumer search. Second, and more importantly, it is a much richer pattern. As with the case of one chain, the profit differential starts out positive, indicating that centralization is generating higher chain profit in the early periods. With the exception of when consumer search is very slow, if one goes out far enough in the horizon then the profit differential is steadily declining, similar to when there is one chain. But there is something else going on in-between those two stages. At least when markets are sufficiently different ($\alpha \geq 4$), the profit differential starts positive and is declining but bottoms out around period 50 and then rises and reaches some peak around period 100. From that point onward, the differential steadily declines. In many cases, this differential remains positive (that is, in favor of centralization) even in period 1000, in contrast to when there is one chain.

Further simulations need to be conducted to understand what lies beneath these dynamics. What is important to recognize is that there are two dynamics at work when there are two chains (and consumer search). As with the case of one chain, stores are learning new practices and thus climbing a landscape. Distinct from the case of one chain, consumers are also learning - about the practices of different stores - and sorting themselves accordingly. This consumer search is altering the landscape over which stores are climbing. Simulations are currently underway to measure this consumer sorting and how organizational structure impacts it.

7.3 Consumer Search

One of the more interesting parameters is the rate of consumer search, Q . Recall that $Q = 0$ corresponds to the case of no competition as consumers are not allowed to move between stores. Each store has a local monopoly. On the other extreme, when $Q = \frac{|\Phi_h|-1}{|\Phi_h|}$, consumers randomly move between stores so that a store's practices have no effect on who buys from them (though it does affect how much each customer buys). In a sense, stores are not competing in that case either. It would appear the only difference between $Q = 0$ and $Q = \frac{|\Phi_h|-1}{|\Phi_h|}$ is that the former involves a fixed landscape and the latter a landscape that is subject to a stationary stochastic process. For intermediate values of Q , consumers are systematically sorting themselves between stores. In light of all of this, it is quite interesting to explore the impact of the rate of consumer search.

Consistent with the claim that $Q = 0$ and $Q = .5$ are essentially equivalent, we find a non-monotonic relationship between the rate of consumer search and equilibrium organizational structures. Examining Table 3, centralization most often occurs for moderate rates of consumer search. Considering the path of differential profits, a rise in the rate of consumer search tends to shift the path down when $Q \geq .05$. When $Q < .05$, the effect of Q is not so apparent though we know from Tables 4 and 5 that the average of that time path, in some instances, increases as Q is raised.

Property 5: For low levels of consumer search, the relative performance of centralization is enhanced as the rate of consumer search is increased. For high levels

of consumer search, the relative performance of decentralization is enhanced as the rate of consumer search is increased.

We have some initial (but highly incomplete) thoughts at this time concerning this result. Recall that, in any period, a consumer is attached to a single store in the sense that he buys from that store unless he chooses to engage in search. With probability Q a consumer searches by buying from another store. If the distance between his preferences and that store is less than what he associates with his favorite store (which is based on his most recent experience with his favorite store), he makes this new store his favorite store. When $Q = 0$, there is complete consumer loyalty as consumers never search and always buy from the same store. When $Q = .5$ (for the case of two stores in a market), there is no consumer loyalty as the probability of buying from a store is the same across stores and is independent of past experience. Thus, as Q is increased, consumers engage in more search and there is less loyalty as a result.

It would seem to be an immediate implication that greater consumer search makes a store's demand more sensitive to its practices. Current practices affect demand in two ways. First, it affects how much is purchased by those consumers who decide to buy from a store. This is its impact on current demand. Second, it affects the set of consumers who choose to visit the store next period and thereby influences future demand. For a given set of consumers buying from a store, a store's demand falls as the distance between its practices and the most preferred practices of those consumers increase. Furthermore, it becomes more likely that consumers who are searching in the current period will find the other store more attractive and choose not to return to its previously preferred store in the future (with the exception of when it engages in search). This lowers future demand. It would then seem that a store's demand becomes more sensitive to its practices as consumer search increases. This we plan to verify with additional simulations.

The attractiveness to centralization is that the resulting uniformity of practices enhances inter-store learning within the chain. Effectively, each store receives a greater number of useful ideas each period as the other stores in its chain are a better source of ideas when they are similarly located in practice space. The implicit cost to centralization is that a store may not be able to adopt a practice that satisfies the consumers in its market. Since consumer search results in demand being more sensitive to a store's practice, this inability under a centralized form for stores to tailor practices to their consumers' preferences may prove to be more detrimental to demand. Dissatisfied consumers don't just buy less, they go to other stores. This enhanced sensitivity of demand makes it all the more important not to veer too far from what consumers desire. As this is better achieved by giving authority to store managers, a decentralized structure performs relatively better when consumers engage in more search. If correct, this would explain why a higher rate of consumer search favors decentralization, at least when Q is sufficiently high. But what is the mechanism by which a higher rate of consumer search favors centralization when Q is sufficiently low? Our plan is to engage in further simulations to see how consumers are sorting themselves and how this is impacted by organizational structure.

An interesting extension is to allow the rate of consumer search to be time-dependent. If stores' practices are settling down over time then it makes sense for consumers to engage in less experimentation since there is less change over any length of time. One could specify the rate of consumer search in period t to have the following form: $Q^t = \rho_1 + \rho_2 e^{-\kappa t}$ where $\rho_1 \geq 0$ and $\rho_2, \kappa > 0$. Or, one could make the rate of search endogenous to what consumers experience. A smaller change in utility due to search could be specified to reduce the rate of search.

