Multimarket Competition, Consumer Search, and the Organizational Structure of Multiunit Firms

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This research explores how market competition influences a firm’s optimal organizational structure. For this purpose, a computational model of competing multiunit firms is developed in which unit managers and corporate staff continually search for better practices, while consumers search among units to find a better match. Organizational structure impacts both the practices at the unit level and the extent of knowledge transfer. An increasing returns mechanism is identified, which results in the relative performance of the centralized form being greater when competition is more intense.

(Decentralization; Market Structure; Adaptation; Spillovers)

1. Introduction

The ubiquity of multiunit firms such as retail chains is testimony to their efficacy. One source of competitive advantage is their superior capacity for learning through the transfer of knowledge among internal units. As noted in Argote (1999), the transferability of a given piece of knowledge depends on the similarities between the current practices of its original provider and the potential recipient. While uniformity of practices then enhances knowledge transfer, it hampers the ability of units to evolve practices that are uniquely adapted to their local market conditions. There is then a basic tension between internal knowledge transfer—which is most effectively achieved through uniform practices imposed by a centralized authority—and local adaptation—which is best achieved through the decentralization of authority.

In earlier work, we explored this tension in the context of a single chain (Chang and Harrington 2000, 2001). In this paper, we enrich that environment by introducing what is arguably the most important element of a firm’s environment—the intensity of competition. How does the choice of an organizational structure, through its impact on the internal flow of knowledge, affect the market performance of multiunit firms? How does the existence of market competition and the consequent competitive interactions among rivals affect the efficacy of different organizational structures in regard to knowledge transfer?

The strategic importance that multiunit firms attach to internal structure in the presence of competition is reflected in the long-run adaptive response of Sears, Roebuck and Co. During the time in which it was the top United States retailer, the chain focused on decentralizing decisions.

The Sears principle of decentralized administration is now the cornerstone of organization policy, responsible to a great extent for the company’s retail success, as well as for some difficulties…. But company officers believe strongly that the advantages of decentralization far outweigh its disadvantages (Emmet and Jeuck 1950, pp. 371–372).

Against this history and in response to declining performance, the position of Sears management noticeably changed in the 1980s as it chose a course of increased centralization.
On the way home from the Midwest trip, [CEO Ed] Brennan said he was impressed with the Target store they’d seen. . . . It was clear to Brennan that Target’s merchants were working from a common, predetermined, and scientifically delineated physical plan that was a far cry from the Sears way, where each store still reflected the tastes and experience of the manager (Katz 1987, p. 256).

Although traditionally a decentralized company made up of autonomous regions, in the 1980s Sears centralized, taking decision-making authority out of the regions and into the headquarters (Sears, Roebuck and Co. 1994, p. 7).

Did Sears make the right move when it chose to centralize? If it was the right move, what changed in Sears’ market environment that made greater centralization appropriate? While Montgomery Ward and department stores had always been there, a new class of competitors emerged on the competitive landscape in the 1960s—the discount department store. The likes of Kmart, Woolco, Target, and, of course, Wal-Mart were increasingly pushing into Sears’ markets. How did these changes in the competitive environment affect the optimal organizational structure from the perspective of Sears? The broader objective of this paper is to investigate the relationship between market structure and organizational structure so as to improve our understanding of these types of issues.

The central insight of this paper is that the centralized organization’s relative performance is enhanced when there is competition and consumers search and compare stores. As shown in our previous work for the case of a single chain, the rate of organizational learning is initially faster under centralization because knowledge transfer is more effective. The insertion of competing chains into the environment is found to magnify the importance of this early learning advantage. By developing appealing practices at a faster rate early on, the centralized chain is more effective at luring customers. Furthermore, a chain’s customer base influences its future practices as a chain adopts those ideas that raise profit, which, of course, depends on who is visiting their stores. By initially capturing those consumer types who are most prevalent in the market, a centralized chain tends to tailor their practices to them, which not only serves to retain those consumers, but also to attract similar consumers from other stores. An initial edge in the market is then turned into a long-run competitive advantage. Increasing the number of competing chains further enhances the relative performance of the centralized form so that we should expect more chains to be centralized when there is more competition.

