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

ABSTRACT

Multiunit chains proliferated rapidly during the last century and now dominate much of the service sector landscape. Fundamental to the success of the multiunit chains is the transfer of capabilities from the chains to their components. We develop and estimate an empirical model of chain-to-component transfer learning in which several factors have direct and interactive effects on transfer learning across the ongoing and newly acquired components of a chain. These factors include the levels, variability, and similarity of a chain and its components’ capabilities, as well as geographic distance. In contrast with past research that typically inferred effects of transfer learning on components’ from changes in performance, we operationalize transfer learning by measuring changes in six structural and service characteristics that lie much closer to the underlying capabilities themselves. We test the model using data on changes in capabilities at the facilities of all federally registered nursing home chains operating in the U.S. between 1991 and 1997.

This study explores how the capabilities of multiunit chains and their components – both established and newly acquired – affect transfer learning across a chain’s components. Multiunit chains are a conspicuous feature of the modern economy. Chains are collections of components that produce similar goods and services in several markets and link together as larger ‘superorganizations’ that make considerable effort to standardize and coordinate the behavior of their components (Ingram & Baum 1997). Chains proliferated during the 20th century and are now coming to dominate every service industry – from retailing to food and travel accommodations to healthcare and human services – that has direct contact between customer and organization (Bradach, 1997; Greve & Baum 2001).

Transfer learning is fundamental to the dynamics of chain organizations (Argote & Ingram 2000). 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). For chains, transfer learning influences the capabilities of their components and, in turn, their components’ performance. Chains’ emphasize replicating and coordinating a standard set of routines or capabilities in multiple locations and the emphasis on replication points to the great importance of transfer learning across a chain’s components.

Transfer learning affects both a chain’s established units and its newly acquired components. Among a chain’s established 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. Research has shown that ownership relationships such as chain membership facilitate transfer learning greatly, by providing the common language, interaction opportunities, and motivation for the extensive sharing of experience (e.g., Baum & Ingram 1998; Darr et al. 1995; Ingram & Baum 1997). These studies, however, typically infer changes in capabilities from evidence of the effects of one organization’s experience on changes in the performance of another. In
contrast, we focus here on service changes that are close to the underlying capabilities themselves. We develop a model of chain-to-component transfer learning that predicts changes in component capabilities as a function of (1) the absolute and relative capabilities of a chain and its components, (2) the variability of capabilities among a chain’s components, and (3) the geographic distance among a chain’s components.

Our empirical study examines transfer learning in the almost 3,000 nursing home chains operating in the U.S. during the 1991-1997 period. Our study of transfer learning within multiunit chains contributes directly to our understanding of organizational change throughout the economy. In addition, changes in nursing home practices have substantial social implications (Banaszak-Holl et al. 1996). The U.S. nursing home industry is known to have significant quality problems and policy-makers continue to search for ways to improve practices across facilities (Institute of Medicine 1986). In the next section, we introduce the concepts of capabilities and transfer learning in more detail, and explain the significance of transfer learning across a chain’s components. After introducing these core ideas, we develop a model of chain-to-component transfer learning, and then present the study design, empirical analysis, findings and implications.

CAPABILITIES, TRANSFER LEARNING AND MULTIUNIT CHAINS

At its most general level, the term capabilities refers to 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, & Shuen 1997). We interpret the notion of capabilities as being synonymous with organizational routines, which are repeated patterns of actions that span multiple actors (Nelson & Winter 1982). In this study, we operationalize capabilities in terms of the types and level of services 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 noted above, occurs when one organization causes a change in the capabilities of another. Transfer learning requires that a ‘sending’ organization stimulate learning in a ‘receiving’ organization. Previous studies provide both quantitative and qualitative evidence that transfer learning affects a receiver’s performance (e.g., production cost) and is a function of a sender’s performance (e.g., total units produced in past periods), other sender characteristics including innovativeness, and recipient characteristics such as size. Beyond
linking sender and receiver characteristics to the receiver’s subsequent performance, recent research has emphasized the importance of the type of relationship between organizations for transfer learning. Studies show that ownership relationships between organizations greatly facilitate transfer learning, with commonly-owned organizations that belong to multiunit systems benefiting more from each other’s experience than independently owned organizations. Darr et al. (1995), for example, found that common ownership of pizza stores by a single franchisee improved their productivity, an improvement they attributed to transfer learning among the commonly owned components. 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. Relatedly, Karim and Mitchell (2000) found that acquisitive medical sector businesses added more new product lines than firms that did not acquire new businesses.

