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The Impact of Chain Organization Size on Efficiency and Quality of Affiliated Facilities—Implications for Multi-Unit Organizational Forms

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This study investigates how the affiliation of dialysis facilities within chain organizations of varying sizes impacts efficiency and quality outcomes of these facilities. We develop our hypotheses by building on the literature base that relates to organizational learning. The paper uses a panel dataset spanning the years 2008–2013. The efficiency of the dialysis facilities is operationalized by means of a data envelopment analysis model. This model considers the number of treatments in the dialysis facility as the output variable. The model uses four inputs—number of dialysis stations, number of full-time equivalents of physicians, number of full-time equivalents of clinical staff, and the number of employee hours per week at a dialysis facility. Quality is operationalized by considering facilities' performance scores on three measures developed by the Center for Medicaid and Medicare Services. The findings point to distinct effects of chain organization size on quality and efficiency performance of dialysis facilities. Specifically, the results obtained by analyzing a dynamic panel data model show that chain organization size has an inverse U-shaped curvilinear effect on quality outcomes and a U-shaped curvilinear effect on efficiency. The findings suggest that dialysis facilities affiliated with chain organizations of varying sizes experience learning effects and causal ambiguities depending on the specific performance measure under consideration. We discuss the implications of our findings for theory and practice and present directions for future research.

Key words: chain size; quality; efficiency; organizational learning; dynamic panel data analysis
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1. Background

Since 1980, the number of patients receiving dialysis treatment for end-stage renal disease (ESRD) has increased by more than 10-fold to almost 750,000 patients (U.S. Renal Data System, 2019) and since the year 2000, almost 25,000 new patients are being added each year to this list (U.S. Renal Data System, 2018). ESRD is the most advanced stage of kidney disease and it requires dialysis, a process of removing waste (diffusion) and unwanted water (ultrafiltration) from the blood (Nordqvist 2014). In 2017, the Center for Medicare and Medicaid Services (CMS), which typically covers 80% of the dialysis costs to the patient, reported that expenditures for ESRD were in excess of $35.9 billion or 7.2% of all CMS expenditures (Saran et al. 2020). These expenditures benefit only 1% of CMS beneficiaries (CMS OMH, 2017). Given the role of healthcare spending in driving the US deficit (Congressional Budget Office, 2016) and high pressure on industry and government officials to reduce rising healthcare costs (Powell et al. 2012), research that can promote the efficiency and quality of dialysis has clear value.

The dialysis industry within the United States is comprised of two large for-profit companies and many medium- to small-sized companies. These companies provide the necessary care for persons whose kidneys are failing and are waiting for, or are ineligible for, a kidney transplant. The wait for a transplant can be years, so patients may receive hundreds of dialysis treatments before receiving one. Dialysis centers are located throughout the United States and the majority of the population can easily obtain access to care (Curran 2018). On average, in our dataset, a facility has 18 treatment stations (σ = 6.96). In an average sized facility, the mean number of patients, all of whom visit three times per week for treatment, is 65. Each treatment utilizes a station for about 4 hours. Registered nurses and dialysis technicians are responsible for operating the stations that assist in the treatment of the patients. At an average facility, there are four registered nurses and 6.4 dialysis technicians. Some facilities use licensed practical nurses and nurse aides for clinical care. Many facilities employ social workers and dieticians. The two leading companies, Fresenius Medical Care and Davita Healthcare Partners, are similar in size and both have been growing rapidly through acquisitions and internal expansion in recent years (Curran 2018). In our dataset, these two companies had 48.5% market share in 2008, and by 2013, they had almost 60% market share. This trend has continued to this day, as they now make up more than 70% of the marketplace (Curran 2018). Unlike hospitals, most dialysis centers are for-profit organizations. Over the years of our dataset, the number of not-for-profit centers decreased as a percentage of the whole from 20% to 15%.

Research has addressed issues pertaining to efficiency and efficacy of dialysis centers but has largely failed to reconcile the two. For instance, Lee et al. (2008) assert that since ERSD is progressive, the stage at which dialysis starts and the amount of dialysis provided to a patient should be determined based on associated cost concerns. However, an alternate study shows that increasing the duration and frequency of dialysis yields the best results for patients (Eloot et al. 2009). Researchers have focused on quality of care by means of identifying best practices related to the delivery of dialysis (Desai et al. 2008, Spiegel et al. 2010) and conforming to the National Kidney Foundation Kidney Disease Outcome Quality Initiative's clinical quality guidelines (National Kidney Foundation Inc, 2006). Overall, studies examining efficiency and quality of dialysis facilities have remained divided. Several operations management scholars have emphasized the need for joint consideration of efficiency and quality (Boyer et al. 2005, Roth and Menor 2003). Roth and Menor (2003) acknowledge that research has not rigorously studied service design or the antecedents to delivering successful patient and clinical outcomes within service operations. The need for a systematic effort toward integrating efficiency considerations into the implementation of CMS dialysis facility performance scoring is clear.

One of the antecedent factors of the efficiency and quality of dialysis facilities that research has identified is *chain organization size*—a structural characteristic indicating if a facility belongs to a chain organization and, if so, the number of facilities within its chain organization. The findings pertaining to the effect of this structural characteristic have been mixed (Hirth et al. 1999, Ozgen 2006, Ozgen and Ozcan 2002, Özgen and Şahin 2010, Pozniak et al., 2010; Shreay et al. 2014). For example, Hirth et al. (1999) found dialysis facilities that belonged to large chain organizations had significantly lower costs but acknowledged shortcomings in their data quality. In contrast, Ozgen and Ozcan (2002) and Shreay et al. (2014) found that dialysis facilities belonging to large chain organizations were less efficient than those that belonged to smaller organizations and independent facilities. In a study using a smaller sample size, Ozgen (2006) found no relationship between chain organization size and efficiency. Saunders and Chin (2013) fail to find a consistent relationship between chain status and quality performance of dialysis facilities. Table 1 presents key findings in prior literature and highlights differences concerning efficiency and quality outcomes within dialysis facilities.

Our paper expands on existing research by considering the effect of the size of chain organizations on the efficiency and quality of dialysis facilities. Several industries have experienced strong growth in multi-unit organizational forms, such as chain organizations and franchises (Argote and Fahrenkopf 2016). This trend prompted Argote and Fahrenkopf (2016) to call for more research into these multi-unit organizational forms as adopted in areas such as healthcare where services can range from standardized to more specialized, where the social consequences of performance are high, and where the workforce is highly skilled. Studies have reported that sharing a parent organization and affiliation through a superordinate relationship, such as being part of the same chain or franchise, supports greater transfer of knowledge than independent organizations achieve (Argote et al. 2003, Baum and Ingram 1998, Darr et al. 1995).

Chain organizations enable the development of transactive memory systems (Wegner 1987), which facilitate the retention and transfer of knowledge among affiliated facilities (Borgatti and Cross 2003, Liang et al. 1995). The knowledge in the repository is embedded within the members, tasks, and tools, and the network formed by these elements of chain organizations (Argote and Hora 2017, Argote and Ingram 2000, Arrow et al. 2000, McGrath and Argote 2001). Within chain organizations, the member–member network represents the associations among decision makers, the task–task network captures the interrelationship between tasks routines and processes, and the tool–tool network represents the interrelationships between tools and systems. The member–task, member–tool, and task–tool networks consider how decision makers, tasks, and tools interrelate with each other within the larger ecosystem created by the chain organization.

