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Transfer learning in ongoing and newly acquired components of multiunit chains: US nursing homes, 1991–1997

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Multiunit chains proliferated rapidly during the twentieth century and now dominate much of the service sector landscape, often growing by acquiring components from other owners. Transfer learning plays a central but only partially understood role in chain strategy, in both ongoing and newly acquired components. Multiunit chains gain potential benefits of reliability and accountability when they standardize activities by transferring capabilities among their components. Moreover, with the importance of acquisition in chain growth, transfer learning plays a key role both in bringing the activities of newly acquired components in line with others in the chain, as well as offering the potential to infuse new capabilities into established units of a chain. We develop a model of chain-to-component and component-to-chain transfer learning in which the levels and similarity of a chain and its components' capabilities have direct and interactive effects on transfer learning across the ongoing and newly acquired components. We test the model using data on changes in capabilities at the facilities of all federally registered nursing home chains operating in the United States between 1991 and 1997. In contrast to past research in the learning curve tradition that uses changes in performance to infer how transfer learning influences components' capabilities, we operationalize transfer learning by measuring changes in service characteristics that lie closer to the underlying capabilities themselves. Our findings suggest that transfer learning among a chain's components tends to be localized within its established and newly-acquired components, providing new insights into the dynamics of chain capabilities. In particular, new acquisitions commonly lead to only limited changes at a chain's established components while chains may find it difficult to bring their newly acquired components in line with chain standards. In turn, this shows that acquisitions tend to change a chain's capabilities more by changing its portfolio of components and less through diffusion of new capabilities throughout the chain.

1. Introduction

Multiunit chains have become a conspicuous feature of modern economies, often growing through acquisition of components from other owners. Transfer learning between components of chains is an important element of chain activity (Ingram and Baum, 1997), with the potential to both standardize activities and diffuse new capabilities throughout a chain, but one that is only partially understood (Argote, 1999; Argote and Ingram, 2000). This article studies transfer learning in multiunit nursing home chains. We distinguish between established and newly acquired chain components to shed light on the role of transfer learning in processes of capability standardization and change within chains. In doing so, we explore the tension between the standardizing influence of a chain's established components and the evolutionary influence of its newly acquired components on the nature of the chain's capabilities, determining whether newly acquired components tend to be recipients or sources of capabilities.

Chains are collections of components that produce similar goods and services in several markets and link together as larger superorganizations (Bradach, 1997). Chains make considerable effort to standardize and coordinate the behavior of their components, because standardization offers reliability and accountability (Ingram, 1996; Baum, 1999). Chains proliferated during the twentieth century 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 (Greve and Baum, 2001).

Transfer learning occurs when one component is affected by the experience of or uses the knowledge of another through sharing practices or by somehow stimulating innovation (Darr and Kurtzberg, 2000). Transfer learning is fundamental to the dynamics of chain organizations and manifests itself through changes in the knowledge and performance of recipient components (Argote and Ingram, 2000).

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. The emphasis on replication points to the great importance of transfer learning across a chain's components (Argote *et al.*, 1990; Baum and Ingram, 1998). A growing body of research, which characterizes multiunit organizations as interorganizational learning communities, indicates that their ability to transfer knowledge effectively among components enhances their productivity and survival chances and is critical to explaining their competitive advantage over independent competitors (Darr *et al.*, 1995; Ingram and Baum, 1997, 2001; Darr and Kurtzberg, 2000).

Transfer learning affects both a chain's established and newly acquired components. Among a chain's established components, transfer learning facilitates an ongoing realignment of activities. For example, a hotel may improve its knowledge of effective customer service by drawing on the experience of other hotels in its chain. Similarly, a book store may improve its performance by implementing a new marketing practice that another store in its chain developed. In these examples, the recipient component learns from the experience of other components in the same chain. Thus, chain components can learn not only from their own experience, but also from the experience of other components in their chains (Baum and Ingram, 1998).

Chain growth often occurs through acquisition (Baum, 1999; Baum *et al.*, 2000). 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. For instance, a discount retailer such as Wal*Mart that acquires stores from other chains (e.g., Woolco outlets in Canada and ASDA supermarkets in the United Kingdom) will need to align the newly acquired units with its systems and image. Moreover, capabilities obtained through newly acquired components may also provide opportunities to learn and diffuse new skills and services throughout the chain (Capron and Mitchell, 1998). Few studies have examined such fine-grained transfer learning, however, and none has distinguished between transfer learning to and from a chain's new and established components.

Several studies show that ownership relationships such as chain membership facilitate transfer learning by providing a common language, interaction opportunities, and motivation for the extensive sharing of experience. These studies, however, typically follow the learning curve tradition, inferring transfer learning from evidence of the effects of one organization's cumulative experience on changes in the performance of another. Darr *et al.* (1995) assessed how the experience of pizza franchises affected the productivity of individual stores in a chain, for example, while Baum and Ingram (1998) examined the extent to which the survival of chain hotels was affected by the experience of other hotels in their chain. A major challenge in assessing knowledge transfer by studying changes in performance is to control for the many other factors also affecting the performance of the recipient component (Argote, 1999).

Transfer learning in chain organizations might also be assessed by measuring changes in the knowledge of the recipient component, although this approach too poses significant challenges. Measuring changes in knowledge is complicated by the fact that many aspects of organizational knowledge are tacit and, additionally, that organizational knowledge resides in multiple repositories (Argote and Ingram, 2000). Walsh and Ungson (1991) identify five potential organizational knowledge repositories: operating procedures and practices; roles and organizational structures; individual members; physical structures; and culture. Thus, assessing transfer learning through changes in knowledge would require measuring changes within these repositories, which are often difficult to observe because they involve tacit and organizationally embedded knowledge.

In contrast to past research in the learning curve tradition that infers transfer learning from changes in chain and component performance, we operationalize transfer learning by measuring changes in component service characteristics that lie closer to the underlying capabilities themselves. Service characteristics represent the capabilities that an organization is able to use to transform inputs into outputs at a given time (Hart 1995; Teece *et al.*, 1997). These changes reflect changes throughout Walsh and Ungson's (1991) set of knowledge repositories and involve transfer of both explicit and tacit knowledge.

We develop a model of chain-to-component and component-to-chain transfer learning that predicts changes in a component's use of a given capability as a function of the absolute and relative levels of the component and its chain's use of the capability. The model assesses how capability usage at a chain's established components and its newly acquired components influences changes in the capabilities of the chain's established and newly acquired components. This separation permits us to examine both the standardizing influence of a chain's established components (Ingram and Baum, 1997) and the evolutionary influence of its newly acquired components on the nature of capabilities employed by the acquiring chain (Capron *et al.*, 1998).

We test the model by examining changes in the use of capabilities by the components of more than 2000 nursing home chains operating in the United States during 1991–1997. Several thousand acquisitions of nursing home facilities occurred during this period. We study changes in four service areas, the provision of which have great human and social implications (Banaszak-Holl *et al.*, 1996): (i) Alzheimer's disease, (ii) rehabilitation, (iii) injection (i.e., availability of injections for medications), and (iv) physical and occupational therapy. Quality problems commonly arise in these service areas in the US nursing home industry, and policy-makers continue to search for ways to improve practices across facilities (Institute of Medicine, 1986).

Our study of transfer learning within multiunit chains also contributes to our understanding of organizational change throughout the economy as this organizational form comes to dominate the service sector (Greve and Baum, 2001). More broadly, attention to transfer learning processes is critical to understanding organizational performance because it is one of the most important routes through which organizations develop and sustain competitive advantage (Capron and Mitchell, 1998; Argote, 1999).

The next section describes the concepts of capabilities and transfer learning in more detail and explains the significance of transfer learning across a chain's components. After developing these core ideas, we present a theoretical model of chain-to-component transfer learning. We then present the study design, empirical analysis, findings, and implications.

2. Capabilities, transfer learning and multiunit chains

At its most general level, the term capabilities refer to activities an organization is able to carry out at a given point in time. More specifically, capabilities are the processes by which a firm uses labor and technology to transform material resources into products and services (Hart, 1995; Teece *et al.*, 1997). Capabilities are combinations of multiple routines, which are patterns of activity embodied in people, roles, administrative structures, and physical assets (Nelson and Winter, 1982). Because capabilities are only semi-decomposable into their underlying routines, they form distinct units of analysis (Karim and Mitchell, 2000).

In this study, we operationalize capabilities as the extent to which the four services are available within a nursing home chain's components, focusing on the provision of specialty beds (Alzheimer's disease and rehabilitation) and specialty services (injection, plus physical and occupational therapy). Changes in provision of these services can require changes in all aspects of a component's knowledge repositories—operating procedures and practices, roles and administrative structures, individual members, physical structures, and culture. At the same time, however, the four service areas vary in the tacitness and embeddedness of their underlying knowledge. The provision of care for Alzheimer's residents involves multiple clinical disciplines and is reliant on tacit knowledge embedded in staff roles and care practices as well as administrative and physical structures. Offering therapy services, in contrast, entails application of more explicit routines. Rehabilitation care and injection services fall between these two extremes, with rehabilitation closer to Alzheimer's and injection closer to therapy.