8 Concluding Remarks

The results and the analysis are both preliminary. Nevertheless, competition appears to have introduced several new factors into the discussion. With consumers searching across stores, a chain with better practices performs better not just by having higher demand per customer but also by having more customers. This latter effect is achieved by inducing searching consumers to become loyal customers. The simulations conducted thus far suggest that these new factors generate some qualitatively new relationships. First, compared to when there is one chain, the centralized organization outperforms for a wider range of parameter configurations when there is competition. Second, an increase in the diversity of markets can actually enhance the relative performance of centralization which runs counter to the intuition from the one chain model. Third, the intertemporal profit paths under centralization and under decentralization exhibit a much more complicated (but still systematic) pattern in the presence of competition. Further simulations are underway to better document these relationships and to shed light on what is driving them.

9 Appendices

9.1 Model of Consumer Preferences

Here we provide a more foundational structure that generates the specification in Section 2.1. Let $\lambda(\underline{w}, \underline{z}^{j,h}(t)) \equiv \sqrt{\sum_{k=1}^N (z_k^{j,h}(t) - w_k)^2}$ denote the distance between a store and a consumer in store practice space. A consumer of type $\underline{w} \equiv (w_1, \dots, w_N)$ is assumed to receive net surplus from buying x units at a price of p from a store with practices $\underline{z} \equiv (z_1, \dots, z_N)$ equal to:

$$\left[A - \lambda(\underline{w}, \underline{z}^{j,h}(t)) \right]^\gamma x^\beta - px \quad (\text{A.1})$$

where $\beta \in (0, 1)$, $\gamma \geq 1$, and A is chosen so that $A > 1 + \lambda(\underline{w}, \underline{z})$ for all $(\underline{w}, \underline{z})$. If a consumer chooses x to maximize his net surplus, demand is then

$$\left(\frac{\beta}{p} \right)^{\frac{1}{1-\beta}} \left[A - \lambda(\underline{w}, \underline{z}^{j,h}(t)) \right]^{\frac{\gamma}{1-\beta}} \quad (\text{A.2})$$

Defining $\Gamma_i^{j,h}(t)$ to be the set of consumers that buy from chain j 's store in market h in period t , store profit is:

$$(p - c) \sum_{i \in \Gamma_i^{j,h}(t)} \left(\frac{\beta}{p} \right)^{\frac{1}{1-\beta}} \left[A - \lambda(\underline{w}, \underline{z}^{j,h}(t)) \right]^{\frac{\gamma}{1-\beta}} \quad (\text{A.3})$$

where c is the constant marginal cost faced by a store.

There are several assumptions one could make here. First, we could assume that p is fixed across firms and then perform a normalization by choosing p , c , and β so that $(p - c) \left(\frac{\beta}{p} \right)^{\frac{1}{1-\beta}} = 1$. This would give us the expression in (3) once we set $\gamma = \sigma(1 - \beta)$. Second, we could interpret p as some cost to acquiring goods that is not specific to a particular store (e.g., the time cost to a consumer) and that a store's price is implicit in our definition of store practices.²² The same normalization would apply in that case. Third, we could assume that each store sets price to maximize current profit. Choosing p to maximize (A.3), the optimal price is $\frac{c}{\beta}$. Since all stores charge the same price, it still makes sense for consumers to rank stores according to distance in store practice space. Store profit is

$$\left[\left(\frac{c}{\beta} \right) - c \right] \left(\frac{\beta^2}{c} \right)^{\frac{1}{1-\beta}} \sum_{i \in \Gamma_i^{j,h}(t)} \left[A - \lambda(\underline{w}, \underline{z}^{j,h}(t)) \right]^{\frac{\gamma}{1-\beta}} \quad (\text{A.4})$$

c and β are then chosen so that $\left[\left(\frac{c}{\beta} \right) - c \right] \left(\frac{\beta^2}{c} \right)^{\frac{1}{1-\beta}} = 1$. With $\gamma = \sigma(1 - \beta)$, we have (3).

²²These dimensions could be price-adjusted. While we have not worked it out, the following example will reveal what we have in mind. Suppose that a dimension is the amount of training given to sales personnel. More training costs more and results in higher prices. A consumer's preferences over this dimension embodies his willingness to trade-off higher prices for more helpful sales people.

The critical factor missing from those formulations is dynamic pricing. In setting price, a store is not taking into account how price affects the set of loyal customers. That is, the price in period t affects $\Gamma_i^{j,h}(t+1)$. Recognition of this effect would induce stores to price below $\frac{c}{\beta}$ and how much below would presumably depend on a store's state variables. This would create price variation across stores. Suppose consumers rank stores based on net surplus. Taking into account optimal demand, net surplus is

$$\left(\frac{\beta}{p^{j,h}}\right)^{\frac{\beta}{1-\beta}} (1-\beta) \left[A - \lambda(\underline{w}, \underline{z}^{j,h}(t))\right]^{\frac{\gamma}{1-\beta}} \quad (\text{A.5})$$

so that price, and not just distance, matters. A second issue is that price competition would seem to intensify when stores in a market have more similar practices. If that was modelled and taken account of by stores then this could affect which ideas are adopted by stores and chains. A store would presumably adopt fewer practices of competing stores even when they would seem to raise the demand of their existing consumers. In addition, the impact of encompassing these factors would probably depend on whether price-setting is decentralized or not. All these issues await further analysis to when we are able to accommodate our model for strategic price-setting.