While the knowledge reservoir that supports these interrelationships can help dialysis facilities improve their performance, the positive effects are contingent upon the compatibility and congruence of the networks formed by the members of the chain

Table 1 Literature Review

Author	Title	Year	Sample size	Key focus	Findings	Limitations
Griffiths et al.	The Production of Dialysis by For-Profit vs. Not-For-Profit Freestanding Renal Dialysis Facilities	1994	1224 facilities	For-profit vs. not-for-profit	For-profit achieves greater throughput with same capital and labor inputs as compared to non-profit facilities	Limited inputs and outputs. Unable to determine cause of results. Patient characteristics were not considered
Hirth	Practice Patterns, Case Mix, Medicare Payment Policy, and Dialysis Facility Costs	1999	437 facilities	Effect of ownership, location, and chain status on dialysis costs	Only members of large chains exhibited cost savings relative to non-chain facilities	Chain organization data were from different source and not thought to be complete. Evaluated costs, not efficiency. Did not consider patient severity
Ozgen and Ozcan	A National Study of Efficiency for Dialysis Centers: An Examination of Market Competition and Facility Characteristics for Production of Multiple Dialysis Outputs	2002	791 facilities	Efficiency of dialysis facilities based on competition and facility characteristics	For-profit more efficient. Large chain members less efficient. Focus leads to better performance	Used binary variable for DEA values. Cause of findings is unclear, since quality was not accounted for (thus facilities may have achieved greater efficiency by cutting corners)
Ozgen and Ozcan	Longitudinal Analysis of Efficiency in Multiple Output Dialysis Markets	2004	140 facilities across 7 years	Whether efficiency improves over time	Finds that lack of technology adoption negates improvement in technical efficiency, thus efficiency over time has not improved much	Did not adjust for variability in patient severity
Ozgen	Does Chain Affiliation Make a Difference in Efficiency of Dialysis Providers in the USA	2006	49 facilities (4 years)	Does chain membership influence efficiency?	Size of chain organization does not improve efficiency, although organizational maturation and learning lead to greater efficiency	The DEA output measure only quantifies the number of people served. Quality, costs, and patient severity/survival are not evaluated. Did not adjust for variability in service offerings
Desai et al.	Identifying Best Practices in Dialysis Care: Results of Cognitive Interviews and a National Survey of Dialysis Providers	2008	Systematic literature review, nine interviews, and focus groups with 250 nurses	Identify practices of top performing dialysis facilities	Identifies and rank-orders 155 best practices	Best practices identified through systematic literature review and ranked via a survey. They were not tested empirically
Spiegel et al.	Dialysis Practices That Distinguish Top- vs. Bottom-Performing Facilities by Hemoglobin Outcomes	2010	423 employees; 90 facilities	Identify practices of top performing dialysis facilities	Identified five characteristics that correlate with hemoglobin targets, a measure of clinical quality: chairside computers, educational videos, frequency of calling in more staff when short staffed, requirement that nurses pass comprehensive exam before starting position, and tech cannulation mastery	Measured ability to achieve targeted hemoglobin levels (clinical quality), but not efficiency
Ozgen and Sahin	Measurement of Efficiency of the Dialysis Sector in Turkey Using Data Envelopment Analysis	2010	830 facilities	Efficiency of dialysis facilities in Turkey	Facilities that are private, affiliated with international chains, older, and located in the capital city were most efficient	Outputs and inputs are different. Data collected from country outside the United States, thus laws and incentives are different

(continued)

Table 1 ***(continued)***

Author	Title	Year	Sample size	Key focus	Findings	Limitations
Saunders and Chin	Variation in Dialysis Quality Measures by Facility, Neighborhood and Region	2013	5616 facilities	Association between dialysis facility quality and dialysis facility characteristics, neighborhood demographics, and region	Being part of a chain does not have a consistent relationship with quality measures	Chain status is operationalized as a categorical variable and the study does not account for the performance of dialysis facilities over time
Shreay et al.	Efficiency of U.S. Dialysis Centers: An Updated Examination of Facility Characteristics That Influence Production of Dialysis Treatments	2014	4343 facilities	Factors associated with efficiency of dialysis facilities in the United States	Large chain organization membership associated with less efficiency	Inputs and outputs are different. Analyses are based on 2010 cross-sectional data. Quality outcomes were not considered and are listed as a limitation of the study

organizations. The need for compatibility and congruence can result in coordination challenges that can increase as the size of the chain organizations increases. Additionally, causal ambiguity, which captures "the degree to which decision makers understand the relationships between organizational inputs and results" (King 2007, Lippman and Rumelt 1982), makes the cause and effect relationships more difficult in these larger multi-organizational forms due to the sheer number, diversity, and complexity of the underlying elements (Szulanski 1996). Within dialysis centers, many aspects exist that may increase causal ambiguity, such as the number and ratio of workers and their roles, state regulations, technologies employed, patient heterogeneity, the suite of services offered, and best practices being used, to name a few. These opposing effects of learning and coordination make the impact of the size of chain organizations on the performance of dialysis facilities less clear. Argote and Fahrenkopf (2016) point to this lack of clarity and call research attention to examining the enabling role of multi-unit organizations in knowledge transfer within the healthcare sector as well as features of these organizations that facilitate or impede knowledge transfer.

The current study responds to the need for additional research by considering data from 2008 to 2013 for US-based dialysis facilities that are registered with the CMS. In total, the data collection effort resulted in 33,249 observations across 6371 US-based dialysis facilities from 2008 to 2013. The results obtained from a dynamic panel data model show that the chain organization size has an inverted U-shaped relationship with *quality* of dialysis facilities. The effect of chain organization size on *efficiency* follows a U-shaped relationship. The findings offer some new insights into the effect of structural factors, transactive memory systems, and causal ambiguity on the performance of dialysis facilities.

This study improves upon past research in a number of ways. First, it considers a sample of dialysis facilities that only offer hemodialysis. This homogeneity ensures that factors related to providing peritoneal dialysis do not confound the effect of chain size on efficiency and quality. The majority of facilities in the United States provide hemodialysis, which accounts for the treatment of 87.3% of US patients (U.S. Renal Data System, 2017) and is just as clinically effective as peritoneal dialysis (Ross et al. 2000). Second, this study addresses the effect of the size of chain organization on the quality of a dialysis facility in addition to efficiency. Studies that have examined quality within chain healthcare operations have generally focused on hospitals or specific departments (Anand et al. 2018, Senot et al. 2015, Theokary and Ren 2011, White et al. 2011). Dialysis facilities, which patients visit frequently and routinely, often without an interaction with a physician, may be quite different from such facilities. Third, this study uses a dynamic panel data spanning six years and attempts to address potential empirical analysis issues that prior research has not considered.

The rest of the paper is structured as follows. In the next section, we develop our research hypotheses. The third section presents the data characteristics, operationalization of variables, and summary statistics. In the fourth section, we present our empirical findings, including the identification strategy for estimation, results from the dynamic panel data model estimation, and robustness checks. In the fifth section, we present the theoretical and managerial insights and conclude the paper by offering directions for future research.

2. Research Hypotheses

According to CMS, "...a chain organization consists of a group of two or more health care facilities or at least one health care facility and any other business or entity owned, leased, or, through any other device, controlled by one organization" (CMS, 2005). This clustered setup provides the basis for forming strategic group membership and improving performance by sharing information or physical resources (Gulati 1999). In essence, business opportunities emanating from social and structural aspects influence the decision of a firm to join a network (Gulati 1998). In the healthcare context, doctors refer patients to specialists within their own network, thus generating such opportunities. Likewise, hospital systems partner and form chain organizations in which each site specializes in a particular area of medicine to provide better quality care across a region (Cuellar and Gertler 2003).

More than 70% of dialysis facilities were affiliated with chain organizations in 2010 (U.S. Renal Data System, 2012), and this number has risen to about 80% in recent years (U.S. Renal Data System 2018). Chain organizations attempt to achieve proper alignment within their network to enhance quality and efficiency, while minimizing the negative impacts of uncertainty that may come from sources outside of their network. These chain organizations have been credited with providing the structure and processes needed to achieve greater quality within the dialysis industry (Nissenson et al. 2000). The routines these chain organizations created serve as a powerful mechanism for transferring knowledge among affiliated dialysis facilities (Kane et al. 2005, Levitt and March 1988, Nelson and Winter 1982, Zander and Kogut 1995). The transfer of knowledge among the members of the chain organization in the form of templates and instantiation of routines can improve observable and replicable tasks undertaken at individual facilities (Argote and Darr 2000, Darr et al. 1995, Jensen and Szulanski 2007).

We propose that the knowledge gained by caring for patients (learning-by-doing) is transferred within facilities and throughout a chain organization to create new organizational routines and standard operating procedures (Prætorius 2016). Being affiliated to a chain organization allows a dialysis facility to exchange knowledge with other facilities within the chain through regular communications of the latest developments in best practices, and personal acquaintances with members of other facilities that provide insights into current and changing policies.

While research has shown that facilities sharing superordinate relationships learn from each other, research on how knowledge transfer between organizations influences performance gains has been mixed. Although the dominant view is that knowledge transfer improves performance (e.g., Lane et al. 2001), studies have also reported that is not necessarily the case (e.g., Katila and Ahuja 2002, Steensma et al. 2005). Furthermore, it is unclear how the size of the chain organization influences the performance of individual units. The notion that chain organizations create transactive memory systems and routines would suggest that larger chain organizations offer more opportunities for exchanging and retaining knowledge. Yet, with a large number of organizations sharing a common superordinate relationship, the need for coordination among the affiliated facilities also increases, which can exert a negative effect on performance. Routines developed in chain organizations can also be a source of inertia, thereby adversely impacting performance. Larger chain organizations can increase causal ambiguity since the variation among practices that a large number of dialysis facilities adopt and the need to coordinate with many other facilities can make it difficult to identify the factors that support efficiency and quality (Dierickx and Cool, 1989). In summary, the literature is unclear regarding efficiency and quality among various sizes of chain organizations. In the following subsections, we develop our research hypotheses in light of the opposing theoretical predictions for the effect of the size of chain organizations on the performance of dialysis facilities.

