Chain-to-Component Transfer Learning in Multiunit Chains of U.S. Nursing Homes, 1991-1997

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Abstract

Nursing home chains have grown at great speed during the last decade and we need to better understand how dynamics of corporate ownership have affected the services in these institutions. This study explores how the capabilities of chains and their components - both existing and newly acquired - affect transfer learning across the component units of the chains. Transfer learning occurs when one organization causes a change in the capabilities of another, either through sharing experience or by stimulating innovation. Attention to transfer learning processes is critical to understanding organizational performance because transfer learning is one of the most important routes through which organizations develop competitive advantage. Within chains, transfer learning leads to changes in the capabilities of component units and, in turn, to changes in component performance. Past research has provided indirect evidence that chain membership increases transfer learning, but typically inferred effects of transfer learning on components’ from changes in performance. By contrast, we examine the effect of transfer learning on structural characteristics that are closer to the underlying capabilities themselves. We develop a model in which capability levels, capability variability, capability similarity, and geographic distance have direct and interactive effects on transfer learning. We test the model in terms of both established units and recently-acquired units of multi-unit chains. The study considers changes in capabilities at the nursing home facilities of about 3000 nursing home chains operating in the U.S. between 1991 and 1997, examining changes in six types of capabilities.
Chain-to-Component Transfer Learning in Multiunit Chains of U.S. Nursing Homes, 1991-1997

How and when do multiunit chains add to or subtract from the capabilities of their component units? Chains are collections of component units that produce similar goods and services, linked together into larger ‘superorganizations’ (Ingram & Baum 1997). This study explores how the capabilities of chains and their components - both existing and newly acquired - affects transfer learning across component units. Transfer learning occurs when one organization causes a change in the capabilities of another, either through sharing experience or by somehow stimulating innovation. Attention to transfer learning processes is critical to understanding organizational performance because it is one of the most important routes through which organizations develop competitive advantage (Capron & Mitchell 1998). Within chains, transfer learning leads to changes in the capabilities of component units and, in turn, to changes in component performance. Past research has shown that ownership relationships such as chain membership influence transfer learning greatly. Changes in capabilities are, however, typically inferred from evidence of the effects of learning on performance (e.g., Baum & Ingram 1998; Darr, Argote & Epple 1995; Ingram & Baum 1997). By contrast, we focus here on changes that are closer to the underlying capabilities themselves.

Our empirical study examines transfer learning in almost 3,000 nursing home chains operating in the U.S. during the 1991-1997 period. Nursing homes provide an excellent context for studying transfer learning, because of the turbulent environment in which nursing homes operate and hence, the need to adjust strategies. A study of transfer learning within nursing home chains has general implications because the multiunit chain organizational form is coming to dominate every service industry - from retailing to healthcare - that has some direct contact between customer and organization (Ingram & Baum 1997). The results of this study thus contribute directly to our understanding of organizational change throughout the economy. In addition, the social implications of change in nursing home practices are substantial (Banaszak-Holl et al. 1996). The U.S. nursing home industry is known to have significant quality problems and policymakers continue to search for ways to improve practices across facilities (Institute of Medicine 1986).

Background: Capabilities, Transfer Learning, Multiunit Chains, and Acquisitions

This section briefly describes the concepts of capabilities, transfer learning, multiunit chains, and acquisitions. We contend that chains are important organizational vehicles for transfer learning and more specifically, that post-acquisition transfer learning within chains is particularly common.

Capabilities

At its most general level, the term capabilities means what an organization is able to do at a given time. More specifically, capabilities are the processes by which a firm uses labor and technology to transform material resources into final products (Hart 1995; Teece, Pisano, and Shuen 1997). We use the notion of capabilities as being synonymous with routines, that is, repeated patterns of actions that span multiple actors (Nelson and Winter 1982). In this study, we
will operationalize capabilities in terms of the types of services that nursing homes offer, focusing on specialty beds, specialty services, staffing, and size. We treat changes in levels of these services as changes in capabilities.

Transfer learning

As we noted above, transfer learning occurs when one organization causes a change in the capabilities of another. Transfer learning requires that the ‘sending’ organization take action to stimulate learning in the ‘receiving’ organization. Previous studies have provided both statistical and qualitative evidence that transfer learning affects a receiver’s performance (e.g., production cost) and is a function of senders’ cumulative performance (e.g., total units produced in past periods), other sender characteristics (e.g., innovativeness), and recipient characteristics (e.g., size). Beyond linking sender and receiver characteristics to the receiver’s subsequent performance, recent studies of transfer learning have emphasized the importance of the type of relationship between organizations that learn from each other. These studies show that ownership relationships between organizations greatly influence knowledge transfer. Darr et al. (1995), for example, present evidence that common ownership of pizza stores improved productivity, because knowledge transfer was greater between stores owned by the same franchisee. Reinforcing these findings, Baum and Ingram (1998) found evidence of transfer learning within U. S. hotel chains but not between unrelated hotels in the Manhattan hotel industry. Karim and Mitchell (2000) found that medical sector businesses undertaking change through acquiring other businesses add more new product lines than medical sector businesses that have not acquired new businesses. These results contrast with the previously dominant idea that knowledge can simply ‘spill over’ across the boundaries of organizations into the general environment, where it is easily consumed by other firms independent of any relationship to the knowledge provider.

It is not surprising that knowledge does not transfer easily between organizations in the ‘open market’ given the well-known difficulties and costs associated with measuring and valuing knowledge. The problems of market-type exchanges include both difficulties in coordinating the use of the knowledge and costs of protecting the value of knowledge (Capron & Mitchell 1998). Knowledge often suffers from the information paradox (Arrow 1962), such that it is difficult to protect the value of knowledge exchanged between unrelated parties. Moreover, the tacit quality of knowledge may necessitate empathy and familiarity between parties to facilitate communication, so that an ongoing relationship between the parties may help preserve the nature of the knowledge, as well as its value. The need for ongoing communication to coordinate knowledge exchange leads to the need for relationship-specific investments, which are difficult and costly to sustain without some form of institutional governance (Teece 1982, 1986; Williamson 1975). Although such institutional governance sometimes requires a fully integrated hierarchy, there also exists a range of collaborative governance forms such as alliances, long-term contracts, franchises and chains (Williamson 1991). Collaborative forms often assist transfer learning, while offering higher-powered ownership incentives and greater benefits of local focus than full integration.