9.2 Pseudo Code

```
// CYBORG.CPP

// "config" is the index for different configurations of organizational forms

// "CONFIG" is the total number of distinct configurations of organizational forms

main( )
{
x = 0;
while (x < X) {


- Assign consumer types in all markets.
- Assign and fix initial default stores for all consumers.
- Initialize store practices  $init\_prac(i, j)$  in  $t = 0 \forall i \in \{1, 2, \dots, L\}, \forall j \in \{1, 2, \dots, S\}$
- Create innovation list  $I(i, j, t) \forall i \in \{1, 2, \dots, L\}, \forall j \in \{1, 2, \dots, S\}, \forall t \in \{1, 2, \dots, T\}$ .


config = 1;
while (config <= CONFIG) {


- Assign organizational forms (Centralization or Decentralization) to all chains on the basis of "config."


t = 0;
```

- Re-initialize store practices to $init_prac(i, j)$;
- Initialize store bins and checklists;
- Re-initialize default stores for all consumers and compute the corresponding default distance for each consumer;

$t = t + 1$;

while ($t < T$) {

 // Stage - 0

 Step 0.0: Set each customer's shopping store for t ;

 Step 0.1: Update store profits and chain profits on the basis of current shoppers;

 // Stage - 1: Internal Innovation

Step 1.0: Evaluate and adopt store innovations;

 Step 1.1: Revise chain profits;

 // Stage - 2: External Innovation

Step 2.0: Evaluate and adopt external innovations in the bins;

 Step 2.1: Revise chain profits;

 // Stage - 3

 Step 3.0: Update the checklists for the stores;

Step 3.1: Revise each consumer's default store;

$t++$;

 }

$config++$;

}

$x++$;

}

- Report output;

Return 0;

}

Step 1.0: Evaluate and adopt store innovations

For each store in each chain {

 Evaluate the profitability of $I(i, j, t)$ for store j of chain i .

 If the idea is profitable for store j of chain i , then do {

- Under Decentralization:

- Store j adopts the idea.
 - Store j 's profit is revised.
 - Intra-chain spillover: $I(i, j, t)$ enters the bins of all other stores of chain i for adoption consideration in $t + 1$.
 - Intra-market spillover: $I(i, j, t)$ enters with probability Q_S the bin of each of store i 's rival stores in the same market for adoption consideration in $t + 1$.
 - Inter-chain spillover: $I(i, j, t)$ enters with probability Q_H the bin of each store of the chains operating store i 's rival stores in the same market for adoption consideration in $t + 1$.
- Under Centralization:
 - If the chain profits improve as the result of mandating $I(i, j, t)$ on all stores of chain i , then do {
 - Intra-chain mandate: All stores of chain i adopt $I(i, j, t)$.
 - For each store of chain i {
 - * Intra-market spillover: $I(i, j, t)$ enters with probability Q_S the bin of each of store i 's rival stores in the same market for adoption consideration in $t + 1$.
 - * Inter-chain spillover: $I(i, j, t)$ enters with probability Q_H the bin of each store of the chains operating store i 's rival stores in the same market for adoption consideration in $t + 1$.

Step 2.0: Evaluate and adopt external innovations in the bins

For each store in each chain {

For each idea in the store's bin as of t (deposited into the bin in $t - 1$) {

Evaluate the profitability of the idea for store j of chain i .

If the idea is profitable for store j of chain i , then do {

- Under Decentralization:
 - * Store j adopts the idea.
 - * Store j 's profit is revised.
 - * Intra-chain spillover: The idea enters the bins of all other stores of chain i for adoption consideration in $t + 1$, if it is not in the stores' check lists.

- * Intra-market spillover: The idea enters with probability Q_S the bin of each of store i 's rival stores in the same market for adoption consideration in $t + 1$, if it is not in the store's check list.
- * Inter-chain spillover: The idea enters with probability Q_H the bin of each store of the chains operating store i 's rival stores in the same market for adoption consideration in $t + 1$, if it is not in the store's check list.

- Under Centralization:

If the chain profits improve as the result of mandating the idea on all stores of chain i , then do {

- * Intra-chain mandate: All stores of chain i adopt the idea.

For each store of chain i {

- * Intra-market spillover: The idea enters with probability Q_S the bin of each of store i 's rival stores in the same market for adoption consideration in $t + 1$, if it is not in the store's check list.

- * Inter-chain spillover: The idea enters with probability Q_H the bin of each store of the chains operating store i 's rival stores in the same market for adoption consideration in $t + 1$, if it is not in the store's check list.

}

}

}

}

}

Step 3.1: Revise each consumer's default store;

For each consumer in each market {

If the consumer did not experiment so that his/her shopping store is same as the default store, then revise the default distance to reflect the innovations made in t in his/her default store.

Else if the consumer experimented and found the experimental store superior to the default store, then the experimental store becomes his/her default store and the default distance is revised to reflect the distance to the new store.

Else (the consumer experimented and found the experimental store inferior to the default store), no revision is made in terms of default store and the default distance.

}

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Table 1: Landscape Ruggedness As a Function of E

Frequency Distribution with $N = 2$ (100 replications)

No. Local Optima	$E = 0$	$E = 1$	$E = 2$	$E = 4$	$E = 6$	$E = 10$	$E = 20$
1	0	4	31	79	90	96	100
2	0	18	53	21	10	4	0
3	100	78	16	0	0	0	0
No. Replications	100	100	100	100	100	100	100

Frequency Distribution with $N = 3$ (20 replications)

No. Local Optima	$E = 0$	$E = 1$	$E = 2$	$E = 4$	$E = 6$	$E = 8$
1	0	0	5	16	18	19
2	0	1	6	4	2	1
3	0	19	9	0	0	0
4	0	0	0	0	0	0
5	20	0	0	0	0	0
No. Replications	20	20	20	20	20	20

Table 2-A: *Ex Ante* Optimal Organizational Form ($L = 1$)

	α					
T	0	1	2	3	4	5
100	C	C	C	C	C	D
500	C	C	C	D	D	D
1000	C	C	D	D	D	D

Table 2-B: Differential Profits ($L = 1$)

	α					
T	0	1	2	3	4	5
100	3.3889E8 (89.6321)	3.3190E8 (80.3624)	2.9724E8 (45.5854)	2.3088E8 (22.8402)	1.2288E8 (9.48985)	-3.8631E7 (-2.16591)
500	7.4925E7 (38.6001)	7.2406E7 (23.3325)	3.3479E7 (7.15453)	-7.9559E7 (-10.3495)	-2.896E8 (-27.9455)	-6.1424E8 (-45.1307)
1000	3.8354E7 (30.4212)	2.8838E7 (12.4085)	-4.1038E7 (-11.1063)	-2.1354E8 (-36.0522)	-5.1658E8 (-61.6725)	-9.5641E8 (-87.4628)

