Centralization vs. Decentralization in a Multi-Unit Organization: A Computational Model of a Retail Chain as a Multi-Agent Adaptive System

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A computational model of a retail chain is developed in which store managers continually search for better practices. Search takes place over a rugged landscape defined over the space of store practices. The main objective of this research is to determine how the amount of discretion given to store managers as to how they run their stores influences the rate of innovation at the store level. We find that greater decentralization enhances firm performance when stores' markets are sufficiently different, the horizon is sufficiently long, and markets are sufficiently stable.
(*Organizational Structure*; *Decentralization*; *Innovation*; *Retail Chain*)

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. 36–37)

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 this research 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

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practices achieved through innovations and organizational learning.

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 a hill-climbing rule. 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. To briefly summarize our findings, 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 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 et al. 1996). This linkage has also been applied to understanding strategy implementation in diversified multiunit 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 multimarket organizations (Anand and Mendelson 1997, Nault 1998). Our work contributes to this literature by explicitly modeling 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 intraorganizational 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.''[1] 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 modeled 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 modeling organizational restructuring as adaptive search for better organizational design given a group of learning agents.[2] Our work is an extension of this body of literature, in 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 Model of a Retail Chain

A retail chain is composed of a corporate headquarters (HQ) and $M \geq 2$ stores. Each store is in a distinct market and has a set of N practices such that store i's operation in any given period is fully described by a vector, $z^i \equiv (z_1^i, z_2^i, \ldots, z_N^i)$, where z_j^i is store i's practice for the jth dimension of its operation and $z_j^i \in \{1, \ldots, R\}$ for all $i \in \{1, \ldots, M\}$, and $j \in \{1, \ldots, N\}$. Thus, there are R feasible practices for each dimension and, at any point in time, a store is represented by a point in $\{1, \ldots, R\}^N$.[3]

2.1. Representation of a Store's Market

All consumers in market i shop at store i, $i \in \{1, 2, \ldots, M\}$. Each consumer has an ideal set of store practices which is represented as an element of $\{(1, \ldots, 1), \ldots, (R, \ldots, R)\}$. Assuming consumer types are in this restricted set reflects complementarities in their preferences that could be due, for example, to different income levels. People with higher income may incur greater search costs, 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 the time spent buying) as might be achieved by having sales personnel work on commission.

The consumer with an ideal set of store practices of $(w, \ldots, w)$ is denoted a type w consumer.

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

[2] The 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.

[3] These practices represent all of those elements that influence the appeal of this store to consumers. It can include the types of products carried (Target has more fashion-oriented clothing than Wal-Mart; Discount Store News, (4/1/96)), the number of products carried (Kohl's product line is narrow but deep; Discount Store News, 4/1/96), and compensation schemes (Sears reduced performance-based incentives for store employees during the 1970s and restored them by 1997; Harvard Business School Case Study, N9-898-007).

The utility to a type w consumer from buying x units at a price of p from store i is specified to be: $u(x; p, w, z^i) = \left[\bar{L} - \sqrt{\sum_{j=1}^{N}(z_j^i - w)^2}\right]^{\gamma} \cdot x^{\beta} - p \cdot x$; where $\beta \in (0, 1)$, $\gamma \geq 1$, and $\bar{L}$ is chosen so that $\left[\bar{L} - \sqrt{\sum_{j=1}^{N}(z_j^i - w)^2}\right] > 1$ for all $(w, (z_1^i, \ldots, z_N^i))$.[4] Letting $d \equiv \sqrt{\sum_{j=1}^{N}(z_j^i - w)^2}$, it can be shown that $\bar{L} - d > 1$ is sufficient for $\partial^2 u/\partial d \partial \gamma < 0$. Hence, an increase in γ reflects a consumer's higher marginal dissatisfaction from actual store practices deviating from most preferred practices. Given the above utility function, a type w consumer's optimal quantity decision is then: $x^*(p, w, z^i) = (\beta/p)^{1/(1-\beta)} \left[\bar{L} - \sqrt{\sum_{j=1}^{N}(z_j^i - w)^2}\right]^{\gamma/(1-\beta)}$.

In market i, consumers are distributed according to a cdf $F_i : \{1, \ldots, R\} \to [0, 1]$. Markets are homogeneous when $F_1 = F_2 = \cdots = F_M$. The computational model assumes the following specification regarding the distribution of consumer types. In a given market, 1,000 consumers are distributed over the type space, $\{1, 2, \ldots, 100\}$, according to a discrete density function which has positive density over 50 neighboring types, where the positive densities approximate a triangular density function.

