Introduction

How and when do multiunit chains affect 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 level and similarity of 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 in the underlying capabilities themselves.

Standardization of capabilities is a key motivation behind transfer learning in chains because it is critical for economies of scale and increased reliability and accountability. Chains 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

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1 Here, we focus on the tendency for components to converge towards their chains’ existing capabilities, although further development of the argument could usefully consider cases in which transfer learning from components to chains causes changes in a chain’s capabilities. We undertake preliminary examination of such “two-way” learning following the analysis section. We use the term “capabilities” as synonymous with the term “routines.”
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. 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.

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. 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 policy-makers continue to search for ways to improve practices across facilities (Institute of Medicine 1986).

At the same time, a theory of transfer learning within chains has broader 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.

Background: Transfer Learning, Multiunit Chains, and Acquisitions

We first briefly describe the concepts of transfer learning in multiunit chains and through acquisition. We contend that chains are important organizational vehicles for learning and more specifically, that post-acquisition transfer learning within chains is particularly common. We argue that the level of chain and component capabilities and the extent of similarity between chain and component capabilities influence transfer learning.

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 freely 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.

Darr et al. (1995) describe three mechanisms that facilitate transfer learning between their related (i.e., commonly owned) components. Regular communication increases the opportunity to share knowledge and report data to each other. Personal acquaintances create empathy, familiarity and trust that smooth the exchange of information. And, face-to-face meetings provide opportunities to share experience and focus explicitly on common problems and their solutions. By bringing members of component organizations together for both task-oriented and social purposes, chains facilitate interorganizational transfer of experience by increasing the opportunity and motivation for transfer and the ability of organizations to successfully apply experience transferred from other organizations.

Transfer learning is particularly 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

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2 The “knowledge paradox” is that 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 A discussion that discriminates the benefits of different collaborative organizational forms is beyond the scope of this study. Our summary argument is that chains will be particularly well suited as an organizational form when components tend to serve discrete local markets in which some direct contact between consumer and organization is required for service provision.
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). Consistent with research on transfer learning in chains, this view holds that imperfections in markets for knowledge create complications for arms length transfer of knowledge resources. The market imperfections, which include both pricing problems and coordination difficulties, lead to a prevalence of resource transfer through acquisitions because they provide the necessary ongoing collaborative interaction required for effective transfer learning. A key conclusion from this line of inquiry is that transfer learning is a fundamental process for chains and their acquired units.

**Opportunity and Constraint in Chain-to-Component Transfer Learning**

In this study, we develop and test the argument that the ability and incentives to transfer knowledge between chains and components are dependent on both the level and similarity of chains’ and components’ capabilities, as both direct and interactive effects. Capabilities in business organizations can be measured on multiple dimensions. After presenting our conceptual framework, we identify and measure levels of several types of capabilities for U.S. nursing home chains and their components.

**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 opportunities for transfer learning to components. In contrast, a higher level of capabilities at a focal component reduces the potential of transfer learning to that particular unit. Components with lower levels of capabilities will, in contrast, have strong incentives to gain new capabilities.

**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 reduces transfer learning incentives, even if similarity increases learning ability. 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 similarity and level 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.

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

**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 and similarity of chain and component capabilities and from the main effects of capability levels and similarity. 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. Table 1 summarizes our arguments.

Insert Table 1 about here.

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

Our discussion of opportunity and constraint in chain-to-component transfer learning motivates the following model of transfer learning from a chain to its components:

\[
\Delta c = \beta_1 C - \beta_2 c - \beta_3 S_{Cc} - \beta_4 (C \times S_{Cc}) + \beta_5 (c \times S_{Cc})
\]

(1)

In this equation, \( C \) 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 in capabilities from time 0 to time 1. \( S_{Cc} \) is similarity between a chain and its component’s capability levels at time 0, defined as (note that \( S_{Cc} \) takes a maximum value of 1):

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

(2)

The interaction terms \((C \times S_{Cc})\) and \((c \times S_{Cc})\) are multipliers of similarity with chain and component capability levels. The parameters \( \beta_1 \) to \( \beta_5 \) are model coefficients estimating the magnitude of each effect.