Multi-unit chains and transfer learning

Multi-unit chains are a form of multi-unit organization, in which collections of component units
provide similar services under common ownership (Ingram & Baum 1997). Chains tend to standardize products, advertising, administration, operating procedures, equipment, and even buildings across components. Standardization raises consumers’ perceptions of reliability - the ability to repeat service at a given quality level - across a chain’s components (Ingram 1996). Standardization increases accountability because chains have a great incentive to monitor and pressure each component to maintain and enhance its standards. Poor quality service at any component can damage the entire chain’s reputation. Reliability and accountability of chain components reduce consumer search and monitoring costs (Baum 1999). In turn, standardization enhances the performance of a chain and its components by reducing operating costs and by creating a reputation for reliability and accountability (Hannan & Freeman 1984).

Chains’ strategic emphasis on standardization points to the importance of transfer learning across their components. Standardization of capabilities is critical for economies of scale and increased reliability and accountability. Among a chain’s existing components, transfer learning facilitates an ongoing realignment of activities. In addition, because much of chain growth occurs through acquisition, transfer learning is critically important to incorporating newly acquired components, which may be very different from the acquiring chain’s existing components, into the chain’s strategy.

Most generally, one can discriminate between hands on and hands off transfer learning mechanisms in multi-unit chains. Hands on mechanisms are methods that involve personal interaction among people at a unit and people from chain headquarters or elsewhere in a chain organization (Darr, et al. 1995). Hands on mechanisms bring members of a chain together for both task-oriented and social purposes, thereby increasing the opportunity and motivation for interorganizational transfer of systems and also increasing the ability of individual units to successfully apply experience transferred from other units. Examples of hands on mechanisms include (1) holding face-to-face meetings between chain and unit staff in order to share experience and focus explicitly on common problems and their solutions, (2) undertaking regular communication in which chain management and unit personnel share knowledge and report data to each other, (3) promoting personal acquaintances across units in order to create familiarity and trust that smooth the exchange of information, (4) rotating personnel among units (e.g., therapy specialists or medical directors may work at several facilities in a chain, creating the tendency to standardize activities among them), and (5) creating chain-specific training programs for staff members.

Hands off governance mechanisms are methods that require only directed requirements or indirect influence, without personal contact. Examples of hands off transfer learning mechanisms include (1) establishing common systems among units (e.g., standard clinical protocols for providing services; standard information systems for a facility’s medical records & human resources administrative needs), (2) establishing common training requirements for staff members, (3) creating standard reporting systems for financial, operating, and health outcome activities, (4) requiring that several units use common equipment and facilities, which will tend to lead to standardization and will typically involve the chain providing capital for investment in particular equipment and facilities, (5) providing plans for building or expanding facilities that will be standardized among units in a chain, (6) managerial fiat in which the chain requires a unit to do particular activities, and (7) vicarious imitation of the chain’s business systems by the unit.
**Acquisition and transfer learning**

Transfer learning will be important following acquisition of a new component by a chain. Chain acquisitions represent a form of related diversification in which there tends to be little consolidation of operations. Transfer learning appears to be both a central motivation (Ingram & Baum 2001) and a key to success for chain acquisitions (Ingram & Baum 1997). Theoretical models of chain acquisition have emphasized the market power and social power incentives for acquiring additional units, neglecting the potential for capability development as chains transfer resources and knowledge to acquired units. Recent research in business strategy, however, has begun to emphasize the importance of acquisitions as a basic mechanism through which organizations change, reconfigure and/or redeploy their resources and capabilities (Capron 1999; Capron, Dussauge & Mitchell 1998; Capron & Mitchell 1998; Karim & Mitchell 2000).

**A Model of Chain-to-Component Transfer Learning**

This study develops a simple model in which the level, variability, and similarity of capabilities, as well as the distance of a unit from the rest of the chain, will influence the ability, opportunity, and incentive for transfer learning from chain to component to take place. After presenting our conceptual framework, we identify and measure levels of several types of capabilities for U.S. nursing home chains and their components.

The discussion will motivate the following model of transfer learning from a chain to its components: The arithmetic signs of the parameters ($\beta$s) coefficients in equation (1) indicate our core predictions concerning transfer learning from chains to components.

\[
\Delta c = \beta_1 C - \beta_2 c +/- \beta_3 V_C +/- \beta_4 D_{Cc} - \beta_5 (C \times S_{Cc}) + \beta_6 (c \times S_{Cc}) - \beta_7 (V_C \times S_{Cc}) +/- \beta_8 (D_{Cc} \times S_{Cc})
\]

In equation (1), $C$ is the chain’s capability level and $c$ is the component’s capability level, each measured at time 0. $\Delta c$ is $(c_{t1} - c_{t0})$, which is the component’s increase or decrease in capabilities from time 0 to time 1. $V_C$ is the variability of capabilities among the units of a chain, which we will operationalize as the variance around the mean per-unit levels. $D_{Cc}$ is the geographic distance of the focal component unit from the rest of the chain, which we will operationalize in terms of mean Euclidian distance from the focal unit to a chain’s other components.

$S_{Cc}$ is similarity between a chain and its component’s capability levels at time 0, defined as follows, such that $S_{Cc}$ takes a maximum value of 1. The intuition underlying this measure of similarity is that chain and component levels determine the direct effects of capabilities on transfer learning, while relative levels determine the moderating effect of capability similarity. In other words, the impact of dissimilarity will be equivalent whether the chain or the component has higher levels of a capability.

\[
S_{Cc} = \frac{C}{c} \text{ if } C < c; \quad S_{Cc} = \frac{c}{C} \text{ if } c < C
\]

The interaction terms ($C \times S_{Cc}$), ($c \times S_{Cc}$), $(V_C \times S_{Cc})$, $(D_{Cc} \times S_{Cc})$ are multipliers of similarity with chain and component capability levels, variability, and distance. The parameters $\beta_1$ to $\beta_8$ are
model coefficients estimating the magnitude of each effect.

**Capability level**

We start by considering the level of capabilities across the chain and within focal components. This part of our argument emphasizes the importance of characteristics of both the sender and recipient. Higher levels of capabilities across a chain create greater abilities and opportunities for transfer learning to components ($\beta_1 > 0$). In contrast, a higher level of capabilities at a focal component reduces the potential of transfer learning to that particular unit, while components with lower levels of capabilities will have strong incentives to gain new capabilities ($\beta_2 < 0$). Indeed, a component with particularly high capabilities may undergo negative transfer learning if a chain want to decrease the unit’s emphasis on a particular activity.