2. A Computational Model of a Retail Chain

The model is a modification of Chang and Harrington (2000) to when there are multiple chains and consumers engage in search. Justification and explanation for many of the model’s assumptions can be found there. A retail chain is modelled as a corporate headquarters (HQ) and a set of stores. There are \( L \) chains and \( M \) geographically distinct markets. \( \Delta_i \subseteq \{1, 2, \ldots, M\} \) denotes the set of markets served by chain \( j \) and \( \Phi_h \subseteq \{1, 2, \ldots, L\} \) 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, \( z_i^{j,h}(t) \equiv (z_1^{j,h}(t), \ldots, z_N^{j,h}(t)) \in \{1, \ldots, R\}^N \), 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.

Each market has a fixed set of 992 consumers with each consumer being defined by a vector of ideal store practices that is referred to as a consumer’s type. A consumer’s type is a random draw from a distribution that is parameterized by his “seed,” which is an element of a proper subset of \( \{1, ..., R\} \). If a consumer’s seed is \( s \), then his type is a random draw from \( \{s-E, \ldots, s+E\}^N \subset \{1, \ldots, R\}^N \), 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 \( \{S_h - G, \ldots, S_h + G\} \subseteq \{1, \ldots, R\} \). In the simulations, \( R = 100, G = 25 \), and \( S_h \in \{40, 42, \ldots, 60\} \). This construction of the distribution of consumer types is independently performed 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 \( |S_{h'} - S_{h''}| \).

Consumer decision making in regard to which store to buy from and how much to buy from that store is assumed to only depend on the distance between \( \ldots \)
the consumer’s ideal store practices and the actual practices of stores. We use Euclidean distance that takes the form \( \sqrt{\sum_{k=1}^{N}(z_k - w_k)^2} \) for a consumer of type \( w = (w_1, \ldots, w_N) \) and a store with practices \( \bar{z} = (z_1, \ldots, z_N) \). A consumer ranks stores according to this metric. Furthermore, it is assumed that the number of units demanded by a consumer equals \( |A - \sqrt{\sum_{k=1}^{N}(z_k - w_k)^2}|^\sigma \) so that it is decreasing in this distance.

Market \( h \) is served by the chains in \( \Phi_h \) 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 across time. A consumer enters each period with a “favorite store” that is the store currently most preferred. 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 \( t \). 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 \( z_k^{j,h}(t) \) 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). 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 is i.i.d across consumers and across time. Note that if \( Q = (|\Phi_h| - 1)/|\Phi_h| \), 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 \( Q \in [0, (|\Phi_h| - 1)/|\Phi_h|] \), where \( Q = 0 \) is absolute loyalty as no experimentation occurs.

Defining \( \Gamma_j^{i,h}(t) \) to be the set of consumers that are shopping at chain \( j \)’s store in market \( h \) in period \( t \), a store’s period \( t \) profit is specified to be

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

This is the sum of consumers’ demands where per unit profit is normalized to one. A chain’s profit is the simple sum of stores’ profits. It is shown in Chang and Harrington (2001) that the profit landscape has multiple optima.

In each period, each store generates one idea. An idea is created by randomly selecting a dimension from \( \{1, \ldots, N\} \) and assigning to it a randomly selected element from \( \{1, \ldots, R\} \). If this idea is adopted by a store, then the store’s practice in the specified dimension is changed to the new value. 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. 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 nonempty set of ideas to consider that comes from two sources. First, a store manager generates one idea each period. Second, the store manager receives, via HQ, the ideas adopted by other stores in its chain in the current period. A store manager sequentially evaluates all these ideas and adopts an idea if it raises current store profit. In evaluating ideas, a store uses its current base of consumers, \( \Gamma_j^{i,h}(t) \). This is motivated by the view that an idea may be temporarily adopted for a short time to see how well it performs.