2.2. Representation of a Store and a Chain

In any period, a store's type is represented by its current practices, which is an element of $\{1, \ldots, R\}^N$. Given practices $z^i \equiv (z_1^i, \ldots, z_N^i)$, store i's current profit function is:

$$(p - c) \int x^*(p, w, z^i)\, dF_i(w)$$
$$= (p - c) \left(\frac{\beta}{p}\right)^{\frac{1}{1-\beta}}$$
$$\times \int \left[\bar{L} - \sqrt{\sum_{j=1}^{N}(z_j^i - w)^2}\right]^{\frac{\gamma}{1-\beta}} dF_i(w). \quad (2.1)$$

A store is assumed to optimally set its price. Using the profit function, the optimal price is: $p^* = \frac{c}{\beta}$. The resulting demand from type w consumers is then: $X_i^*(w, z^i) = (\beta^2/c)^{1/(1-\beta)} \left[\bar{L} - \sqrt{\sum_{j=1}^{N}(z_j^i - w)^2}\right]^{\gamma/(1-\beta)}$. Store i's current profit is:

$$\left[\left(\frac{c}{\beta}\right) - c\right] \int X_i^*(w, z^i) dF_i(w)$$
$$= \left[\left(\frac{c}{\beta}\right) - c\right] \left(\frac{\beta^2}{c}\right)^{\frac{1}{1-\beta}}$$
$$\times \int \left[\bar{L} - \sqrt{\sum_{j=1}^{N}(z_j^i - w)^2}\right]^{\frac{\gamma}{1-\beta}} dF_i(w). \quad (2.2)$$

What is important for our analysis is that a store's profit is decreasing in the distance between its practices and those desired by its customers. Finally, the profit for the chain is a simple sum of stores' profits.

3. Structure of the Landscape

A store's landscape can be thoroughly characterized by evaluating the Profit Function (2.2) for all practices. Due to the computational constraint, however, we limit our evaluation in this section to only two-dimensional store practice space ($N = 2$). Given a triangular density with the peak consumer type at 50 and the parameter values of $R = 100$, $M = 2$, $c = 10$, and $\beta = 0.5$, let $z^*(\gamma) \equiv (z_1^*(\gamma), z_2^*(\gamma))$ denote the local optimum of a landscape as a function of γ, where $z_i^*(\gamma)$ is the store's practice in the ith dimension at the local optimum. Table 1 provides the local optima for $\gamma \in \{1, 3, 5, 7\}$ with (50, 50) being the global optimum. Note that complementarities in consumers' preferences lead to $z_1^*(\gamma) = z_2^*(\gamma)$. Also, an increase in γ raises the number of local optima for a store. These properties also apply to the chain's landscape.

4. Modeling of Innovation

While the results reported in this paper only have stores generating new ideas, let us describe the more general model that involves HQ also generating ideas. In each period, HQ and stores generate ideas. A typical idea has the following properties. An idea spans K dimensions of the store, where $K \in \{1, \ldots, P\}$ and $P \in \{1, \ldots, N\}$ is a parameter. The K

[4] While consumers are assumed to value all dimensions the same, we believe results are robust to this assumption.

Table 1 Local Optima for a Store with $N = 2$

Set of Local Optima for a Store

γ					$z^*(\gamma)$				
1				(49, 49)	(50, 50)	(51, 51)			
3			(48, 48)	(49, 49)	(50, 50)	(51, 51)	(52, 52)		
5		(47, 47)	(48, 48)	(49, 49)	(50, 50)	(51, 51)	(52, 52)	(53, 53)	
7	(46, 46)	(47, 47)	(48, 48)	(49, 49)	(50, 50)	(51, 51)	(52, 52)	(53, 53)	(54, 54)

dimensions are randomly selected from $\{1, \ldots, N\}$ without replacement. For each of those K dimensions, there is a random draw from $\{1, \ldots, R\}$. The degree of sophistication (or equivalently, the degree of complexity) in a given idea is measured by P, the maximum number of dimensions that an idea can encompass. For the remainder of the analysis we will fix $P = 1$ so that all ideas are one-dimensional.[5]

To make the process of idea generation a bit more concrete, let us consider an example with $N = 5$, $R = 100$, and $P = 1$. Suppose the current store practice is (25, 56, 71, 33, 89) and an innovation involves changing the practice in the third dimension from 71 to 95. The new store practice accommodating this change would be (25, 56, 95, 33, 89). If this idea is implemented by another store currently employing (11, 29, 54, 49, 65), its new practice is (11, 29, 95, 49, 65).

In each period, the ideas generated by HQ and the stores are considered for adoption sequentially with the order being randomly determined. Let I_h^t and I_k^t denote the dimension encompassed by the period t idea of HQ and store k, respectively. Since ideas are one-dimensional, then $I_h^t, I_k^t \in \{1, \ldots, N\}$. $\Omega \subseteq \{1, \ldots, N\}$ will represent the set of dimensions controlled by HQ. An organizational form is defined by Ω. The adoption rules are as follow.

- Consider an idea generated by HQ. If $I_h^t \in \Omega$, then HQ has authority over the idea. If its adoption by all stores would raise chain profit, then it is mandated. Otherwise, the idea is discarded. On the other hand, if $I_h^t \notin \Omega$, then HQ does not have authority over the idea. If at least y stores, where $y \in \{1, \ldots, M\}$, would benefit from the adoption of this idea then HQ passes the idea to all stores for their independent evaluation and adoption. Otherwise, the idea is discarded. The recommended idea is considered independently by each store's manager and adopted if it raises the store's profit. Otherwise, it is discarded by the store.
- Consider an idea generated by a store, k. If $I_k^t \in \{1, \ldots, N\} - \Omega$, then the manager of store k has authority over the idea. He immediately adopts the idea if and only if it raises his store's profit. Otherwise, he discards the idea. If the idea is adopted by the store, it is then observed by HQ. HQ passes it to all stores for potential adoption if and only if at least y stores would benefit from its adoption. Otherwise, it is discarded at the HQ level. The recommended idea is considered independently by each store's manager and adopted if it raises the store's profit. Otherwise, it is discarded by the store. Conversely, if $I_k^t \notin \{1, \ldots, N\} - \Omega$, then the manager of store k does not have authority over the idea. He sends the idea up to HQ if its adoption would raise store k's profit. Otherwise, it is discarded at the store-level. The idea that is sent up to HQ is mandated if it raises the chain's profit. Otherwise, it is discarded at the HQ-level.
- "y" is chosen to maximize long-run chain profit.