**Capability similarity**

We next consider how the similarity between the chain’s capabilities and those of the component member influences transfer learning. We argue that capability similarity will tend to reduce transfer learning incentives, even if similarity increases learning ability ($\beta_5 < 0$). Subsequently, any benefits of similarity arise as a conditioning effect on the influence of capability level. Our arguments build on discussions that arise in the organizational learning, strategic management and organizational ecology literatures.

These three literatures all suggest that an organization’s ability to undertake transfer learning increases with similarity and decreases with dissimilarity in capabilities. An organization needs prior knowledge closely related to potential new knowledge before it can assimilate the new knowledge, and consequently, prior knowledge creates strong path-dependencies for organizations. Organizational theorists have labeled this path dependency in organizational knowledge as absorptive capacity (Cohen & Levinthal 1990). Likewise, the strategy literature, as represented in Porter’s (1987) skill-transferring model, suggests that acquirers seek targets with closely related primary characteristics (e.g., logistics, operations, marketing, sales and service) and support activities (e.g., company infrastructure, human resource management, technology development, procurement). A parallel argument also arises in the organizational ecology literature, which argues that differences in size and product mix lead organizations to compete in different ways for resources and to use different operating, management and strategic capabilities (e.g., Aldrich 1979; Hannan & Freeman 1977; McKelvey 1982; Carroll 1985). By extension, these views suggest that chain-component differences will make transfer learning to components less likely, for two reasons. First, the chains will have less incentive to standardize currently different activities and, second, because the chains and components lack experience needed to transfer knowledge even to the extent that they wish to do so.

Despite the possibility that learning ability increases with similarity, the actual effect of similarity on knowledge transfer must be conditioned on the potential for learning benefits. The direct effect of similarity on transfer learning may well be negative, rather than positive, because similarity imposes a constraint on learning: When a component’s capabilities are very similar to those of its chain, there may be little potential benefit from learning.
Consider three stylized capability levels - low, moderate, and high. Strong constraints to transfer learning incentives arise at the two extremes of chain-component similarity, low-low and high-high. When chain and component both have low capabilities, there will be little potential for transfer learning, because the chain has little to offer the component. At the other extreme, in the high-high case, a component with high levels of a capability will gain few benefits from transfer learning, even if the chain to which it belongs is also highly skilled. Although the component may gain from refinements to its capabilities, the component will be unlikely to make significant leaps to new capability levels through transfer learning.

Only in the moderate-moderate case do transfer learning ability and incentives to learn begin to converge. At moderate levels of capabilities, the component may have an experiential base on which to build and the moderate level of capabilities at the chain may provide transfer opportunities. Even here, though, similarity may limit transfer opportunities. Moreover, some transfers may make the chain and component more dissimilar: If a moderate-capability chain attempts to create a high-capability component, it may defeat the benefits of standardization so central to the chain strategy. Thus, contrary to previous arguments, we hypothesize that similarity between the chain and component at best will only moderately increase the likelihood of transfer.

By contrast, dissimilarity can enhance transfer learning. The dissimilarity case in which chain capabilities are high and component capabilities are low is the most obvious. The main effect of the high chain capabilities will lead to substantial transfer learning. In addition, components with low initial capabilities on a particular dimension may be particularly receptive to receiving new capabilities from a chain that possesses particularly strong skills on that dimension, for two reasons. First, the component may value improving a capability area in which it is weak, while the chain may view the situation as an opportunity for improving the component in its own right and increasing standardization across components. Second, the new capabilities will tend to have less conflict with the component’s existing repertoire of practices in that area than in situations in which a component is already skilled and may strongly resist disruption to what it perceives as its already successful practices. While resistance to change is common, even in situations where a firm and its staff lack skills, resistance is often less when people who must change believe that there is a problem that the change will address. Thus, the situation in which chain capabilities are high and component capabilities are low presents an opportunity for ‘capability infusion.’

A less intuitive and somewhat more ambiguous situation is the case in which chain capabilities are low and component capabilities are high. Our earlier argument concerning capability levels suggests that transfer learning will be low when chain’s capabilities are low and the component’s capabilities are high. Beyond these main effects, we consider three possible outcomes given this type of dissimilarity. First, there might be no joint effect of the low chain-high component dissimilarity combination, if the main effects provide all the influences. If so, then this dissimilarity combination would inhibit transfer learning less than the similarity combination we discussed above, such that our basic prediction concerning similarity would hold. Second, the imbalance in capabilities might enhance transfer learning if the chain attempts to reinforce the component’s strength with whatever parts of its own capabilities are particularly strong. Chains might be more likely to build on a component’s strength if the capabilities of a newly acquired component represent an opportunity for market growth for the chain or allow the chain to move
into technologically new areas of service. Again, our basic prediction concerning the main effect in which similarity reduces transfer and, conversely, dissimilarity increases transfer would hold in the reinforcement situation.

Alternatively, the combination of low chain and high component capabilities can lead to “transfer unlearning”, which would weaken our prediction concerning the effect of similarity on transfer learning. By transfer unlearning, we mean that the chain might substitute some its own strength in another capability (b) for the component’s strength in the focal capability (a), pursuing the incentive of chain-wide standardization. In sum, the presence of multiple possibilities concerning similarity reinforces the ambiguity for the similarity prediction that arises at moderate levels of similarity.

**Capability level x similarity interactions**

Unlike the main effects of similarity on transfer learning, the effect of the interaction between capability levels and similarity is more straightforward. Joint consideration of the ability and incentives for transfer learning suggests that similarity will tend to have mediating effects on the impact of capability level. In particular, two mediating effects are likely, one positive and one negative.

As a positive mediating effect, similarity may help offset the limits on transfer learning imposed by high component capabilities. Although high-capability components may have relatively little to learn, the similarity to their chain will help create an absorptive capacity that allows the components to refine and improve shared capabilities even if there is little potential to transfer novel capabilities from the chain ($\beta_7 > 0$).

In contrast with its positive mediating effect on component capabilities, similarity may also limit the benefits of high chain capabilities ($\beta_6 < 0$). High-capability chains will have less to offer similar components (components that already have achieved high capabilities) than dissimilar components (low capability components).

**Capability variability and variability x similarity interactions**

We continue by considering capability variability, addressing both the main effect and the interaction with similarity. The argument here starts by restating the assumption that chains emphasize standardization and, therefore, will tend to prefer homogeneous components. As a result, chains will tend to use transfer learning in order to bring components in line with chain norms, where the transfer learning may result in a decrease or increase in component capabilities.

Thus, the main effect of variability is uncertain ($\beta_3 > < 0$). If a chain has high variability among its units, it may add to low capability units and/or subtract from high capability units.