Transfer learning, as we noted above, occurs when one component is affected by or uses the knowledge of another either through sharing experience or by somehow stimulating innovation. Thus, transfer learning requires that a 'sending' organization stimulate change in a 'receiving' organization (Ingram, 2002). Previous studies provide both quantitative and qualitative evidence that transfer learning affects a receiver's performance (e.g., production cost, survival) as a function of a sender's experience (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 emphasizes the importance of the type of relationship between organizations for transfer learning, suggesting that common ownership is a strong conduit for transfer learning that makes diffusion comparably rapid (Darr *et al.*, 1995; Greve, 1995, 1996; Ingram and Baum, 1997, 2001; Darr and Kurtzberg, 2000). These results contrast with the dominant idea that knowledge can simply spill across the boundaries of organizations into the general environment, where others can easily consume knowledge independent of any relationship to the knowledge provider.

Capabilities may not transfer easily between organizations in an open market because firms face well-known difficulties and costs entailed in measuring, valuing, protecting, and coordinating the use of complex knowledge (Mowery *et al.*, 1996). Knowledge may also suffer from the information paradox (Arrow, 1962), which makes it difficult to protect the value of knowledge exchanged between unrelated parties, 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.

Moreover, the tacit quality of some forms 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 (Williamson, 1975; Teece, 1982, 1986). Although such institutional governance sometimes requires a fully integrated hierarchy, a range of collaborative governance forms such as alliances, long-term contracts, franchises, and chains also exist (Williamson, 1991; Oxley, 1997). 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 attempting to replicate them in multiple locations within distinct components 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. As well as generating scale economies and lowering 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, transfer learning is critically important to incorporating newly acquired components into the chain's strategy as well as taking advantage of an acquired component's capabilities to help a chain revise its strategy. Transfer learning appears to be both a central motivation and a key to success for chain acquisitions (Ingram and Baum, 1997, 2001). Theoretical models of acquisitions by chains have emphasized the market and social power incentives, neglecting the potential for capability development as chains transfer resources and knowledge to and from acquired components. Recent research in business strategy, however, emphasizes the importance of acquisitions as a basic mechanism through which organizations change, reconfigure, and redeploy their resources (Capron *et al.*, 1998; Capron, 1999; Baum *et al.*, 2000).

3. A model of chain-to-component transfer learning

We advance a model that predicts changes in the level of capability usage in a given component of a chain. In the model, the level and similarity of chain and component capabilities influence the ability, opportunity, and incentive for chain-to-component transfer learning. More formally

$$\Delta c = -\beta_1 c + \beta_2 C \pm \beta_3 S - \beta_4 (C \times S) + \beta_5 (c \times S) \tag{1}$$

In equation (1), c is a focal component's level of use of a given capability, while C is a chain's level of use of that capability, which we measure as the mean level of use for a chain's components. Both c and C are measured at time 0. Δc is the change in the component's use of the capability from time 0 to time 1 (i.e., $c_{t1} - c_{t0}$). S is the similarity between a component and its chain's levels of use of the capability at time 0.

We define similarity as follows:

$$S = \frac{C}{c} \text{if } C < c; \quad S = \frac{C}{c} \text{if } c < C; \quad \text{and 1 if } C = c = 0 \tag{2}$$

S measures the degree to which a component and its chain use a given capability and the extent to which use of that capability accounts for a comparable proportion of their overall activities. S is a conceptually appropriate measure of similarity because it focuses on the degree to which the chain and its component engage in a common set of activities.

This operationalization of S has important advantages over alternatives. A difference score (i.e., $C - c$) is unweighted, with a value of zero indicating similarity, and asymmetric, with both 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 such that a value of one would indicate similarity, whereas zero and infinity would both indicate maximal dissimilarity. S, in contrast, is weighted and bounded, ranging between zero (highly dissimilar) and one (identical), is symmetric with equivalent scores whether the chain or the component has higher levels of a capability, approximately linear, and insensitive to outliers.

The interaction terms ($C \times S$) and ($c \times S$) are multipliers of similarity with chain and component capability levels. The parameters β_1 to β_5 are model coefficients estimating the magnitude of each effect; the arithmetic signs of the parameters indicate our core predictions.

Below, we develop our theoretical model focusing on the concepts of chain and component capabilities. Because we are interested in distinguishing the influence of a chain's established and newly acquired components' capability usage on changes in the capabilities of both its established and newly acquired components, the analysis distinguishes between the capabilities of a chain's "ongoing" and "newly acquired" components. In turn, we distinguish between the similarity of capabilities of ongoing and newly acquired components.

In practice, then, we estimate two forms of equation (1):

$$\begin{aligned}\Delta c_{\text{ongoing}} = &-\beta_1 c + \beta_{2a} C_{\text{ongoing}} \pm \beta_{3a} S_{\text{ongoing}} \\ &- \beta_{4a}(C_{\text{ongoing}} \times S_{\text{ongoing}}) + \beta_{5a}(c \times S_{\text{ongoing}}) \\ &+ \beta_{2b} C_{\text{new}} \pm \beta_{3b} S_{\text{new}} - \beta_{4b}(C_{\text{new}} \times S_{\text{new}}) + \beta_{5b}(c \times S_{\text{new}})\end{aligned} \tag{1a}$$

$$\begin{aligned}\Delta c_{\text{new}} = &-\beta_1 c + \beta_{2a} C_{\text{ongoing}} \pm \beta_{3a} S_{\text{ongoing}} \\ &- \beta_{4a}(C_{\text{ongoing}} \times S_{\text{ongoing}}) + \beta_{5a}(c \times S_{\text{ongoing}}) \\ &+ \beta_{2b} C_{\text{new}} \pm \beta_{3b} S_{\text{new}} - \beta_{4b}(C_{\text{new}} \times S_{\text{new}}) + \beta_{5b}(c \times S_{\text{new}})\end{aligned} \tag{1b}$$

where ongoing signifies a chain's ongoing components, defined as components a chain has owned for more than two observation periods (an observation period in our sample is about one year), and new signifies components that a chain has acquired within the past two periods. A two period window provides a practical distinction between ongoing and newly acquired components while providing a reasonable time period for acquisition-related activity to unfold.[1]

3.1 Capability level

We start by considering the level of capabilities both within the focal component and across the chain. Components making less use of the capability may have strong incentives to acquire the new capability from the chain while greater use of a capability at a focal component (c) reduces the potential for transfer learning to that particular component ($\beta_1 < 0$). Indeed, a component making particularly extensive use of a capability may undergo 'negative transfer learning' if a chain wants to decrease the component's emphasis on that service area and replace it with either a focus on another specialized service stressed by the chain or conversion back to more traditional, generic services. By contrast, greater use of a capability across a chain (C) creates greater abilities and opportunities for transfer learning to components ($\beta_2 > 0$).

We expect the component-capability relationship (c, in equation 1) to hold for both ongoing and newly acquired facilities. Either class of component has lower incentive to transfer in capabilities that it already makes extensive use of ($\beta_1 < 0$ for both $\Delta c_{\text{ongoing}}$ and Δc_{new}).

It is not clear, though, whether the two chain capability variables (C_{ongoing} and C_{new}) will have the same effect on transfer learning for ongoing and newly acquired facilities. At least three relationships are possible, either alone or in combination, depending on whether post-acquisition transfer learning tends to emphasize standardization

[1]A third measure of similarity comparing C_{ongoing} and C_{new} is also possible, but including such a measure would complicate the analysis and make it difficult to interpret the results because its elements are non-linear combinations of elements of S_{ongoing} and S_{new}.

with respect to a chain's existing capabilities or opportunities for changing a chain's capabilities.

1. Chains might transfer capabilities from their ongoing components to newly acquired components to bring them in line with the chain's standard service platform (i.e., $\beta_{2a} > 0$ for Δc_{new}).
2. Chains might transfer novel capabilities obtained from their newly acquired components to their ongoing components to alter their capabilities and cope with changing environmental conditions and demands or adopt innovations (i.e., $\beta_{2b} > 0$ for $\Delta c_{ongoing}$).
3. A system bifurcation might arise as a result of different absorptive capacities and relationships across ongoing and new components, such that chains tend to transfer "established" capabilities among ongoing units and "novel" capabilities among newly acquired components ($\beta_{2b} > 0$ for Δc_{new} and $\Delta c_{ongoing}$).

Thus, the analysis offers the opportunity to determine whether acquired components tend to be recipients or sources of capabilities and, if they are capability sources, how widely the new capabilities diffuse through an acquiring chain.

