Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Clustering, Agency Costs and Operating Efficiency: Evidence from Nursing Home Chains

Susan F. Lu, Gerard J. Wedig,

MANAGEMENT SCIENCE
Vol. 59, No. 3, March 2013, pp. 677–694
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.1120.1611

Clustering, Agency Costs and Operating Efficiency: Evidence from Nursing Home Chains

Susan F. Lu, Gerard J. Wedig
William E. Simon Graduate School of Business Administration, University of Rochester,
Rochester, New York 14627 {susan.lu@simon.rochester.edu, wedig@simon.rochester.edu}

Models of horizontal integration typically describe a trade-off between multiunit efficiencies and managerial agency costs. In extreme cases where managers cannot be incented contractually, private ownership is thought to be the primary organizational substitute. In this paper we explore geographic clustering as an alternative strategy for controlling managerial agency costs within the chain form of organization. Clustering may facilitate scale efficiencies in both monitoring and supervision, resulting in reduced agency costs and improved application of the chain's business model. We test this hypothesis in the nursing home industry, which is characterized by managerial contract costs resulting from multitask models of production. We find that clustered nursing homes achieve higher quality, conditional on labor inputs and patient characteristics. The clustering effect is concentrated on reductions in minor/potential harm violations, which are difficult to observe without close monitoring. Several proxies for local organizational experience ("local learning") cannot account for our findings, which are robust to a variety of alternative clustering definitions and competing explanations based on gaming behavior. Further tests indicate that chains endogenously pursue clustering, presumably to realize the benefits of improved quality outcomes.

Key words: clustering; horizontal integration; monitoring; healthcare markets
History: Received May 3, 2011; accepted June 13, 2012, by Bruno Cassiman, business strategy. Published online in *Articles in Advance* December 10, 2012.

1. Introduction

Models of horizontal integration typically describe a trade-off between multiunit efficiencies (e.g., the value of branding) and managerial agency costs (Brickley et al. 2003, Lafontaine and Slade 2007). According to these models, chains possess scalable advantages that explain their existence, including branding, superior business models, and learning strategies (Baum 1999, Jin and Leslie 2009). Unlike production scale economies, these advantages vary across product and market contexts, resulting in uneven patterns of horizontal integration. An important theme in the existing literature (and related work on franchising) is that chains prevail where they can provide their managers with efficient incentive contracts or take other steps to minimize managerial agency costs. In extreme cases where managers cannot be incented contractually (because of contract costs), private ownership is thought to be the primary organizational substitute (Hubbard 2004). To date, there has been little research on alternatives to independent ownership in markets characterized by significant managerial contract costs, such as may arise where multiple dimensions of managerial effort are required.[1]

In this paper we study nursing home chains' use of geographic "clustering" as an endogenous strategy to improve the operational performance of their individual units. We hypothesize that clustering enhances monitoring and supervision by the parent organization, to the extent that monitoring and supervision are scalable activities (the "Monitoring Hypothesis"). The nursing home industry is arguably an ideal laboratory for testing this hypothesis. Nursing homes operate in markets where managerial effort is used to enhance multiple dimensions of quality. However, because quality is multidimensional and often hard to measure, it is difficult to write efficient incentive contracts to incent quality production. Franchising, another possible incentive tool, is also nonexistent in this industry.[2] In this setting, enhanced monitoring and supervision may play an important role in improving unit performance.

There is some existing evidence that chains and franchises cluster their units geographically. Kalnins and Lafontaine (2004) described the use of clustered ownership in the franchised fast food industry, noting that clustering may allow franchise owners to closely monitor their individual units. Other examples of endogenous clustering behavior have been documented in the nursing home industry in Canada

[1] A classic example is found in Shepard (1993), where multiple required dimensions of managerial effort (in this case running a full-service gas station) increase contracting costs and the likelihood of independent ownership.

[2] Franchising is not practiced in the nursing home industry, perhaps because of the highly litigious environment in which nursing homes operate. Franchising may result in a significant agency cost given that plaintiffs can sue the parent organization.

(Baum et al. 2000). To date, formal research on the effects of clustering has primarily focused on organizational learning. For example, Kalnins and Mayer (2004) studied the effects of clustering within pizza restaurants and found that clustering reduces the likelihood of business failure. Kalnins and Mayer (2004) viewed clustering as a device to transmit tacit knowledge and local market intelligence about strategic matters, such as business location. They employed formal measures of local organizational learning (aggregate experience in the market) to test this hypothesis. In a similar vein, Ingram and Baum (1997) and Baum and Ingram (1998) studied the effect of local learning on the failure rates of Manhattan hotels.