Table 3 : Equilibrium Organizational Forms ($L = 2$): $(Q_H, Q_S) = (0, 0)$

$T = 500$						
α	0	2	4	6	8	10
Q=0.0	CC	CC	DD	DD	DD	DD
Q=0.01	CC	CC	CC	CC	DD	DD
Q=0.03	CC	CC	CC	CC	CC	DD
Q=0.05	CC	CC	CC	CC	CC	DD
Q=0.1	CC	CC	CC	CC	CD	DD
Q=0.2	CC	CC	CC	CC	DD	DD
Q=0.3	CC	CC	CC	DD	DD	DD

$T = 1000$						
α	0	2	4	6	8	10
Q=0.0	CC	DD	DD	DD	DD	DD
Q=0.01	CC	CC	CC	CC	DD	DD
Q=0.03	CC	CC	CC	CC	CD	DD
Q=0.05	CC	CC	CC	CC	DD	DD
Q=0.1	CC	CC	CC	CC	DD	DD
Q=0.2	CC	CC	CC	DD	DD	DD
Q=0.3	CC	CC	CC	DD	DD	DD

Table 4: *Ex Ante* Differential Profits over $T = 500$

$V_C(C) - V_D(C)$						
Q	$\alpha = 0$	$\alpha = 2$	$\alpha = 4$	$\alpha = 6$	$\alpha = 8$	$\alpha = 10$
0.0	7.52015E7 (36.8594)	2.60357E7 (5.18581)	-3.09131E8 (-29.359)	-1.07768E9 (-60.7265)	-2.31718E9 (-103.125)	-3.92036E9 (-139.000)
0.01	1.06743E9 (6.89302)	1.78965E9 (8.39199)	2.51608E9 (11.0429)	1.62516E9 (6.91144)	-2.17266E9 (-7.91324)	-7.81869E9 (-25.928)
0.03	1.17033E9 (6.24956)	1.5857E9 (6.44884)	2.48909E9 (9.23195)	2.88279E9 (10.3751)	5.64886E8 (1.98453)	-3.86957E9 (-11.932)
0.05	9.38039E8 (4.78435)	1.80381E9 (6.9658)	2.28123E9 (7.54865)	2.47305E9 (8.77318)	4.75627E8 (1.76083)	-3.62816E9 (-11.4427)
0.1	9.42832E8 (5.56449)	1.45446E9 (6.41167)	1.72033E9 (7.55651)	1.37621E9 (5.97726)	-2.98219E8 (-1.34684)	-3.84603E9 (-14.9869)
0.2	4.68891E8 (4.43655)	5.35055E8 (3.88564)	9.22512E8 (6.26429)	5.63764E8 (3.51788)	-1.69619E9 (-11.1953)	-5.22292E9 (-27.2971)
0.3	2.66788E8 (4.48528)	5.56102E8 (7.14646)	6.04815E8 (6.62926)	-3.82278E8 (-4.22914)	-3.01165E9 (-23.5571)	-6.77588E9 (-46.9648)
$V_C(D) - V_D(D)$						
Q	$\alpha = 0$	$\alpha = 2$	$\alpha = 4$	$\alpha = 6$	$\alpha = 8$	$\alpha = 10$
0.0	7.57337E7 (41.8714)	3.06836E7 (6.07732)	-2.98655E8 (-27.9538)	-1.08873E9 (-61.4661)	-2.31714E9 (-95.4077)	-3.91758E9 (-133.053)
0.01	9.79462E8 (6.94583)	2.08475E9 (10.4819)	2.40177E9 (12.0186)	1.58151E9 (6.7527)	-1.53914E9 (-5.8225)	-5.33135E9 (-18.5289)
0.03	1.24477E9 (6.89076)	1.75507E9 (6.9682)	2.59069E9 (9.88731)	2.89363E9 (10.4723)	1.14968E9 (3.92979)	-2.75533E9 (-9.32099)
0.05	1.24606E9 (5.85702)	1.63209E9 (7.68158)	2.1043E9 (8.21962)	2.37288E9 (8.69759)	8.45507E8 (2.89663)	-2.68556E9 (-9.39281)
0.1	8.2743E8 (5.0367)	1.17671E9 (5.72087)	1.71191E9 (7.40798)	1.37677E9 (6.02276)	6.0871E7 (0.280014)	-3.05974E9 (-12.1678)
0.2	4.34485E8 (4.30164)	7.77008E8 (6.38082)	8.78123E8 (6.44518)	6.78457E8 (4.46191)	-1.16506E9 (-7.76831)	-4.13316E9 (-24.0254)
0.3	3.31254E8 (5.79767)	4.94533E8 (7.23547)	5.66481E8 (6.8144)	-1.94289E8 (-2.10017)	-2.10955E9 (-20.2941)	-5.01034E9 (-39.3241)