3.2 Capability similarity

We make no prediction concerning the main effect of similarity, *S*. Alternative arguments suggest either greater or lesser transfer learning as a result of component-chain similarity.

Components that are similar to their chains might have greater capacity for absorbing additional levels of those skills ($\beta_3 > 0$). Such a relationship would reflect research in organizational learning and strategic management that suggests that the potential for transfer learning occurring between two organizations increases with the similarity and decreases with the dissimilarity in their 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 learning theorists have labeled this path dependency in organizational knowledge as absorptive capacity (Cohen and Levinthal, 1990). Consistent with this view, the strategy literature, as represented in Porter's (1987) skill-transferring model, suggests that acquirers seek targets with closely related primary activities (e.g., logistics, operations, marketing, sales and service) and support activities (e.g., company infrastructure, human resource management, technology development, procurement) that operate in markets similar to those of the acquirer. Supporting these ideas, a learning curve study by Darr and Kurtzberg (2000) showed how the cumulative experience of pizza stores categorized as "cost cutters" or "expansionists" influenced the unit cost of production in stores with the same strategy but not of stores using the other strategy. Darr and Kurtzberg concluded that task and structural similarity among strategically similar pizza stores increased their ability to use knowledge acquired from others.

Alternatively, though, chains might have little desire to enhance the capabilities of components that are already similar to the chains' operating norms ($\beta_3 < 0$). Although similarity increases the effectiveness of transfer learning aimed at refining existing capabilities to achieve lower production costs and other incremental performance enhancements, similarity may also reduce the incentive to change the level of use of a capability. Therefore, we treat the direction of β_3 as an empirical question.

3.3 *Capability level × capability similarity interaction*

Although we do not predict main effect influences for similarity, we do expect specific directional effects for the interactions of similarity with the chain and component capability measures. Joint consideration of the ability and incentives for transfer learning suggests that similarity will moderate the influence of capability levels.

We expect similarity to have a negative mediating effect on chain capabilities ($\beta_4 < 0$). Components with capability use levels that are already similar to their chain's use levels should prompt less transfer learning activity and experience less transfer learning in capability levels.

By contrast, similarity is likely to have a positive mediating effect on component capabilities ($\beta_5 > 0$). Although components that already have high levels of use of a capability typically will have relatively little incentive to add to that use, units that are members of chains that emphasize such capabilities will be more likely to continue to add to that skill base.

As a starting point, we expect similar coefficients for the capability × similarity interactions based on ongoing and newly acquired components (i.e., $\beta_{4a} \approx \beta_{4b}$ and $\beta_{5a} \approx \beta_{5b}$). It is also possible, however, that, as we suggested above, chains tend to follow only partially integrated strategies among their ongoing and newly acquired components, and in particular, that transfer learning localizes within ongoing and newly acquired components. If this is the case, then we would expect the interactions based on ongoing components to be greater than those based on newly acquired components for $\Delta c_{\text{ongoing}}$ (i.e., $\beta_{4a} > \beta_{4b}$ and $\beta_{5a} > \beta_{5b}$) while the opposite would hold for Δc_{new} (i.e., $\beta_{4a} < \beta_{4b}$ and $\beta_{5a} < \beta_{5b}$).

3.4 *Synopsis*

In summary, the model assesses opportunities and constraints for transfer learning within chains. We expect greater transfer learning for capabilities for which a chain has high existing levels of usage and less transfer learning when a component has high levels of a capability. Similarity between chain and component will moderate these effects, however, facilitating transfer learning at high capability components and tempering transfer learning from high capability chains. The analysis, which distinguishes between chains' ongoing and newly acquired components, will provide an opportunity to examine whether newly acquired components tend to be primarily recipients or sources of capabilities or, alternatively, both.

A desirable property of our model is its realistic representation of knowledge transfer and capability change as a self-damping process. According to our predictions, if C is large then c increases toward C, which also increases S and, in turn, $C \times S$. Increases in c and $C \times S$, however, dampen increases in c. Any further increase in c dampens future increases in c, ultimately stabilizing c at some value that would remain unchanged so long as C remained unchanged. 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.

The model also contains exploratory mechanisms, depending on how acquisitive a chain is and the service characteristics of the components it acquires. Specifically, by distinguishing between ongoing and newly acquired components, the model allows for the possibility that chains obtain new capabilities through acquisitions, providing a source of change in levels of C. Thus, the model specifies conditions under which chains can initiate knowledge transfer and capability change and under which transfer ceases.

4. Data and methods

4.1 The US nursing home industry: data and example

We tested our model using data on nursing home chains and their components in the continental United States between January 1991 and September 1997. The US nursing home industry offers an intriguing case of transfer learning. Nursing homes in the United States began during the eighteenth and nineteenth centuries as non-profit facilities, often run by religious organizations or by county governments. A limited degree of chaining began when church-affiliated groups opened multiple facilities in the late nineteenth and early twentieth centuries. For-profit chain activity in the industry then took off in the 1930s, in response to publicly-funded elder-care reimbursement programs that were part of the New Deal. By the beginning of our observation period, the proportion of chain-owned nursing homes exceeded 40%, with a large majority of the chains involving for-profit ownership. Chain ownership expanded to almost 50% during the mid-1990s. Nursing home chains tend to be quite small, with 87% operating 10 or fewer homes at the end of our study period, but several national and regional chains operated several hundred facilities each.

The continuing growth in chain activity stems from three major factors. First, third-party payment opportunities from Medicare and Medicaid grew during the 1980s and early 1990s attracting multiunit for-profit operators. Second, chains offered the potential to achieve economies of scale that would help provide operating efficiency that was necessary because of the relatively low level of payment from the most common payer, Medicaid. Third, chains offer the potential to manage the creation and diffusion of therapy, rehabilitation, and other patient care activities that residents and their families have increasingly begun to desire.

One large chain provides a useful example of transfer learning activity at established and acquired facilities during the 1990s.[2] Beverly Healthcare is one of the major nursing home chains in the United States founded in 1963, the chain has grown to operate several hundred facilities in 2005. At the beginning of our study period, in 1991, Beverly operated roughly 300 facilities and acquired more than 400 homes during the observation period. During the 1990s, Beverly systematically increased the level of multiple services such as therapy services, rehabilitation care, and specialized Alzheimer's disease care at its facilities. For instance, the proportion of residents receiving occupational and physical therapy services in Beverly nursing homes increased from about 10% in 1991 to 20% by 1997.

In part, the Beverly chain achieved its growth in therapy services by diffusing capabilities to its established homes, typically by setting service goals for its facilities and then sharing specialized staff members among facilities within regions; the established homes increased their therapy service intensity by an average of 2% a year. In addition, the facilities that Beverly targeted for acquisition offered high levels of therapy services at the time of purchase, with an average of about 25% of residents of acquired facilities receiving therapy services; the acquired facilities offered even higher levels of therapy services after the acquisitions, growing at an average rate of 3% a year, again often sharing staff members among facilities in order to diffuse skills and contain costs. Thus, Beverly achieved increased usage of specialty services by transfer learning within both its established components and its newly acquired components.

To assess overall transfer learning patterns in the industry, we use a longitudinal data set linking yearly files of the federal *On-line Survey Certification and Reporting System* (OSCAR) data for the period January 1991 and September 1997. The OSCAR files include information from state-based inspections of all Medicare-/Medicaid-certified nursing homes operating in the continental United States starting in January 1991. OSCAR includes facility-level information on nursing home structure (e.g., size, staffing, services offered) and system membership (e.g., multiunit organization affiliation and name). Inspections are mandated on an annual basis, although occasionally the time between inspections can exceed two years (the mean inspection period in our data is 374 days). The data include over 105,000 records, covering nearly 20,000 unique nursing homes. We also use the Area Resource File, a federally available collection of health statistics across geographic units, 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

[2]The information in this example comes from the OSCAR data set, from published sources such as the Medical and Health Care Marketplace Guide, and from interviews with executives of nursing home chains.

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 US healthcare sector. We identified 2225 unique nursing home chains in the data.[3] We coded acquisitions when a change in ownership status of a nursing home occurred between inspections; the data set includes approximately 4500 acquisitions.

4.2 Variables

The OSCAR data provided information about four key service areas, including (i) specialty bed intensity—Alzheimer's beds, (ii) specialty bed intensity—rehabilitation beds, (iii) specialty service intensity—injection services, and (iv) specialty service intensity—therapy services. Changes in the levels of provision of these services reflect changes throughout Walsh and Ungson's (1991) categorization of organizational knowledge repositories, including operating procedures and practices, roles and administrative structures, individual members, physical structures, and culture. At the same time, the likely extent of change varies by service area. The provision of Alzheimer's beds, which involves the integration of multiple clinical disciplines and is reliant on tacit knowledge embedded in staff roles and care practices as well as administrative and physical structures, requires the most extensive changes. For instance, offering Alzheimer's services often requires locked hallway doors and physical separation of residents with Alzheimer's disease from other residents of a nursing home facility. Rehabilitation beds also require changes across multiple repositories, although they are not as complex or extensive. Offering therapy and injection services, in contrast, require narrower changes to operating procedures, practices and staffing, with fewer administrative, structural or cultural changes.