Rather than a main effect, the primary influence of variability may arise as an interaction with similarity. The influence will tend to be negative, as high variance chains have little incentive to transfer capabilities to units that are already similar ($\beta_8 < 0$).
Geographic distance and distance x similarity interactions

We conclude by considering the effect of geographic distance, that is, the distance of a focal unit from the other units of a chain. Two views arise with respect to the effect of distance on transfer learning, the learning view and the governance view. The learning view suggests that the closer a unit is to the rest of its chain, the more transfer learning will take place. In this view, proximity provides greater opportunities for hands on interaction mechanisms that facilitate transfer learning ($\beta_4 < 0$).

The governance view, by contrast, suggests that distance creates governance problems, where governance includes needs for coordination, monitoring, and control of a unit’s activities. Such distance-induced problems raise the incentive to use standardization to facilitate governance, because standardized units are more straightforward to observe, measure, and control from a distance. In turn, the standardization incentive raises the incentive for transfer learning. In this case, the chain will tend to rely on a combination of hands off and hands on mechanisms for transfer learning ($\beta_4 > 0$).

A contingency view fits in the middle between the learning and governance arguments. In the contingency view, there will be a tendency to shift from learning to governance over time, as a unit becomes more absorbed within a chain. This difference would tend to show up in the comparison of recently-acquired units of a chain and ongoing units. Recently-acquired units might be most sensitive to learning issues of distance, such that only nearby units undergo substantial transfer learning soon after being acquired. Over time, as a unit becomes integrated into a chain, the governance effects may well take hold, so that distant established units would undergo the greatest transfer learning.

Similarity will tend to moderate both the learning and governance views. In the learning case, similarity will help overcome distance problems ($\beta_9 > 0$). In the governance view, similarity lowers standardization incentives ($\beta_9 < 0$).

Synopsis

In summary, our arguments suggest that transfer learning outcomes and rates are a function of the opportunities and constraints resulting from the interaction of level, variability, distance, and similarity of chain and component capabilities. We expect transfer learning to increase with chain capabilities, to decrease with component capabilities, and to decrease with similarity. We also expect similarity to temper the negative effect of component capabilities and the positive effect of chain capabilities. We further expect little transfer learning at units that are similar to chain averages in highly variable chains. We compare opposing arguments concerning distance, suggesting that a learning view may tend to apply to recently-acquired units, while a governance view may apply more to established units of a chain.

We expect substantial differences among recently-acquired units of a chain and more established units. First, as we discussed above, we expect a transitional effect of distance on transfer learning, in which newly acquired components will gain greatest transfer learning if they are close to the rest of the chain, while established units will undergo greatest transfer learning when...
they are distant from the center of the chain and thereby require standardization to facilitate governance. Second, it is likely that newly acquired units will incur the greatest influence from capability levels and similarity, while the effects of distance may tend to emerge only over time.

A notable desirable property of the model that we present here is its realistic representation of knowledge transfer as a self-damping process. If \( C > c \) then \( c \) increases toward \( C \), which also increases \( S_{Cc} \). Increases in \( c \) and \( S_{Cc} \), however, tend to dampen increases in \( c \). Any further increase in \( c \) would only serve to dampen future increases in \( c \), ultimately stabilizing \( c \) at some value that would remain unchanged so long as \( C \) did not change. This stability is the result of negative feedback, which occurs when an increase (decrease) in one variable in a model (i.e., \( c \)) sets in motion changes in other variables in the model that lead ultimately to a decrease (increase) in the initial variable. Thus, contained within the model are both conditions under which knowledge transfer is initiated and under which it ceases.

**Data and Methods**

We tested our model using data on nursing home chains and their components in the continental United States between January 1991 and September 1997. We draw our data from a longitudinal data set linking yearly files of the federal OSCAR (On-line Survey Certification and Reporting System) data, which includes information from the state-based inspections of all Medicare and Medicaid certified nursing homes operating in the continental U.S. Data include facility-level information on nursing home strategy and structure (e.g., size, staffing and services), resident case mix (e.g., percentage incontinent), chain membership, and any deficiencies recorded during annual inspections. In total, the data include over 105,000 records, covering nearly 20,000 unique nursing homes.

Key to our analyses is the operationalization of chain membership and the occurrence of acquisitions. The OSCAR data include the name of the multi-institutional corporation to which a nursing home belongs. Approximately half of the nursing homes in these data report a corporate owner. We coded chain membership from names reported in the OSCAR data. We assessed inconsistencies by comparing the spelling of names, inter-temporal relationships with specific homes, and geographic linkages. Finally, we checked corporate ownership for large chains using 1990-1998 volumes of the *Medical and Healthcare Marketplace Guide* (Dorland’s Biomedical Publications), an annual publication providing information on commercial companies operating in the U.S. healthcare sector. We identified nearly 3,000 unique multiunit corporate owners in the data. Acquisitions - approximately 5,000 in number - were coded as a change in corporate ownership status of a nursing home. The proportion of chain nursing homes increased from 40% to 48% during 1991-1997, although most chains tend to be quite small with less than 7% of corporate owners operating more than 10 homes. Thus, extensive chaining of nursing homes exists, but it is still primarily a small-scale phenomenon.

After developing our coding scheme for corporate chains, we identified six key capabilities of nursing homes using the OSCAR data for our analyses. The capabilities variables are:

1. *Component size* (number of beds)
2. *Staff intensity* (registered nurses, practical nurses, aids, and support staff, per resident)
3. **Specialty bed intensity - Alzheimer’s disease** (beds dedicated for residents with Alzheimer’s disease, per total beds)
4. **Specialty bed intensity - Rehabilitation** (beds dedicated for residents requiring rehabilitation services per total beds)
5. **Specialty service intensity - Injection** (residents receiving injection services, per total residents)
6. **Specialty service intensity - Therapy** (residents receiving physical or occupational therapy, per total residents)

The size of a nursing home affects the capabilities required to operate it effectively. In this sense, home size represents an indirect measure of nursing home capabilities.

Staffing intensity is contingent upon case mix and payment rate models, and hence represents a key part of the operating strategy for a nursing home. In this study, we include FTEs of all employees, both nursing and ancillary, in our staffing measure. Staff intensity is a direct measure of nursing home capabilities related to operating efficiency.