The last part requires some explanation. The task is to specify a reasonable rule for HQ to use in deciding whether to pass an idea to all stores. Since no particular rule obviously dominates, we consider a class of rules, defined by $y \in \{1, \ldots, M\}$, and choose that rule that maximizes chain performance. Notice that $y = 1$ is equivalent to passing every idea to the stores so that HQ does not actively screen ideas. $y = M$ corresponds

[5] Additional simulations for $P \in \{3, 5, 10\}$ show that all of our qualitative results are robust.

to passing an idea along only if it would be adopted by all stores so that uniform practices in the affected dimensions would prevail.[6]

Underlying the adoption process is the following information flow. For brevity, it is only decribed for when ideas are generated by store managers. In each period, a store manager thinks up new ideas and identifies those that would improve store profit. If he has the authority, those ideas are adopted. A representative from HQ (typically, a district manager) then arrives at the store. The district manager observes any newly adopted practices and the store manager informs him of any new ideas (to the store manager's liking) that have not been implemented. This information is communicated to the corporate staff, which identifies the ideas they like and then either informs stores of these ideas or instructs them to adopt them.[7]

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 the model, we implicitly assume it is done instantly and costlessly.[8] 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 his 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. Therefore, it cannot perform the same fine-tuning that store managers do.

5. Stable Markets and Convergence to Local Optima

5.1. Simulation Design[9]

Two extreme organizational forms are considered: full decentralization (store managers control all dimensions) and full centralization (HQ controls all dimensions).[10] For each set of parameter values, the computational experiment consists of 500 replications of the innovation procedure. Each replication involves a randomly drawn vector of initial store practices (which are assumed to be identical for the stores) and a sequence of TM new practices, one for each of the M stores in each of T periods. We let $T \in \{500, 1{,}000, 1{,}500\}$. Two classes of output data were collected for each set of parameter values. First, the ex ante optimal organizational form based on average chain profit over the horizon averaged over the 500 replications. Second, the frequency with which an organizational form is the ex post optimum (out of the 500 replications) in terms of average chain profit over the horizon.

[6] A more general approach would be to define an organizational form by the pair (Ω, y) and contrast the performance of all possible pairs. Presenting so much information would be overwhelming so instead we just compare $(\Omega, y^*(\Omega))$ where $y^*(\Omega) \in \arg\max V(\Omega, y)$ and $V(\cdot)$ is the chain's average profit. Let us also note that all qualitative results would persist if we instead simply set $y = 1$ for all organizational forms.

[7] Note that the internal diffusion of ideas is facilitated solely by HQ. It would be interesting to consider direct interstore learning in future work. See Darr et al. (1995) for a discussion of the impact that such direct learning has on organizational performance within the context of franchised stores.

[8] With large changes in store practices, in practice a chain will often if not always institute it in a few stores as a form of experimentation. If the experiment is successful then new practice will be adopted chainwide. While experimentation is then a relevant feature of this process, we chose not to overload the model with too many features at once.

[9] The simulation programs were written in ANSI standard C and compiled and run on VAX and ALPHA systems. The source code is available upon request from Myong-Hun Chang.

[10] Initial runs considered all possible organizational forms which means all values of $|\Omega|$ from $\{0, 1, \ldots, N\}$. However, we found that the optimal structure was almost always either full centralization, $|\Omega| = N$, or full decentralization, $|\Omega| = 0$. To save on computational time, we focused our attention on those two structures.

It is assumed that the M markets can be classified into two separate types on the basis of consumer distributions; specifically, $F_i(w) = F_I(w)$ for $i = 1, \ldots, M/2$ and $F_i(w) = F_{II}(w)$ for $i = M/2 + 1, \ldots, M$. In any given market of Type I (II), 1,000 consumers are distributed over the type space, $\{1, 2, \ldots, 100\}$, according to a triangular density over 50 neighboring types. Letting $\bar{w}_I$ and $\bar{w}_{II}$ denote the peak (dominant) consumer types in markets of Types I and II, respectively, it is assumed that $\bar{w}_I = 50 - \alpha$ and $\bar{w}_{II} = 50 + \alpha$, where α is the degree of intermarket heterogeneity. Results are presented only for $M = 2$, although they have been found to be qualitatively robust to when $M = 4$ and $M = 6$.

For the simulations, the following parameter values were assumed: $\beta = 0.5$, $c = 10$ for $\gamma \in \{1, 3, 5\}$ and $c = 10{,}000$ for $\gamma = 7$,[11] $R = 100$, $N = 10$, $K = P = 1$, $\Omega \in \{0, 10\}$, $M = 2$, $\alpha \in \{0, 1, 2, 3, 4, 5\}$, $\gamma \in \{1, 3, 5, 7\}$, and $S = 500$ (# of replications). We further assume that HQ generates no ideas, while each store manager generates one idea per period. All stores are endowed with an identical set of practices that is randomly selected from $\{1, \ldots, 100\}^{10}$.