In parallel, the diffusion of innovations literature views shared ownership as a strong conduit for transfer learning that makes diffusion comparably rapid (e.g., Greve 1995, 1996), which is a special case of the general finding that diffusion follows social ties (Davis 1991; Davis & Greve 1997).

These results contrast with the previously dominant idea that knowledge can simply ‘spill over’ across the boundaries of organizations into the general environment where other firms can easily consume the knowledge, independent of any relationship to the knowledge provider. However, capabilities may not transfer easily between organizations in an ‘open market’ because firms experience well-known difficulties and costs measuring, valuing, protecting, and coordinating the use of the knowledge (Capron & Mitchell 1998). Knowledge may also suffer from the information paradox (Arrow 1962), making it 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 (Nonaka and Takeuchi 1995), 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 transfer learning 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.

Chains leverage their capabilities by replicating them in multiple locations within component units that provide similar services under common ownership (Ingram and Baum 1997). As a result, chains tend to standardize products and services, advertising, administration, operating procedures, equipment, and even buildings across components. In addition to generating scale economies and reducing operating costs, standardization raises consumers’ perceptions of reliability – the ability to repeat service at a given quality level – across a chain’s components (Ingram 1996). Standardization also increases accountability because a chain has a great incentive to monitor and pressure each of its components to maintain and enhance the chain’s standards. Poor quality service at any component can damage the entire chain’s reputation. In addition, reliability and accountability reduce consumer search and monitoring costs (Baum 1999).

Multiunit chains’ strategic emphasis on standardization and coordination points to the importance of transfer learning across their components. 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. 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 and social power incentives, neglecting the potential for capability development as chains transfer resources and knowledge to acquired components. 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 model in which several factors influence the ability, opportunity, and incentive for chain-to-component transfer learning to take place. The factors that we focus on include the level, variability, and similarity of capabilities, as well as the distance of a
component from the rest of the chain. We first present a conceptual framework, and then identify and measure levels of six types of capabilities for U.S. nursing home chains and their components.

The discussion motivates the following model of transfer learning from a chain to its components:

$$\Delta c = \beta_1 c - \beta_2 c \pm \beta_3 V_C \pm \beta_4 (C \times S_{Cc}) - \beta_5 (C \times S_{Cc}) - \beta_6 (V_C \times S_{Cc}) \pm \beta_7 (D_{Cc} \times S_{Cc})$$  \(1\)

In equation (1), \(C\) is the chain’s capability level, which we measure as the mean for a chain’s ongoing components, 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 ongoing components of a chain, and \(D_{Cc}\) is the geographic distance of the focal component from the rest of the chain. We define \(C\), \(S_{Cc}\), \(V_C\), and \(D_{Cc}\) in terms of ‘ongoing’ components – those the chain has operated for at least two years – to avoid confounding these variables with the characteristics of new components, which may be very different from the acquiring chain’s ongoing components before being incorporated into the chain’s strategy.

\(S_{Cc}\) is similarity between a chain and its component’s capability levels at time 0, defined as follows:

$$S_{Cc} = \frac{C}{c} \text{ if } C < c; \ S_{Cc} = \frac{c}{C} \text{ if } c < C; \ \text{and } 1 \text{ if } C = c = 0$$  \(2\)

\(S_{Cc}\) measures the degree to which a given component and its chain (represented as the mean of its ongoing components) engage in the same activity and the extent to which that activity accounts for a comparable proportion of their overall activities. We selected \(S_{Cc}\) as the operationalization of similarity because it is conceptually appropriate, with its focus on the degree to which the chain and component engage in a common set of activities. This operationalization has important advantages over several alternatives. A simple difference score (i.e., \(C-c\)) is unweighted, with a value of zero indicating similarity, and asymmetric, with increasingly positive or negative values indicating greater dissimilarity depending on whether the chain or the component has higher (lower) levels of a capability. An unconditional ratio score (i.e., \(C/c\)) is exponential, sensitive to outliers, and unbounded, ranging from zero to infinity, with a value of 1 would indicate similarity whereas zero and infinity would both indicate maximally dissimilar. \(S_{Cc}\), in contrast, is weighted and bounded, ranging between zero (dissimilar) and 1 (identical), is symmetric, with equivalent scores whether the chain or the component has higher
(lower) levels of a capability, and is approximately linear and insensitive to outliers.