2.1. Relationship Between Chain Organization Size and Efficiency

McGrath and Argote (2001) note that groups go through three major processes—coordination processes, adaptation processes, and learning processes. As part of its coordination processes, a group, such as a chain organization, pursues its purposes by establishing, enacting, monitoring, and modifying the member–task–tool relational patterns (Argote and Hora 2017, Argote and Ingram 2000). Adaptation processes create a two-way exchange of embedding contexts and embedding members. Finally, the outcomes of the coordination and adaptation processes begin to affect the development and modification of the group.

To gain a better understanding of how the outcomes affect the development and modification of the group, it helps to consider the technical and organizational systems within any organization. Studies have noted that organizations' technical and organizational systems affect each other (Spender 1996, Trist and Murray 1993). Hence, when a dialysis facility tries to change its practices aimed at improving its efficiency, technical changes will require organizational changes and vice versa (Leonard-Barton 1988, Levina and Vaast 2006). Thus, learning from other facilities within a chain organization requires a dialysis facility to adapt organizational rules, procedures, and structures from others. However, organizational inertia hinders internal adaptation and re-engineering efforts (Argote and Hora 2017, Henderson and Clark 1990, Tripsas and Gavetti 2000). Existing organizational rules and routines create a constrained view of the practices others in the network adopt (Tyre and Orlikowski 1994). In addition, misaligned incentives and other agency issues may hinder positive changes in practice (Thomke 2001).

Due to the lack of clarity about the emerging rules and routines in a growing chain organization, dialysis facilities may see a drop in their efficiency as the chain organization grows. In a small chain, dialysis facilities are connected to facilities that are relatively homogeneous, and thus, the desired efficiency improvements across the chain will consist of specialized know-how that suits their specific context. As the chain organization size increases, the set of dialysis facilities will start transitioning from a homogeneous group to one in which the facilities have different operating policies and procedures. Knowledge transfer will lead to superficial learning only, and the ambiguities associated with cause and effect relationships will result in oversimplifications and erroneous generalizations (Cohen and Bacdayan 1994, Gick and Holyoak 1987, Weigelt and Sarkar 2009). This will result in lower efficiency levels than when the chain organization size was small. Figure 1a presents this relationship.

Along with the efficiency losses emanating from the lack of homogeneity and the resulting ambiguity within larger chains, the mechanism of economies of scale and increased demand for larger chains also has an impact. This results in a distinct relationship between chain size and efficiency. Larger chain organizations are able to organize the delivery of care by aggregating dialysis services, which takes advantage of economies of scale. The size of larger chain organizations presents opportunities for pooling customer demands as well as pooling the resources that filling those demands require (Cattani and Schmidt 2005). The pooling of identical services reduces variability through the portfolio effect (Ata and Van Mieghem 2009, Hopp 2001, Joustra et al. 2010), and the reduced variability in delivering dialysis care can further improve efficiency. Studies focusing on multihospital systems that have a similar structure as chain organizations have reported that these systems offer more opportunities to share common facilities and workforce resources (Smith-Daniels et al. 1988, Trogen and Yavas 2002) and provide the scale and scope to compete effectively (Jack and Powers 2009). In essence, as chain organizations grow, they are better positioned to match capacity with demand resulting in efficiency gains.

In addition to the benefits accrued from capacity and demand management, studies focusing on healthcare have also pointed to another force in action with increasing consolidation, which is especially relevant for very large chain organizations. Specifically, large chain organizations are able to garner higher demand through the incentives of patients' referring physicians (Wilson 2016). Wilson (2016) notes that, "Many nephrologists have formed affiliations with the largest dialysis providers, and have an equity stake in specific dialysis clinics" (p. 298). Studies of physician partnerships with healthcare organizations show that they increase referrals due to the underlying financial incentives (Baker et al. 2016, Helmchen and Lo Sasso 2010, Koch et al. 2017, Van Dijk et al. 2013). The resulting increased demand results in higher utilization of resources of large chain organizations (Mathews and Athavaley 2012), thereby providing a further boost to efficiencies, as shown in Figure 1b.

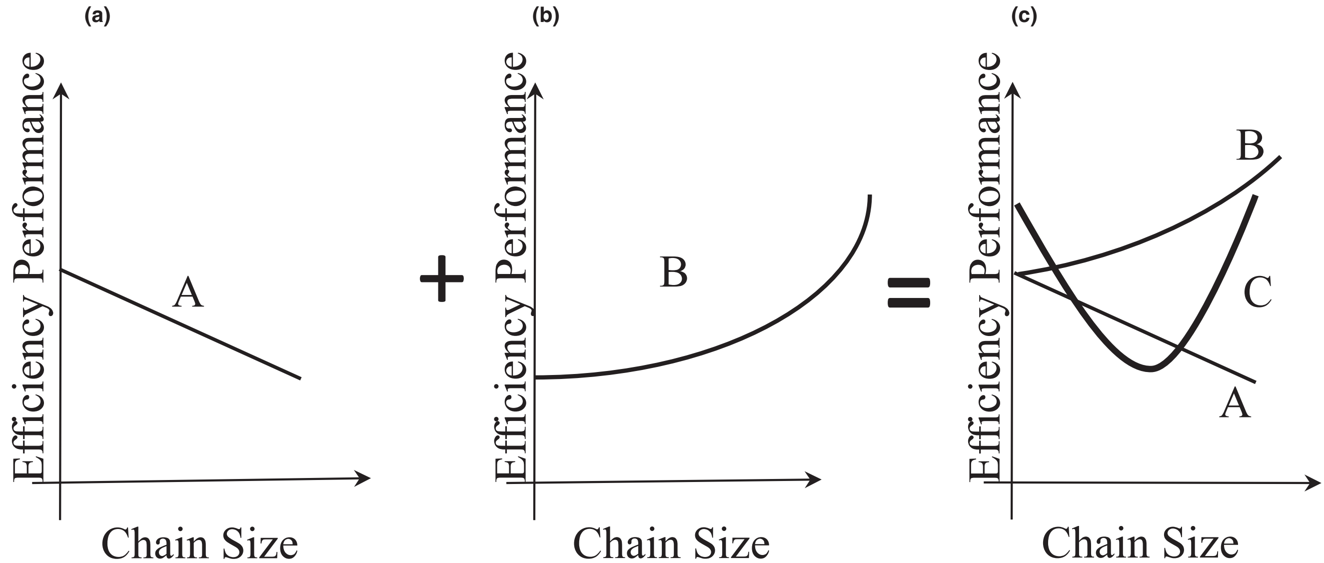
Figure 1c shows the combined effect of the mechanisms presented in Figure 1a and b. Initially, the mechanism of coordination complexity among heterogeneous dialysis facilities dominates, which reduces efficiency as chain organizations grow from small to medium size. However, as chain organizations grow very large, they start to see efficiency gains due to economies of scale and market power. Based on this reasoning, we hypothesize:

H1. *There is a U-shaped relationship between the size of chain organizations and the efficiency of dialysis facilities.*

2.2. Relationship Between Chain Organization Size and Quality

In healthcare, as in other contexts, the diffusion of knowledge enables the adoption of best practices that can lead to better patient outcomes and may be a source of competitive advantage (Szulanski 1996). An independent dialysis facility has a limited ability to gain from the knowledge base accumulated by other dialysis facilities. By contrast, within a chain organization, workers can share best practices across facilities and thereby improve their performance. Chain organizations may also have greater resources to train workers. It stands to reason then that the larger the chain organization, the greater the knowledge base throughout the organization as well as the available resources for training. Research comparing large chain organizations to smaller chain organizations shows size correlates with the ability to provide patients with certain amenities, such as the services of dieticians and social workers (Shinkman 2016). As compared to independent and small chain organizations, dialysis facilities belonging to large chain organizations can tap into varied sources of knowledge that can aid in improving quality. Systems are adopted that enable the management and dissemination of knowledge across the many facilities within the chain organization. The availability of more staff

Figure 1 Relationship between Size of Chain Organization and Efficiency Performance



Notes. Line A: As the number of facilities within a chain organization increases, the increased heterogeneity in terms of policies and procedures decrease efficiency. Curve B: As the number of facilities within a chain organization increases, the ability to match capacity with demand results in an increase in efficiency such that this increase is at a faster rate as chain organizations become very large. Curve C: Combining A and B, efficiency performance will show a U-shaped relationship with the number of facilities within a chain organization.