Table 5: *Ex Ante* Differential Profits over $T = 1000$

$V_C(C) - V_D(C)$						
Q	$\alpha = 0$	$\alpha = 2$	$\alpha = 4$	$\alpha = 6$	$\alpha = 8$	$\alpha = 10$
0.0	3.86801E7 (30.3594)	-4.79358E7 (-11.6624)	-5.37581E8 (-58.1574)	-1.54308E9 (-104.072)	-3.04763E9 (-161.667)	-4.93689E9 (-216.553)
0.01	7.59508E8 (4.46317)	1.84795E9 (6.62641)	2.91274E9 (10.8023)	1.85892E9 (8.3212)	-2.43454E9 (-9.64863)	-8.90957E9 (-32.2979)
0.03	8.89979E8 (4.77617)	1.4695E9 (5.46213)	2.21282E9 (7.85628)	2.33693E9 (8.44592)	-4.28766E8 (-1.57153)	-5.65415E9 (-18.8542)
0.05	6.53274E8 (3.5233)	1.60168E9 (6.12869)	1.85471E9 (6.15633)	1.69471E9 (6.21503)	-8.3838E8 (-3.32623)	-5.63892E9 (-19.4821)
0.1	7.58645E8 (4.89702)	1.21979E9 (5.51895)	1.28206E9 (5.84005)	4.5732E8 (2.17456)	-1.74325E9 (-8.77645)	-5.954E9 (-25.1815)
0.2	3.05576E8 (3.2137)	3.70836E8 (2.95246)	4.90417E8 (3.62873)	-3.86248E8 (-2.82473)	-3.24946E9 (-23.5836)	-7.4013E9 (-41.8166)
0.3	1.75134E8 (3.20774)	3.80922E8 (5.33293)	1.47077E8 (1.94553)	-1.37609E9 (-17.5825)	-4.70428E9 (-41.1941)	-9.09193E9 (-71.6987)
$V_C(D) - V_D(D)$						
Q	$\alpha = 0$	$\alpha = 2$	$\alpha = 4$	$\alpha = 6$	$\alpha = 8$	$\alpha = 10$
0.0	3.80739E7 (29.1877)	-4.31583E7 (-10.4619)	-5.29325E8 (-58.2843)	-1.54552E9 (-105.059)	-3.03125E9 (-155.136)	-4.9202E9 (-209.612)
0.01	7.41514E8 (4.88798)	2.0675E9 (8.57812)	2.71949E9 (11.7756)	1.9287E9 (7.9811)	-1.68429E9 (-6.80693)	-6.32018E9 (-24.0562)
0.03	8.81263E8 (4.9599)	1.53747E9 (5.82456)	2.33148E9 (8.61367)	2.50437E9 (8.82873)	2.38493E8 (0.819825)	-4.2915E9 (-15.5529)
0.05	9.36998E8 (4.68683)	1.42214E9 (6.6102)	1.75793E9 (6.775)	1.6651E9 (6.15224)	-2.8402E8 (-1.03252)	-4.4934E9 (-17.3294)
0.1	5.75856E8 (3.92599)	9.86166E8 (4.8511)	1.26019E9 (5.73791)	4.78007E8 (2.25374)	-1.32281E9 (-6.63777)	-5.05077E9 (-23.8735)
0.2	2.61428E8 (2.97274)	4.90909E8 (4.41226)	4.20498E8 (3.36207)	-2.7053E8 (-2.04403)	-2.61984E9 (-20.501)	-6.07752E9 (-44.6793)
0.3	2.08042E8 (4.1607)	2.98216E8 (4.96984)	7.99309E7 (1.14179)	-1.11716E9 (-15.9781)	-3.55309E9 (-44.0181)	-6.89209E9 (-75.3652)

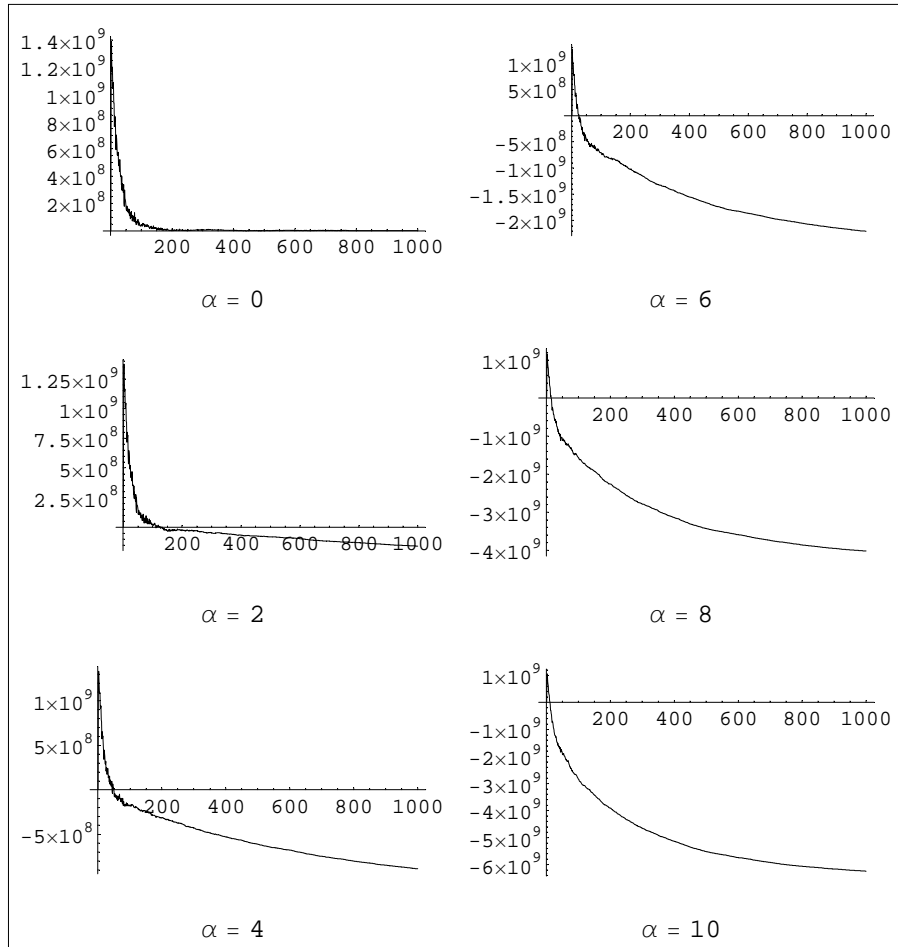


Figure 1 : $V_c(C) - V_D(C)$ over $T = 1000$ for $Q = 0$ ($L = 2$)