The arithmetic signs in equation (1) – \( \beta_1 > 0, \beta_2 < 0, \beta_3 < 0, \beta_4 < 0, \beta_5 > 0 \) – indicate our core predictions concerning transfer learning from chains to components. We expect that component capabilities will increase when chain capabilities \((C)\) are high and when components with high capabilities are similar to their chains \((c \times S_{Cc})\). By contrast, component capabilities will tend to decrease when component capabilities \((c)\) are already high, when components and chains are similar \((S_{Cc})\), and when chains with high capabilities are similar to the component \((C \times S_{Cc})\). In effect, the similarity interaction with high chain capability \((C \times S_{Cc})\) dampens the positive transfer learning effect of chain capabilities \((C)\), while the similarity interaction with high component capability \((c \times S_{Cc})\) offsets the negative transfer learning effect of high component capabilities \((c)\). We again note that the main effect of similarity \((S_{Cc})\) is the most ambiguous of these predictions, as similarity coupled with moderate levels of capabilities may sometimes be a

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4 This model of chain-to-component transfer learning could be rewritten, symmetrically, for component-to-chain transfer as: \( \Delta C = \beta_1 c - \beta_2 C - \beta_3 S_{Cc} - \beta_4 (c \times S_{Cc}) + \beta_5 (C \times S_{Cc}) \). Empirically, however, it would be difficult to disentangle transfer learning from specific components within a chain when estimating this model.
fruitful occasion for transfer learning, while dissimilarity stemming from high component-low chain capabilities might inhibit transfer learning.

A notable desirable property of this model 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. OSCAR covers almost every nursing home in the U.S. Data include facility-level information on nursing home strategy and structure (e.g., size, staffing and services), resident case mix (e.g., % 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.

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5 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.
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 is the largest operating expense within a nursing home and any increase in the number of nurses or aides, while potentially improving resident care, also increases costs. 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. Specialty beds represent a service innovation in the health care industry in response to increasing competition driven by changing regulations, technology and policy concerning long-term care (Banaszak-Holl et al. 1996). For instance, the period of the study was a time of great expansion and high turbulence of rehabilitation services in nursing homes, as facilities competed for the Medicare market during the 1990s. 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.

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6 Medicare pays about four times more for nursing home care than Medicaid pays, but expects rehabilitation services to be available to improve a resident’s health so that the resident can return to their previous living arrangement within 100 days. Payment for rehabilitation services was covered as an ancillary service and in this case nursing homes needed to specify within specified categories the the volume of rehabilitative services residents received.
In parallel with specialty beds, the availability of specialty care services such as injections, physio- and occupational therapy, ostomy, respiratory, suction, intravenous (IV) therapy, or 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 (\(S_{Cc}\)) as defined in equation (2), as well as the capabilities-similarity interaction variables (\(C \times S_{Cc}\) and \(c \times S_{Cc}\)). Table 2 reports summary statistics for the variables.

![Insert Table 2 about here.]

We estimate 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. Moreover, new chain-component relationships formed through acquisitions are likely to be qualitatively different from established chain-component relationships, with acquisitions triggering more chain-to-component transfer. Therefore, we estimated the model 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 (unreported) for time dependence (observation calendar year) 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 “new relationship” 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 for the six specifications of the model.

7 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.

8 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 in Table 3 are all close to 2.0, suggesting little autocorrelation in the data.
Results

Table 3 presents the model coefficients. In this table, 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. That is, positive coefficients imply greater transfer learning from chains to components.

Insert Table 3 about here.

Overall, the empirical estimates in Table 3 provide broad support for the theoretical model, with 83% of the coefficients having the expected sign (77% significant at $p < .05$). The main effects of capability level strongly support our predictions (all 24 coefficients in the $C$ and $c$ columns have the expected sign and all but one is significant at $p < .05$). As expected greater chain capabilities ($C$) lead to more transfer learning by components and greater component capabilities ($c$) lead to less transfer learning. The interaction terms also tend to have the expected tempering effects on capability levels, although with slightly less consistency than the main effects of capability levels (20 of 24, or 83% of the interaction coefficients have the expected sign; 18 of 24, or 75% significant at $p < .05$).

The primary exceptions to the expected results are the main effects of similarity ($SC_c$). Similarity is about as likely to be positive as it is to have the expected negative influence on transfer learning. Although similarity takes the expected negative influence in a majority of ‘ongoing relationships’ cases (4 of 6 cases, 67%), similarity is more likely to have an unexpected positive influence on transfer learning in ‘new relationships’ created by acquisitions (only 2 of 6, 33% similarity coefficients are negative). 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.

The difference in the similarity results for ongoing relationships and newly formed relationships is instructive. The frequency of the unexpected positive influence of similarity on transfer learning following acquisition suggests that the absorptive capacity of similarity often is highly important when two organizations have recently created a relationship. In these cases, similarity may facilitate quick transfer of resources and capabilities to the target component, rather than limiting knowledge transfer opportunities. Only over time, then, as the component becomes an established part of the chain, does similarity engender the expected inhibiting effect on transfer learning. Acquisitions present important opportunities for transfer learning during which a substantial degree of buyer-target similarity may be required to achieve potential learning benefits.