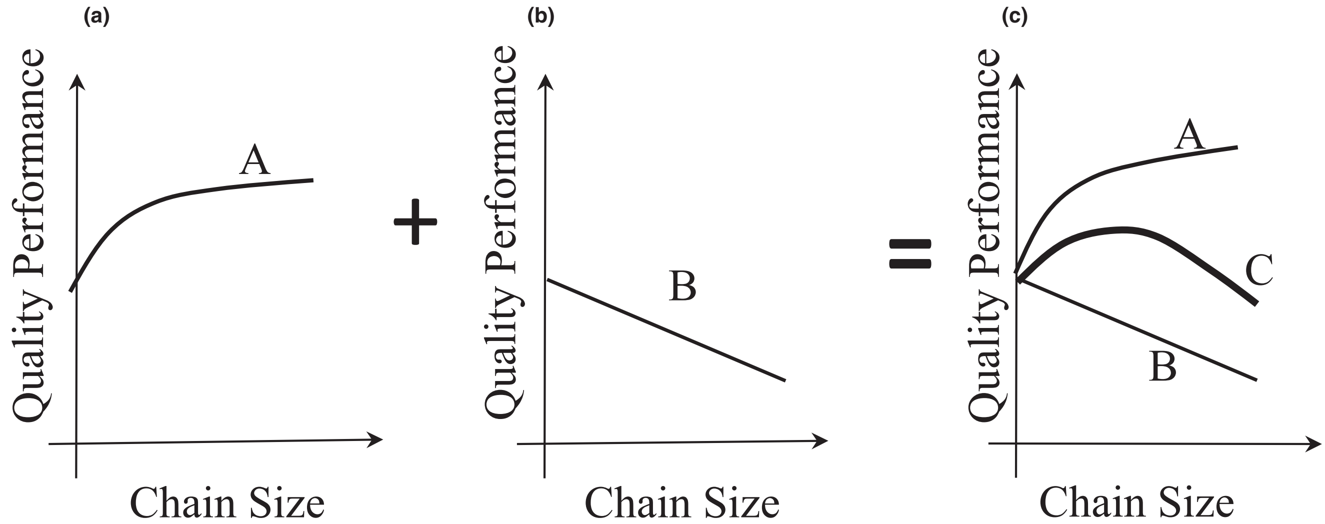
resources may result in greater sharing of knowledge and best practices (Cohen and Levinthal 1990), which can improve quality. Affiliation with a chain organization offers dialysis facilities the ability to pool capacity among themselves, which may improve quality as well (Kc and Terwiesch 2009).

The knowledge transfer routines in a chain organization have the potential to improve the performance of facilities that are connected by means of a superordinate relationship. In a study focusing on franchises that share such superordinate relationships, Darr et al. (1995) suggest that franchises that have common owners witness higher performance improvements than those that belong to different owners. As these multiunit organizations grow, several facilities within a chain are able to share the routines and associated knowledge. This helps in improving the quality of the facilities that are part of these chain organizations. These moderately sized chain organizations foster the development of transactive memory systems (Hollingshead and Brandon 2003, Kanawattanachai and Yoo 2007, Lewis 2004) through the formation of a shared social identity (Liao et al. 2015) and sharing of information related to expertise residing in individual dialysis facilities (Moreland and Myaskovsky 2000). Thus, as chain organizations form and begin to grow, we expect quality performance to continue to increase, but at a slowing rate as chain organization size increases, as there is a limit to the quality benefits of shared knowledge and culture. This is presented in Figure 2a.

As chain organizations grow, they will have to coordinate with one another, which results in an effect that is distinct from the one presented in Figure 2a. Larger chain organizations must coordinate among facilities with differing cultural and organizational contexts (Simonin 1999). Large chain organizations experience greater causal ambiguity in coordinating across several facilities than moderately sized chain organizations (Argote and Fahrenkopf 2016). The adoption of new practices may be slow, as spreading tacit knowledge is difficult (Powell 1998) and coordination complexity is high (Lin et al. 2012). The challenges associated with increased complexity and coordination needs suggest that as a chain organization grows beyond a certain size, the advantages of spreading best practices throughout its member facilities taper off (Argote and Epple 1990). Knowledge begins to become localized due to greater distances between facilities and maintaining a consistent culture is difficult (Anderson Jr and Parker 2013). Coordination issues increase, which reduce quality performance as shown in Figure 2b.

The combined effect of knowledge sharing (curve A) and coordination complexity (line B) results in an inverted U-shaped relationship between chain organization size and quality performance such that quality improves as chain organizations attain moderate size

Figure 2 Relationship between Size of Chain Organization and Quality Performance



Notes. Curve A: As the number of facilities within a chain organization increases, increased knowledge sharing improves quality performance. Line B: As the number of facilities within a chain organization increases, increased coordination complexity reduces quality performance. Curve C: Combining A and B, quality performance will show an inverted U-shaped relationship with the number of facilities within a chain organization.

but then declines as they continue to grow into large-sized chain organizations. We illustrate this in Figure 2c. Initially, the learning effect through knowledge sharing dominates as intermediate-sized chain organizations develop and utilize shared routines. However, as the number of facilities within a chain organization increases beyond a certain number, increased coordination complexity prompts facilities to rely on their own localized knowledge rather than accessing the collective knowledge of the chain organization. Therefore, we expect quality performance to decrease after chain organizations grow to a certain size, as each facility added will create stronger barriers to knowledge sharing. Hence, we hypothesize:

H2. *There is an inverted U-shaped relationship between the size of chain organizations and the quality of dialysis facilities.*

3. Data, Operationalization of Variables, and Summary Statistics

Data for 33,249 observations across 6371 US-based dialysis facilities registered with the CMS were collected from 2008 to 2013. This dataset includes comparative information regarding the performance of various dialysis facilities. These data were merged with data from the Healthcare Cost Report Information System reported by CMS for the same time period, which provides financial and human resource-related information for the dialysis facilities. After the datasets were merged, only facilities that exclusively offer hemodialysis were retained. This reduced the sample by about 50% to 16,861 observations across 4899 facilities. Focusing on facilities offering hemodialysis reduces potential confounds in our analyses that could arise from the patient mix at dialysis facilities, thus allowing us to understand the operational differences between facilities better. Next, any facility with missing data was dropped, making the final sample size for the study equal to 4899 observations across 1917 facilities.

3.1. Chain Size

The size of a chain organization (*ChainSize*) is operationalized as a continuous variable. Independent facilities were coded as 0 (n = 340). The variable equals the number of dialysis facilities within their chain organizations. The mean of this continuous variable across all six years is 880, with a standard deviation of 736. It ranges from 0 to 1826. We standardize this variable for our analyses.

3.2. Efficiency

Extensive research addresses labor demands in healthcare (e.g., Baker 1976, Bard and Purnomo 2006, Chao et al. 2003, Jun et al. 1999), as well as the need for physical assets such as equipment (e.g., Belien and Demeulemeester 2007, Blake and Donald 2002, Oliveira and Bevan 2006, Rajagopalan and Hadjinicola 1993). Prior research has emphasized that no single measure can describe capacity because it depends on both equipment and labor (White et al. 2011). Accordingly, we consider both the labor and physical resources of a facility in our operationalization of efficiency of dialysis facilities.

This research uses the data envelopment analysis (DEA) technique to assess the relative efficiency of dialysis facilities. DEA makes it possible to determine the performance frontier of the most efficient facilities and to compare a facility's performance to that of its peers (Rosenzweig and Easton 2010). A few other studies examining efficiencies of dialysis facilities have utilized DEA models (Griffiths et al. 1994, Ozgen 2006, Ozgen and Ozcan 2002, 2004, Özgen and Şahin 2010).

DEA is an empirically based, data-driven, deterministic method that does not require a functional relationship between inputs and outputs. Charnes et al. (1978) developed the Charnes, Cooper, and Rhodes (CCR) model, which allows researchers to assess the relative efficiency of a decision-making unit (DMU) with multiple inputs and outputs. When utilizing the CCR model, the goal is to maximize the relative efficiency score, the ratio of the weighted sum of outputs to the weighted sum of inputs, of an individual facility *k*, against the entire group of facilities *s*, so that efficiency scores of the units in the set do not exceed a value of 1.