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 \(\beta_9\) are model coefficients estimating the magnitude of each effect, and the arithmetic signs of the parameters indicate our core predictions.

**Capability level**

We start by considering the level of capabilities both across the chain and within the focal component. 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 for transfer learning to that particular component, while components with lower capability levels 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 wants to decrease the component’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 facilitates transfer \((\beta_5 < 0)\). Subsequently, any benefits of similarity arise as a conditioning effect on the influence of capability level.

Our arguments concerning similarity build on discussions in the organizational learning, strategic management and organizational ecology literatures. These three literatures 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) and that operate in markets similar to those of the acquirer. A parallel argument
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). Taken together, these views suggest that chain-component differences will make transfer learning to components less likely both because the chains have fewer incentives to standardize currently different activities and, because the chains and components lack the experience they would need 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 to be derived from learning.

By contrast, dissimilarity may enhance transfer learning. The dissimilarity case in which chain capabilities are high and component capabilities are low is the most obvious in this regard. 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 more ambiguous, situation occurs when chain capabilities are low and component capabilities are high. Our earlier argument concerning capability levels suggests that chain-to-component 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 combination 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 might 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 of 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 Capability similarity interaction**

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 offset the limits on transfer learning that high component capabilities impose. 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 Capability variability x similarity interaction**

We continue by considering the variability in capabilities across a chain’s components, addressing the main effect of capability variation within a chain, as well as its interaction with similarity. The argument here starts by restating the assumption that chains emphasize standardization and, therefore, will 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 components, it may add to low capability components and/or subtract from high capability components.

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

**Geographic distance and distance x similarity interaction**

We conclude by considering the effect of geographic distance, that is, the distance of a focal component from the other components of a chain. Two views arise with respect to the effect of distance on transfer learning, a learning view and a governance view. The learning view suggests that the closer a component 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 with the learning view, suggests that distance creates governance problems, and increases the need for coordination, monitoring, and control of a component’s activities (Brickley & Dark 1987). Distance links with the types of mechanisms through which learning occurs. Two broad classes of mechanisms – hands on and hands off – facilitate transfer learning within multiunit chains. Hands on mechanisms involve personal interaction among people within a component and people from chain headquarters or other chain components (Darr et al. 1995). Hands on learning brings together members of the chain for either task-oriented or social purposes, thereby increasing the opportunity and motivation for
transfer of capabilities and the ability of components to successfully apply capabilities transferred from other parts of the chain. In contrast, hands off governance mechanisms operate without personal contact and may include such mechanisms as establishing common systems and training requirements among components (e.g., service protocols, information and reporting systems), use of common equipment and facilities designs, managerial fiat in which the chain requires a component to do particular activities, or vicarious imitation by components. With hands off learning, chain headquarters has less opportunity to control component activity and components receive information that is less rich on how to actually implement changes. Such distance-induced problems raise the incentive to use standardization to facilitate governance, because standardized components are more straightforward to observe, measure, and control from a distance. In turn, the standardization incentive raises the incentive for transfer learning ($\beta_i > 0$).

A contingency view builds on both learning and governance arguments. In the contingency view, there will be a tendency to shift from learning to governance over time, as a component becomes more absorbed within a chain and its operations mirror the desired standard model. This difference should produce differences in the effect of distance on chain-to-component transfer learning for recently acquired components of a chain and ongoing components. In particular, recently acquired components may be most sensitive to the effects of distance on learning. Facilitated by their proximity, newly acquired components that are close to the rest of the chain will likely experience the greatest changes in capabilities soon after being acquired. Over time, however, governance effects may become more pronounced, resulting in more distant established components experiencing the greatest transfer learning aimed at integrating them further into the chain.

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

**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 dampen the negative effect of component capabilities and the positive effect of chain capabilities. We further expect little transfer learning at components 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 components while a governance view may apply more to established components of a chain.

In turn, we expect substantial differences among recently acquired components of a chain and more established components. 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 components 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 components will be most strongly affected by capability levels and similarity, while the effects of distance and variability will be more significant for ongoing components of a chain.