5.2. Results

The numerical output is presented in Tables 2 and 3. Table 2 reports the organizational structure that generated higher average chain profit over the first T periods (with that average profit being averaged over the 500 replications). Table 3 reports the frequency, out of the 500 replications, with which a given organizational structure yielded higher average chain profit over the first T periods.

PROPERTY 1. Centralization is more likely to outperform decentralization when markets are sufficiently similar (α is low), while decentralization is more likely to outperform centralization when markets are sufficiently different (α is high).

Examining Table 2, decentralization outperforms centralization is terms of average performance (averaged over the 500 replications) when $\alpha > 2$. Centralization outperforms when $\alpha = 0$, $\alpha = 1$ (and $\gamma = 3, 5, 7$), and $\alpha = 2$ ($\gamma = 5$, 7 and $T = 500$).[12] Turning to Table 3 and considering, for example, $(\gamma, T) = (5, 500)$, we find that average profit (over the horizon) for centralization exceeded that for decentralization in 268 of the 500 runs when $\alpha = 1$ (compared to 225 runs in which decentralization outperformed centralization), 222 runs when $\alpha = 2$ (compare to 278), and 152 runs when $\alpha = 3$ (compared to 348).

Since centralization imposes uniformity of practices, it is not surprising that decentralization outperforms when stores' markets are sufficiently different. In that situation, it is preferable to allow each store manager to tailor practices to his own unique market. Requiring common practices as occurs under centralization would involve, for at least one market, having practices that are quite inadequate for pleasing the market's consumers.

What is more intriguing is that centralization is preferred when markets are not too different. The benefits of decentralization are clear as it allows each store to tailor its practices to its market. What we believe to be the detrimental aspect is that as stores come to target different consumers, the extent to which they learn from each other's practices diminishes. For example, if Store 1 comes to target Consumer 45 (presumably because the peak of the consumer distribution in Store 1's market is close to 45) and Store 2 comes to target Consumer 53, then a practice implemented by Store 1—which might make some dimension have a value of, say, 46—is unlikely to raise store profit if adopted by Store 2. In contrast, if both stores target Consumer 49, then each store can learn from one another and this can lead to higher chain profit even if neither store is achieving a global optimum for its market. In short, there is a significant short-run advantage to the uniformity induced under centralization in that it promotes spillover of ideas across stores.

In order to substantiate this conjectured explanation of Property 1, let us begin by examining a single run. For a chain with two stores, there are two ideas to be evaluated in any period, so that over a horizon

[11] c was raised to 10,000 for $\gamma = 7$ so as to deflate the magnitude of profits. It has no impact on our comparison of organizational forms.

[12] The optimal value of y under decentralization tended to be 1 so that it is optimal to couple a decentralized structure with indiscriminate transfer of ideas by HQ.

Table 2 **Ex Ante Optimum (Static Markets)**

	$P=1$																	
	$T=500$						$T=1{,}000$						$T=1{,}500$					
	α						α						α					
	0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5
$\gamma=1$	C	D	D	D	D	D	C	D	D	D	D	D	C	D	D	D	D	D
$\gamma=3$	C	C	D	D	D	D	C	C	D	D	D	D	C	C	D	D	D	D
$\gamma=5$	C	C	C	D	D	D	C	C	D	D	D	D	C	C	D	D	D	D
$\gamma=7$	C	C	C	D	D	D	C	C	D	D	D	D	C	C	D	D	D	D

Table 3 **Frequency of Ex Post Optimality**

		$P=1$																	
		$T=500$						$T=1{,}000$						$T=1{,}500$					
		α						α						α					
		0	1	2	3	4	5	0	1	2	3	4	5	0	1	2	3	4	5
	D	15	310	417	481	498	500	14	323	474	500	500	500	14	349	493	500	500	500
$\gamma=1$	C	33	189	83	19	2	0	35	177	26	0	0	0	35	151	7	0	0	0
	N	452	1	0	0	0	0	451	0	0	0	0	0	451	0	0	0	0	0
	D	27	252	314	421	474	496	25	258	393	485	499	500	23	265	432	495	500	500
$\gamma=3$	C	59	245	186	79	26	4	61	242	107	15	1	0	63	235	68	5	0	0
	N	414	3	0	0	0	0	414	0	0	0	0	0	414	0	0	0	0	0
	D	26	225	278	348	407	472	28	208	322	438	487	499	27	206	361	473	499	500
$\gamma=5$	C	64	268	222	152	93	28	62	287	178	62	13	1	63	291	139	27	1	0
	N	410	7	0	0	0	0	410	5	0	0	0	0	410	3	0	0	0	0
	D	25	221	243	299	366	417	24	198	271	379	451	485	24	206	283	425	485	495
$\gamma=7$	C	69	253	256	201	134	83	71	283	229	121	49	15	71	278	217	75	15	5
	N	406	26	1	0	0	0	405	19	0	0	0	0	405	16	0	0	0	0