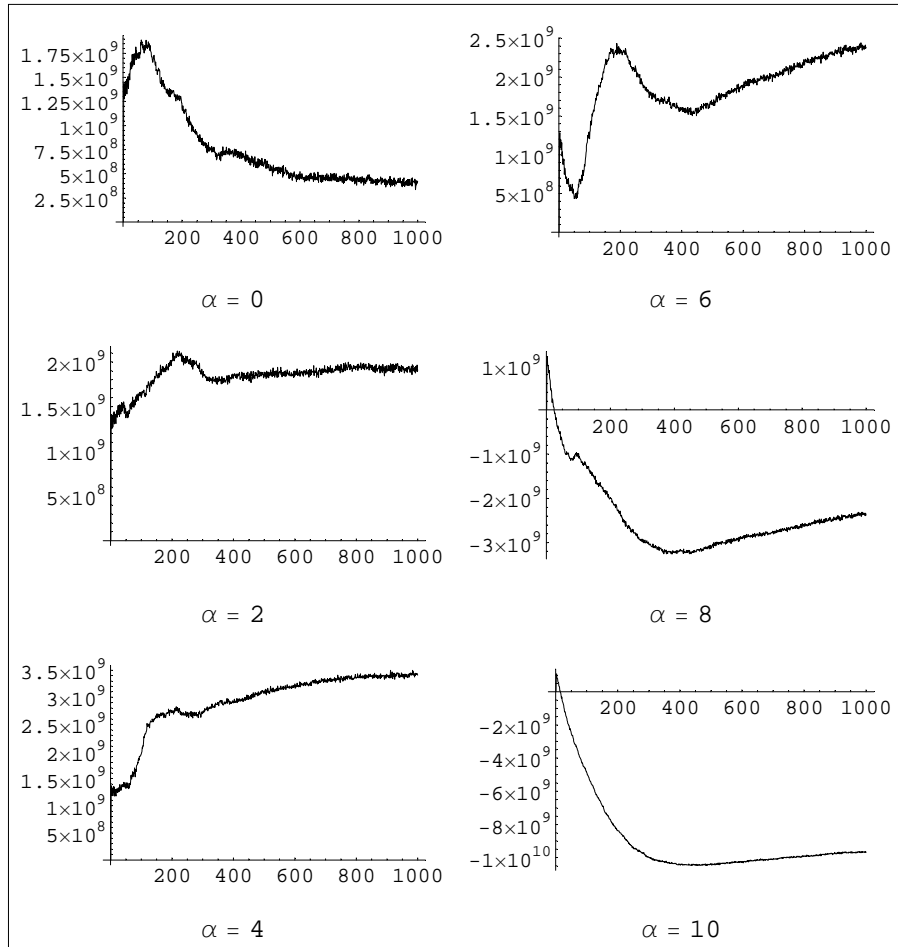


Figure 2 : $V_c(C) - V_D(C)$ over $T = 1000$ for $Q = 0.01$ ($L = 2$)

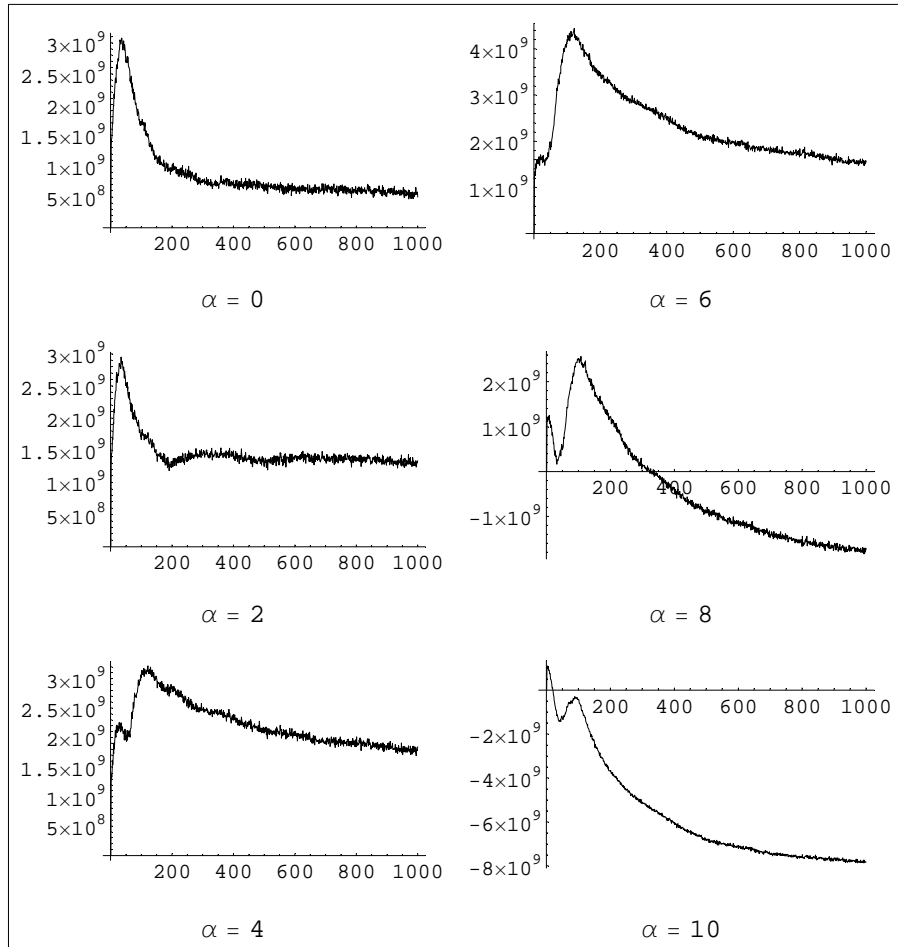


Figure 3 : $V_c(C) - V_D(C)$ over $T = 1000$ for $Q = 0.03$ ($L = 2$)