This study employs another version of the DEA model, the Banker, Charnes, and Cooper (BCC) model (Banker et al. 1984). The CCR model assumes constant returns to scale. This means that as inputs increase, the outputs increase proportionally. The BCC model works under the assumption of variable returns to scale. The BCC model shown in Equation 1 is a dual formulation of the CCR problem with an added convexity constraint $\sum_s \lambda_s = 1$. This additional convexity constraint allows for variable returns to scale. Given that we are utilizing an input-oriented BCC model, the lambda values are the weights assigned to inputs and outputs of units in order to achieve lower inputs than the unit under consideration while maintaining at least the same output levels. If this occurs, the unit under consideration is inefficient.

$$\begin{aligned}
&\text{minimize } E_{kk}\\
&\text{subject to: } \sum_s \lambda_s I_{sx} - E_{kk} I_{kx} \leq 0\,\forall\, x\\
&\qquad\qquad\quad \sum_s \lambda_s O_{sy} - O_{ky} \geq 0\,\forall\, y\\
&\qquad\qquad\quad \sum_s \lambda_s = 1\\
&\qquad\qquad\quad \lambda_s \geq 0\,\forall\, s.
\end{aligned} \tag{1}$$

The input-oriented BCC model of DEA is employed to rank the dialysis facilities in terms of their relative efficiency compared to all the other facilities being analyzed for each year. Thus, the model was run six times for each year of data collected. The model uses four inputs—number of dialysis stations, number of full-time equivalents of physicians (based on a 40-hour work week), number of full-time equivalents of clinical staff (based on a 40-hour work week), and the number of employee hours per week at a dialysis facility. The number of dialysis stations across all six years has a mean of 17.69 and a standard deviation of 6.96. The number of full-time equivalents of physicians is measured as the number of physician hours worked divided by 40 hours per week; thus, every 40 hours worked is equal to one full-time physician's work in a week. This measure has a mean of 0.14 or 5.6 hours per week across all six years and a standard deviation of 0.52. The number of full-time equivalents of clinical staff is measured similarly such that the number of clinical staff hours worked divided by 40 hours per week provides the number of clinical staff that works during an average week. The measure has a mean of 10.61 and a standard deviation of 9.28 across all six years. The number of employee hours per week at a dialysis facility is measured as the number of shifts per week that are typically staffed at a dialysis facility for all positions multiplied by the number of hours an employee typically works per week. This measure provides an indication of the level of human resources that a dialysis facility may have at any given time to care for patients. It has a mean of 60.04 and a standard deviation of 235.39 across all six years. The DEA model considers one output—the number of dialysis treatments. The mean and standard deviation across all six years of the number of treatments are 10,043 and 5850, respectively.

The input and output considerations in the BCC model make it easier to examine how a facility's capacity, flexibility, and labor affect its throughput. The model achieves this by considering inputs that are related to process quality. The number of dialysis stations relates to a facility's capacity. Those facilities with additional capacity will have the needed slack to ensure high quality outcomes (Goldstein and Iossifova 2012). The number of full-time equivalents of physicians and other medical staff also enhances process quality, because they have more opportunities to learn and share knowledge, as well as more capacity (or slack) to ensure the use of quality management practices (Ding 2014, Orszag and Emanuel 2010). These physical and human resources in dialysis facilities support collaboration, learning, and process improvements, thus increasing the number of treatments a facility can provide. Each facility is a DMU, and if it is on the efficiency frontier, it is considered to be *efficient* and assigned a value of 1. Any DMU less efficient than the efficiency frontier is inefficient and will have a score of less than 1. The data were analyzed using MaxDEA Pro 6.6 software. In 2008, the DEA model identified the greatest number of efficient DMUs in the dataset with 1.93% of the DMUs having a relative efficiency score of 1.00. The smallest number of efficient DMUs occurs in 2011, when only 0.03% of DMUs had a relative efficiency score of 1.00. The minimum score a facility scored across all the years was 0.02. *Efficiency* across all six years has a mean of 0.42 with a standard deviation of 0.22.

3.3. Quality Outcomes

To monitor quality outcomes and understand their impact on dialysis facilities, CMS uses three performance measures developed under the ESRD Quality Incentive Program (QIP) that addresses anemia management and hemodialysis adequacy. QIP is a purchasing program created by the 2008 Medicare Improvements for Patients and Providers Act with a mandate to motivate quality improvement within facilities by linking quality outcome scores to reimbursements. A facility may earn up to 10 points for each one of three performance measures for a total of up to 30 points. Measurements are taken at the end of a dialysis treatment session. The QIP score consists of three unequally weighted variables (MedPac, 2011). The first, the percentage of patients' hemoglobin levels that are below 10 grams per deciliter (g/dL) accounts for 50% of the QIP score. The second captures the percentage of patients with hemoglobin levels above 12 g/dL, which accounts for 25%. Finally, hemodialysis adequacy, a measurement of whether enough waste products were removed from the blood as measured by a urea reduction ratio of 65% or greater, accounts for 25%. This weighting reflects the fact that low hemoglobin is highly dangerous to dialysis patients. We use the QIP score to operationalize the quality outcome (*Quality*). More than a quarter of the facilities scored the maximum possible, 30 points, and this variable has a mean of 20.79 with a standard deviation of 7.80 across all six years.

3.4. Controls

Several characteristics of dialysis facilities and their patients may influence efficiency and quality; thus, we control for them in the model. The implications of not-for-profit and for-profit (*ProfitStatus*) hospitals and healthcare centers continue to be debated (Audi 2014, Griffiths et al. 1994, Rotarius et al. 2006). Both for-profit and not-for-profit dialysis facilities must achieve quality care, but the level of and the focus on quality may differ between the two types of ownership structures. Griffiths et al. (1994) and Ozgen and Ozcan (2002) find that for-profit facilities are more efficient, but the scope of their studies do not include the drivers of these differences. We control for the for-profit or not-for-profit status of dialysis facilities, coding for-profit facilities as 1. The variable has a mean of 0.82 and a standard deviation of 0.38 in our sample across all six years.

Patient severity (i.e., the baseline condition of patients the facilities serves) may affect the number of patients treated at a facility. Patient severity is known to affect quality outcomes (Desai et al. 2008) and the duration of time needed for each dialysis treatment (Charra et al. 1996, Tentori et al. 2012). Research studies suggest that facilities may select their patients based on their severity (Barro et al. 2006, Kc and Terwiesch 2011). We control for the severity (*PatientSeverity*) of patients visiting a dialysis facility. In this study, patient severity is the percentage of patients who have hemoglobin values greater than 10.0 g/dL and less than 12.0 g/dL. Hemoglobin levels between these two values signal greater health. Thus, those facilities with lower scores have more patients in poorer condition. The *PatientSeverity* variable has a mean of 75.54 with a standard deviation of 21.89 across all six years.

The Survey and Certification Program certifies ESRD facilities for participation in Medicare by validating that the care and services provided meet specified safety and quality standards, called "Conditions for Coverage." Facilities must be certified and pass ongoing monitoring that determine if they meet basic requirements. The longer a facility has been certified, the greater the depth of knowledge it should have, which is expected to influence performance positively (Hays and Hill 2001). We control for the number of years a facility has been certified (*YearsCertified*). This variable has a mean of 12.65 years with a standard deviation of 8.60 across all six years. We control for the size of a dialysis facility by considering the expenses it incurs for drugs (*DrugExpenses*). This variable has a mean of $187,745 and a standard deviation of $154,248 across all six years. The number of non-clinical staff (*NumberofNon-clinicalStaff*) and the number of reported ESRD patients being treated at a facility varies (*NumberofESRDPatients*) and has implications for how a facility handles patient volume and treatment, such that busier facilities' quality and efficiency may differ from those with fewer patients in their care. The variables across all six years have means of 3.58 employees and 62.94 patients with standard deviations of 4.50 and 43.46, respectively. We normalize *DrugExpenses*, *NumberofNon-clinicalStaff*, and *NumberofESRDPatients* by considering their log transformations. Table 2 presents the summary statistics and correlations of the variables considered in this study.

4. Results

In this section, we start by discussing the endogeneity issues that could impact our inference of the effect of our explanatory variable, chain size, on quality and efficiency, and our strategies for dealing with them.

We then present findings pertaining to the determinant of quality and efficiency, as well as several robustness tests.