A desirable property of the model that we advance here is its realistic representation of knowledge transfer as a self-damping process. According to our predictions, 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 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 use a longitudinal data set linking yearly files of the federal OSCAR (*On-line Survey Certification and Reporting System*) data. The OSCAR files include information from state-based inspections of all Medicare/Medicaid certified nursing homes operating in the continental U.S. from 1991 to 1997. OSCAR includes facility-level information on nursing home structure (e.g., size, staffing, services offered), resident case mix (e.g., the proportion of residents requiring assistance with
Activities of Daily Living and who are incontinent), system membership (e.g., multiunit organization affiliation and name), and counts of health and non-health related deficiencies reported during state inspections. Inspections are mandated on an annual basis, although the time between inspections can be two years or more (the mean inspection period in our data is 374 days). In total, the data include over 105,000 records, covering nearly 20,000 unique nursing homes. We also use the Area Resource File, as well as data available through the website maintained by the U.S. Health Care Financing Administration (HCFA), including the annual State Data Books on Long Term Care Programs and Market Characteristics produced for HCFA (Harrington, et al. 1999), and other sources to obtain control variables for market and state characteristics.

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 through line-by-line inspection of the records and 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 2,225 unique nursing home chains in the data. Acquisitions – approximately 4,000 in number – were coded as a change in ownership status of a nursing home between inspections. The proportion of chain nursing homes increased from 40% to 48% during 1991-1997, although most chains tend to be quite small with roughly 87% operating 10 or fewer homes. Thus, extensive chaining of nursing homes exists, but it is still primarily a small-chain phenomenon.

**Independent Variables**

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

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, and operating, management and strategic capabilities are expected to vary with size (e.g., Aldrich 1979; Hannan & Freeman 1977). As in traditional organizational studies, size can be used to measure differences in structural capabilities, albeit as an indirect and occasionally problematic measure (Kimberly 1976).

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. These services differ significantly from more standard nursing care services and require additional skills or training among the staff, more extensive medical equipment, and even unique facility design features. The availability of specialty beds for nursing home residents is important because these beds represent service innovations driven by changing regulations, technology, and policy concerning long-term care (Banaszak-Holl, et al. 1996). Specialty bed intensity is a measure of capability differentiation because the types of equipment and staff skill requirements vary by specialty. These are the two most common types of specialized beds available in nursing homes, with other types of specialty care beds representing less than 1% of all nursing home beds. Changes in the level of providing a particular type of specialty care bed provide a direct indicator of chain-to-component transfer learning. OSCAR includes consistent information on the number of specialty-care beds for Alzheimer’s and rehabilitation.

In parallel with specialty beds, the availability of specialty care services such as
injections, physiotherapy and occupational therapy, ostomy, respiratory therapy, suction, intravenous therapy, and tracheotomy each provide direct measures of nursing home capabilities, as they are directly related to the routines used by nursing home staff and the medical technology available within a home. OSCAR includes consistent information on the availability of physical and occupational therapy and injection services---some of the most common specialty services within the nursing home industry.

We computed six capability measures for each component individually (for each capability, the variable $c$ in 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 and any components acquired within the last two inspection periods from these calculations. In turn, we used the component and chain measures to compute chain-component similarity ($S_{cc}$) as defined in equation (2). We measured capability variability ($V_{c}$) as the variance around the mean level of each type of capability at a chain’s ongoing components (i.e., those acquired at least two years earlier). We then measured distance ($D_{cc}$) as the mean Euclidean distance from a focal component to the other ongoing components in a chain during a given calendar year. We created the similarity interaction variables ($C \times S_{cc} , c \times S_{cc} , D_{cc} \times S_{cc} , V_{c} \times S_{cc}$) as multiplicative interactions. We excluded components of the chain that had been acquired during the last two inspection periods from calculations of $C, S_{cc}, V_{c},$ and $D_{cc}$ to avoid confounding these measures with the characteristics of new components, which may have been different from the acquiring chain’s ongoing components prior to acquisition.

Estimation

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. Further, as we noted above, transfer learning in new chain-component relationships formed through acquisitions is likely to differ qualitatively from transfer learning in established chain-component relationships. Therefore, we estimated the
models separately for subsamples of components in ongoing chain relationships starting before 1991, and new chain relationships in their first two inspection periods after acquisitions.