Now consider a centralized organization. In any period, a store manager generates an idea and
3. Simulation Design

Simulations were performed when each chain serves all markets, $\Delta_i = \{1, \ldots, M\} \forall j$. 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 i.i.d. across chains), and TLM ideas; as each store generates one idea per period and there are $M$ stores per chain, $L$ chains, and $T$ periods. We set $T = 1,000$, as it appears to be of sufficient length for the profit paths to have settled down. Initially, 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 is calculated when the chain is centralized and when it is decentralized. Let $v_C^{i,j}(O)$ denote the profit of a centralized chain in period $t$ for replication $i$, when the other chain has organizational structure $O$. Similarly, define $v_D^{i,j}(O)$ for when the chain is, instead, decentralized. One of the measures we will report is the time series on $(1/X) \sum_{i=1}^{X} [v_C^{i,j}(O) - v_D^{i,j}(O)]$. Next, define $V_C(O; T) \equiv \sum_{t=1}^{T} (1/T) v_C^{i,j}(O)$ and $V_D(O; T) \equiv \sum_{t=1}^{T} (1/T) v_D^{i,j}(O)$ as average chain profit across the first $T$ periods for a centralized and decentralized chain, respectively. Defining $\delta_T(O; T) \equiv V_C(O; T) - V_D(O; T)$, we can construct the following test statistic:

$$\bar{\delta}(O; T) \equiv (1/X) \sum_{i=1}^{X} V_C^{i,j}(O; T) - (1/X) \sum_{i=1}^{X} V_D^{i,j}(O; T).$$

This statistic is used to determine whether one form outperforms another.

Simulations were 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 $\alpha \in \{0, 2, \ldots, 10\}$ so that $\alpha$ measures the degree of intermarket heterogeneity. In expectation, markets are identical when $\alpha = 0$. The following additional parameter values are assumed: $\sigma \in \{3, 10\}$, $R = 100$, $E \in \{0, 2\}$, $N \in \{10, 20\}$, $G = 25$, $Q \in \{0, 0.05, 0.1, 0.2\}$, and $X \in \{800, 1,000\}$. The simulation programs were written in C++ and compiled with Microsoft Visual C++.²

4. 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, which is covered in greater detail in Chang and Harrington (2000, 2001). There, we found that centralization outperforms when markets are not too different. Figure 1 shows the time series on profit under centralization minus profit under decentralization in period $t$, averaged across all replications. The case of a single chain is $Q = 0$ (and is equivalent to assuming $L = 1$); as with no consumer search, each store has a permanently loyal set of consumers. As shown, the centralized structure is superior in the early periods, which is when learning is most active. That superiority dissipates across 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 long run.

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 previous 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

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¹ By 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.

² The source code is available upon request from Myong Chang.
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 does not tend to work for another type of consumer. While some drifting apart in stores’ practices is appropriate, given that they serve different markets, the tendency is for this to be excessive, which causes the rate of interstore learning to be excessively retarded. The virtue of a centralized structure is that it enhances interstore learning by keeping stores close in store practice space so that they are targeting similar consumers. With these two countervailing forces, a centralized structure outperforms as long as markets are not too different.

5. The Case of Competing Chains
Let us initially consider the case of two competing chains, $\mathcal{L} = 2$, where both chains have stores in the same three markets. The runs in this section assume, unless noted otherwise, $\sigma = 3$, $E = 2$, $N = 20$, and $X = 800$ while the other parameter values were set at those levels specified in §3.

On the basis of average chain profit, Table 1 reports the equilibrium organizational structures. These results were generated as follows. For each replication, we calculated the path of chain profit under decentralization and under centralization. After replicating 800 times, the profit in each period was averaged across replications. This gave us a time series for average chain profit under each
Table 1  Equilibrium Organizational Forms (L = 2)

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<td>Q = 0.0</td>
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<td>Q = 0.025</td>
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<td>Q = 0.05</td>
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<td>Q = 0.2</td>
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<td>T = 1,000</td>
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<td>Q = 0.0</td>
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<td>Q = 0.2</td>
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Note. Those configurations marked with an asterisk are statistically significant at the 5% level.

organizational form. Profit was then averaged across 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 1 is the set of equilibrium market structures for a particular parameter configuration. CC (DD) denotes an equilibrium with two centralized (decentralized) structures. An equilibrium is statistically significant if the difference in payoffs between the equilibrium structure for a firm and the alternative structure, given the other firm’s equilibrium organizational structure, is rejected as being the same at the 5% level.