Support for the model parameters other than similarity is particularly strong for newly formed relationships resulting from acquisitions. Among newly acquired firms, parameter estimates for the main and interaction effects of chain ($C$, $C \times SC_c$) and component ($c$, $c \times SC_c$) capabilities are significant in the predicted direction for all capabilities except the interaction terms of rehabilitation specialty intensity (22 of 24 coefficients, 92%). By contrast, a slightly smaller number of capability coefficients are significant in the expected direction for ongoing relationships (19 of 24 coefficients, 79%). These results suggest that capabilities-driven chain-
to-component transfer learning may be triggered by recent acquisitions, in contrast to more established relationships that are more likely to approach their ‘transfer equilibria.’ The lack of support for the model predictions in the equation for rehabilitation services for newly acquired components may stem from the high turbulence and relatively recent creation of the rehabilitation services market. Rather than tempering the transfer of rehabilitation knowledge, similarity may actually allow firms to expand rehabilitation capabilities more quickly in response to market demand.

Together, the comparison of the ‘new’ and ‘ongoing’ relationship results suggests an intriguing contrast. Capabilities matter in both types of cases, but are particularly important for new relationships in which the greatest potential for capability change will tend to arise. The main effect of similarity, meanwhile, has the expected tempering of the capabilities effects in ongoing relationships, but often provides a basis for rapid capability transfer in new relationships.

Although all estimated models are statistically significant ($p < .05$ or better), the models for specific capabilities provide differing levels of overall fit. The fit, as measured by the $R^2$ statistic, is at least moderate for all but the component size (number of beds) models. The weak fit of the component size models ($R^2 = .01$) may stem from the more limited ability to change nursing home size, which is influenced by regulatory review as well as by capital cost and chain strategy.

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 size, 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, $C < (C \times S_{Cc})$. And, while main versus interaction effect coefficient magnitudes for component therapy and injection services intensity are $c > (c \times S_{Cc})$, for Alzheimer’s bed intensity they are $c < (c \times S_{Cc})$. 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 our 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 our findings, we illustrate graphically the static and dynamic implications of the estimates for several representative equations. Figures 1 to 3 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). 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 therapy (Panel A) and injection (Panel B) specialty service intensity changes for newly formed relationships. The pattern of changes in capability level (the vertical axis) across combinations of chain and component capability levels 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 off the ‘similarity diagonal,’ however, because the main effects for similarity ($S_{Cc}$) are weak in the two equations represented in the figure.

Insert Figures 1-3 about here.

The panels in Figures 2 and 3 illustrate the dynamics of transfer learning over time for three initial values of $C$ (.2, .5 and .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 2, 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 is identical within each panel (i.e., in each panel, the right-hand side of the surface is flat).

For the panels in Figure 3, 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 .5, as in Figure 2, panel b. Compared to Panel B of Figure 2 (in which
component-to-chain learning is 0), the component capability lines in the panels in Figure 3
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 ‘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 are sloped), such that the equilibrium
now depends on both the starting value of component capability and the rate of component-to-
chain transfer.

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.
We found general support for the model with intriguing variation in the main effects of similarity
on post-acquisition transfer learning.

Our attention to transfer learning processes within chains is premised on 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.

As Figure 1 shows, 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. 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 thus 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.

Our findings extend and reinforce two growing research streams. First, is the stream of research that characterizes multunit 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. Potential Influences On Transfer Learning Rate From Chains To Components, As Functions Of The Level And Similarity Of Chain And Component Capabilities