For analysis, we pooled inspections across periods and estimated a single model on the pooled cross-sections using time series regression models (time between inspections is a control variable in the model). Each component is represented in the sample for the years in which they were chain members. Pooling repeated observations on the same organizations is likely to violate the assumption of independence from observation to observation and result in the model's residuals being autocorrelated. First-order autocorrelation occurs when the disturbances in one time period are correlated with those in the previous time period, resulting in incorrect variance estimates. This renders OLS estimates inefficient. Therefore, we estimated random-effects GLS models, which correct for autocorrelation of disturbances due to constant firm-specific effects (Kennedy 1992).

One further complication is the closure of some chain components during the study period (less than 10% of the facilities in the study). To the extent that such components differ systematically from those that remain in the sample, this can result in an estimation problem commonly referred to as sample selection bias due to attrition. This potential sample selection occurs because the disappearing facilities leave the sample without their final performance being represented in the data. To check for this possible bias, in a supplementary analysis we estimated models that correct for possible sample selection bias due to attrition using Heckman’s (1979) two-stage-least-squares procedure. Our main findings did not change substantively in those analyses.

**Control Variables**

In addition to the variables that constitute our theoretical model of chain-to-component transfer learning, all equations include multiple time-varying controls for other capabilities, time, chain, market and state characteristics. Appendix A provides descriptive statistics for all theoretical and control variables.

Two sets of variables examined other capability effects. $C_{new}$, which we computed in the same manner as $C$ in the theoretical model, but based on components a chain has not yet operated through two inspection periods, measures how the capabilities of recently acquired units affect transfer learning in the chain. We also measured ‘cross-effects’ for all five non-focal chain and component capabilities (i.e., $C_{nonfocal}$ and $c_{nonfocal}$) to account for any complementarity
or substitution interactions among capabilities.  

Two sets of variables control for time. Calendar year addresses basic time dependence for each observation. The “post-acquisition” equations also control for the number of inspection periods since acquisition.

We defined three other chain characteristics. Chain size recorded the number of homes each chain operated during a given year. Cumulative acquisitions recorded the number of acquisitions a chain made before the focal year, to control for possible effects of cumulative acquisition experience on transfer learning (we expect this variable to have its strongest effect post-acquisition). Chain greater focus provided a measure of chain specialization, denoting cases in which a chain’s components, on average, offered fewer services than the focal component.

We defined four market controls at the county level. Beds per capita recorded the total nursing home beds per county population. Market concentration denoted the Hirschman-Herfindahl Index (HHI = sum of squared shares of beds of all nursing homes in the county). Number of nursing homes recorded the number of facilities in each county. Rural denoted a nine-value code for the urban/rural status of the county (using the rural/urban continuum in the Area Resource File), because operating requirements can differ greatly in rural and urban areas.

We defined six controls at the state level. These included the mean Medicaid reimbursement rate across this period, the mean Medicaid expenditures per Medicaid population, the mean Medicare expenditures per Medicare population, and the State population over 65 years of age. We also noted whether the state had a Certificate of Need requirement and whether the state had imposed a Construction moratorium that limited new nursing home construction (Harrington et al. 1999). Because the Medicare/Medicaid programs are key payers for nursing home care and other state regulation has significantly affected nursing home chains’ ability to build new beds in markets, these factors may have significant effects on a chain’s impetus for transfer learning, particularly post-acquisition.

RESULTS

Tables 1 and 2 present the random-effects GLS model coefficients, with Table 1 presenting the results for post-acquisition cases (in their first two inspection periods after acquisitions) and Table 2 presenting the results for ongoing components, operated by the chain for at least two years. 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. Appendices B1 and B2 report control variable estimates for all models that Tables 1 and 2 summarize.

*Insert Tables 1 and 2 about here*

Table 1 presents the post-acquisition transfer learning results. The model for each capability improves significantly ($p < .05$ or greater) over a baseline model including only the control variables.