The availability of beds dedicated to specialized medical services within a nursing home, such as the ability to provide care for residents with Alzheimer’s disease, AIDS, Hodgkin’s disease, and other special needs such as rehabilitation care, represents specialized skill sets within nursing homes. Specialized units designed to treat these types of resident problems require additional skills or training among the staff, more extensive medical equipment, and even unique facility design features. Specialty bed intensity is a measure of capability differentiation because the types of equipment and staff skill requirements vary by specialty. Changes in the level of providing a particular type of specialty care bed provide a direct indicator of transfer learning from chain to component. OSCAR includes consistent information on the number of specialty-care beds for Alzheimer’s and rehabilitation. These are the two most common types of specialized bed services in nursing homes, with other types of specialty care beds representing less than 1% of all nursing home beds.

In parallel with specialty beds, the availability of specialty care services such as injections, physiotherapy and occupational therapy, ostomy, respiratory, suction, intravenous therapy, and tracheotomy each provide direct measures of nursing home capabilities. OSCAR includes consistent information on the availability of therapy (physical and occupational) and injection services. These services require trained nursing home staff and medical technology highly specific to these services.

We computed variables for the six capability measures for each component individually (the variable $c$, from equation 1). As dependent variables, we calculated one-period changes for each capability for each chain component ($\Delta c$). A period is the time between state inspections, which averages about one year. We then used the individual component measures to create mean value measures for each chain as a whole ($C$), omitting the focal facility from these calculations. In turn, we used the component and chain measures to compute chain-component similarity ($SCc$) as defined in equation (2). We measured capability variability ($V$) as the variance around the mean per-unit levels of each type of capability. We then measured distance ($D$) as the mean Euclidean distance from a focal unit to the other units in a chain during a given calendar year. We created the similarity interaction variables ($C \times SCc$, $c \times SCc$, $D \times SCc$, and $V \times SCc$) as multiplicative
interactions.

We estimated six specifications of our chain-to-component transfer model in equation (1), one based on each set of capability variables. Because we are interested in chain-to-component transfer learning, which, by definition, independent nursing homes cannot experience, our analyses include observations only for those nursing homes that were chain components at the start of each observation year.

As we noted above, transfer learning in new chain-component relationships formed through acquisitions is likely to be qualitatively different from transfer learning in established chain-component relationships. Therefore, we estimated the models separately for sub-samples of components in ongoing chain relationships that started before 1991, and new chain relationships in their first two inspection periods after acquisitions.

All equations include controls for time dependence (observation calendar year), chain size (units), and ‘cross-effects’ for all five non-focal chain and component capabilities (i.e., $C_{\text{nonfocal}}$ and $c_{\text{nonfocal}}$) to account for any complementarity or substitution interactions among capabilities. The “post-acquisition” equations also control for time since the acquisition (number of inspection periods, where each inspection period is about a year). We use conventional least-squares regression to estimate parameters in the model for each of the six capabilities.

Results

Tables 1 and 2 present the model coefficients, with Table 1 presenting the results for post-acquisition cases (within two periods of acquisition) and Table 2 presenting the results for ongoing units. In the tables, a positive coefficient means a greater increase in component capabilities from time 0 to time 1 (i.e., between inspection periods), while a negative coefficient means a greater decrease in component capabilities.

Insert Tables 1 and 2 about here.

Table 1 presents the post-acquisition transfer learning results. The models provide moderate overall explanatory power for four of the capability analyses (therapy, injection, rehab, staffing), with R-square statistics ranging from 0.26 to 0.54. Two models have little overall explanatory power, with R-squares from 0.01 (total beds) to 0.07 (Alzheimers beds), but do demonstrate significant impact of several effects. The particularly weak explanatory power of the total beds model likely results from restricted variation in the change in beds, owing to state regulations that make it difficult to add or subtract beds at a home.

The results in Table 1 present moderate support for the overall post-acquisition model, with 54% of the coefficients being significant in the expected direction. There is a strong fit for the capability level predictions (100% for both chain and component capability levels. There is also reasonable fit for the post-acquisition moderating effect of similarity on capability levels (83% of similarity x component capability coefficients, 67% of similarity x chain capability coefficients; in both cases, the other coefficients have the expected signs although at insignificant levels). By contrast, the distance (0%), distance x similarity (17%), and variability x similarity (33%) interactions.
influences have little of the expected impact. These weak influence are consistent, though, with the argument that capability levels may have the greatest immediate impact following acquisitions, with other effects tending to show up only over time.

It is notable that the main effects of similarity ($S_{Cc}$) is about as likely to be positive as it is to have the expected negative influence on transfer learning. Similarity is more likely to have an unexpected positive influence on post-acquisition transfer learning (only 2 of 6, 33% similarity coefficients are negative; by contrast 4 of 6 coefficients are positive, with two reaching significance). Therefore, the results suggest that chain-component similarity influences the rate of transfer learning most systematically as a moderator of chain and component capability level effects, rather than as a main effect.

Table 2 reports the results for ongoing periods. The overall explanatory of these six models is similar to that of the post-acquisition models, with reasonable fit for four cases and weak fit for the same two cases as in Table 1 (Alzheimers beds, total beds)

The results in Table 2 provide striking support for most aspects of the model in equation (1), with 73% of the coefficients taking significant expected signs. The capability level ($c=100\%, C=83\%$) effects again tend to have the expected impact, with only chain capabilities having no influence on change in total beds. Similarity continues to have a moderating effect on most capability level measures ($c \times S=83\%, C \times S=67\%$). In addition, the expected effects of distance ($D; 83\%$), similarity ($S; 50\%$), similarity x distance ($D \times S; 67\%$), and similarity x variability ($V \times S; 50\%$) become more common in Table 2 than they were in the post-acquisition analyses of Table 1.

In the both the post-acquisition and the ongoing periods analyses, the main sources of unexpected results are in the total beds models. This outcome likely stems from the little variability in the total beds measure, as we discussed above.

Beyond our simple comparison of the direction of coefficient estimates, which generally supports the theoretical model, the relative magnitudes of the model parameters vary in several notable ways. Some parameters vary systematically in all equations. For example, the main effect coefficients for component capabilities ($c$) typically have larger magnitude than the main effect coefficients for chain capabilities ($C$), suggesting that component capability levels generally play a larger role in determining the rate of chain-to-component transfer learning in our sample. The exception to this pattern is the equation for component total beds in the post-acquisitions model, again perhaps because of the greater time and capital cost needed to change a nursing home’s size.