500 replications
D: HQ control = 0 preferred.
C: HQ control = 10 preferred.
N: Indifference.

of 1,500 periods there is a sequence of 3,000 ideas. To each idea we assign a number from {0, 1, 2} which is equal to the number of stores that would benefit from that idea (that is, its profit would rise) given the store practices for that period. What we need to show to validate our conjecture is that there is a greater number of ideas benefiting both stores under centralization than under decentralization. For $\alpha=1$, Figure 1 shows the resulting series under decentralization while Figure 2 shows it under centralization. First note that the pattern is roughly the same during the first 300 periods or so in that many ideas are beneficial to both stores under either structure. Thereafter the patterns diverge as, under decentralization, the frequency of ideas that would benefit both stores decreases dramatically. Most of the ideas generated from then on tend to benefit only one store. In contrast, the presence of mutually beneficial ideas persists under centralization so that what one store discovers and adopts is often desirable to the other store.

Figure 1 Decentralization

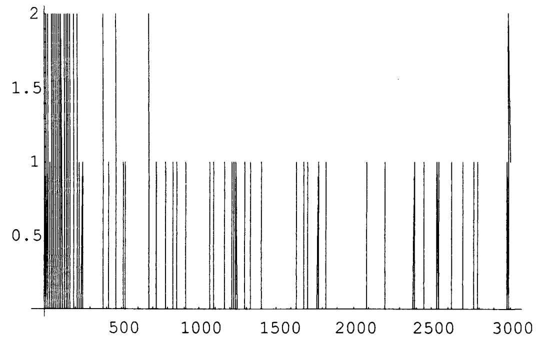
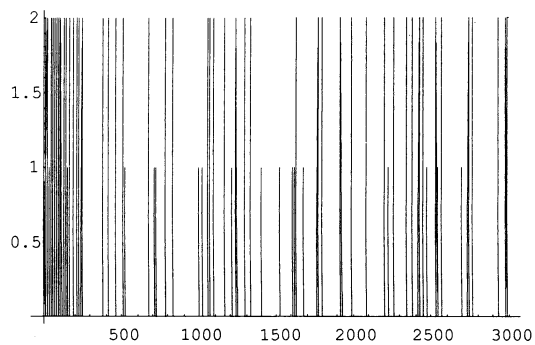
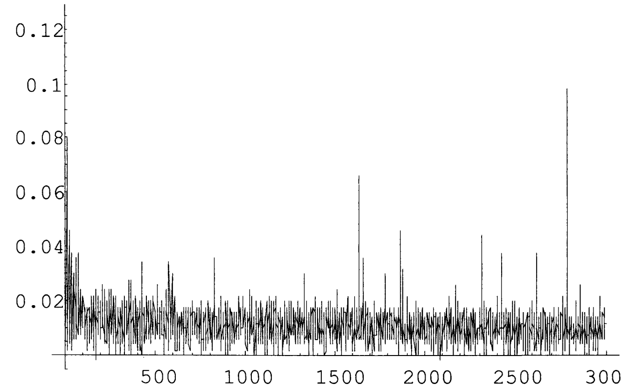


Figure 2 Centralization



The above evidence was for a single simulation run. We next performed a large number of runs and constructed a measure of the likelihood that an idea in a given period benefits both stores. Five hundred replications of the previous simulation were carried out, each time using a fresh set of initial practices and sequence of 3,000 ideas. For each replication, the number of stores benefited by an idea was calculated for each idea. Upon completing the 500 runs, we computed for each organizational structure and for each element of the 3,000 length sequence, the frequency of the cases that benefited both stores as a fraction of the 500 runs. Figure 3 captures the differential proportion under centralization and decentralization for $(\alpha, \gamma) = (1, 3)$; that is, the proportion of runs in which a given idea benefited both stores under centralization minus the same measure under decentralization. It shows that a centralized organization has a greater likelihood of generating ideas that benefit both stores.[13, 14]

Figure 3 Differential Likelihood of a Given Idea Benefiting Both Stores Under Centralization and Decentralization $[\alpha = 1, \gamma = 3]$



PROPERTY 2. Centralization is more likely to outperform over short horizons ($T = 500$), while decentralization is more likely to outperform over long horizons ($T = 1{,}500$).

An important factor in this result is that the global optimum under decentralization has higher chain profit than the global optimum under centralization. A decentralized structure allows for the possibility that each store achieves its global optimum by exactly tailoring its practices to what is desired by its consumers. Centralization rules out that possibility by virtue of mandating common practices. As achieving a global optimum is more likely with a longer horizon,

[13] Additional simulations confirmed these results for $(\alpha, \gamma) \in \{(1, 1), (3, 1), (3, 3)\}$.

[14] Using the logic of simulated annealing, David Easley and Bentley MacLeod make the very interesting conjecture that centralization is outperforming because it is better at getting stores off of inferior local optima. While that is possible, it cannot be all that is going on for the following reason. When $\alpha = 0$, it can be proven that centralization is no better than decentralization in getting stores off of local optima, yet we find that centralization outperforms. Furthermore, it is not clear that this explanation would predict a higher rate of interstore learning.

decentralization tends to perform relatively better as the horizon increases.[15]

Property 3. Centralization is more likely to outperform when consumers are sufficiently sensitive to store practices (γ is high), while decentralization is more likely to outperform when consumers are sufficiently insensitive to store practices (γ is low).