<table>
<thead>
<tr>
<th>Chain capabilities (C)</th>
<th>Component capabilities (c)</th>
<th>Chain Capability High (High transfer rate, because many capabilities available)</th>
<th>Chain Capability Moderate (Moderate transfer rate)</th>
<th>Chain Capability Low (Low transfer rate, because few capabilities available)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Component Capability High</strong> (Low transfer rate, because low room for improvement)</td>
<td>Similar (high (S_{Cc}), with (C = c)): Limited transfer potential</td>
<td>(C \times S_{Cc}): Similarity reduces benefits of capability infusion</td>
<td>(c \times S_{Cc}): Absorptive capacity stemming from similarity moderates negative effect of low transfer space</td>
<td>Dissimilar (low (S_{Cc}), with (c &gt; C)): Transfer potential ambiguous, because neutral, reinforcement, &amp;/or substitution by chain of component capability are possible</td>
</tr>
<tr>
<td><strong>Component Capability Moderate</strong> (Moderate transfer rate)</td>
<td>Similar (high (S_{Cc}), with (C = c)): Limited transfer potential, but shared experience may help take advantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Component Capability Low</strong> (High transfer rate, because much room for improvement)</td>
<td>Dissimilar (low (S_{Cc}), with (C &gt; c)): High transfer potential from infusion of chain capability</td>
<td>(C \times S_{Cc} &amp; c \times S_{Cc}): (S_{Cc}) is low, so interaction has little effect on transfer</td>
<td></td>
<td>(C \times S_{Cc}): Similarity helps find transfer opportunities despite low chain skills</td>
</tr>
</tbody>
</table>
Table 2. Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Ongoing relationships (n=30,201)</th>
<th>New relationships (n=7,260)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>s.d.</td>
</tr>
<tr>
<td>1. Component size increase (c_{t1}(-c_{t0}))</td>
<td>0.39</td>
<td>8.33</td>
</tr>
<tr>
<td>Component size (c)</td>
<td>108.08</td>
<td>53.73</td>
</tr>
<tr>
<td>Chain mean size (C)</td>
<td>107.60</td>
<td>32.21</td>
</tr>
<tr>
<td>Component-chain similarity (S)</td>
<td>0.76</td>
<td>0.18</td>
</tr>
<tr>
<td>Component x Similarity (c x S)</td>
<td>83.34</td>
<td>40.52</td>
</tr>
<tr>
<td>Chain x Similarity (C x S)</td>
<td>82.52</td>
<td>32.40</td>
</tr>
<tr>
<td>2. Staff intensity increase (c_{t1}(-c_{t0}))</td>
<td>-0.07</td>
<td>1.27</td>
</tr>
<tr>
<td>Component staff intensity (c)</td>
<td>1.07</td>
<td>1.28</td>
</tr>
<tr>
<td>Chain mean staff intensity (C)</td>
<td>1.21</td>
<td>2.04</td>
</tr>
<tr>
<td>Component-chain similarity (S)</td>
<td>0.78</td>
<td>0.22</td>
</tr>
<tr>
<td>Component x Similarity (c x S)</td>
<td>0.74</td>
<td>0.44</td>
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<tr>
<td>Chain x Similarity (C x S)</td>
<td>0.79</td>
<td>0.43</td>
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<tr>
<td>3. Alzheimer’s bed intensity increase (c_{t1}(-c_{t0}))</td>
<td>0.00</td>
<td>0.06</td>
</tr>
<tr>
<td>Component Alzheimer’s intensity (c)</td>
<td>0.02</td>
<td>0.09</td>
</tr>
<tr>
<td>Chain mean Alzheimer’s intensity (C)</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Component-chain similarity (S)</td>
<td>0.39</td>
<td>0.47</td>
</tr>
<tr>
<td>Component x Similarity (c x S)</td>
<td>0.01</td>
<td>0.03</td>
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<tr>
<td>Chain x Similarity (C x S)</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>4. Rehabilitation bed intensity increase (c_{t1}(-c_{t0}))</td>
<td>0.01</td>
<td>0.08</td>
</tr>
<tr>
<td>Component Rehabilitation intensity (c)</td>
<td>0.01</td>
<td>0.07</td>
</tr>
<tr>
<td>Chain mean Rehabilitation intensity (C)</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>Component-chain similarity (S)</td>
<td>0.54</td>
<td>0.49</td>
</tr>
<tr>
<td>Component x Similarity (c x S)</td>
<td>0.00</td>
<td>0.02</td>
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<tr>
<td>Chain x Similarity (C x S)</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>5. Injection services intensity increase (c_{t1}(-c_{t0}))</td>
<td>0.00</td>
<td>0.09</td>
</tr>
<tr>
<td>Component Injection intensity (c)</td>
<td>0.11</td>
<td>0.08</td>
</tr>
<tr>
<td>Chain mean Injection intensity (C)</td>
<td>0.11</td>
<td>0.03</td>
</tr>
<tr>
<td>Component-chain similarity (S)</td>
<td>0.68</td>
<td>0.24</td>
</tr>
<tr>
<td>Component x Similarity (c x S)</td>
<td>0.08</td>
<td>0.05</td>
</tr>
<tr>
<td>Chain x Similarity (C x S)</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td>6. Therapy services intensity increase (c_{t1}(-c_{t0}))</td>
<td>0.00</td>
<td>0.17</td>
</tr>
<tr>
<td>Component Therapy intensity (c)</td>
<td>0.17</td>
<td>0.21</td>
</tr>
<tr>
<td>Chain mean Therapy intensity (C)</td>
<td>0.16</td>
<td>0.11</td>
</tr>
<tr>
<td>Component-chain similarity (S)</td>
<td>0.54</td>
<td>0.29</td>
</tr>
<tr>
<td>Component x Similarity (c x S)</td>
<td>0.10</td>
<td>0.12</td>
</tr>
<tr>
<td>Chain x Similarity (C x S)</td>
<td>0.09</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Variable definitions: 1. No. of beds, 2. Total staff per total residents, 3. Alzheimer’s beds per total beds, 4. Rehabilitation beds per total beds, 5. Residents receiving Injection services per total residents, 6. Residents receiving therapy services per total residents
Table 3. Empirical Estimates for Equations Predicting Change in Component Capabilities, $\Delta c$.