Specialty bed intensity—Alzheimer's beds (beds dedicated for residents with Alzheimer's disease, per total beds) and *Specialty bed intensity—rehabilitation beds* (beds dedicated for residents requiring rehabilitation services per total beds) denote the presence of

[3]Approximately, 5% of nursing homes reported belonging to a chain and provided a corporate name but no other facilities were found to belong to that corporation. We did not include these holding company nursing homes as components of chains.

capabilities needed for particular types of care. The availability of beds dedicated to specialized 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, represent specialized skill sets within nursing homes. These services differ significantly from traditional, generic nursing care services requiring additional trained staff and further training of its existing staff to implement new roles and clinical and administrative practices, more extensive medical equipment, and even unique facility design features. The availability of specialty beds for nursing home residents is important because it represents service innovations driven by changing regulations, technology, and policy concerning long-term care (Banaszak-Holl *et al.*, 1996). 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. Increases 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.

Specialty service intensity—Injection services (residents receiving injection services, per total residents) and *Specialty service intensity—Therapy services* (residents receiving physical or occupational therapy, per total residents) also denote the presence of capabilities needed for particular types of care. In parallel with specialty beds, the availability of specialty services such as medication injections, physiotherapy and occupational therapy, ostomy, respiratory therapy, suction, intravenous therapy, and tracheotomy each provide direct measures of nursing home capabilities that are directly related to the routines and medical technology used within a home. OSCAR includes consistent information on the availability of physical and occupational therapy and injection services, two of the most common specialty services in the nursing home industry.

We computed the component capability measure, c, separately for each component and capability. As dependent variables, we calculated one-period changes for each capability measure for each chain component, Δc (i.e., change in Alzheimer's bed, rehabilitation bed, injection service, and therapy service intensity).[4] We used the individual component measures to create mean value measures for each chain as a whole, C_{ongoing} and C_{new}, omitting the focal facility. As we explained above, the C_{ongoing} variables omitted any components acquired within the last two inspection periods

[4]A period is the time between state inspections, which averages about one year in our data. Because the time between inspections varies, we rescaled the dependent variables to account for variation in the time between inspections. The rescaling involved dividing the capability difference score by the number of years between inspections (where "years between inspections" equals "days between inspections/365"); thus, each dependent variable records the annualized change in the relevant capability measure (as a result of the annualizing, some dependent variable values exceed one in absolute magnitude).

while the C_{new} variable included only components acquired within the past two periods.

In turn, we used the component and chain measures to compute the similarity variables. We calculated chain-component similarity, S, as in equation (2), creating similarity measures for both ongoing and newly acquired units, as we discussed earlier ($S_{ongoing}$ and S_{new}). We created the similarity interaction variables as multiplicative interactions, producing interactions for capabilities of both ongoing and newly acquired components, $c \times S_{ongoing}$, $C_{ongoing} \times S_{ongoing}$, $c \times S_{new}$, and $C_{new} \times S_{new}$, as in equations 1a and 1b.[5]

Table 1 provides descriptive statistics for the theoretical variables (we lagged all independent variables by one period relative to the dependent variables).

4.3 Estimation

We estimated four specifications of our chain-to-component transfer model in equation (1), one specification based on each capability variable. We estimated the four models for each of two subsamples: components in ongoing chain relationships (equation 1a) and new members of a chain in their first two inspection periods after acquisitions (equation 1b). 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.

[5]Correlation among covariates is a common concern when using interactions. We considered using mean differences as a way of addressing this concern but found that it was more appropriate to use direct values of the variables while checking for any instability in the estimates that might result from adding the interaction terms. Interaction terms estimate the effect of one covariate on a dependent variable at a given level of another covariate. Mean differencing, such as comparing the value of a variable to an industry mean value, changes the level at which the coefficients are estimated. In the regression $y = \beta_1 X_1 + \beta_2 X_2 + \beta_3(X_1 \times X_2)$, for example, without mean differencing the presence of the interaction results in conditional estimates for X_1 when $X_2 = 0$ and for X_2 when $X_1 = 0$. With mean differencing, the conditional estimates are for X_1 when X_2 = mean X_2 and for X_2 when X_1 = mean X_1. So, the question in specifying interaction terms appropriately is whether zero or the mean value is the most meaningful level of the variable on which to condition the main effects. In our case, zero is the most meaningful conditioning point, for two reasons. First, mean differencing with respect to industry average values would involve an equilibrium assumption about capability usage levels that often is not warranted and clearly does not hold in our empirical context, which was undergoing substantial competitive changes during the study period. Moreover, the values of the X variables include zero, so that conditioning on zero is empirically meaningful. Second, mean differencing of the similarity variables (e.g., with respect to chain average similarity), which are the common variables in all the interaction calculations, would not produce meaningful variables; instead, mean differencing would produce a directional dissimilarity measure, which is conceptually inappropriate. This would require a further transformation to convert the similarity variables back into similarity indices. For instance, we might take ratios of the similarity variables to the mean of similarity, comparable to the way in which we compute the similarity variables, which would result in a ratio of ratios. We would find it difficult to interpret such a ratio of ratios index.

Table 1 Descriptive statistics: theoretical variables

Variable	Ongoing components				Newly acquired components			
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
Dependent Variable: injection services	0.00	0.09	–1.93	1.32	0.00	0.10	–1.23	0.94
Dependent Variable: therapy service	0.00	0.18	–1.73	1.84	0.00	0.18	–1.40	1.24
Dependent Variable: rehab beds	0.00	0.08	–1.99	2.00	–0.01	0.12	–1.41	1.74
Dependent Variable: Alzheimer's beds	0.00	0.06	–1.38	1.23	0.00	0.05	–1.08	1.04
Component: therapy services	0.18	0.21	0.00	1.00	0.22	0.26	0.00	1.00
Component: injection services	0.11	0.08	0.00	1.00	0.12	0.10	0.00	1.00
Component: rehab beds	0.01	0.08	0.00	1.00	0.02	0.12	0.00	1.00
Component: Alzheimer's beds	0.03	0.09	0.00	1.00	0.02	0.08	0.00	1.00
Chain (ongoing): therapy services	0.16	0.12	0.00	1.00	0.16	0.14	0.00	1.00
Chain (ongoing): injection service	0.11	0.04	0.00	0.73	0.10	0.07	0.00	1.00
Chain (ongoing): rehab beds	0.01	0.04	0.00	1.00	0.01	0.04	0.00	1.00
Chain (ongoing): Alzheimer's beds	0.03	0.05	0.00	1.00	0.03	0.06	0.00	0.98
Chain (new): therapy services	0.12	0.17	0.00	1.00	0.17	0.15	0.00	1.00
Chain (new): injection services	0.07	0.07	0.00	1.00	0.10	0.05	0.00	0.69
Chain (new): rehab beds	0.01	0.04	0.00	1.00	0.01	0.04	0.00	1.00
Chain (new): Alzheimer's beds	0.02	0.05	0.00	1.00	0.03	0.05	0.00	1.00
Similarity (ongoing): therapy services	0.52	0.30	0.00	1.00	0.40	0.32	0.00	1.00
Similarity (ongoing): injection services	0.64	0.26	0.00	1.00	0.53	0.33	0.00	1.00
Similarity (ongoing): rehab beds	0.55	0.49	0.00	1.00	0.55	0.50	0.00	1.00
Similarity (ongoing): Alzheimer's beds	0.41	0.47	0.00	1.00	0.43	0.48	0.00	1.00
Similarity (new): therapy services	0.35	0.36	0.00	1.00	0.50	0.33	0.00	1.00
Similarity (new): injection services	0.37	0.37	0.00	1.00	0.58	0.31	0.00	1.00
Similarity (new): rehab beds	0.76	0.43	0.00	1.00	0.61	0.48	0.00	1.00
Similarity (new): Alzheimer's beds	0.72	0.44	0.00	1.00	0.52	0.48	0.00	1.00

For analysis, we pooled inspections across periods and estimated a single model on the pooled cross-sections using time series regression models. 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. This would result in first-order autocorrelation that occurs when the disturbances in one time period are correlated with those in the previous time period, leading to biased variance estimates and rendering Ordinary Least Squares (OLS) estimates inefficient. Therefore, we estimated random-effects Generalized Least Squares (GLS) models, which correct for autocorrelation of disturbances due to constant firm-specific effects (Kennedy, 1992).