4.1. Identification Strategy

The research design initially considers an ordinary least squares (OLS) estimate of the effect of chain size, chain size squared, and other controls on quality and efficiency as follows:

$$Eff_{i,t} = \alpha_1 + \beta_1 ChainSize_{i,t} + \beta_2 ChainSize^2_{i,t} + \sum_j Controls_{i,j,t} + \varepsilon_{i,t}, \quad (2)$$

$$Qual_{i,t} = \alpha_1 + \beta_1 ChainSize_{i,t} + \beta_2 ChainSize^2_{i,t} + \sum_j Controls_{i,j,t} + \varepsilon_{i,t}, \quad (3)$$

The OLS estimates considered in Equations (2) and (3) would be biased due to at least three sources of endogeneity. The first, and perhaps the most important, is reverse causality, or the possibility that past quality and efficiency levels of dialysis facilities affect current levels of chain size. Thus, estimating Equations (2) and (3) without accounting for past quality and efficiency levels, respectively, may yield biased estimates. The second potential source of endogeneity is unobservable heterogeneity or the possibility that there are unobserved factors that systematically influence chain size that are also correlated with the level or nature of quality or efficiency of affiliated dialysis facilities. In other words, there may be unobserved factors that neither our use of the past values of quality/efficiency nor our use of numerous other control variables fully capture. If this is the case, estimating Equations (2) and (3) would have an omitted variable bias. The third potential source of endogeneity is that except for *ProfitStatus*, the values of the control variables could also be driven by their past levels.

To account for these three sources of endogeneity, we exploit the fact that we have a panel dataset. In particular, we modify Equations (2) and (3) to estimate a dynamic unobserved effects model of the following forms:

$$Eff_{i,t} = \alpha_1 + \gamma_1 Eff_{i,t-1} + \gamma_2 Eff_{i,t-2} + \beta_1 ChainSize_{i,t} + \beta_2 ChainSize^2_{i,t} + \sum_j Controls_{i,j,t} + \eta_i + \varepsilon_{i,t}, \quad (4)$$

$$Qual_{i,t} = \alpha_1 + \gamma_1 Qual_{i,t-1} + \gamma_2 Qual_{i,t-2} + \beta_1 ChainSize_{i,t} + \beta_2 ChainSize^2_{i,t} + \sum_j Controls_{i,j,t} + \eta_i + \varepsilon_{i,t}. \quad (5)$$

In other words, we explicitly account for the possible effect of past quality and efficiency levels on current chain size (reverse causality) by including lagged efficiency ($Eff_{i,t\text{-}1}$ and $Eff_{i,t\text{-}2}$) and lagged quality ($Qual_{i,t\text{-}1}$ and $Qual_{i,t\text{-}2}$). We explicitly account for unobserved heterogeneity by including firm fixed effects (η_i). We estimate these modified dynamic panel models by using the difference generalized method of moments (GMM) estimator (Arellano and Bond 1991). The main elements of the GMM estimation procedure can be summarized as follows. First, we take the first differences of Equations (4) and (5) to eliminate the firm-specific fixed effect. We then estimate this first differenced model using the lagged levels of our endogenous control variables—*PatientSeverity, YearsCertified, DrugExpenses*, *NumberofNon-clinicalStaff*, and *NumberofESRDPatients* (from time $t-1$ and $t-2$)—as instruments for the first differenced variables at time t. We consider *ChainSize* as endogenous variable and

Table 2 Descriptive Statistics and Correlations

	Mean	SD	Quality outcomes	Efficiency	Chain size	Profit status	Patient severity	Years certified	Drug expenses	Non-clinical staff	Num. ESRD patients
Quality outcomes	20.79	7.80	1								
Efficiency	0.42	0.22	−0.058**	1							
Chain size	879.83	736.1	0.112**	0.067**	1						
Profit status	0.82	0.38	0.078**	0.163**	0.487**	1					
Patient severity	75.54	21.89	0.187**	−0.220**	0.081**	−0.043**	1				
Years certified	12.65	8.60	0.226**	0.035**	0.023**	−0.107**	−0.046**	1			
Drug expenses	187845	154248	0.113**	−0.005	0.071**	0.149**	0.003	0.170**	1		
Non-clinical staff	3.58	4.50	0.035**	0.057**	−0.061**	0.001	−0.023**	0.093**	0.207**	1	
Num. ESRD patients	62.94	43.46	0.131**	−0.015	0.117**	0.226**	−0.014	0.156**	0.746**	0.218**	1

Notes. **Indicates significance at the 0.01 level. All measures are unstandardized.

include its two-year lag as instruments. To clearly ascertain the effect of chain organization size and rule out the explanation of potential trade-off between quality and efficiency, we also include two-year lag of efficiency as endogenous variable in Equation (5). We carry out two-step estimation with Arellano–Bond Windmeijer (2005) bias-corrected robust variance covariance estimator using the *xtabond* command in Stata. The results of our GMM estimation appear in Table 3.

4.2. Determinants of Efficiency and Quality

The results for H1 support a U-shaped relationship for the effect of chain size on efficiency ($\beta_{ChainSize} = -1.36$, $p < 0.01$; $\beta_{ChainSize^2} = 1.25$, $p < 0.01$). Specifically, as chain organization size increases, efficiency initially decreases and then increases. The results support an inverted U relationship for the effect of chain size on quality ($\beta_{ChainSize} = 8.07$, $p < 0.05$; $\beta_{ChainSize^2} = -7.35$, $p < 0.05$), which lends support for H2. Hence, quality initially increases along with chain organization size but begins to decrease at a certain size. The findings pertaining to control variables suggest that facilities with a greater number of non-clinical staff are more efficient ($\beta = 0.500$, $p < 0.05$) and those with a greater number of patients are less efficient ($\beta = -0.281$, $p < 0.01$). Both of these results are expected since more patients will slow down service, and additional staff will provide greater resources for servicing patients efficiently. More surprising is the opposite results pertaining to efficiency and quality with regard to the number of severe patients. Facilities with more severe patients have lower efficiency ($\beta = -0.020$, $p < 0.01$), but higher quality ($\beta = 0.163$, $p < 0.05$).

Although the exogeneity assumption cannot be tested directly (as discussed in Rossi (2014), among several others), Arellano and Bond (1991) suggest two useful tests to gauge the suitability of our instrument set and the use of the dynamic estimation procedure in general. The first is a test of second-order serial correlation. If we have included enough lags of past quality and efficiency in Equations (4) and (5), then there should be no second-order serial correlation in residuals after estimation. The second test is the Sargan test of overidentification, which utilizes the fact that we use several lags as instruments. We find no second-order serial correlation in our tests, which implies that including two lags of quality and efficiency is sufficient for dynamic completeness. The results of the *abond* test for serial correlation in Equations 4 and 5 are $z = -1.54$, $p = 0.12$; $z = 0.20$, $p = 0.84$, respectively. This suggests that variables from period $t-3$ or later, such as we have used, are good candidates for instruments. We also find from our overidentification tests that we cannot reject the null hypothesis that the instruments are valid. The results of the Sargan test for overidentification in Equations 4 and 5 are $chi^2\ (17) = 25.98$, $p > 0.05$; $chi^2\ (16) = 23.25$, $p = 0.11$, respectively. We note that these tests do not conclusively prove that our instruments are completely exogenous because they are based on the assumption that at least one of our lagged variables is a valid instrument in the first place. Nevertheless, they do provide some support for the use of dynamic GMM estimation.

To better understand the curvilinear results, we follow the recommendations of Lind and Mehlum (2010). First, the Sasabuchi (1980) U-test after the two-step GMM estimation was performed to test for the significance of a curvilinear relationship by using the unstandardized values for chain organization size.

Table 3 Two-Step Difference GMM Estimation Results

	Equation 1 Efficiency coefficients	Equation 1 Efficiency SE	Equation 2 Quality coefficients	Equation 2 Quality SE
Independent variables				
Chain Organization Size	−1.364**	(0.485)	8.070*	(4.128)
Lag 1 (t−1)	−0.778	(0.459)	−4.525	(3.127)
Lag 2 (t−2)	0.798	(0.527)	9.119**	(3.529)
Chain organization size squared	1.245**	(0.456)	−7.349*	(3.656)
Efficiency			−3.547*	(1.553)
Lag 1 (t−1)			−4.326	(2.269)
Lag 2 (t−2)			−0.482	(4.174)
Control variables				
Profit status	−0.955	(5.089)	−18.471	(35.968)
Lag 1 (t−1)	8.406*	(3.539)	25.349	(24.075)
Lag 2 (t−2)	−5.507	(3.866)	25.722	(19.877)
Patient severity	−0.020**	(0.007)	0.163*	(0.078)
Lag 1 (t−1)	−−0.001	(0.003)	0.032	(0.024)
Lag 2 (t−2)	−0.007**	(0.002)	−0.031*	(0.016)
Years certified	1.486	(0.966)	−7.003	(5.149)
Lag 1 (t−1)	−1.180	(1.058)	4.732	(5.146)
Lag 2 (t−2)	0.038	(0.149)	1.062	(2.570)
Drug expenses†	−0.119	(0.105)	−0.106	(1.028)
Lag 1 (t−1)	0.045	(0.111)	0.389	(0.940)
Lag 2 (t−2)	0.073	(0.131)	0.480	(0.945)
Number of non-clinical staff†	0.500*	(0.237)	−1.994	(2.695)
Lag 1 (t−1)	−0.478	(0.271)	3.676	(1.961)
Lag 2 (t−2)	−0.481**	(0.164)	−0.124	(1.216)
Number of HD patients†	−0.281**	(0.061)	−0.894	(0.903)
Lag 1 (t−1)	−0.105*	(0.051)	−0.855	(0.652)
Lag 2 (t−2)	−0.083*	(0.040)	−0.249	(0.371)
Dependent variable				
Lag 1 (t−1)	−0.658**	(0.151)	0.155**	(0.034)
Lag 2 (t−2)	−1.101**	(0.236)	−0.001	(0.024)
Chi-square	908.06**	(*df* = 24)	762.45**	(*df* = 27)
N of instruments	41		43	
N of groups	1917		1917	
N of observations	4899		4899	