Recalling our discussion of the structure of a store's landscape, Property 3 implies that the relative effectiveness of centralization rises with the ruggedness of the landscapes faced by the stores and the chain. To understand this result, compare $\gamma = 1$ and $\gamma = 3$ when $\alpha = 2$. The set of local optima is shown in Table 4. Consider $(\alpha, \gamma) = (2, 1)$. If Store 1 receives an idea converting some dimension to, say, 48, this idea is unlikely to generate beneficial interstore spillovers under either organizational form. While it is apt to be valuable to Store 1 (as it has a local optimum at 48), an idea with value 48 is neither part of a local optimum for Store 2—so that under decentralization it would probably not be adopted by Store 2—nor part of a local optimum for the chain—so that under centralization, HQ would probably not mandate the idea. Now consider that same idea when $\gamma = 3$. Under decentralization, it probably will not result in interstore learning as 48 still fails to be part of a local optimum for Store 2. However, it is now part of a local optimum for the chain so that the idea, when passed by Store 1 to HQ, is likely to be mandated under centralization. More generally, as γ increases, the set of local optima expands so that there is more overlap between the local optima of stores and between the local optima of the chain and a store. However, it seems that the overlap between the chain and stores expands faster. In the example above, the set of overlap between the chain and Store 1 (2) expands from {49} to {48, 49, 50} ({50, 51, 52}) while the set of overlap between the optima of the stores goes from the empty set to {50}. Hence, it becomes more likely that a store will pass an idea up to HQ that HQ finds to enhance chain profit. What this means is that the opportunity for interstore spillovers is expanding at a faster rate under centralization relative to decentralization, as γ is increased. While the increased ruggedness of stores' landscapes enhances interstore learning under decentralization, the opportunities accelerate faster under centralization.[16]

Table 4 Local Optima for Stores and Chain

	Set of Local Optima	
	$(\alpha, \gamma) = (2, 1)$	$(\alpha, \gamma) = (2, 3)$
Store 1	{47, 48, 49}	{46, 47, 48, 49, 50}
Store 2	{51, 52, 53}	{50, 51, 52, 53, 54}
Chain	{49, 50, 51}	{48, 49, 50, 51, 52}

The basic force underlying the results of this section is the following trade-off associated with a more decentralized structure. Moving authority down the hierarchy allows store managers to modify their operational routines over time so that each store's operation is reasonably well adapted to its local market environment. The downside to this uncoordinated process of improvement is that it may lead to an eventual divergence in practices across stores. As stores migrate to different parts of the landscape, a new practice uncovered and adopted at one store will be incompatible with the current practices of other stores in the chain. In essence, stores gradually come to target distinct consumers, and this limits the extent of interstore learning. This has the effect of slowing down the rate of innovation as stores end up searching independently. The upside is that the practices that they do adopt, though fewer in number, are better suited to their environment. In contrast, a centralized structure enhances interstore learning by mandating common practices and keeping stores at the same point on the landscape. With these two countervailing effects, we find that a decentralized structure outperforms only

[15] When $P = N$, decentralization outperforms in finite time, almost surely. The reason is that in each period there is positive probability of each store finding and adopting an N-dimensional idea that is a global optimum. We want to thank David Easley for this point.

[16] That interstore learning under decentralization increases with landscape ruggedness is directly evidenced by the average distance between stores falling as γ rises. When $\alpha = 1$, average store distance falls from 4.43 to 3.61 to 3.01 as γ rises from 1 to 3 to 5. When $\alpha = 3$, average store distance falls from 10.68 to 8.94 to 7.70 as γ rises from 1 to 3 to 5. With more local optima, it is more likely that stores will end up targeting the same optimum.

when markets are sufficiently heterogeneous, the horizon is sufficiently long, and consumers are sufficiently insensitive to store practices.[17]

6. Fluctuating Markets and Perpetual Innovation

The previous analysis showed that centralization can outperform decentralization but only in the shortrun. The market environment was specified to be unchanging so that the chain and stores were searching a fixed landscape. Now let us enrich this model by allowing the landscape to change due to movements in consumer preferences. How does a continually changing environment alter the relative performance of these organizational structures?

Given the same triangular density for consumer types as assumed in stable markets, let x_i^t denote the peak type in market i in period t so that positive densities of consumer types range from $x_i^t - 25$ to $x_i^t + 25$. Our focus is on market fluctuations in which the distribution of consumers shifts over time in a stochastic manner. Allowing for the possibility that the changes in consumer tastes may be correlated across markets, we introduce a parameter ρ which is the probability that the market shifts in any given period are perfectly correlated. With probability $(1-\rho)$, we assume that the market shifts are independent. When $\rho < 1.0$, there is apt to be a built-in bias for decentralization induced by the increasing degree of crossmarket heterogeneity over time. To control for this artificial bias, we restrict the movement of the peak consumer types to a fixed interval between $50 - A$ and $50 + A$. The simulation results reported here assume $A = 8$, though the qualitative results were found robust to $A = 2$ and $A = 4$.