4.4 Control variables

In addition to the variables that constitute our theoretical model of chain-to-component transfer learning, all equations include multiple time-varying variables to control for additional capability, component, chain, environmental, and temporal factors that might influence change in component capability levels. Table A.1 presents descriptive statistics for the control variables.

Three sets of variables controlled for further possible capability effects. First, we estimated "cross-effects" of chain and component capabilities to account for any possible complementarities or substitution effects among capabilities. That is, in the model for each capability, we included the values of the theoretical variables (i.e., *c*, *C*, and *S*) for the three other capabilities. Second, we controlled for the *variability* of each capability among other ongoing components of a focal component's chain. Chains with high variation among ongoing components may seek to bring them in line with chain standards, resulting in greater change (it is not clear whether the changes would involve increases or decreases in capabilities at a focal component). Alternatively, chains may vary in the degree to which they emphasize standardization, with some chains seeking benefits of local responsiveness and adaptation rather than economies of standardization (Chuang and Baum, 2003), which might lead to less change in highly variable chains. Third, we controlled for the average level of each capability of other components to account for possible industry-wide tendencies toward increasing or decreasing provision of particular services (e.g., *Industry mean: Therapy services*).

At the component level, we defined four other control variables at the component level. Component size (*Component number of beds*) may reflect differences in structural capabilities, albeit as an indirect and occasionally problematic measure (Kimberly, 1976). *Component staff intensity* measures a nursing home's operating efficiency. Staff intensity (registered nurses, practical nurses, aids, and support staff, per resident) is contingent upon case mix and payment rate models and hence represents a key element of the operating strategy for a nursing home that may influence its capability choices. The study includes Full Time Equivalent (FTEs) of all employees, both nursing and ancillary, in our staffing measure.[6] *Component distance from chain center* measures the mean Euclidean distance of a component to other components in its chain. More distant components might be less susceptible to transfer learning if distance is barrier to knowledge transfer but might be more susceptible to transfer learning if chains attempt to standardize more far flung components because distance creates a barrier to managing differentiated facilities. *Component acquired from other chain* is a dummy variable denoting cases in which a component of a chain had previously been part of a different chain rather than operated independently. Components that were previously owned by another chain may have different propensities for transfer learning than those that were operated independently.

At the chain level, we defined six additional controls. Three variables address variation in chains' transfer learning experience and thus their propensity to change their components' capabilities. *Chain mean beds* recorded the mean number of beds in a chain's ongoing components. *Chain number of homes* recorded the number of components a chain operated during a given year. *Chain 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 also controlled for three factors that may influence the particular types of services chains may offer. *Chain service focus* provided a measure of chain specialization, denoting cases in which a chain's components, on average, offered fewer types of services than the focal component. *Variability*, which measured the variance in the levels of each capability across a chain's ongoing components controlled for the propensity of chains' emphasizing standardization to homogenize their components. *For-profit ownership* indicated whether the chain had for-profit status, which may influence the types of services it emphasizes.

We defined two sets of market controls at county and state levels. Three variables capture local competition levels at the county level, which may affect the propensity of chains to differentiate their components, thus affecting service characteristics. *County market concentration* measured the Hirschman-Herfindahl Index, defined as the sum of squared shares of beds of all nursing homes in the county. *County nursing homes* recorded the number of facilities in each county. *County beds per capita* recorded the total nursing home beds per county population. The final county-level factor, *County rural area*, 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.

At the state level, we controlled for the Medicaid reimbursement rate across this period, the mean Medicaid expenditures per Medicaid population, the mean Medicare expenditures per Medicare population, and the 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 and Medicaid programs are

[6]We also examined measures based on narrower staff groups: one based on Registered Nurses (RNs) and a second based on professionals; the narrower measures provided similar estimates.

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 influence a chain's impetus for transfer learning.

We included *Calendar year* in our models to control for possible temporal variation in the use of the difference capabilities not accounted for by the industry-level mean capability levels. As well, we included a set of dummy variables to control for the number of inspection periods since a focal component had been acquired – one and two periods post acquisition in the Δc_{new} subsample; three and four or more periods post acquisition in the $\Delta c_{\text{ongoing}}$ subsample.

5. Results

Tables 2 and 3 present the random-effects GLS model coefficients for ongoing and newly acquired components, respectively. Positive coefficients indicate greater increases in component capability usage between inspection periods; negative coefficient indicates greater decreases. Table A.2 reports control variable estimates for the models that Tables 2 and 3 summarize.

Each table reports three models for each of the four capabilities, starting with the main effects for c, C, and S in models 1a–d, then adding the S_{ongoing} interactions in models 2a–d, and finally adding the S_{new} interactions in models 3–3d. Estimates for the main effects are generally robust across the specifications in both tables, although in several cases the main effects of S_{new} and S_{ongoing} change sign when their interactions with the capability variables are included. Such instability of main effects is common in interaction models (Jaccard *et al.*, 1990) indicating the dependence of the effect of similarity on the direction of capability change on levels of chain and component capability usage (recall that the model makes no prediction for the main effect of similarity). We focus our discussion on the fully-specified models, 3a–d.

The estimates for models 3a–3d in Table 2 support the transfer learning model for ongoing chain components, particularly with respect to the capability levels of the chains' other established components. In total, 21 of 28 (75%) coefficients take the expected direction at statistically significant levels (the binomial probability of correctly predicting 21 of 28 coefficients correctly is .007).[7]

There is a strong fit for the component (c) and chain (C_{ongoing}) capability predictions, with all coefficients for c (β_1) and C_{ongoing} (β_{2a}) statistically significant in the expected directions. Similarly, S_{ongoing} has the expected moderating influences for both C_{ongoing} and c in all models (β_{4a} and β_{5a}, in the upper panel of Table 2). Thus, an ongoing component's transfer learning is strongly and systematically influenced by its own capability levels and the capability levels of other ongoing components in its chain.

[7]Binomial probabilities are calculated as $P_{(k \text{ of } n)} = [n!/k!(n-k)!](p^k)(q^{n-k})$, where n is the number of trials, k is the number of correctly predicted trials, p is the probability of the predicted outcome, and q is $1 - p$.

Table 2 Random effects GLS models of chain-to-component transfer learning: ongoing components

Variable	Model coefficient	Pred.	Therapy services			Injection services			Rehab beds			Alzheimer's beds			Model 3 support (%)
			Model 1a	Model 2a	Model 3a	Model 1b	Model 2b	Model 3b	Model 1c	Model 2c	Model 3c	Model 1d	Model 2d	Model 3d	
C	β_1		–0.62*	–0.65*	–0.67*	–0.77*	–0.99*	–1.00*	–0.59*	–0.74*	–0.74*	–0.25*	–0.35*	–0.34*	100
$C_{ongoing}$	β_{2a}	+	0.59*	0.68*	0.70*	0.70*	0.64*	0.63*	0.53*	0.39*	0.38*	0.38*	0.45*	0.44*	100
$S_{ongoing}$	β_{3a}		0.002	0.019*	0.014**	0.013*	–0.029*	–0.027*	0.006*	–0.0001	–0.001	0.006*	0.008*	0.008*	
$C_{ongoing} \times S_{ongoing}$	β_{4b}	–		–0.23*	–0.29*		–0.14*	–0.10**		–1.87*	–1.84*		–0.94*	–0.98*	100
$c \times S_{ongoing}$	β_{5a}	+		0.13*	0.17*		0.63*	0.57*		2.02*	2.07*		0.80*	0.85*	100
C_{new}	β_{2b}	+	0.02*	0.03*	–0.05*	0.03**	0.04*	0.06*	–0.05*	–0.05*	–0.02	–0.03*	–0.03*	–0.01	25
S_{new}	β_{3b}		0.015*	0.015*	–0.003	–0.002*	–0.004***	–0.005***	–0.004**	–0.002	0.000	–0.001	–0.002	0.002	
$C_{new} \times S_{new}$	β_{4b}	–			0.24*			–0.13*			–0.45*			0.00	50
$c \times S_{new}$	β_{5b}	+			–0.06**			0.13*			0.17***			–0.14**	50
Observations				36,391			36,391			36,473			36,460		75 (average)

Two-tailed tests. Table A.2 reports control variable estimates.

*$P < .001$.