The results in Table 1 present moderate support for the overall post-acquisition model, with 62% of the coefficients significant in the expected direction. There is a strong fit for the component capability ($c$) prediction, with all coefficients in the expected direction (100%); but support is weaker for the chain capability ($C$) prediction, which is supported for half the capabilities examined (50%). Support for the main effect of similarity ($S$) is weaker still, supported for only two capabilities (33%). There is, however, a good fit for the predicted moderating effect of similarity on both component and chain capability levels (83% for both $C \times S_{Cc}$ and $c \times S_{Cc}$). The distance ($D_{Cc}$) and distance x similarity ($D_{Cc} \times S_{Cc}$) predictions receive moderate support with coefficients consistent with the predictions for half of the main effects of distance (50%) and two-thirds of the distance x similarity interaction effects (67%). With only two capabilities supporting the predicted variability x similarity ($V_{C} \times S_{Cc}$) interaction (33%), chain capability variability has little of its expected impact on post-acquisition chain-to-component transfer learning. The weak-to-moderate influences of distance and variability in Table 1, coupled with the stronger effects of component capabilities and the capabilities x similarity interactions are consistent, though, with the idea that component and chain capability levels have their greatest impact immediately following acquisitions, with other effects tending to show up only over time, as we show in the analysis of ongoing components below.

It is notable that the main effects of similarity ($S_{Cc}$) are equivocal, being nearly as likely to be positive as to have the expected negative influence on transfer learning. These results suggest that chain-component similarity influences post-acquisition 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 components. Again, the model for each capability improves significantly ($p < .05$ or greater) over a baseline model including only the control variables.
The results in Table 2 provide striking support for most aspects of the chain-to-ongoing-component transfer-learning model in equation (1), with 83% of the coefficients significant in the expected direction. Component capability level \( c \) effects again are fully supported (100%). In addition, for ongoing components, chain capability level \( C \) also has the expected impact in all models (100%). The main effect of similarity \( S \) is also much more systematic, and in the predicted direction for five of six capabilities (83%). Similarity also continues to have a robust moderating effect, with coefficients for both \( C \times S_{Cc} \) and \( c \times S_{Cc} \) significant in the predicted direction for all capabilities (100%). Coefficients for the similarity x variability \( (V_{C} \times S_{Cc}) \) interaction also yield stronger support for the predicted negative effect than in the post-acquisition analyses, with supportive estimates in four models (67%) for ongoing components (two were supportive in post-acquisition models). Distance \( D \) is significant for four capabilities (67%) and its interaction with similarity \( (D_{Cc} \times S_{Cc}) \) is significant in the expected direction for half the capabilities (50%).

Beyond simple comparison of the direction of coefficient estimates in Tables 1 and 2, which generally support the theoretical model, particularly for ongoing components, the relative magnitudes of the estimated 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 in the equation for changes in size of ongoing chain components, perhaps owing to the greater time and capital cost needed to change a nursing home’s size.

Additionally, in all models for both post-acquisition and ongoing components, the relative magnitudes for chain capability level and its interaction with similarity are consistent, with \( C < (C \times S_{Cc}) \). Although this is also true for four types of component capabilities (i.e., \( c < (c \times S_{Cc}) \)), the opposite is true for both post-acquisition and ongoing cases in the other two cases (therapy and injection specialty services), with \( c > (c \times S_{Cc}) \). When the parameter for \( C \) (or \( c \)) is smaller than that for the interaction between capability level and similarity, the ‘constraining’ effect of similarity comes to dominate more rapidly than the ‘opportunity’ 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 capabilities that a facility requires to provide either therapy or injection services may explain why chains experience more "transfer inertia" for these services. To some extent, nursing homes must interpret what capabilities go into providing a particular type of specialty service. While all services will require a combination of tacit knowledge and clearly defined medical technology, the extent of tacit knowledge is far greater for less medically intensive services, such as rehabilitative or Alzheimer's care. Chains may find that they can acquire some knowledge of more medically intensive services through general continuing medical education courses. Hence, they may invest less transfer learning in these services. As a result, components may vary dramatically in what they provide for more ambiguous services, while the provision of injection and therapy implies much more specific treatments and staff requirements within a component facility. Thus, the differences in the effects of similarity for specialty services may lie in the nature of the capabilities that facilities are learning or unlearning, where injection and therapy capabilities may be less likely to and slower in transfer learning than rehabilitative or Alzheimer's care.

These variations in parameter estimates affect the shape of the relationship between chain and component capabilities and the rate of transfer learning. However, the multiple interaction terms in the chain-to-component transfer-learning model make it difficult to grasp the intuitive 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. We present the entire range for illustrative purposes, although not all these combinations appear in our data. 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.