Let x_i^0 be the peak type of the initial consumer distribution in market i at $t = 0$, where x_i^0 is randomly drawn from $\{50 - A, \ldots, 50 + A\}$, $i = 1, 2$. In each period from $t = 1$ and on, the triangular densities in either or both markets shift by one unit with probability d and remain unchanged with probability $1 - d$. These changes are assumed to be perfectly correlated with probability ρ and independent with probability $(1 - \rho)$. The exact market shift dynamics follow the algorithm specified below:

- With probability ρ, the market shifts are perfectly correlated:
  If $50 - A < x_1^t < 50 + A$ and $50 - A < x_2^t < 50 + A$,
  $$\text{then } (x_1^{t+1}, x_2^{t+1}) = \begin{cases} (x_1^t + 1, x_2^t + 1) & \text{with probability } d/2, \\ (x_1^t, x_2^t) & \text{with probability } 1 - d, \\ (x_1^t - 1, x_2^t - 1) & \text{with probability } d/2. \end{cases}$$
  If $x_1^t = 50 - A$ and/or $x_2^t = 50 - A$,
  $$\text{then } (x_1^{t+1}, x_2^{t+1}) = \begin{cases} (x_1^t, x_2^t) & \text{with probability } 1 - d, \\ (x_1^t + 1, x_2^t + 1) & \text{with probability } d. \end{cases}$$
  If $x_1^t = 50 + A$ and/or $x_2^t = 50 + A$,
  $$\text{then } (x_1^{t+1}, x_2^{t+1}) = \begin{cases} (x_1^t, x_2^t) & \text{with probability } 1 - d, \\ (x_1^t - 1, x_2^t - 1) & \text{with probability } d. \end{cases}$$
- With probability $1 - \rho$, the market shifts are independent:
  If $50 - A < x_i^t < 50 + A$,
  $$\text{then } x_i^{t+1} = \begin{cases} x_i^t + 1 & \text{with probability } d/2, \\ x_i^t & \text{with probability } 1 - d, \\ x_i^t - 1 & \text{with probability } d/2. \end{cases}$$
  If $x_i^t = 50 - A$,
  $$\text{then } x_i^{t+1} = \begin{cases} x_i^t & \text{with probability } 1 - d, \\ x_i^t + 1 & \text{with probability } d. \end{cases}$$
  If $x_i^t = 50 + A$,
  $$\text{then } x_i^{t+1} = \begin{cases} x_i^t & \text{with probability } 1 - d, \\ x_i^t - 1 & \text{with probability } d. \end{cases}$$
  for $i = 1$ and 2.

Using the above rule of market dynamics, the search process is simulated over 1,500 periods. The structure

[17] A referee properly notes that one can think about centralization as one device for achieving integration among stores. Other integration-enhancing devices are discussed in Daft (1998, pp. 124–131) and Jones (1995, pp. 57–64).

Figure 4 Chain Profit Path over 1,500 Periods with $\rho = 1.0$ and $d = 1.0$

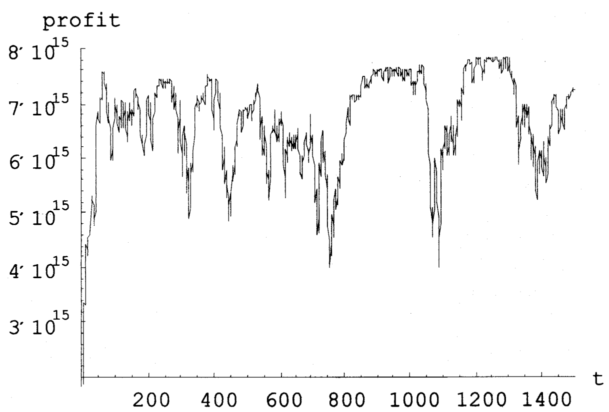
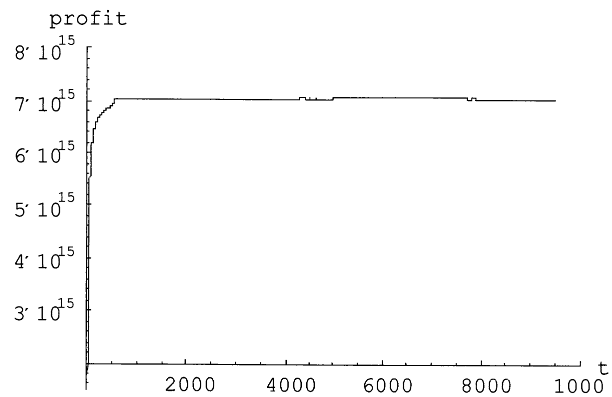


Figure 5 Moving Average Profit Path with $\rho = 1.0$ and $d = 1.0$



is otherwise identical to that specified in the preceding section, and indeed that model is the special case of $d = 0$ with (x_1^0, x_2^0) being fixed and symmetric around type 50.

When market fluctuation is allowed, two technical problems arise in comparing the simple profit path of the chain under different organizational forms. First, there is typically an initial transition to the point where profit is fluctuating around some steady-state mean. Second, market dynamics can cause considerable randomness in the profit path. Figure 4 obtained from a single simulation with $\rho = 1.0$ and $d = 1.0$ captures a typical profit path exhibiting these properties in the presence of severe market volatility. To surmount these two obstacles to estimating long-run profit, we use *Welch's procedure* to average the output processes generated from multiple replications.[18] Figure 5 plots a moving average profit path as described in Welch's procedure for $\rho = 1.0$ and $d = 1.0$, where the value of the profit at $t = 1{,}000$, for instance, is an average of the profits from $t = 500$ to $t = 1{,}500$. It seems quite clear from Figure 5 that the moving average at $t = 1{,}000$ is on the steady-state path. Based on this evidence, we use average profit over periods 500 to 1,500 (and averaged across 500 replications) as a measure of performance.