We analyze a representative measure of nursing home quality: deficiency citations. We measure the effects of clustering on this metric, conditional on inputs such as nursing hours, patient health status, and other controls. Given these controls, we are able to rule out nonprice competition over inputs or other considerations of market structure as factors in our findings. In addition, we restrict our sample to unbranded chain units to rule out reputation building as a possible explanation for any results.[3] Conditional on these controls, we find that clustering increases the measured quality of care in nursing homes. For example, our instrumental variables regressions show that the addition of a sibling unit in the local market reduces deficiency citations by 6.6% at the mean. Furthermore, upon closer examination, we find that the improvement is concentrated in the area of minor and potential harm violations which, although important to a nursing home's reputation, cannot be easily observed without close monitoring. Finally, we also show that several measures of local organizational learning (e.g., collective chain experience in a local market) do not account for these effects. Thus, although we do not directly measure monitoring, we argue that enhanced monitoring and supervision by the chain provides both a reasonable and highly plausible explanation for our results. Consistent with the prior literature, we also conduct tests of dynamic entry to supplement our main tests of the effects of clustering on operational quality. Using a conditional discrete-choice model, we find that the preexisting geographic proximity of sibling units enhances the odds of market entry. These results suggest that our main findings on nursing home quality are not statistical artifacts, but instead the product of a deliberate strategy employed by chains. As in the cases of fast food restaurants and hotels, we are able to show that chains pursue clustering as an endogenous strategy that has perceived benefits.

Our primary contribution to this literature is to document a different type of benefit from clustering and to propose a different mechanism for its conveyance (i.e., monitoring and supervision). We document the effects of clustering on an operational dimension (e.g., service quality) as opposed to a strategic dimension (e.g., business location and survival) of firm performance. Moreover, we narrow the number of possible explanations for these improvements, making a strong case that the benefits of clustering are realized by enhancing the monitoring and supervision of individual units by their parent organization. As a result, our findings make important contributions to the broader literature on chains and horizontal integration. First, we show that clustering significantly improves the operational performance of business units in an industry characterized by contracting frictions. These results address what Hubbard (2008, p. 342) refers to as a dearth of work that "quantifies the effects of ... organizational decisions" of this type. More importantly, our results provide a more complete way to think about the marginal decision between chain versus independent ownership. Our research implies that the ability of chains to cluster units must be factored into the trade-off between horizontal integration and independent ownership. Finally, we provide an explanation for a puzzle in the literature regarding the ability of chains to increase the revenue of their preexisting units through placement of new units in a local market. Entry of this type might be expected to result in cannibalization of existing unit revenues (Kalnins 2004).[4] Our findings suggest that the clustering effect of new, same-company entry improves quality (without requiring additional inputs). This may help to attract more demand and thus generate higher revenue for all company-owned units.

2. Nursing Homes, Clustering, and Quality

We focus on the nursing home industry and, specifically, skilled nursing facilities (SNFs) to test our main

[3] Other research has proposed that clustering improves operational results because chains enjoy reputational spillovers from good performance in clustered, local markets (see Jin and Leslie 2009 for a restaurant chain example). Blair and Lafontaine (1999) suggest that clustering may generate a brand awareness externality as well as economies of scale in marketing. We limit our sample to nonbranded nursing homes to rule out reputational effects. Later, we add branded nursing homes to the sample to demonstrate the robustness of our findings.

[4] Kalnins (2004) found that a newly franchised unit encroaches upon the revenue of the existing hotels franchised by the same franchisor. By contrast, cannibalization effects disappear when hotels are company owned. Kalnins (2004) argued that reputation and scalable marketing cannot explain revenue increases in company-owned hotels. Our results provide an alternative explanation for this phenomenon.

hypothesis. SNFs comprise a service-driven industry whose features have been well chronicled elsewhere (Giacalone and Duetsch 2001). Briefly, SNFs provide relatively constant nursing care to individuals with limitations on activities of daily living (ADLs). Residents may also receive physical, occupational, or other rehabilitative therapies. There are over 16,000 such facilities in the United States, most of which are associated with chains. For example, in 2004, 6,594 (61.6%) of all *for-profit* nursing homes were members of chains. Geographic clustering is common among chain nursing homes, but it is not universal.