Notes. $^{**}p < 0.01$ and $^{*}p < 0.05$. Robust clustered standard errors are reported.
†Denotes log-transformed variable.

Then, the Fieller (1954) interval estimation test was performed to determine the inflection point and confidence intervals. For efficiency, we find the extreme point at 882 (t = 2.03, p = 0.021) facilities with a confidence interval of 580–1500. This indicates that efficiency decreases until the chain organization grows larger than 882 facilities. For quality outcomes, the extreme point is found at 796 (t = 10.08, p < 0.001) facilities with a confidence interval ranging from 768 to 819. This shows that quality will increase until a chain organization grows to 796 facilities. These results show that the inflection points are within the range of values in the dataset and the curvilinear results are significant.

4.3. Robustness Checks

By itself, the estimation described above would be sufficient to account for reverse causality while also accounting for unobservable heterogeneity, but Arellano and Bover (1995) suggest that lagged levels may be weak instruments for first differences and could lead to biased inference if relied on exclusively. As such, Arellano and Bover (1995) and Blundell and Bond (1998) argue that we can improve the GMM estimator by also including the equation in levels in the estimation procedure. We can then use the first-differenced variables (from time $t-1$ and $t-2$) as instruments for the endogenous variables in levels in a "stacked" system of equations that includes the equations in both levels and differences. This produces a "system" GMM estimator that essentially involves estimating Equations (4) and (5) in a combined system in both first differences and levels.

To check the robustness of our results, we run the model by using the system GMM estimator, which includes an additional moment condition to obtain an estimator with improved precision and better finite-sample properties. We use STATA's *xtdpdsys* command for this estimation. The results of our system GMM estimation appear in Table 4. As shown, the effect of chain size on quality is positive and significant (β = 4.05; p < 0.05) and the effect of chain size squared is negative and significant (β = −3.76; p < 0.05). For efficiency, the chain size has a negative and significant effect (β = −0.674; p < 0.01) and the chain size squared has a positive and significant effect (β = 0.596; p < 0.01). These results provide further confidence for our finding that the chain organization size exerts an inverted U-shaped effect on quality and a U-shaped effect on efficiency.

Furthermore, we considered additional alternative estimators. First, a mixed effects model was run for each equation. Then, an ordinary least-squares (OLS) regression was performed. For both of these models pertaining to efficiency, the effect of chain size is negative and significant and the effect of chain size squared is positive and significant. This further lends credence to the U-shaped relationship between chain organization size and efficiency. For the model with quality as the dependent variable, the chain size has a positive and significant effect and the chain size squared has a negative and significant effect. This provides additional support for an inverted U-shaped relationship between chain organization size and quality.

Table 4 System GMM Estimation Results

	Equation 1 Efficiency coefficients	Equation 1 Efficiency SE	Equation 2 Quality coefficients	Equation 2 Quality SE
Independent variables				
Chain organization size	−0.674**	(0.210)	4.045*	(1.895)
Lag 1 (t−1)	−0.682	(0.394)	−4.090	(2.933)
Lag 2 (t−2)	0.781*	(0.354)	4.342	(2.671)
Chain organization size squared	0.596**	(0.201)	−3.764*	(1.921)
Efficiency			−2.201*	(1.660)
Lag 1 (t−1)			−2.086	(1.787)
Lag 2 (t−2)			−4.359	(2.337)
Control variables				
Profit status	−0.828	(3.334)	−32.593	(18.284)
Lag 1 (t−1)	2.586	(2.086)	32.695*	(16.571)
Lag 2 (t−2)	−1.704	(2.376)	1.721	(14.139)
Patient severity	−0.019**	(0.006)	0.151*	(0.065)
Lag 1 (t−1)	−0.012**	(0.003)	−0.008	(0.035)
Lag 2 (t−2)	−0.009**	(0.002)	−0.023*	(0.017)
Years certified	1.274	(0.767)	−1.111	(2.222)
Lag 1 (t−1)	−0.988	(0.633)	2.015	(2.525)
Lag 2 (t−2)	−0.276	(0.262)	−0.827	(1.387)
Drug expenses†	0.056	(0.049)	−0.026	(0.609)
Lag 1 (t−1)	0.052	(0.030)	0.237	(0.411)
Lag 2 (t−2)	−0.098*	(0.045)	0.682	(0.415)
Number of non-clinical staff†	0.811*	(0.110)	−1.871	(1.370)
Lag 1 (t−1)	−0.046	(0.108)	2.395	(1.095)
Lag 2 (t−2)	−0.175	(0.126)	−0.238	(1.053)
Number of HD patients†	0.049	(0.045)	−0.658	(0.421)
Lag 1 (t−1)	0.024	(0.034)	−0.321	(0.317)
Lag 2 (t−2)	0.029	(0.033)	0.115	(0.297)
Dependent variable				
Lag 1 (t−1)	−0.673**	(0.106)	0.221**	(0.070)
Lag 2 (t−2)	−0.772**	(0.117)	−0.015	(0.018)
Chi-square	3543.75** (*df* = 24)		133,075.09** (*df* = 27)	
N of instruments	49		52	
N of groups	2468		2468	
N of observations	7367		7367	

Notes. **p < 0.01 and *p < 0.05. Robust clustered standard errors are reported.
†Denotes log-transformed variable.

5. Discussion and Conclusion

Our results support the two hypotheses and show that medium-sized chain organizations have lower efficiency and higher quality than smaller and larger chain organizations. This suggests that the growing size of chain organizations has distinct effects on efficiency and quality. The initial decrease in efficiency as chain organizations grow from small to medium size accords well with the findings in Ozgen and Ozcan (2002), but our findings suggest that once chain organizations attain a certain scale, they are able to take advantage of their size and become more efficient (Miles and Snow 1992). With respect to quality, we find a curvilinear relationship such that dialysis facilities belonging to smaller and larger chain organizations have lower quality outcomes than ones that belong to medium-sized chain organizations. The curvilinear effect of chain size on quality expands our understanding by suggesting that the knowledge repository developed in medium-sized chain organizations help affiliated dialysis facilities. However, as chain organizations grow beyond a certain size, the resulting causal ambiguity reduces the quality performance. The following sections discuss the implications for theory and practice as well as directions for future research.

5.1. Theoretical Implications

The efficiency of dialysis facilities is characterized by explicit input elements that impact the number of dialysis treatments completed at a dialysis facility. In a moderately sized chain organization, dialysis facilities face the causal ambiguity of how the level of capital resources (the number of dialysis stations), human resources (the number of physicians and clinical staff), and labor hours (employee hours per week) impact the number of dialysis treatments completed at the facility. Additionally, these moderately sized chain organizations are unable to attain the scale necessary to increase the utilization of existing resources at the affiliated dialysis facilities. When the size of these chain organizations grows beyond a particular threshold, the diversity of dialysis facilities within these chain organizations expands the knowledge reservoir. This allows for the ability to match capacity with increased demand, which can especially improve the accurate completion of routine tasks. Within these larger ecosystems, dialysis facilities are able to sample the facilities that are most similar to them in terms of explicit input elements and adopt best practices for achieving greater efficiency. Demand management through referrals from affiliated persons and organizations grows in these larger organizations leading to increases in utilization of facility resources. The joint effect of the forces of economies of scale and demand management increases the efficiency of dialysis facilities affiliated with large chain organizations.