Other parameter estimates vary in magnitude across models. For example, in the models for newly acquired components, the main versus interaction effect coefficient magnitudes for chain therapy services intensity are $C > (C \times S_{Cc})$, while for injection services equation the relative magnitudes are the opposite, $C < (C \times S_{Cc})$. When the parameter for $C$ (or $c$) is smaller than the similarity interaction term parameter, the transfer ‘constraining’ effect of similarity comes to dominate more rapidly than the ‘opportunity’ posed by main effects of either a chain’s high capability level (high $C$), or a component’s low level (low $c$). Thus, when the interaction term
dominates, the relationship will exhibit a greater ‘transfer inertia.’ Potentially, the differences in the findings for the specialty bed and specialty service capabilities may arise from differences in the ways in which these services are provided. State inspectors collecting data on the number of beds devoted to the care of individuals in rehabilitation or with Alzheimer’s disease do not specify what treatments and staff requirements are necessary to meet the needs of these residents. Subsequently, component facilities may vary dramatically in what they actually provide for these services. On the other hand, the provision of injection and therapy services implies much more specific treatments and staff requirements within a component facility.

These variations in parameter estimates affect the shape of the relationship between chain and component capabilities and the rate of transfer learning. However, the interaction terms in our models make it difficult to intuit the impact of these variations. Therefore, to aid in interpreting the findings, we illustrate graphically the static and dynamic implications of the estimates for several representative equations. Figures 1 to 4 illustrate the relationships.

The two panels in Figure 1 show predicted values for $\Delta c$ (increase or decrease in component capability) across all possible combinations of values of $C$ (chain capability) and $c$ (component capability) in post-acquisition cases. Although not all these combinations appear in our data, we present the entire range for illustrative purposes. Figure 1 is based on our results for changes in injection services (Panel A) and Alzheimer beds (Panel B). The figures hold distance and variability constant, in order to show the influence of differences in capability levels, which had the greatest impact on the post-acquisition cases.

The pattern of changes in capability level (the vertical axis) across combinations of chain and component capability levels in Figure 1 fits well with the predicted effects summarized in Table 1. In both panels, the rate of component capability change is closest to zero (i.e., the rate of change is lowest) along the ‘similarity diagonal.’ Rates are highest where chain and component capability differences are maximal, with large increases (decreases) in component capabilities associated with conditions of high (low) chain and low (high) component capabilities. Component capability change is only slightly greater along the ‘similarity diagonal,’ however, because the main effects for similarity ($SCc$) are weak in the two equations represented in the figure.

One difference in the injection services and Alzheimer beds patterns in Figure 1 is notable. The increase or decrease of Alzheimer beds is much more striking than the comparable slope of the injection services surface. This difference likely arises because it is relatively easy for units to change the use of beds to and from general purpose to Alzheimer’s residents, with staff requiring only moderate changes in skills. By contrast, changing the provision of injection services may require changing staff members and operating systems, making it more resistant to change than the Alzheimer’s case.

Figure 2 then illustrates patterns for ongoing units, focusing on injection services. We start by holding distance and variability constant (panel A of Figure 2), next vary distance (panel B), and then add variability (panel C). Note that panel A has a similar shape to the comparable surface.
in Figure 1, for post-acquisition cases. Adding distance, in panel B, then moderates the surface somewhat, where the main effect lies in dampening the capability decline in the lower left of the figure. That is, when distance is great, chains tend not to reduce the capabilities of their units, even if the chains are weak along the capability dimension. Adding variability, in panel C, then reverses the effect. We now find that the dampening effect in the lower left returns, while the capability enhancement effect in the upper right disappears. That is, chains with highly variable units tend to reduce the capabilities of the high capability units, especially at units that are far from the rest of the chain. Moreover, high variance chains tend not to add capabilities to lower capability distant units. The results in panel C speak to the multiple influences of capability levels, distance, and variability on capability change.

Insert Figure 2 about here.

The panels in Figures 3 and 4 next illustrate the dynamics of transfer learning over time for three initial values of \( C \) (0.2, 0.5 and 0.8) across all possible starting values for \( c \) (0 to 1). Given starting values for \( C \) and \( c \), we computed the estimated value of \( \Delta c \) and used this value to update \( c \) for the next period. We used parameter estimates from the model for newly formed relationships and changes in the intensity of injection services to generate this illustration. We simulated the predicted change in injection service intensity for ten periods into the future based on estimates for the first two periods after acquisitions to assess the implied long-term implications of the estimated initial transfer rate.

For the three panels in Figure 3, we fixed chain capability (\( C \)) at each of the three initial values, consistent with a pure one-way, chain-to-component transfer. Each curved line within Figure 2 represents the change in component capabilities over time, with one line for each starting point of component capabilities. As the figures show, over time (i.e., moving from left to right along each capability line within the panels), the model parameters move the transfer learning process toward equilibrium, reaching higher equilibrium component values for higher chain capabilities. Note that the change in component capabilities may involve transfer learning or unlearning (the capability lines ascend or descend), depending on whether the chain or component has greater initial capability level. Moreover, regardless of the starting value for component capability level, the equilibrium component capability level converges toward an identical level within each panel (i.e., in each panel, the right-hand side of the surface is becoming flat).

Insert Figure 3 about here.

For the panels in Figure 4, we assume two-way transfer learning, such that chains can learn from components as well as components from chains. We set the rate of component-to-chain transfer equal to 10\% (Panel A), 50\% (Panel B), and 90\% (Panel C) of the rate of estimated chain-to-component transfer. For purposes of comparison to the one-way learning patterns, we set the starting value for \( C \) to 0.5, as in Figure 3, panel b. Compared to Panel B of Figure 3 (in which component-to-chain learning is 0), the component capability lines in the panels in Figure 4 change less (ascend less via learning or descend less via unlearning), and capabilities transfer reaches equilibrium more quickly, the faster is the rate of component-to-chain transfer. In other words, high capability components lose fewer capabilities when there is two-way transfer learning than when there is only one-way transfer learning, while low capability components
gain fewer capabilities with two-way transfer learning. These differences between two-way and one-way learning occur because component-to-chain transfer leads to ongoing mutual adjustment of capabilities, with the speed of the adjustment increasing with the rate of component-to-chain transfer. Permitting component-to-chain transfer also causes the equilibrium component capability level to vary (the right hand sides of the panels remain sloped), such that the equilibrium now depends on both the starting value of component capability and the rate of component-to-chain transfer.

*Insert Figure 4 about here.*

**Discussion and Conclusion**

We developed and estimated a model of chain-to-component transfer learning applicable to both established chain-component relationships and new relationships formed through acquisitions. The model includes the effects of capability level, capability variability, capability similarity, and geographic distance. We found general support for the model with intriguing variation in the some effects of between transfer learning in post-acquisition and ongoing cases. In particular, transfer learning at newly acquired units tended to incur the greatest influence from capability levels, with moderating effects of similarity, while the effects of distance tended to emerge only over time.