**$P < .01$.

***$P < .05$.

Table 3 Random effects GLS models of chain-to-component transfer learning: newly acquired components

Variable	Model coefficient	Pred.	Therapy services			Injection services			Rehab beds			Alzheimer's beds			Model 3 support (%)
			Model 1a	Model 2a	Model 3a	Model 1b	Model 2b	Model 3b	Model 1c	Model 2c	Model 3c	Model 1d	Model 2d	Model 3d	
C	β_1		−0.45*	−0.47*	−0.47*	−0.71*	−0.72*	−0.74*	−0.37*	−0.30*	−0.38*	−0.19*	−0.20*	−0.20*	100
$C_{ongoing}$	β_{2a}	+	−0.05**	−0.001	−0.04	0.02	0.09*	0.11*	−0.03	−0.03	−0.02	0.07*	0.08*	0.08*	50
$S_{ongoing}$	β_{3a}		−0.009	0.005	0.011	−0.008**	0.018**	0.025*	0.012*	0.018*	0.019*	0.010*	0.009*	0.008*	
$C_{ongoing} \times S_{ongoing}$	β_{4b}	−		−0.16***	−0.02		−0.34*	−0.38*		1.30*	0.90*		−0.08	−0.09	25
$c \times S_{ongoing}$	β_{5a}	+		0.08	−0.03		0.10**	0.02		−1.88*	−1.51*		0.09**	0.10**	25
C_{new}	β_{2b}	+	0.45*	0.45*	0.62*	0.57*	0.58*	0.46*	0.78*	0.82*	0.82*	0.35*	0.35*	0.45*	100
S_{new}	β_{3b}		−0.005	−0.002	0.028*	−0.014*	−0.011***	−0.041*	0.023*	0.024*	0.023*	0.009*	0.010*	0.017*	
$C_{new} \times S_{new}$	β_{4b}	−			−0.45*			0.21***			−2.05*			−0.45*	75
$c \times S_{new}$	β_{5b}	+			0.19*			0.13**			1.67*			0.22*	100
Observations				7894			7894			7921			7918		68 (average)

Two-tailed tests. Table A.2 reports control variable estimates.

*$P < .001$.

**$P < .01$.

***$P < .05$.

By contrast, the results in Table 2 are weaker with respect to the capabilities of newly acquired components. C_{new} has a significant positive influence on change in ongoing components' capabilities in only one case (25%) while the S_{new} interactions take their predicted mediating effects for only 50% of the cases (β_{2b}, β_{4b}, and β_{5b} in the lower panel of the table). Moreover, even the significant C_{new} and S_{new} interactions typically have much lower magnitude than the comparable coefficients for capabilities of ongoing components. Thus, capability usage levels at newly acquired components have a smaller and less systematic impact on transfer learning at a chain's ongoing components.

The estimates for the main effect of similarity, for which we made no prediction, fluctuate in Table 2. Both $S_{ongoing}$ and S_{new} yield a mix of positive, negative, and insignificant coefficients (β_{3a} and β_{3b} in the upper and lower panels of the table). This fluctuation in results is consistent with the presence of the competing incentives of absorptive capacity and transfer learning constraints that we outlined in our theoretical specification of the model.

Table 3 replicates the analysis in Table 2 for post-acquisition transfer learning among newly acquired chain components. The estimates for models 3–3d of Table 3 again support the transfer learning model for newly acquired members of a chain, particularly with respect to the capability levels of the chain's other new components. In total, 19 of 28 (68%) coefficients take the expected direction at statistically significant levels (the binomial probability of correctly predicting 19 of 28 coefficients correctly is .045).

There is a strong fit for the component (c) and chain (C_{new}) capability predictions, with all coefficients significant in the expected direction (β_1 plus β_{2b} in the lower panel of Table 3). In addition, S_{new} has the expected moderating influence for c in all four cases and C_{new} in three of four cases (β_{4b} and β_{5b} in the lower panel of Table 3). Thus, a newly acquired component's own capability levels and the capability levels of other newly acquired components in its chain strongly and systematically influence its transfer learning.

Table 3 again reveals a contrast between the capability levels of a chain's newly acquired and ongoing components. $C_{ongoing}$ has the expected positive impact in only 50% of the cases (β_{2a} in the upper panel of the table) while the $S_{ongoing}$ interactions with c and $C_{ongoing}$ are significant in the expected direction in only one case each (β_{4a} and β_{5a} in the upper panel).

Again, then, we find a bifurcation in chains' transfer learning. Newly acquired components are influenced more strongly and systematically by the capabilities of other newly acquired chain components. Ongoing components are influenced more strongly and systematically by the capabilities of other ongoing chain components.

The main effects of similarity are more stable in Table 3 than in Table 2. Three of four coefficients in models 3a–d are positive and significant for both $S_{ongoing}$ and S_{new} (β_{3a} and β_{3b}). This suggests that, following the organizational disruptions that typically accompany an acquisition, similarity creates an absorptive capacity that facilitates knowledge transfer between chain components. Notably, in this case, similarity of a newly acquired component with both ongoing ($S_{ongoing}$) and newly acquired (S_{new}) components tends to promote transfer learning.

The interaction terms in the chain-to-component transfer learning model make it difficult to grasp intuitively how variation in the model's parameter estimates affect the nature of the relationship between chain and component capabilities and the degree of transfer learning. To aid in interpreting the findings, therefore, Figure 1 graphically illustrates the implications of the estimates for several representative equations.

The four panels in Figure 1 show predicted values for Δc (increase or decrease in component capability) across all possible combinations of values of C (chain capability) and c (component capability). Panels A and C show predictions for changes in therapy services and Alzheimer's bed for ongoing components ($\Delta c_{ongoing}$) based on coefficients for c, $C_{ongoing}$, $S_{ongoing}$, $c \times S_{ongoing}$, and $C_{ongoing} \times S_{ongoing}$ from models 3a and 3d in Table 2. Panels B and D show the predictions for new components (Δc_{new})

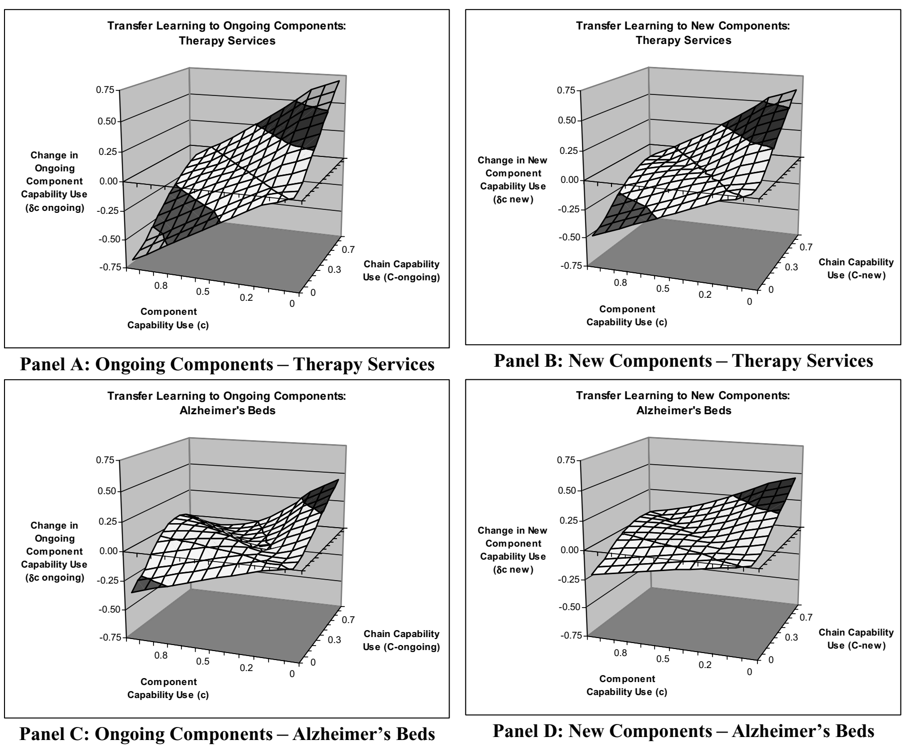

Figure 1 Transfer learning to ongoing and new components based on combinations of component and chain capability use. (**A**) Ongoing components—therapy services, (**B**) new components—therapy services, (**C**) ongoing components—Alzheimer's beds, and (**D**) new components—Alzheimer's beds.

based on coefficients c, C_{new}, S_{new}, $c \times S_{new}$, and $C_{new} \times S_{new}$ from models 3a and 3d in Table 3.

The patterns of changes in capability level (vertical axis) across combinations of chain and component capability levels in Figure 1 illustrate the core predictions of the transfer learning model. In all four panels, change is greatest where chain and component capability differences are maximal, with large increases (decreases) in component capability use associated with conditions of high (low) chain and low (high) component capability use (the left front and right rear corners of the graphs in each panel). In addition, the level of component capability change is closest to zero along the "similarity diagonal," which runs from the front right to back left corner of the graph in each panel.

Several differences in the shapes of the capability change surfaces for therapy services and Alzheimer's beds patterns in Figure 1 are notable. The slope is much steeper for therapy services (Panels A and B) than for Alzheimer's beds (Panels C and D). Additionally, while the therapy services slope is nearly linear, a relatively flat plateau appears in the middle of the Alzheimer's surface. These different patterns of predicted capability changes suggest that changes in Alzheimer's beds availability tend to occur primarily at extremes of component and chain capabilities, whereas therapy services changes occur more incrementally throughout the range of chain and component capability usage.