Figure 2(a) plots the differential in chain profit between a centralized and a decentralized organization across time, \( (1/X) \sum_{i=1}^{X} [v_{C}^{i}(Q, C) - v_{D}^{i}(Q, D)] \), for when the competing chain is centralized (and results are similar when the competitor is decentralized). The pattern on the differential profit path is fairly systematic. It initially dips and becomes negative so that, in the early periods, decentralization is mildly outperforming. It then rises, and except when markets are heterogeneous, becomes positive so that centralization is outperforming. Typically peaking between periods 100 and 200, it then steadily declines, which means that a decentralized organization is increasingly performing better. Depending on the parameter values, differential profit in period 1,000 could be either positive or negative; meaning that either a centralized or decentralized organization could be outperforming in the long run. Unreported results show that consumer search has effectively settled down by period 500, and in some cases, much earlier.

In trying to understand this pattern, we have a working hypothesis as to how learning is occurring across time and how it varies with the organizational form. In stage 1, stores’ initial practices are highly suboptimal so that a store can probably effectively learn on its own as most new ideas are improvements on existing practices. Centralization underperforms because interstore learning is not that important, and it results in the imposition of unprofitable practices on some stores. In stage 2, as stores get out of having highly suboptimal practices, they are likely to move into the basin of attraction for a set of optima. At this point, finding useful ideas becomes more difficult. Perhaps, it is here that interstore learning starts becoming important, and is why the profit differential is increasing and positive. In stage 3, stores now begin to hit the limit of centralization because it constrains them to having identical practices while, under decentralization, stores can approach their global optimum. As a result, the profit differential is decreasing and may become negative.

Comparison of Monopoly and Duopoly. In contrasting the case of one and two chains, the results are quite striking. The relative performance of centralization is distinctly greater when consumers engage in comparison shopping among competing stores. Table 1 shows that centralization is never the preferred organizational form when there is one chain \( (Q = 0) \), but is typically the preferred form when there is competition \( (Q > 0) \). 3 Figure 1 shows that the time series on the profit differential between centralized and decentralized forms is much higher when there are two chains \( (Q = 0.1) \), compared to when there is one chain \( (Q = 0) \), and this holds whether the competing chain is centralized or decentralized. Furthermore,
the asymptote appears to be positive rather than negative (for example, examine Figure 1 when $\alpha = 2$). Centralization can then outperform in the long run in the duopoly model, which was not found in the monopoly model.

**Property 1.** The relative performance of centralization is greater in a duopoly than a monopoly.

To explore what might be causing this property, we have developed more detailed measures of performance shown in Figures 2(b)–(c). For a particular period, the differential in per capita demand is defined to be the number of units demanded per consumer for a centralized chain minus that for a decentralized chain. It measures how close store practices are to the desired practices of its customers. The differential in the number of loyal customers is defined to be the number of loyal customers per store for a centralized chain minus the number of loyal customers per store for a decentralized chain. Both of these measures are averaged across the replications.

The pattern seems to be the following. Per capita demand is increasing (except perhaps for the early periods), indicating that a centralized chain is satisfying its customers better. This advantage peaks on the order of period 100 and steadily falls thereafter. It generally appears to be asymptoting a negative value so that, in the long run, per capita demand is higher for the decentralized chain. Holding a chain’s customer bases fixed, the decentralized chain should, in the long run, have its practices closer to those desired by its customers for the simple reason that it is not constrained to offering uniform practices across markets. However, the degree of heterogeneity across markets in a chain’s customer bases is apt to vary with the organizational form. A chain that is more successful in attracting consumers may actually have lower
per capita demand because its customer base is more
diverse. As per capita demand is higher in the long
run under decentralization, it appears that either the
decentralized chain has a more homogeneous cus-
tomer base or, if it does not, its ability to tailor its
practices to each market offsets having a more diverse
customer base.