<table>
<thead>
<tr>
<th>Capability</th>
<th>Chain-Component Relationship</th>
<th>Parameters of Equation (1)</th>
<th>$R^2$ (D-W)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$C$ $c$ $S_{Cc}$ $C\times S_{Cc}$ $c\times S_{Cc}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$Predicted$ $sign$</td>
<td>+ - - - +</td>
<td></td>
</tr>
<tr>
<td>1. Component Size</td>
<td>Ongoing</td>
<td>.000 -.018* -2.191* .011 .008</td>
<td>.01 (2.07)</td>
</tr>
<tr>
<td></td>
<td>New</td>
<td>.035* -.018* 4.603* -.048* .029*</td>
<td>.01 (2.14)</td>
</tr>
<tr>
<td>2. Staff Intensity</td>
<td>Ongoing</td>
<td>.010* -.881* -.664* -.163* .553*</td>
<td>.52 (1.90)</td>
</tr>
<tr>
<td></td>
<td>New</td>
<td>.018* -.862* -.530* -.216* .451*</td>
<td>.53 (1.95)</td>
</tr>
<tr>
<td>3. Alzheimer’s Bed Intensity</td>
<td>Ongoing</td>
<td>.101* -.237* .000 -.253* .290*</td>
<td>.07 (2.12)</td>
</tr>
<tr>
<td></td>
<td>New</td>
<td>.083* -.221* .001 - .897* .743*</td>
<td>.06 (2.09)</td>
</tr>
<tr>
<td>4. Rehabilitation Bed Intensity</td>
<td>Ongoing</td>
<td>.078* -.580* -.003* .336* .154*</td>
<td>.23 (1.99)</td>
</tr>
<tr>
<td></td>
<td>New</td>
<td>.129* -.506* .002 -.050 -.547*</td>
<td>.26 (1.97)</td>
</tr>
<tr>
<td>5. Injection Services Intensity</td>
<td>Ongoing</td>
<td>.286* -.889* -.008* -.379* .534*</td>
<td>.38 (2.04)</td>
</tr>
<tr>
<td></td>
<td>New</td>
<td>.224* -.889* .008 -.329* .534*</td>
<td>.39 (2.04)</td>
</tr>
<tr>
<td>6. Therapy Services Intensity</td>
<td>Ongoing</td>
<td>.423* -.521* .017* -.132* -.007</td>
<td>.27 (2.19)</td>
</tr>
<tr>
<td></td>
<td>New</td>
<td>.316* -.485* .001 -.141* .106*</td>
<td>.25 (2.08)</td>
</tr>
<tr>
<td>% coefficients with predicted sign</td>
<td>Ongoing: All=83% (Significant: 77%)</td>
<td>100% 100% 67% 67% 83%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>New: All=83% (Significant: 77%)</td>
<td>100% 100% 33% 100% 83%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Combined: All=83% (Significant: 77%)</td>
<td>100% 100% 50% 83% 83%</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
- * $p < .05$
- D-W = Durbin-Watson statistic
- The ongoing relationship sample includes 30,201 component-year observations, the new relationship sample includes 7,260 observations
- All equations include controls for time dependence and cross-effects for the five non-focal chain and component capabilities (i.e., $C$ and $c$); new relationship equations also control for time since the acquisition
Figure 1. Estimated Change in Component Level of Specialty Services Intensity Following Acquisition
Figure 2. Estimated Change Over Time in Component Level of Injection Specialty Services Intensity Following Acquisition
Figure 3. Estimated Change Over Time in Component Injection Specialty Services Intensity Following Acquisition (with 2-way transfer).

Panel A: (Chain Capability Level = .5-(.1xΔc))

Panel B: (Chain Capability Level = .5-(.5xΔc))

Panel C: (Chain Capability Level = .5-(.9xΔc))