2.1. Relevant Features of the Nursing Home Industry

An ideal industry setting for our tests is one in which firm success is closely tied to a noncontractible dimension of managerial effort. The nursing home industry fits this description for a variety of reasons. First, quality of care is an essential element of financial success, both for establishing reputation and for avoiding costly litigation. Managers play a vital role in managing and deploying nursing and other resources to guarantee quality. Second, some dimensions of service quality are difficult to identify ex ante and verify ex post.[5] Managerial contracts that reward high quality may be difficult to write, because quality has multiple dimensions, leading to a multitask principal–agent problem (Holmstrom and Milgrom 1991).[6] Third, the managerial incentive problem is not solved through franchising in this industry, due to fear of opportunistic behavior by either franchisors or franchisees. Opportunistic behavior is especially costly in this industry due to potential litigation costs.[7] In summary, the features of the nursing home industry define a setting with significant potential managerial agency problems not easily addressed by contracts or incentives.

It is noteworthy (and not surprising) that chains view clustering as a device for improving operational performance. Clustering makes managers less likely to shirk on the noncontractible aspects of quality and also improves operational efficiency. According to marketing materials from Kindred Healthcare, "clustering" (a term that they use in their materials) provides "A framework and strategy to improve operations in sites of service that are geographically proximate.... A competitive strategy to differentiate Kindred in local markets."[8]

Presently, we consider the possible economic effects of clustering with an emphasis on quality.

2.2. Clustering and Quality

Nursing homes typically form geographic clusters by purchasing available units nearby to one another (as opposed to building entirely new units close to one another). Constructing new units in a market is not always permitted because most states require certificate of need (CON) approval prior to certifying a new nursing home (Harrington et al. 1997). CON or construction moratorium approvals are rationed by states to control Medicaid expenditures (Feder and Scanlon 1980). In cases where new entry is constrained, clustering may be achieved by purchasing an existing unit from another owner. If we view the number of nursing homes in a given market as fixed (because of CON regulations or construction moratorium laws that effectively blockade entry), then clustering achieved through acquisition of existing units may have favorable competitive effects to the extent that it facilitates collusion among a fixed supply of competitors.

Our empirical work abstracts from these various competitive dynamics. The effects of competition should be reflected in measures such as profits or input intensity (a form of quality competition). Our empirical work focuses instead on operational efficiency ("residual" quality, conditional on inputs). This allows us to highlight learning and monitoring effects. Crucially, because we focus our attention on unbranded chain units, any effects of clustering on quality are unlikely to result from efforts to enhance brand reputation.[9]

Clustering may directly affect operations in at least two ways. First, clustered units may be able to learn from one another. Kalnins and Mayer (2004) documented that franchised pizza restaurants in Texas are less likely to fail both where their owner (franchisee) has gained experience operating other such restaurants in the local market and where same-franchise owners have also gained experience in the local area. The authors inferred that the restaurant's owner and

[5] For instance, frequent turning of elderly patients from side to side helps to prevent pressure ulcers and skin breakdown. However, it is difficult for outsiders to clearly measure how well nurses perform this task, which must be closely monitored by managers.

[6] Lu (2012) verifies that report card releases have resulted in behaviors that are consistent with multitask incentive conflicts in nursing homes.

[7] Fear of litigation may also account for the fact that most nursing homes are unbranded, which further reduces the value of franchising.

[8] Online presentation for investors, November 2010; see the website of Kindred under the category of investor/presentations & conferences (http://phx.corporate-ir.net/phoenix.zhtml?c=129959&p=irol-presentations, accessed November 2010).

[9] According to the 2004 Online Survey Certification and Reporting Database, 69% of chain-affiliated for-profit nursing homes do not brand their homes because this helps chains to hide their "deep pockets" and thus reduce expected litigation costs. The unbranded aspect of most nursing homes allows us to separate the monitoring effect from the potential reputational effects of geographical clustering.

other, same-franchise owners gain local knowledge, both tacit and formalized, that may be communicated to all of the franchise's local units. For example, local knowledge may be useful in choosing the location of a new store. Moreover, the authors also found that the effects of owner and franchise knowledge may be synergistic (interactive); an owner with more existing experience may be able to make better use of the knowledge gained by other owners' same-franchise experience (this is consistent with the theory of absorptive capacity) (Cohen and Levinthal 1990). The favorable spillovers of learning and experience among clustered units may extend to the nursing home industry. Local knowledge may assist with addressing matters such as unit location, hiring practices, and regulatory compliance (Baum et al. 2000). However, the effects of local experience on operational quality are less certain. Local experience is arguably less important for the production of quality than it is for strategic decisions such as choosing the best location within an area.