There is a similar pattern with respect to the dif-
ference in the number of loyal customers between a
centralized and decentralized chain with one signifi-
cant difference. When the rate of consumer search is
not too high, \( Q \in [0.05, 0.1] \), and markets are not too
different, \( \alpha \in [2, 4] \), the differential number of loyal
customers is asymptoting a positive number; indicat-
ing that, in the long run, the centralized chain has
more customers. Going back to Figure 2(a), this is
why centralization is outperforming in the long run,
which is a property not observed in the absence of
competition.

Let us now consider some possible explanations for
why centralization is performing relatively better in
the presence of competition and consumer sorting. To
begin, it is important to recognize that there are two
dynamics at work. As with the case of one chain,
stores are learning new practices and, thus, climbing
a landscape. Distinct from the case of one chain, con-
sumers are also learning about the practices of differ-
ent stores, and sorting themselves accordingly. This
sorting of consumers means that the landscape that
stores face is changing across time. We know for the
one-chain model, that both organizational forms ben-
fit from more homogeneous markets—as it enhances
interstore learning—but the centralized form benefits
relatively more given its constraint that practices be
uniform. When there is only one chain, the chain’s
customer base is fixed and equal to the market popu-
lation of consumers. When there are multiple chains
and consumers can search, the heterogeneity of a
chain’s customer base is no longer exogenous. Hence,
even if markets are highly heterogeneous, it is possi-
able for a chain’s customer bases across markets to be
relatively similar as consumers sort themselves. What
may be true then is that, holding \( \alpha \) fixed, the effective
heterogeneity in a chain’s customer bases is less when
there are two chains than when there is a single chain.
In other words, the landscape of a chain evolves to
being constructed upon a more homogeneous cus-
tomer base. This differentially benefits the centralized
form and may be one reason for Property 1.

While it seems quite compelling that this force
is operative, we believe more is occurring. If Prop-
erty 1 is exclusively due to the effective degree of
intermarket heterogeneity being less under duopoly
then, roughly speaking, the results should be qualit-
atively similar to those for the one-chain model but
for a lower value of \( \alpha \). However, in the one-chain
model, the decentralized form always outperforms
in the long run, while in the two-chain model, the
centralized form outperforms for certain parameter
configurations. Indeed, this result runs counter to
the logic behind why the decentralized form eventu-
ally does better in the one-chain model. Because
the unconstrained global optimum is for stores to
have different practices (and this is only achievable
by a decentralized form), the peak of the landscape is
higher under decentralization. Given that, in the long
run, we expect an organizational form to often get
close to its global optimum, decentralization should,
on average, outperform if one runs the model long
enough. Why does this logic not carry over to the
two-chain model? In the one-chain model, a chain’s
landscape is exogenous as it is determined by the
demand functions of a fixed consumer population. In
the two-chain model, it is endogenous as it depends
on a chain’s customer base. We conjecture that the
centralized form can outperform in the long run
because the landscape it is climbing is superior to the
landscape under decentralization. While the decen-
tralized form may do a better job of getting close to
its landscape’s global optimum, the centralized form
is climbing a better landscape.

The next question is: Why is the centralized form’s
landscape better? Recall from the one-chain model
that centralization does better early on in the horizon
due to a higher rate of interstore learning. This means
better practices, higher consumer demand, and more
profit. Eventually, however, decentralization catches
up. What is important in the one-chain model is that
at the point that stores in a decentralized organization
start learning at a faster rate, they are climbing the
same landscape as a centralized chain; that is, it faces
the same consumer population. For the case of competing chains, it is also true that centralization does better early on, but it results not only in higher per capita demand, but also more loyal customers. In that a store and chain’s landscape is determined by the set of customers visiting its stores, a centralized chain, in say period 200, is climbing a better landscape than a decentralized chain in period 200. In that the decision to adopt a new idea depends on the profit it generates from one’s current customers, the ideas that a chain adopts depends on who are its current customers.