*Insert Figure 1 about here*

The pattern of changes in capability level (the vertical axis) across combinations of chain and component capability levels in Figure 1 illustrate several of the predicted transfer-learning
effects. In both panels, the rate of component capability change is closest to zero (i.e., the level of change is lowest) along the ‘similarity diagonal,’ which runs from the front to back corner of the two panels in the figure. Change is greatest 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 (the left and right corners of the panels in Figure 1). Component capability change is only somewhat greater along the ‘similarity diagonal,’ however, because the main effects for similarity ($S_{C_c}$) are not significant in the two equations represented in the figure.

One difference in the injection services and Alzheimer beds patterns in Figure 1 is notable. The effect of component and chain capabilities on changes in component provision is much stronger for changes in Alzheimer beds than for changes in the availability of injection services, while the opposite is the case for the decrease, with injection services steeper. Empirically, this difference reflects the differences of the relative magnitudes of the coefficients for component and chain capability levels, and their interactions with similarity. Conceptually, this difference likely arises because it is relatively easy for components 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 a more difficult capability to add, but relatively easy to cease.

Figure 2 illustrates patterns for ongoing components, focusing on therapy services intensity. We focus on therapy services because the estimates for this capability demonstrate the predictions in Equation 1 of the theoretical model. We start by holding distance and variability constant at a value of zero (Panel A of Figure 2), and in the next figure we set variability at .20 (panel B), then we vary chain-component distance by 50 (Panel C), and finally set both variability and distance effects at .20 and 50 respectively (Panel D). Note that panel A has a similar shape to the surfaces in Figure 1, for post-acquisition injection services and Alzheimer’s bed intensities. Setting variability to 0.2 in Panel B moderates the surface, and the main effect is that the increase in capabilities in the right corner of the figure dampens, and the decline in the left corner of the figure accentuates. That is, as component variability increases, a chain becomes less likely to increase the capabilities of their ongoing components, even when the chain has a high level of the capability, and more likely to decrease the capability when they do
not possess it. Setting distance to 50 in Panel C has an analogous, though somewhat weaker, effect; combining the effect of chain capability variability and chain-component distance in Panel D amplifies the two separate effects.

*Insert Figure 2 about here.*

We next generate simulation results that will help us examine the importance of past capabilities and similarity to other chain components in affecting the component's capabilities over the long term. In doing so, we assume that variability and distance do not change over the period and hence, we do not include them in the analyses. The panels in Figures 3 and 4 illustrate the dynamics of transfer learning over ten periods for three initial values of chain capabilities, $C$; in Panel A, $C= 0.2$, in Panel B, $C = 0.5$, and in Panel C, $C = 0.8$. In these models, we allow $c$ to vary initially from 0 to 1 and subsequent values of $c$ are determined by the results of the simulation. 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 post-acquisition model for injection services intensity 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 one-way, chain-to-component transfer. Each curved line within Figure 3 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% in Panel A, 50% in Panel B, and 90% in Panel C, relative to 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.*

**Control Variables**

Several control variables also influence chain-to-component transfer learning (Appendices B1 and B2). We focus here on the \( \text{Cnew} \) variables in the appendices, in order to compare the influence of the capabilities of a chain’s recently acquired units (the \( \text{Cnew} \) vector) to the capabilities of a chain’s established units (the \( C \) vector). The appendices show that the capabilities of the units that a chain has acquired during the past two periods affect transfer learning to focal homes. The \( \text{Cnew} \) effect is particularly strong for transfer learning to acquired units, as all six cases of focal \( \text{Cnew} \) capabilities in Appendix B1 show that greater transfer learning occurs when chains have recently acquired homes with strong capabilities. Indeed, for transfer learning to acquired homes, the effect of the \( \text{Cnew} \) vector tends to be stronger than the effect of the \( C \) vector. In addition, four of the six \( \text{Cnew} \) cases are significant for transfer learning to ongoing units (Appendix B2), although with magnitudes that are less than for the \( C \) vector. The significance of the \( \text{Cnew} \) variables suggests that chains often use recent acquisitions as a
source of capabilities to transfer to other units, particularly as a means of reshaping the newer portions of their system.

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, although the importance of chain-level effects differs for transfer learning in post-acquisition and ongoing cases. Transfer learning at newly acquired components was most strongly affected by previous capability levels of both the component and chain and by the moderating effects of component-to-chain similarity, while the effects of geographic distance and chain capability variability were much stronger for ongoing chain components.