Empirically, the difference in the patterns for therapy services and Alzheimer's beds reflects variation in the magnitudes of the coefficients for chain and component capability levels and their interactions with similarity. Conceptually, this difference likely arises because, as we noted earlier, it is quite easy for components to change the relatively explicit procedures and practices that underlie therapy service capabilities, whether through retraining or through the replacement of existing staff and equipment. In contrast, the provision of Alzheimer's beds requires more numerous and complex care practices that involve multiple clinical disciplines and knowledge embedded in staff roles, administrative structures, and the physical structure of the component and so are far more difficult to alter.[8]

6. Discussion and Conclusion

To understand better chains' patterns of transfer learning, we developed and estimated a model of chain-to-component and component-to-chain transfer learning applicable to both established chain–component relationships and new relationships that chains formed by acquiring components from other owners. In contrast to past research on multiunit organizations in the learning curve tradition, which infers transfer learning from changes in chain and component performance, we operationalize transfer

[8]Notably, rehabilitation bed change exhibits a similar mid-range plateau for both ongoing and new components (akin to Alzheimer's beds) while the injection services pattern is close to linear (much like therapy services).

learning by measuring changes in component service characteristics that lie closer to the underlying capabilities that a component is able to use to transform inputs into outputs at a given time.

The model focuses on the effects of component and chain capability levels and their similarity. We found general support for the model, along with a partial bifurcation of transfer learning between a chain's ongoing and newly acquired components. Capability levels of ongoing components strongly and systematically influence transfer learning at other ongoing components, while capability levels of newly acquired components strongly and systematically influence transfer learning to other newly acquired components. Transfer learning effects between ongoing and newly acquired components are much weaker and less systematic. As a result of this bifurcation, a chain's ongoing components should tend to converge, as should separately—and potentially divergently from established facilities—the capabilities of its newly acquired components.

An important question raised by our findings is whether the apparent bifurcation between ongoing and newly acquired components reflects intentional strategy or results from constraints on transfer learning. One interpretation of this finding is that, even within a chain, the development of relationship-specific routines, processes, and trust required for effective transfer learning takes substantial investment and time to develop. And, as a result, that little transfer learning takes place between newly acquired and ongoing components because they lack such relationship-specific assets and are not yet sufficiently similar to facilitate transfer. Indeed, attempting to force transfer under such conditions could be worse than useless; it could be harmful if the attempted transfers disrupt a chain's ability to manage existing capabilities (Mitchell, 1992; Greve, 1999). Thus, even if a chain might benefit from standardization, barriers between established and new components appear to limit, at least initially, the potential to transfer capabilities in order to standardize.

The fact that transfer learning does appear to take place between newly acquired components, though, suggests a more nuanced inference about investments in relationships among components. That is, relationships between newly acquired and ongoing components may be slow to develop, owing to entrenched routines, practices at and personal relationships among more established ongoing chain components. The disruptive influence of being acquired may, however, assist the chain to create transfer learning relationships among its less entrenched recent acquisitions by opening them to outside influence. It is also possible that newly acquired components' capabilities are more similar to one another than they are to the capabilities of ongoing components, which may result if a chain acquires several new components with similar capabilities over a short time frame. Moreover, if the newly acquired components were acquired as a group from another chain, they may also have strong preexisting formal and personal ties that facilitate their interaction. Hence, time *per se* may not be the major impediment to creating transfer processes between new and ongoing components; rather, it is the presence of entrenched personnel and practices. Clearly, additional research is needed to determine the prevalence and better specify the sources of this apparent schism between new and ongoing components. Still, its implications for our understanding the dynamics of chains' capabilities are quite striking.

Chains change at both the component and chain level. 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 failure.

At the chain-level, changes take place in two ways. First, component-to-chain learning occurs through a system-level diffusion of a chain's existing capabilities leading component capabilities to converge toward average chain capabilities over time. Second, chain-level change involving new capabilities takes place as chains acquire new components with different service characteristics. From this perspective, chains are more like collaborative alliances than integrated hierarchies. 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 acquiring distinctive components as local 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 change in the components that the chain subsequently acquires.

Our findings suggest, however, that new acquisitions commonly lead to only limited changes at a chain's established components and, additionally, that chains may find it difficult to bring their newly acquired components in line with chain standards. The first of these findings implies that acquisitions tend to change a chain's capabilities more by changing its portfolio of components and less through diffusion of new capabilities throughout the chain. Such inertia has the advantage of protecting chains from engaging in potentially disruptive and costly diffusion of capabilities that may prove harmful to their ongoing components. But it also means that chain-level change can occur through transfer learning only if a chain consistently acquires components with capabilities that diverge from its current standard over a period of time sufficient to change the composition of its ongoing components.

To the extent that chains are aware of the second finding regarding the challenge of aligning newly acquired components with the chain's standard (or simply seek opportunities to repeat their past successes), they will tend to acquire components with service characteristics and underlying capabilities close to their existing standard and so expose themselves to few novel capabilities. Taken as a whole, our findings reinforce prior research indicating that chains are fundamentally exploitive, deriving competitive advantage primarily by reproducing and incrementally updating their capabilities to create economies of standardization (Baum *et al.*, 2000). They also point to the need for additional research examining the influence of similarity between ongoing and newly acquired components on chains' patterns of transfer learning.

Like any study, ours has limitations, among which we highlight four. First, our results are most generalizable to industries with conditions similar to the nursing home sector. The key features include ongoing competitive change in market requirements and frequent buying and selling of components, which are common conditions in industries such as the hotel, hospital, supermarket, and banking sectors. Second, the fact that our study is limited to acquisitions as a source of new components may limit its generalizability to contexts in which chain growth occurs primarily through creating new components. Third, the model we advanced underemphasizes the potential role of chains' spatial arrangements in shaping their patterns of transfer learning. Although we controlled for the average distance of each component to the other members of its chain, incorporating of the role of distance into the model in a more nuanced way is an important next step. Fourth, although we come closer to measuring capabilities than prior studies of transfer learning, we still ultimately infer that chains have changed the capabilities of their components when we observe changes in the services that the components provide. Nonetheless, we believe that the results contribute substantively to our understanding of the conditions under which transfer learning takes place within chains.

Our study advances two growing research streams. First, we extend research that characterizes multiunit chains as interorganizational learning communities (Darr *et al.*, 1995; Ingram and Baum, 1997, 2001; Greve, 1999). Our attention to transfer learning processes within chains stems from the belief that how chains change and deploy their knowledge is a key source of their competitive advantage. Our results complement past research on multiunit organizations in the learning curve tradition in two ways. One, we provide evidence of changes in component service characteristics and their underlying capabilities—changes inferred in learning curve research from changes in component performance. And, two, we specify factors that enable and constrain transfer learning and thus the conditions under which more or less transfer learning should be anticipated.

Second, we expand research-characterizing acquisitions as basic to processes of business change, reconfiguration, and resource redeployment (Capron *et al.*, 1998; Karim and Mitchell, 2000) to the domain of chains. Our findings point to potentially fundamental differences in the role of acquisitions for multiunit than other organizational forms.

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 important insight into the transformation of the economy. We hope our theoretical model, which appears to offer a robust theoretical account of transfer learning in chains, provides an impetus for such work.

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Appendix

Table A1 Descriptive statistics: control variables

Variable	Ongoing components				Newly acquired components			
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
Component characteristics								
Component number of beds	107.42	52.78	4	500	103.27	54.30	5	500
Component staff intensity	1.14	1.63	0	20	1.28	1.93	0	20
Component distance from chain center	8.42	8.15	0.00	49.58	11.30	9.21	0.00	49.58
Component acquired from other chain	0.04	0.20	0.00	1.00	0.47	0.50	0.00	1.00
Chain characteristics								
Variability: chain therapy services	0.02	0.04	0.00	0.50	0.03	0.04	0.00	0.50
Variability: chain injection services	0.00	0.01	0.00	0.45	0.01	0.01	0.00	0.33
Variability: chain rehab beds	0.01	0.03	0.00	0.50	0.01	0.02	0.00	0.50
Variability: chain Alzheimer's beds	0.01	0.02	0.00	0.50	0.01	0.02	0.00	0.50
Chain mean beds	107.26	35.88	10	500	94.56	53.81	10	500
Chain number of homes	124.9	226.8	2	823	78.68	149.66	2	823
Chain cumulative acquisitions	17.61	31.30	0	298	47.7	72.1	0	298
Chain service focus	0.47	0.50	0.00	1.00	0.47	0.50	0.00	1.00
For-profit ownership	0.81	0.39	0.00	1.00	0.89	0.31	0.00	1.00
Market characteristics								
County beds per capita	0.001	0.001	0.00	0.02	0.001	0.001	0.00	0.02
County market concentration	0.22	0.23	0.00	1.00	0.19	0.22	0.00	1.00
County nursing homes	31.80	65.60	1	408	38.14	70.51	1	408
County rural area	3.00	2.76	0.00	9.00	2.68	2.60	0.00	9.00