We can now pull all this together to describe an increasing returns story. Due to a higher rate of interstore learning, a centralized chain attracts more customers early on. It then adopts those ideas well suited for such customers, which serves to retain them and attract like-minded consumers. The further conversion of such consumers into loyal customers makes the chain even more inclined to adopt practices suitable for those consumer types. In this way, the early advantage of the centralized chain through interstore learning is fed into a feedback loop to maintain an advantage in the long run. As a result, a decentralized chain may not be able to catch up because it is adopting ideas for a smaller niche of consumers. In other words, the rate at which a chain climbs a landscape (by coming up with better practices for its current customers) influences the shape of its future landscape (by affecting the set of loyal customers). A centralized chain climbs its landscape faster early on and this results in its future landscape being more attractive.

In conclusion, let us offer a remark about robustness of this finding. It would seem important that chains and stores engage in myopic hill climbing—an idea is adopted if it raises profit based on the current customer base. Such a simplistic strategy rules out adopting ideas so as to attract customers who are not currently visiting one’s stores. It is clear that such a consideration is present in the business strategies of actual chains. Nevertheless, we believe this mechanism is still broadly relevant in that a chain’s customer base is its least costly source of information about which ideas are valuable. How well an idea plays out with one’s current customers should, quite generally, influence whether the idea is adopted. As long as that is true, the mechanism will be operative though, in a richer model, other forces will come into play.

**Effect of the Intensity of Competition.** Let us now more fully explore the impact of competition on the performance of various organizational structures by considering alternative market structures. In the previous section, the case of two chains and 992 consumers in each market was compared with that of one chain and 496 consumers in each market. In this manner, the profit potential for a chain was the same when comparing monopoly and duopoly. A slightly different experiment is conducted here as we raise the number of chains while holding market size fixed at 992 consumers. This experiment addresses what happens to a chain’s optimal organizational structure in response to an exogenous change in the number of competitors. However, for most qualitative results, it makes little difference whether the number of consumers per market or the average number of consumers per chain is kept fixed.

All results are for when there are three markets and on average 10% of consumers search in each period. In each market, there are $L$ chains and we consider $L \in \{2, 3, 5, 10\}$. Table 2 reports the equilibrium organizational structures based on the average payoff after 100 and 1,000 periods. These results confirm our previous findings for the case of one and two chains. First, greater intermarket heterogeneity enhances the relative performance of decentralization. For example, consider $T = 1,000$ and $L = 3$. All chains are centralized when $\alpha \in \{4, 8\}$, but all are decentralized when

<table>
<thead>
<tr>
<th>$T$</th>
<th>$L$</th>
<th>$\alpha$</th>
<th>Configuration</th>
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<tbody>
<tr>
<td>100</td>
<td>2</td>
<td>4</td>
<td>CC</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8</td>
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<td></td>
<td></td>
<td>12</td>
<td>DD</td>
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<td></td>
<td></td>
<td>16</td>
<td>DD</td>
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<tr>
<td>1,000</td>
<td>2</td>
<td>4</td>
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<td></td>
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<td>$10C/0D$</td>
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<td>10</td>
<td>$6C/4D$</td>
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<td>10</td>
<td>$2C/8D$</td>
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<td></td>
<td>3</td>
<td>4</td>
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<td>10</td>
<td>$5C/5D$</td>
</tr>
</tbody>
</table>
When \( L = 5 \), the industry goes from being entirely centralized to partially centralized to entirely decentralized as \( \alpha \) is raised from 8 to 12 to 16.

**Property 2.** A higher fraction of chains is decentralized when markets are more heterogeneous (that is, a higher value for \( \alpha \)).

Consistent with Property 1, the next result shows that the appeal of centralization is enhanced when competition is intensified. Consider the case of \( T = 1,000 \). When \( \alpha = 4 \), all firms are centralized for all market structures; even when there are 10 chains. When \( \alpha = 12 \), all firms are decentralized when there are two or three chains. As competition increases to where there are five chains, two of the chains now choose to centralize. In a market with intense competition, 8 out of 10 chains are centralized.

**Property 3.** A higher fraction of chains is centralized when there is more competition (that is, a higher value for \( L \)).