A second and arguably more relevant effect of clustering is improved monitoring and supervision. Clustering units may facilitate more frequent visits from regional managers and other chain management, at a lower marginal cost. Clustering effectively reduces the travel time from unit to unit and thus increases the probability of monitoring. This may lead to an increase in managerial effort, a reduction in shirking along noncontractible quality dimensions, and a more efficient application of the chain's business format.

Direct observation of managerial effort and actions by supervisors may provide more effective and precise measurement of actual managerial effort as well as of quality itself. Formal models of the potential linkage between clustering, effort, and quality are relatively simple to derive. For these purposes we appeal to the multitask linear contract model of Holmstrom and Milgrom (1991) (Such a model is also discussed in Lafontaine and Slade 2007). According to this simple model, clustering reduces monitoring costs, leading to greater monitoring and a more precise signal of managerial effort. This increases the linkage between the observed effort signal and managerial pay, ultimately leading to an increase in effort and quality, given inputs.

In addition, any reduction in the cost of monitoring may also lead to quality improvements independent of managerial incentives. More frequent monitoring may enable ownership to give more effective instruction to management regarding the chain's tacit knowledge over quality production. This would also lead to an increase in quality. In this case, the main effect of clustering is not the generation of tacit knowledge per se, but instead monitoring and supervision which assist in the application of the chain's existing tacit knowledge base. Below, we also present a test that can be used to distinguish the effects of clustering on efficiencies of this type from its direct effects on harder-to-detect agency costs.[10]

3. Data and Patterns of Clustering and Quality

Our primary data source is the 2004 nursing home Online Survey Certificate and Reporting Database (OSCAR), which includes the addresses of all Medicare and Medicaid certified nursing homes operating throughout the United States. OSCAR provides information on owner identity, dates of ownership changes, quality, and other nursing home characteristics. We supplement the OSCAR file with financial data from Medicare's SNF cost reports as well as demographic information from the Bureau of Census.

Nursing homes are a "mixed industry" with for-profit companies comprising 66% of homes in 2004, nonprofit organizations 28%, and government entities 6%. We focus our analysis exclusively on for-profit chains to ensure that our results are not driven by nonprofit objectives.[11] The horizontal integration literature suggests that clustering may be driven by reputation, monitoring/efficiency, or both. To get a "clean" assessment of the monitoring effect, we exploit the fact that chains choose not to brand most of their units, as reflected in the manner in which they name their units (69%).[12] Our final sample consists

[10] It may be argued that clustering also facilitates scale economies in certain activities that may be used to improve quality of care (e.g., having a dedicated, "roving" manager of risk management). We argue that division of labor is not a characteristic of clustering but rather a characteristic of the size of the local market (i.e., "roving" personnel may work across different nursing home chains in a local market on a contract basis). For this reason, we argue that scale economies in quality production are not a competing explanation for any results that we obtain for clustering per se. Furthermore, we present tests that can be used to distinguish between explanations that improve all dimensions of quality (i.e., scale economies) versus explanations that focus on harder to observe dimensions of quality (i.e., agency cost explanations).

[11] For example, it may be argued that nonprofit and government ownership provides softer incentives for profit maximization, leading to higher levels of noncontractible quality (Glaeser and Shleifer 2001).

[12] That is, we measure branding of individual nursing homes by determining whether the chain's name is included in the nursing home's name. We argue that this is a valid way to assess whether a nursing home's quality "spills over" to assessments of the chain as a whole. We justify this assumption in two ways. First, it is apparent that nursing home chains themselves believe that customers do not make connections between an individual nursing home and its larger chain unless the connection is indicated in the nursing home's name. For example, a plaintiff attorney that specializes in nursing home litigation asserts, "large nursing home operators carefully name facilities with the intent of shielding the parent company from possible liability in the case of an injury or a