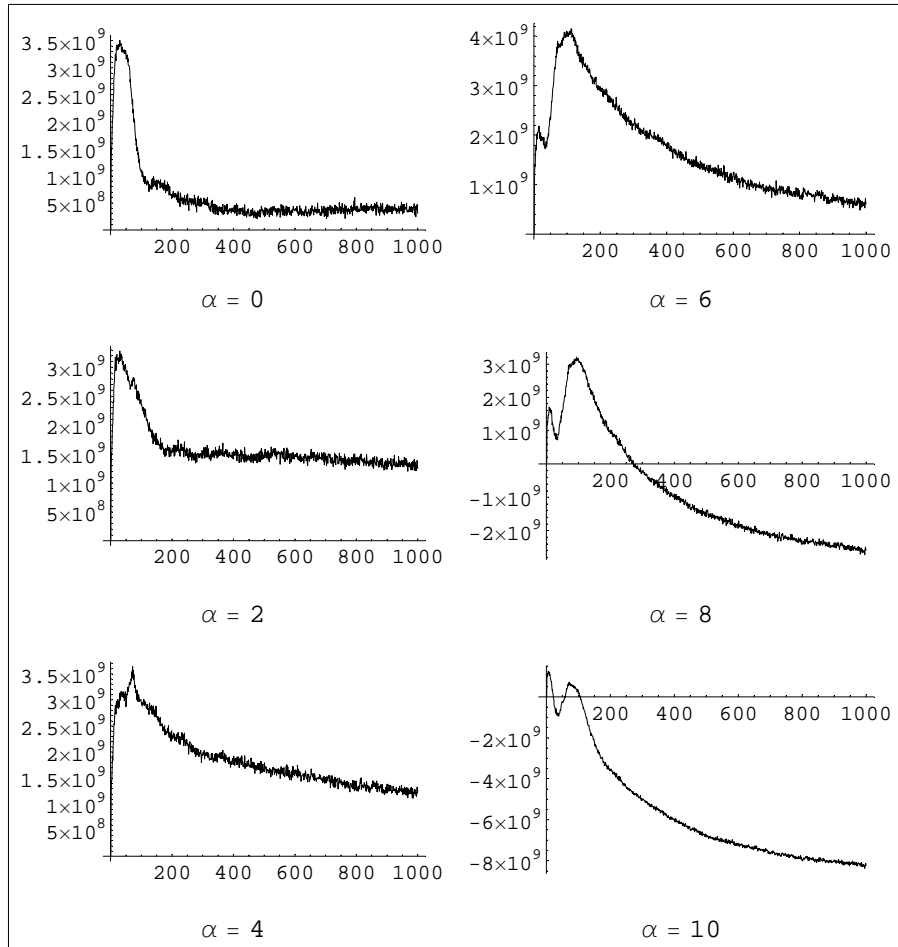


Figure 4 : $V_c(C) - V_D(C)$ over $T = 1000$ for $Q = 0.05$

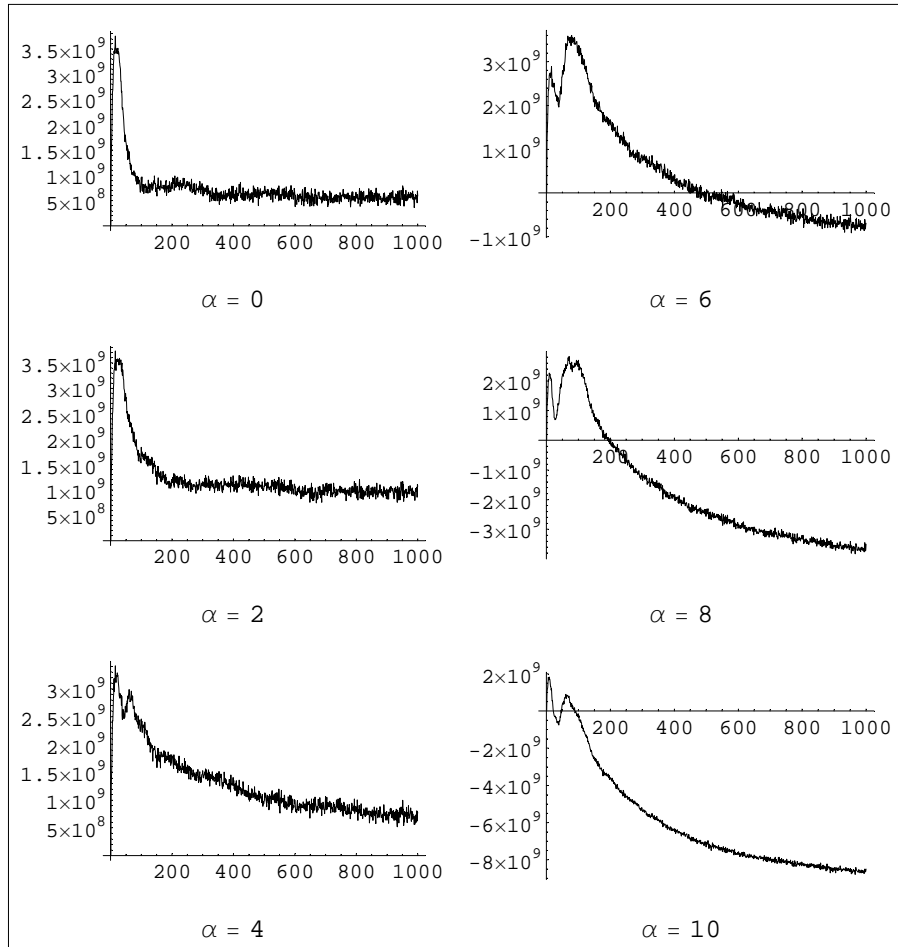


Figure 5 : $V_c(C) - V_D(C)$ over $T = 1000$ for $Q = 0.1$