Our attention to transfer learning processes within chains stems from the belief that how chains change and deploy their knowledge is key to their performance. A fundamental question, therefore, is what are the potential performance implications of the support for our model? Three observations are relevant here. First, the need to standardize leads chains to prefer to operate similar components and those chains that do standardize outperform those that do not (Baum, 1999; Ingram 1996; Ingram & Baum 1997). Second, capabilities may not transfer easily between chains and components that emphasize different capabilities. Forcing chain-to-component transfer of dissimilar capabilities could be worse than useless; it may be harmful if the chain’s managers are unable to differentiate capabilities that apply from routines that do not (Mitchell 1992; Greve 1999; Ingram & Baum 1997). Third, chains are more knowledgeable about the nature of competition they face in their current service specialties than they are about competition in other service areas in which they would be exposed to a different and unfamiliar set of competitors. Performance often declines when chains develop new specialized services.

Taken together, these three observations suggest that the greater the variety of capabilities that chains transfer to components in chain-to-component transfer learning, the poorer the performance of the components will be. Given this conclusion, the damping effects of the similarity × capability interactions (i.e., $C \times S_{C_c}$ and $c \times S_{C_c}$) on capability transfer is consistent with the notion of absorptive capacity, the standardization benefits at the core of the chain strategy, and, in turn, with enhancing performance.

As Figures 1 and 2 show, however, notwithstanding the moderating effects of similarity, component capabilities changed most when chain and component were most dissimilar. High-capability chains transferred knowledge and resources to low-capability components, while low-capability chains required high-capability components to switch to capabilities with which the
chain had more experience (but may not fit the component). Thus, although support for our transfer learning model is consistent with improved performance, it also points clearly to the boundary conditions within which those benefits occur, and emphasizes the greater importance of similarity for transfer learning within newly acquired components.

More broadly, our results have intriguing implications for our understanding of business dynamics, that is, how business organizations change over time in the face of constraints to change. Chains involve change at two levels of analysis, at the level of the component and at the level of the chain. At the component level, our model suggests that many changes occur through chain-to-component transfer learning. As an organizational form, the chain is an example of an integrated mode of organization, sharing features with fully integrated hierarchies. Like integrated hierarchies, chain ownership provides a desirable vehicle for organizational change in order to transfer capabilities that face substantial degrees of market failures.

In addition to component level change, chain-level changes can also take place, in two distinct ways. First, component-to-chain learning may occur, leading to a system-level evolution of capabilities, although we suspect that chain-to-component transfer dominates component-to-chain learning. Again, the partially integrated organizational chain form both protects and coordinates capability transfer. Second, and more common than component-to-chain transfer, chain-level change will take place as chains add and divest components. In this sense, chains are more like collaborative alliances than an integrated hierarchy. The existence of only limited points of interorganizational contact within a chain, as in most alliances, permits chains to adapt (at least partially) to changes in local markets by adding and divesting chain components as market demand and competitive conditions change. Such corporate activity will change both the structure of the transacting chain, in terms of its size, market distribution, and pattern of capabilities, and lead to subsequent change in the individual components that the chain buys and sells. Our model shows that acquisitions and divestitures often lead to substantial component level changes that align the acquired unit with the capabilities of its new owner.

Our results, then, suggest that a chain’s ability to undertake component and chain level change through capability transfer may be severely circumscribed by the performance-driven tendency toward standardization based on the chain’s prior capabilities. These path-dependency constraints increase the tendency for major component-level changes to occur through acquisition and divestiture of components with heterogeneous capabilities.

By extrapolating from our model, we can identify how chains influence several key dimensions of business dynamics. First, chains undertake component-level changes through chain-managed capability transfer to components and the process in and of itself constrains the scope of change. Second, chains may undertake system-level changes through internal diffusion of capabilities across components, in the face of constraints on change. Third, chains facilitate both component- and system-level changes by acquiring and divesting components. Such corporate recombination helps overcome some of the system-level limits on change.

The findings extend and reinforce two growing research streams. First, is the stream of research that characterizes multiunit chains as ‘interorganizational learning communities’ (Darr et al. 1995; Greve 1999; Ingram & Baum 1997, 2001). In addition to supporting this characterization,
our study also moves this stream forward by focusing on changes in the underlying capabilities themselves, rather than studying changes in performance and simply inferring the prior occurrence of changed capabilities. We also contribute to research that characterizes acquisitions as basic to processes of organizational change, reconfiguration, and/or capability and resource redeployment (Capron 1999; Capron et al. 1998; Capron & Mitchell 1998; Karim & Mitchell 2000). Given the prevalence of the chain organizational form across service industries, and the central roles of acquisitions and knowledge transfer in chain growth and expansion, future research combining ideas on multiunit chains, acquisitions, and transfer learning could provide great new insight into the transformation of the economy.
References


Ingram, P. 1996. Organizational form as a solution to the problem of credible commitment: The


Table 1. Post-Acquisition Periods: Estimates for Equations Predicting Change in Component Capabilities, $\Delta c$ (7260 component-year observations).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>H</th>
<th>Therapy</th>
<th>Injection</th>
<th>Rehab</th>
<th>Alzheimer</th>
<th>Staffing</th>
<th>Total Beds</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>-</td>
<td>-0.510 ***</td>
<td>-0.894 ***</td>
<td>-0.514 ***</td>
<td>-0.220 ***</td>
<td>-0.882 ***</td>
<td>-0.010 *</td>
<td>100%</td>
</tr>
<tr>
<td>$C$</td>
<td>+</td>
<td>.225 ***</td>
<td>.343 ***</td>
<td>.173 ***</td>
<td>.196 ***</td>
<td>.016</td>
<td>.035 **</td>
<td>100%</td>
</tr>
<tr>
<td>$D$</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>.007 *</td>
<td>-0.02</td>
<td>0%</td>
</tr>
<tr>
<td>$V$</td>
<td>.317 ***</td>
<td>-.300 **</td>
<td>.016 *</td>
<td>-.233 **</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S$</td>
<td>-</td>
<td>-.017+</td>
<td>.007</td>
<td>.006+</td>
<td>0.002</td>
<td>-.425 ***</td>
<td>5.331 **</td>
<td>33%</td>
</tr>
<tr>
<td>$c \times S$</td>
<td>+</td>
<td>.115 *</td>
<td>.539 ***</td>
<td>.398 **</td>
<td>.727 ***</td>
<td>.456 ***</td>
<td>.004</td>
<td>83%</td>
</tr>
<tr>
<td>$C \times S$</td>
<td>-</td>
<td>-.004</td>
<td>-.505 ***</td>
<td>-.138</td>
<td>-.961 ***</td>
<td>-.209 ***</td>
<td>-.052 **</td>
<td>67%</td>
</tr>
<tr>
<td>$D \times S$</td>
<td>+</td>
<td>.002 **</td>
<td>0</td>
<td>0</td>
<td>-.006</td>
<td>0.007</td>
<td>17%</td>
<td></td>
</tr>
<tr>
<td>$V \times S$</td>
<td>-</td>
<td>-.421 **</td>
<td>.388 *</td>
<td>-.060 **</td>
<td>0.093</td>
<td>0</td>
<td>0</td>
<td>33%</td>
</tr>
<tr>
<td>Total predicted</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>54%</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.26</td>
<td>0.40</td>
<td>0.27</td>
<td>0.07</td>
<td>0.54</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DW</td>
<td>2.08</td>
<td>2.08</td>
<td>1.99</td>
<td>2.1</td>
<td>1.95</td>
<td>2.02</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:
- $* p < .05, ** p<.01, *** p<.001$
- Shaded cells are predicted effects
- D-W = Durbin-Watson statistic