These results establish the robustness of our earlier findings. There is, however, a new result as well. In Figure 3, the differential between average profit under centralization and average profit under decentralization (when \( T = 1,000 \)) is plotted when there are three chains. The top row of figures is when a firm’s competitors are both centralized, the second row is when one competitor is centralized, and the last row is when both competitors are decentralized.
The left column is for low intermarket heterogeneity ($\alpha = 4$), the middle column for moderate intermarket heterogeneity ($\alpha = 8$), and the right column for high intermarket heterogeneity ($\alpha = 12$). When $\alpha = 4$, the relative performance of centralization is decreased as more competitors are decentralized; as reflected by the curve shifting down. In contrast, when $\alpha = 12$, the relative performance of centralization is increased as more competitors are decentralized. The case of $\alpha = 8$ lies in between. This relationship is confirmed for when $L \in \{5, 10\}$.

**Property 4.** When intermarket heterogeneity is low, the relative performance of centralization is greater when a higher percentage of competing chains is centralized. When intermarket heterogeneity is high, the relative performance of centralization is lower when a higher percentage of competing chains is centralized.

To explain Property 4, it is important to distinguish between intermarket heterogeneity—which measures how different consumers are across markets (and which we have measured by $\alpha$)—and what we will call a chain’s demand heterogeneity—which measures how differently, across markets, a chain’s demand (and profit) is for the same practice. There is no difference between the two concepts when there is only one chain, but there can be a difference when there are competing chains. To see this point, suppose all three markets are identical and there is a single competitor. The same practice will deliver the same demand and profit in all three markets when that competitor is centralized. The reason is that, in all three markets, there is the same population of consumers (because intermarket heterogeneity is zero) and the competitor’s practices are the same (because the competitor has uniform practices). In that case, a chain’s demand heterogeneity is zero. Now, suppose the competitor is decentralized and, furthermore, has different practices in different markets. For the same practice, a chain will generally realize different demand and profit across markets, not because the population of consumers varies, but because the practices of the competing chain varies across markets. Thus, the extent to which a practice that is effective in one market is also effective in a second market depends, not only on the degree to which consumer populations are similar across markets, but also on the similarity in competitors’ practices across markets.

We know that less intermarket heterogeneity makes centralization relatively more attractive because it reduces the loss of demand in some markets from having uniform practices. By the same logic, the performance of centralization is enhanced when a chain’s demand heterogeneity is lower. Indeed, it is demand heterogeneity rather than intermarket heterogeneity that is critical. As just argued above, when intermarket heterogeneity is low, a chain’s demand heterogeneity is lower when more rivals are centralized. This enhances the relative performance of centralization and, thus, explains the first part of Property 4. A similar argument works for the second part as, more broadly, uniformity in one’s rivals’ practices make a chain’s demand heterogeneity similar to intermarket heterogeneity. Thus, if intermarket heterogeneity is high and rivals are centralized, then a chain’s demand heterogeneity is high. This worsens the relative performance of the centralized form. If, instead, rivals are decentralized, then heterogeneity in their practices tends to match intermarket heterogeneity, which homogenizes the residual sets of consumers that a chain faces across markets.

### 6. Concluding Remarks

Our purpose in this paper was to take a first step to understanding the strategy-structure nexus in complex multiunit organizations, by examining how the presence of market competition in a firm’s environment influences the relative performance of different organizational structures, where structure influences the transfer of new ideas. The results, thus far, have clearly established that competition introduces several new forces. 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. Compared to when there is one chain, the centralized organization outperforms for a wider range of parameter configurations. As competition is increased, this superiority of centralization is further enhanced.
There are many directions that future work can take. Research is in progress to allow stores to not only learn from other stores in their chain, but to also learn from competing stores in their market. A second avenue is to endogenize the flow of ideas by allowing store managers to determine how to allocate effort between execution—efficiently implementing existing routines—and exploration—discovering new routines. The incentive of a store manager for pursuing new ideas could be significantly impacted by whether they would have the authority to implement those new ideas (Aghion and Tirole 1997). Following the lead of March (1991), understanding the dynamical implications of the exploration-exploitation trade-off would seem to be essential toward the development of a more complete theory of organizational structure for multunit firms.

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References

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