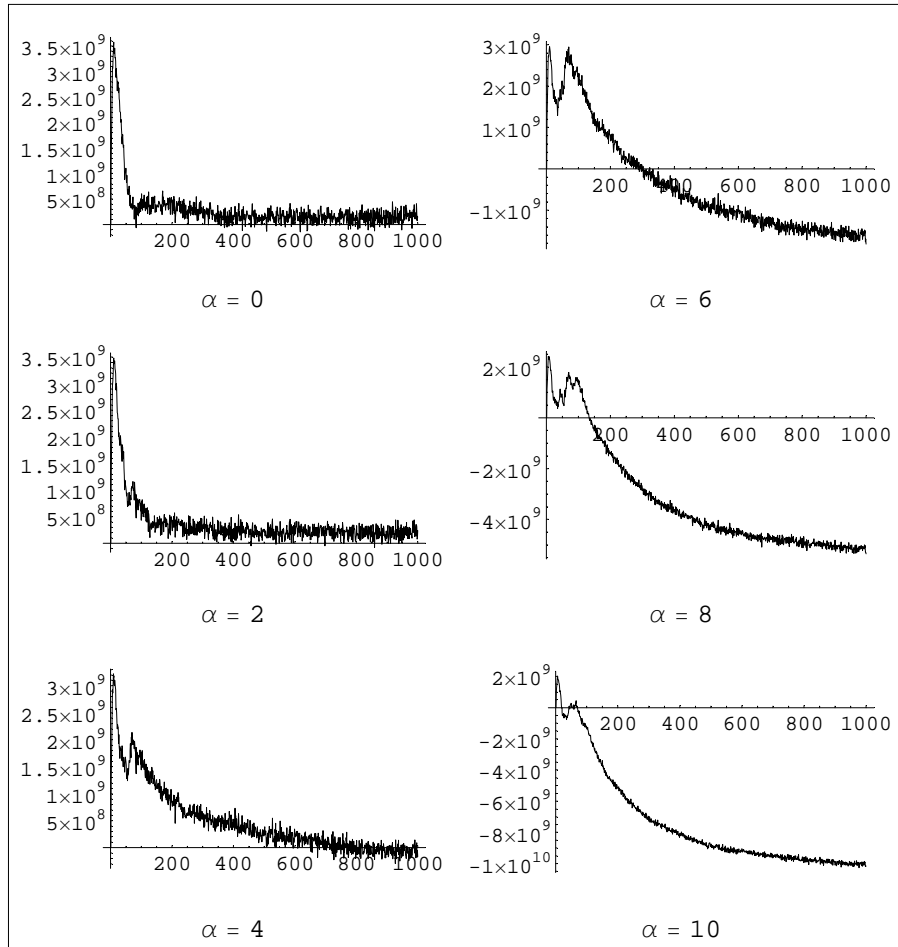


Figure 6 : $V_c(C) - V_D(C)$ over $T = 1000$ for $Q = 0.2$

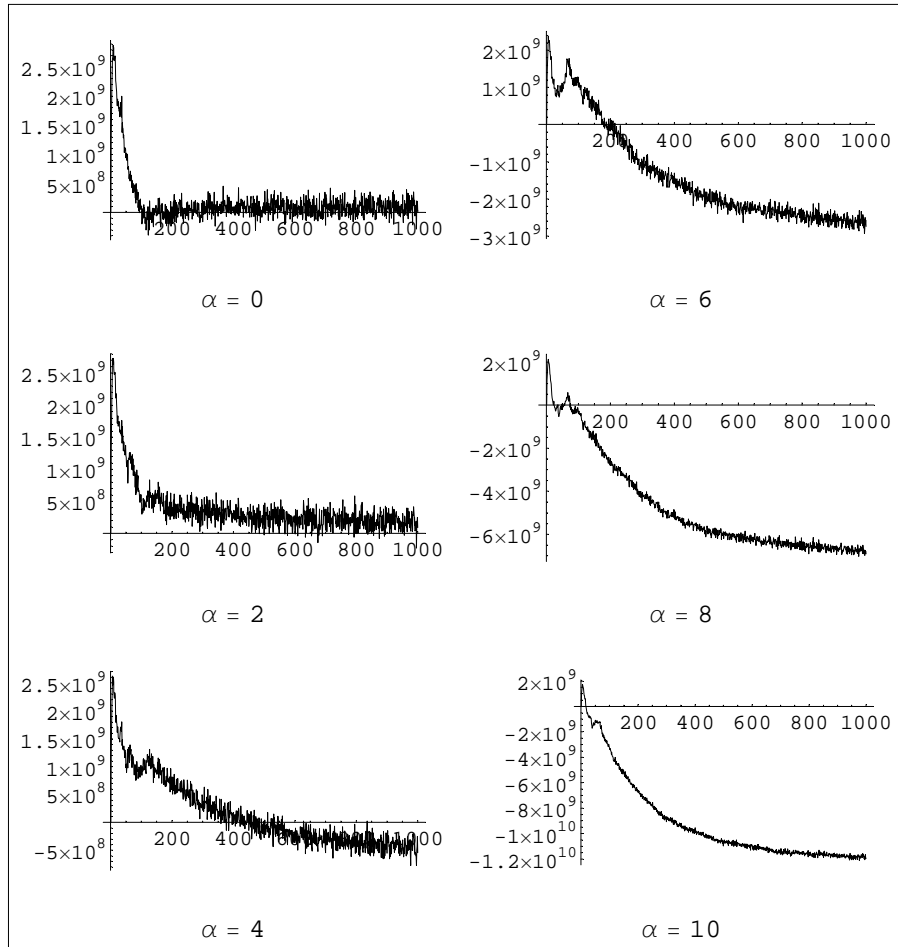


Figure 7 : $V_c(C) - V_D(C)$ over $T = 1000$ for $Q = 0.3$ ($L = 2$)