All equations include controls for time dependence, chain size (units), time since acquisition, and cross-effects for the five non-focal chain and component capabilities.
Table 2. Ongoing Periods: Estimates for Equations Predicting Change in Component Capabilities, $\Delta c$ (30,201 component-year observations).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>H Therapy</th>
<th>Injection</th>
<th>Rehab</th>
<th>Alzheimer</th>
<th>Staffing</th>
<th>Total Beds</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>-.552***</td>
<td>.889***</td>
<td>-.594***</td>
<td>-.209***</td>
<td>.868***</td>
<td>-.012**</td>
<td>100%</td>
</tr>
<tr>
<td>$C$</td>
<td>.307***</td>
<td>.270***</td>
<td>.112***</td>
<td>.216***</td>
<td>.014**</td>
<td>-.006</td>
<td>83%</td>
</tr>
<tr>
<td>$D$</td>
<td>.001***</td>
<td>0</td>
<td>.0002**</td>
<td>.0002*</td>
<td>.021***</td>
<td>.033*</td>
<td>83%</td>
</tr>
<tr>
<td>$V$</td>
<td>.358***</td>
<td>.244***</td>
<td>-.011**</td>
<td>-.228***</td>
<td>-.0001*</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>$S$</td>
<td>-.011*</td>
<td>-.008+</td>
<td>0.001</td>
<td>0.004**</td>
<td>-.472***</td>
<td>-1.784*</td>
<td>50%</td>
</tr>
<tr>
<td>$c \times S$</td>
<td>.042+</td>
<td>.520***</td>
<td>.404***</td>
<td>.198***</td>
<td>.525***</td>
<td>-.001</td>
<td>83%</td>
</tr>
<tr>
<td>$C \times S$</td>
<td>-.015</td>
<td>-.311***</td>
<td>-.167+</td>
<td>-.281***</td>
<td>-.176***</td>
<td>.023*</td>
<td>67%</td>
</tr>
<tr>
<td>$D \times S$</td>
<td>0</td>
<td>0</td>
<td>-.0003**</td>
<td>-.0002+</td>
<td>-.016***</td>
<td>-.066*</td>
<td>67%</td>
</tr>
<tr>
<td>$V \times S$</td>
<td>-.531***</td>
<td>-.583***</td>
<td>-.080***</td>
<td>-.02</td>
<td>.0004**</td>
<td>0</td>
<td>50%</td>
</tr>
</tbody>
</table>

Total predicted 73%

R$^2$ 0.27 0.38 0.23 0.07 0.49 0.01

DW 2.13 1.98 1.93 2.08 1.87 2.04

Notes:
- * $p < .05$, ** $p < .01$, *** $p < .001$
- Shaded cells are predicted effects
- D-W = Durbin-Watson statistic
- All equations include controls for time dependence, chain size (units), and cross-effects for the five non-focal chain and component capabilities.
Figure 1. Post-Acquisition Units: Effect of Chain and Component Capabilities on Change in Injection Services and Alzheimer Bed Intensity

A. Injection Services (V=0, D=0)

B. Alzheimer's Beds (V=0, D=0)
Figure 2. Ongoing Units: Effect of Chain and Component Capabilities on Change in Injection Services Intensity

A. Injection Services ($V=0, D=0$)

B. Injection Services ($V=0; D=20$)

C. Injection Services ($V=0.2; D=20$)
Figure 3. Estimated Change Over Time in Component Level of Injection Specialty Services Intensity Following Acquisition

Panel A: (Chain Capability Level = .2)

Panel B: (Chain Capability Level = .5)

Panel C: (Chain Capability Level = .8)
Figure 4. Estimated Change Over Time in Component Injection Specialty Services Intensity Following Acquisition (with 2-way transfer).
Endnotes

1 We focus on the tendency for components to converge toward their chain’s capabilities, although further development of the argument could usefully consider cases in which transfer learning from components to chains causes changes in chain’s capabilities. We undertake preliminary examination of such two-way learning following the analysis section.

2 The “information paradox” arises because it is difficult for a potential buyer to determine the value of a piece of knowledge unless a seller discloses the knowledge to the buyer. Once the information is disclosed, however, the buyer no longer needs to purchase the knowledge. This problem creates incentives to internalize ownership, so that the creator and user of a piece of knowledge exist within the same ownership structure.

3 Approximately 5% of nursing homes reported belonging to a chain and provided a corporate name but no other facilities were found to belong to that corporation. We did not consider these nursing homes, which are sometimes part of a health provider system that includes facilities other than nursing homes (e.g., assisted living or hospital beds), as components of chains.

4 Empirically, effects of non-focal capabilities measures on transfer learning of focal capabilities tended to be weak. The limited effect likely occurs because cross-effects would arise only for specialties that share related underlying operating routines. In practice, though, the capabilities we measure tend to be distinct from each other. Alzheimer’s disease treatment, for instance, differs substantially from rehabilitation and therapy services, which also differ greatly from injection services. Hence, one would expect few positive or negative complementarities across those groupings other, perhaps, from limited substitution effects.

5 Although pooling repeated observations on the same organizations can violate the assumption of independence from observation to observation and result in the model’s residuals being autocorrelated, because the number of organizations is high relative to observations in our sample this should not pose too severe an estimation problem. Durbin-Watson statistics reported with the results are all close to 2.0, suggesting little autocorrelation in the data.