The interactions among knowledge elements can negatively affect knowledge transfer (Rivkin 2000). In large-sized chain organizations, dialysis facilities are likely to focus on one element of the shared routine and neglect the interdependencies that might exist among routines (Gupta et al. 2015). Additionally, the results seem to suggest that the tacit knowledge pertaining to quality improvement is likely residing in transactive memory systems, making them more difficult to transfer among dialysis facilities associated with large chain organizations. In contrast, knowledge pertaining to efficiency gains is likely to be embedded in tools and routine that are easier to transfer (Argote and Hora 2017).

Prior research has shown that the underlying elements of members, tasks, tools, and their resulting network of interrelationships influence the effect of transactive memory systems on performance (Argote and Fahrenkopf 2016). Evidence suggests that copying transactive memory systems across members of a group can be difficult (Gino et al. 2010, Heavey and Simsek 2015). Environmental dynamism, the strength of ties with other members of a group, and transactive memory systems interact to influence performance. Our result pertaining to quality suggests that when chain organizations are moderately large, the ties among dialysis facilities within the chain organization are potentially strong and the dynamism within the ecosystem is relatively low. These conditions are conducive for improving the quality dimension of performance that relies on tacit knowledge. However, as the chain organization size increases, it is likely that the affiliated dialysis facilities are spread across larger distance, both geographically and culturally (Simonin 1999). For example, the two leading dialysis providers in the United States each have facilities located in almost every state. The resulting lack of shared norms, values, and institutions (Mowery et al. 1996; Van Wijk et al. 2008) may weaken ties among them (Darr et al. 1995) and hinder knowledge exchange. Additionally, large chain organizations create a dynamic and complex environmental context within which learning needs to take place. These conditions now cause the deterioration of quality performance.

Our results suggest that chain organizations face different trade-offs as they grow in size. When small, a chain organization may focus more on profitability so that it remains solvent. As it increases in size, the chain organization gives more attention to quality so as to attract patients as well as to potentially become a good acquisition target (Pozniak et al. 2010). Once a chain organization becomes large, its focus may shift back to efficiency to take advantage of economies of scale. Overall, the results point toward different sets of needs and skills based on the size of the chain organizations.

5.2. Implications for Practice

The need to increase economies of scale has prompted chain organizations to acquire and merge with existing dialysis facilities, as well as open new locations. A 2015 article in *Modern Healthcare,* showing that almost 15% of the facilities in the nation's largest dialysis chain organization provider were in the lowest quality category, supports our results (Rice 2015). The findings in our study offer important managerial implications for chain organizations as well as facilities that are part of these multi-unit organizational forms to manage quality and efficiency.

For chain organizations, the results call attention to being cognizant of the advantages and disadvantages of their growing size. Our study indicates that as chain organizations grow from a small size to an intermediate size, their efficiency drops and quality improves. We find that the efficiency bottoms out when chain organizations grow to have about 882 dialysis facilities whereas quality reaches its peak when the number of dialysis facilities in a chain organization reaches to about 796. After reaching these inflection points associated with efficiency and quality, facilities within the chain organizations become more efficient, but their quality levels suffer. This presents implications for decision makers to carefully think about the underlying mechanisms. The initial drop in efficiency as chain organization size increases may reflect the investments facilities affiliated with medium-sized chain organizations make when adding dialysis stations and personnel to address the demand growth. Yoder et al. (2013) show that the percentage of facilities with more than 26 hemodialysis stations in small- to medium-sized chain organizations is higher than in large chain organizations. It may be that facilities affiliated with medium-sized chain organizations do not fully utilize their stations, thereby bringing down the efficiency. Their quality however increases, since staff in these medium-sized chain organizations has more time to give to each patient.

As chain organizations grow in size, it is likely that they see an increase in demand due to cross referrals among facilities within the chain. This increase in demand eventually provides the needed efficiency gains through economies of scale, but the associated deterioration in the quality of care raises concerns. It is possible that the approaches large chain organizations take to increase staff capacity, which differ from those taken by medium-sized chain organizations, could contribute towards deterioration in quality. Larger chain organizations tend to employ fewer registered nurses and licensed practical nurses as a percentage of their staff than medium-sized organizations (Yoder et al. 2013). To offset the cost associated with staffing, large chain affiliated facilities employ higher levels of patient care technicians as compared to medium-sized chain organizations (Yoder et al. 2013), which can lower their quality levels (Wolfe 2011). As chain organizations grow, decision makers should appropriately manage the staffing patterns so as to avoid erosion of quality with a corresponding increase in efficiency.

To address both efficiency and quality performance, chain organizations should be strategic and develop appropriate coordination capabilities so that affiliated facilities can improve their quality while retaining efficiency gains through economies of scale. Technological innovations may make it easier to spread tacit knowledge pertaining to quality-oriented best practices. Opportunities for enabling interactions among people involved with clinical care, as well as nonclinical support services, can enhance learning and improve the quality of care. To facilitate quality improvement efforts, chain organizations can oversee the establishment of cross-disciplinary teams comprised of members from the affiliated dialysis facilities as well as the area manager from the chain organization (Farley et al. 2012). Organization-wide policies and procedures, including standards for clinical processes and quality improvement activities, should be widely communicated with affiliated dialysis facilities. Performance goals and objectives for dialysis facilities should be established and appropriate reporting structure of quality improvement initiatives and performance should be put in place. Chain organizations should provide feedback to affiliated facilities and, when needed, offer training and cross learning opportunities to the affiliated dialysis facilities.

For facilities within the chain organization, the results present implications for awareness of the influence of the contextual environment that chain organizations create. An independent facility has a better understanding and awareness of its resources and practices than facilities within chain organizations. Our results show that as these independent facilities join others to form a small- to medium-sized chain organization, they are able to improve quality but their efficiency suffers. The efficiency suffers, as these facilities have to coordinate efforts toward pooling their resources. As the size of chain organizations crosses a certain threshold level, the affiliated facilities gain economies of scale and increased demand, such that their efficiencies improve. However, they also witness growing heterogeneity and have difficulty managing the associated ambiguities, which have detrimental effects on their quality performance. An awareness of the changes in the environmental context and adoption of proactive adaptation measures, such as information exchange site visits to other affiliated facilities and training of staff members, can help manage efficiency and quality. Our results may be useful in other service settings beyond healthcare that have multiunit organizational forms, in that becoming part of a network, such as joining a chain organization, can have a positive or negative effect on efficiency and quality, depending on the size of the network.

5.3. Limitations and Future Research Directions

This study has a few limitations that present directions for future research investigations. First, differences between regional chain organizations may exist that this research did not fully capture. We submit that some chain organizations may not follow the average effects found in this study, and these anomalies may offer directions for future research. Second, other contextual factors may influence efficiency and quality beyond the size of the chain organization that we consider in this study. A study examining prevailing practices and interactions among members, tasks, and tools embedded in chain organizations would shed further insights. Researchers should seek out and evaluate additional antecedents to efficiency and quality, such as teamwork, organizational learning, and relationship development. Additionally, future research might consider patient age, weight, diabetes status, prescription drug use, dialysis-related infections, and nutritional habits to further build on the results obtained in this study.

The differential impacts of the size of chain organizations on quality and efficiency performance call attention to specific characteristics of competencies that need to be managed within the larger ecosystems. Our study does not capture training mechanisms that are in place within individual dialysis facilities or those instituted by chain organizations. Future studies need to consider how chain organizations can develop transactive memory systems that can handle competencies that are tacit as well as articulated, complex as well as simple, and interconnected as well as independent. This will provide directions for the ways in which chain organizations can manage causal ambiguity as they grow in size. Future studies are needed to explicitly account for these dimensions of knowledge and their individual and simultaneous effects on the pattern of relationships between chain size and various performance dimensions. Finally, future studies may explore how growth through mergers, acquisitions, or other means influences the relationships explored in this study.

Our study provides insights into the challenges of moving routines and transaction memory systems residing in chain organizations to the affiliated dialysis facilities. Additional research is needed to identify how the knowledge repository within these chain organizations coevolves with the underlying components within these multi-organizational units. Future research studies should examine conditions that can either aid or impede the transfer of knowledge among units embedded in these superordinate relationships.

The rise in kidney disease throughout the United States and worldwide has led to a rapid change in the dialysis industry, with increasing consolidation of facilities within the healthcare industry. Our research findings indicate that very large chain organizations, which are for-profit, have lower clinical quality scores and higher efficiency. Contextual factors are changing too, such that the Affordable Care Act is forcing healthcare service providers to change business models. For example, peritoneal dialysis is cheaper than hemodialysis, and just as effective, which may make it a more popular choice going forward. The evolution of these strategic shifts within this industry is uncharted and should provide interesting avenues for future research.

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