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., $C \times S_{Cc}$ and $c \times S_{Cc}$) 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.

Nonetheless, as Figures 1 and 2 show, component capabilities changed most when chain and component were most dissimilar, notwithstanding the moderating effects of similarity. 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.

The results point to notable differences in the ease of transfer learning that relates to the type of capability being transferred. For example, the transfer-facilitating effects of chain-component similarity generally observed to overcome the negative effects of high component capabilities are dampened in the case where there are high specialty services component capabilities, suggesting that the transfer of specialty services presents distinct challenges compared to the transfer of other capabilities. The impact on transfer learning of potential differences in capability types is further illustrated in Figure 1, which highlights differences between transfer of injection services capabilities and Alzheimer beds capabilities. Therefore the type of capability targeted for transfer may influence the ease or effectiveness of transfer, and so may impact the chain’s performance inasmuch as standardization is achieved more or less readily at greater or lesser cost to the chain.

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. 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 is the dominant form of transfer learning, and, as we noted in our discussion of the control variable effects, the generally
positive coefficients for new component capability levels provides some initial evidence that chains do diffuse capabilities from newly acquired components to their ongoing components.

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 often lead to substantial component level changes that align the acquired component with the capabilities of its new owner.

Our results suggest that a chain’s ability to undertake component and chain level change through capability transfer may lead to standardization based on the chain’s prior capabilities, indicating possible strategic use of transfer learning to enhance performance through standardization. These path-dependency constraints increase the tendency for major component-level changes to occur through acquisition 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


Table 1. Chain-to-Component Transfer Learning: Estimates for Random Effects Models of Change in Recently Acquired Component Capabilities, $\Delta c$ (6,976 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>
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<td>$c$</td>
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<td>-.484***</td>
<td>-.728***</td>
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<td>-.961***</td>
<td>-.011**</td>
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Total Predicted Correctly 62%

Log-likelihood
-7060.90  -16407.20  -18017.30  -21327.80  -31028.89  -49215.80

Notes:
- $+ p < .10$, $* p < .05$, $** p < .01$, $*** p < .001$, one-tailed tests
- Shaded cells support the chain-to-component transfer-learning model.
- Control variable estimates for each model are given in Appendix Table A1.
Table 2. Chain-to-Component Transfer Learning: Estimates for Random Effects Models of Change in Ongoing Component Capabilities, $\Delta c$ (30,034 component-year observations).

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<th>Alzheimer</th>
<th>Staffing</th>
<th>Total Beds</th>
<th>Support</th>
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Total Predicted Correctly 83%

Log-Likelihood  
-37427.5 -88148.3 -85267.7 -96928.3 -140583.2 -243584.6

Notes:  
* * * p < .05, ** p<.01, *** p<.001, one-tailed tests  
* Shaded cells support the chain-to-component transfer-learning model.  
* Control variable estimates for each model are given in Appendix Table A2.
Figure 1. Post-Acquisition Components: Effect of Chain and Component Capabilities on Change in Injection Services and Alzheimer Bed Intensity
Figure 2. Ongoing Components: Effect of Chain and Component Capabilities on Change in Therapy Services Intensity
Figure 3. Estimated Change Over Time in Post-Acquisition Component Injection Services Intensity
Figure 4. Estimated Change Over Time in Post-Acquisition Component Injection Services Intensity (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. The analysis controls for the possibility of such two-way learning, but it is not our main focus here.

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 Examples of hands-on mechanisms include (1) face-to-face meetings between chain and component staff to share experience and focus explicitly on common problems and their solutions, (2) regular communication in which chain management and component personnel share knowledge and report data to each other, (3) promotion of personal acquaintances across components in order to create familiarity and trust that smooth the exchange of information, (4) rotation of personnel (e.g., specialists, medical directors) among components, and (5) creation of chain-specific training programs for staff members.

4 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.

5 We also examined measures based on narrower staff groups, one based on Registered Nurses (RNs), and a second based on professionals. The estimates for these narrower measures are broadly similar to those for the global staffing measure, so we present results for it here.

6 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, 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.

7 For illustrative purposes, the figure uses the maximum value of distance and a mid-point of therapy services variability that arose in the data. Similar patterns arise with other parameter choices.