Table A1 Continued

Variable	Ongoing components				Newly acquired components			
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
State certificate of need	0.51	0.50	0.00	1.00	0.44	0.50	0.00	1.00
State construction moratorium	0.17	0.38	0.00	1.00	0.20	0.40	0.00	1.00
State Medicaid $/Medicaid population	999.61	541.92	19.61	3235.00	915.31	538.99	19.61	3235.00
State Medicare $/Medicare Population	139.69	81.49	5.38	434.78	153.20	84.19	5.38	434.78
State Medicaid reimbursement rate	75.26	14.76	50.32	155.50	74.75	14.07	50.32	155.50
State population over 65 years of age	1261.00	992.10	49.00	3519.00	1407.00	1070.00	49.00	3519.00
Industry mean: therapy services	0.19	0.03	0.13	0.24	0.20	0.03	0.13	0.24
Industry mean: injection services	0.11	0.00	0.10	0.12	0.11	0.00	0.10	0.12
Industry mean: rehab beds	0.01	0.01	0.00	0.03	0.01	0.01	0.00	0.03
Industry mean: Alzhimer's beds	0.03	0.01	0.01	0.03	0.03	0.01	0.01	0.03
Time factors								
Calendar year	1995.0	1.64	1992	1997	1995.0	1.55	1992	1997
1 Period post-acquistion	NA				0.53	0.50	0.00	1.00
2 Periods post-acquistion	NA				0.47	0.50	0.00	1.00
3 Periods post-acquistion	0.08	0.26	0.00	1.00	n/a			
4+ Periods post-acquistion	0.09	0.28	0.00	1.00	n/a			

Table A2 Control Variable Estimates for Tables 2 and 3 (Models 3a to 3d)

Variable	Table 2: ongoing components				Table 3: newly acquired components			
	Therapy services	Injection services	Rehab beds	Alzheimer's beds	Therapy services	Injection services	Rehab beds	Alzheimer's beds
Capability cross-effects								
Component: therapy services		0.029*	0.015*	0.002		0.068*	0.026*	0.003
Component: injection services	0.113*		0.020*	–0.020*	0.137*		–0.028*	–0.021*
Component: rehab beds	0.132*	0.025*		–0.008	–0.253*	0.008		–0.009
Component: Alzheimer's beds	–0.069*	–0.046*	0.002		–0.027	–0.024**	–0.007	
Chain (ongoing): therapy services		–0.026*	–0.030*	–0.003		–0.001	0.014	0.006
Chain (ongoing): injection services	–0.053		0.015	0.015	0.160*		–0.005	0.009
Chain (ongoing): rehab beds	–0.306*	–0.040		–0.004	0.134**	0.111*		–0.056***
Chain (ongoing): Alzheimer's beds	0.017	0.025	–0.007		–0.050	–0.043**	0.022	
Chain (new): therapy services		–0.004	–0.005	0.004		–0.058*	–0.015	–0.014**
Chain (new): injection services	–0.033		–0.022**	0.012	–0.194*		–0.057**	0.034
Chain (new): rehab beds	–0.012	–0.014		–0.026***	–0.160**	–0.049		–0.065***
Chain (new): Alzheimer's beds	0.004	0.002	–0.020**		–0.022	–0.009	–0.051***	
Similarity (ongoing): therapy services		–0.005	–0.003**	–0.003**		–0.007**	–0.003	–0.004
Similarity (ongoing): injection services	–0.025*		0.003**	0.002	–0.008		0.006	–0.006**
Similarity (ongoing): Rehab beds	–0.002	0.005*		0.000	–0.008	–0.004		–0.003
Similarity (ongoing): Alzheimer's beds	–0.005	0.002	–0.003*		0.020*	0.005	–0.006**	
Similarity: (new): therapy services		0.000	–0.004*	0.000		–0.003	–0.001	–0.001
Similarity (new): injection services	0.004		0.003**	–0.003***	–0.042*		0.005	–0.002
Similarity (new): rehab beds	–0.023*	0.005*		–0.003**	–0.009	–0.008***		–0.005**
Similarity (new): Alzheimer's beds	–0.001	–0.001	0.000		–0.001	–0.001	–0.009*	

Table A2 Continued

Variable	Table 2: ongoing components				Table 3: newly acquired components			
	Therapy services	Injection services	Rehab beds	Alzheimer's beds	Therapy services	Injection services	Rehab beds	Alzheimer's beds
Component characteristics								
Component number of beds (× 100)	–0.010*	–0.002	–0.002**	–0.001	–0.033*	–0.009*	–0.003	0.002
Component staff intensity	0.009*	0.002*	0.000	0.000	0.003***	–0.001***	0.001	0.000
Component distance from chain center (× 100)	0.057*	0.010	0.003	–0.004	–0.011	–0.001	0.000	0.025**
Component acquired from other chain	0.004	0.003	0.004	–0.005***	–0.008	0.002	0.002	0.000
Chain characteristics								
Variability: chain therapy services	0.408*	–0.006	0.034***	0.002	0.231*	–0.047	–0.029	–0.069***
Variability: chain injection services	–0.443*	0.645*	0.046	0.068**	–0.130	–0.020	–0.086	–0.025
Variability: chain rehab beds	0.380*	0.019	0.281*	0.020	–0.253**	–0.095	0.324*	0.090**
Variability: chain Alzheimer's beds	–0.042*	0.007	–0.007	0.064***	0.360*	–0.032	–0.083	0.108**
Chain mean beds (× 100)	0.013*	0.006*	0.004**	–0.001	0.010	0.005	0.004	0.002
Chain number of homes (× 100)	–0.008*	0.000	0.001	0.001	0.000	–0.003	0.002	–0.004**
Chain cumulative acquisitions (× 100)	–0.013***	0.012*	–0.004	0.004	0.022**	0.003	0.006	0.004
Chain service focus	0.015*	0.006*	0.006*	0.009*	0.006	0.009*	0.009*	0.009*
For-profit ownership	0.000	–0.002	0.001	0.003***	–0.010	0.000	0.005	–0.001
Market characteristics								
County beds per capita	–1.333	–0.742	0.606	0.068	–3.454	–2.918**	2.252	0.967
County market concentration	–0.003	0.001	0.001	–0.003	–0.047*	–0.012**	0.004	–0.003
County nursing homes (× 100)	0.002	0.002**	–0.001	–0.002*	0.000	0.001	–0.001	0.000
County rural area	–0.002*	0.000	0.000	0.000***	–0.001	0.001	–0.001	0.000
State certificate of need	–0.001	0.002**	–0.002**	0.001	0.008	0.007*	0.000	–0.001
State construction moratorium	0.003	0.000	–0.002	0.000	0.019*	0.004	0.001	0.005***
State Medicaid $/Medicaid population (× 100)	–0.007***	0.003*	0.002*	0.000*	–0.008	0.002	0.000	0.000

Table A2 Continued

Variable	Table 2: ongoing components				Table 3: newly acquired components			
	Therapy services	Injection services	Rehab beds	Alzheimer's beds	Therapy services	Injection services	Rehab beds	Alzheimer's beds
State Medicare $/Medicare population (× 100)	0.014	0.001	–0.005	0.031*	0.178*	–0.010	–0.020	0.029
State Medicaid reimbursement rate (× 100)	0.135	–0.020	0.047	–0.010	–0.520***	–0.020	0.104	–0.060
State population over 65 years of age (× 100)	0.005*	–0.002*	0.001*	–0.001*	0.003	–0.180**	–0.001	–0.004
Industry mean: therapy services	1.148***	–0.410**	0.036	–0.162	–1.269	0.000	–0.710	–0.198
Industry mean: injection services	–1.624***	0.408	0.304	–0.078	–1.643	–3.241*	1.474**	–0.331
Industry mean: rehab beds	2.468*	–0.335	–0.008	0.032	–1.653	1.713**	–0.857	0.029
Industry mean: Alzhimer's beds	2.920	–2.735*	–0.468	–0.497	–4.235	–2.260**	–1.344	–1.084
Time factors								
Calendar year	–0.046***	0.020***	0.001	0.004	0.042	0.000	0.020	0.006
1 Period post-acquistion (v. 2 periods)					–0.020*	0.117*	–0.001	–0.002
3 Periods post-acquistion (v. not acquired during study)	–0.006	–0.012*	–0.001	0.001				
4+ Periods post-acquistion (v. not acquired during study)	0.012*	–0.005*	–0.002	–0.003*				
Constant	91.773***	–39.401***	–2.070	–7.774	–83.306	–233.000*	–39.541	–11.854

Two-tailed tests. Observations as given in Tables 2 and 3.

*$P < .001$.

**$P < .01$.

***$P < .05$.