The ex ante optimal organizational forms (as specified previously for stable markets) are reported in Table 5 for different pairs of (ρ, d) for $\gamma = 3$ and $\gamma = 5$. The following property appears to be present when the market environment is subject to random fluctuations.

Table 5 Ex Ante Optimum (Fluctuating Markets)

	$\gamma = 3$; $A = 8$										
	d										
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
$\rho = 1.0$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$
$\rho = 0.7$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	C	C	C	C	C
$\rho = 0.3$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	C	C	C	C	C	C	C	C
$\rho = 0.0$	$\mathbb{D}$	$\mathbb{D}$	C	C	C	C	C	C	C	C	C
	$\gamma = 5$; $A = 8$										
	d										
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
$\rho = 1.0$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$
$\rho = 0.7$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	$\mathbb{D}$	C	C	C	C	C	C
$\rho = 0.3$	$\mathbb{D}$	$\mathbb{D}$	C	C	C	C	C	C	C	C	C
$\rho = 0.0$	$\mathbb{D}$	$\mathbb{D}$	C	C	C	C	C	C	C	C	C

PROPERTY 4. Centralization is more likely to outperform decentralization when market fluctuations are sufficiently large (d is close to 1), while decentralization is more likely to outperform when market fluctuations are sufficiently small (d is close to 0).

Property 4 is quite consistent with the findings of the previous section. There we found that centralization performs better over shorter horizons which suggests that centralization results in stores learning at

[18] Detailed discussions of this procedure are in Law and Kelton (1991) and Welch (1983).

a faster rate when their practices are farther away from an optimum. In that a higher value of d means more change in the landscape, it results in the stores being pushed farther away from an optimum. Quite contrary to the usual claim that volatility in markets requires a more flexible decentralized organizational form, we find that it is the centralized organization with coordinated search that is more effective in responding to a new environment. It is also worth noting that continual change in stores' environments results in a centralized structure being preferred even in the long run.

As seen in Table 5, Property 4 is robust to varying degrees of correlation among market fluctuations. Furthermore, we note the following property with respect to ρ.

PROPERTY 5. Centralization is more likely to outperform decentralization when market fluctuations are less correlated (ρ is close to 0), while decentralization is more likely to outperform when market fluctuations are more strongly correlated (ρ is close to 1).

Shocks to consumer preferences that are common across all markets then favor decentralized organization, while market-specific shocks tend to favor centralized organization. Unfortunately, we are unable to come up with an explanation for this phenomenon.

7. Conclusion

In this paper, we constructed a computational model of a retail chain in which store managers come up with ideas for new practices. The effect of the allocation of authority on average chain profit was explored. Our analysis revealed that while a more decentralized structure ensures that ideas adopted for a store are well suited to a store's market, this comes at the cost of reduced interstore learning. What a store learns of value from the adopted practices of other stores depends on the similarity in their markets but also on the similarity in their current practices. By maintaining common practices across stores, learning spillovers are enhanced under centralization.

One way to view this result is that centralization imposes a constraint—stores are required to have similar practices—and this constraint enhances performance.[19] One then wonders what other constraints might be useful. One idea is to give store managers limited authority by allowing HQ to veto new ideas that are too different from what other stores are doing. This would serve to allow for some decentralization while preventing stores from getting too far apart. An entirely different class of solutions is to redesign incentives rather than organizational structure. The problem is that a store manager ignores those ideas that do not benefit his own store although the idea may benefit other stores in the chain. Rewarding store managers for passing along ideas that are eventually adopted by other stores would help alleviate this problem.[20] Ultimately, however, one wants store managers to largely devote themselves to the performance of their own store and, as long as that is true, incentive contracts would not seem to be a full solution. Further research needs to explore other possible solutions to this fundamental dilemma faced by multi-unit firms.[21]

[19] Comments made by Ann Bell and Eric Maskin were especially helpful here.

[20] However, Rotemberg and Saloner (1993) identify some problems with such reward mechanisms.

[21] The comments and suggestions of Ann Bell, David Easley, Bruce Hamilton, Jon Harford, Bentley MacLeod, Eric Maskin, Scott Page, Tim Van Zandt, Peyton Young, three anonymous referees, an associate editor, and participants of seminars at the Brookings Institution (Center for Social and Economic Dynamics), Cleveland State, Georgetown, Pompeu Fabra, Rochester (Simon School of Business), Vanderbilt (Owen School of Management), and Washington University (Olin School of Business), and at the 1998 UBC Summer Industrial Organization Conference, 1999 Conference on Institutions: Complexity and Difficulty (Santa Fe Institute), 1999 Society for Computational Economics Conference, Computational and Mathematical Organization Theory Workshop (INFORMS-1999 Meetings), and Decentralization Two Conference (UCLA) are gratefully acknowledged.

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