Table 1 Variable Definitions, Means, and Standard Deviations

Variable	Definition	Obs.	Mean	SD
	Full sample			
Siblings (*distance*)	Number of sibling units within 25 miles	4,002	1.8	3.2
Siblings (*travel time*)	Number of sibling units within 45-minute travel time	4,002	2.0	3.6
Total citations	Number of deficiency citations	4,002	6.5	5.5
Minor/potential harm	Number of minor/potential harm deficiency citations	4,002	6.2	5.3
Jeopardy/actual harm	Number of jeopard/actual harm deficiency citations	4,002	0.3	0.8
Elderly (65+)	65+ elderly population within 25 miles	4,002	13.3	19.6
Total demand	Total nursing home residents within 25 miles	4,002	5,310	7,809
Learning	Distance-based collective local experience (in years) of sibling units	3,983	0.6	1.8
Staffing	Total nursing hours per resident day	4,002	3.8	2.3
ADL	Percentage of patients who cannot perform daily activities without assistance	4,002	16.4	8.3
Bedridden	Percentage of patients who spend most of their time in bed or in a chair	4,002	4.9	5.3
Pain	Percentage of patients who have moderate to severe pain	4,002	6.6	5.8
Restrained	Percentage of patients who are physically restrained	4,002	7.7	7.3
Beds	Total beds	4,002	107.7	48.2
Medicaid	Proportion of Medicaid patients	4,002	0.7	0.2
Hospital-based	Nursing home is affiliated with a hospital	4,002	0.02	0.15
Family organization	Nursing home has a family monitoring committee	4,002	0.4	0.5
HHI_zip	HHI index in a zip code	4,002	0.5	0.4
log *income*	Log of household income in the zip code	4,002	10.6	0.3
Percentage black	Black population/population in a zip code	4,002	0.1	0.2
Units	Number of units a chain owns	4,002	69.1	96.7
	Top 12 chain sample			
Siblings	Number of sibling units for home i if a member of chain j	828	0.4	1.4
Distance to headquarters	Distance from home i to the headquarters of chain j/10	828	107.6	66.1
Preexisting unit	Chain acquisition target has a sibling unit nearby (see Table 8)	828	0.2	0.4
Similarity_income	$\lvert$market (zip) income for nursing home (NH) i − average market income for chain's other units $j\rvert$	828	10.7	8.1
Similarity_black	$\lvert$market (zip) % black population for NH i − average market % black pop for chain's other units $j\rvert$	828	0.1	0.2
Similarity_ADL	$\lvert$avg number of ADLs for NH i's patients − avg number of ADLs for patients in chain's other units $j\rvert$	828	3.7	3.6
Units	Number of units a chain owns	828	134.4	92.5
Years since first opening	Years since chain opened its first nursing home	828	37.9	2.1
Years since last opening	Years since chain opened its most recent nursing home	828	3.6	1.0
HHI_zip	HHI index in a zip code	828	0.5	0.4
log *income*	Log of zip code household income	828	10.6	0.3
Percentage black	Black population/population in a zip code	828	0.1	0.2

of 4,002 unbranded for-profit, chain-affiliated nursing home units. Table 1 provides definitions, means, and standard deviations of the variables that we use in our study.

3.1. Clustering Patterns Among Nursing Home Chain Units

Clustering is widely employed by both national and local multiunit owners. Table 2 shows the extent to which chains use clustering as a strategic device to locate their units. We use the number of siblings within 25 miles to define clustering. We classify chains into four quartiles according to their total number of units to check whether clustering behavior exists across all quartiles and whether clustering is correlated with chain size. Table 2(a) indicates that clustering exists across all four quartiles of chain size. Furthermore, large chains cluster more units around each of their nursing homes, on average. This may be because larger chains have more total units available to cluster around any given unit.

We also explore the covariates of clustering because this helps us to identify exogenous variables that are correlated with clustering and guard against omitted variable bias in our main work. Identifying these covariates also provides useful intuition (if not rigorous tests) for why many nursing homes are not clustered, given the apparent usefulness of clustering as a device for improving operational performance.

Table 2(b) lists five different variables that covary with nursing home clustering behavior. The selected variables describe features of the geographic area in which the nursing home is located and span demographic, tax, legal, and regulatory features of the region. The selected variables also have an a priori plausible relationship with clustering behavior. For example, demographically, we expect that it may

death" (Rosenfeld 2009). Identifying an owner of a given nursing home is generally difficult if it is not signaled by the brand name. In related work, we verify empirically that chains are less likely to "brand" nursing homes in the manner described here (i.e., with a common name) in high litigation states (Brickley et al. 2011).

Table 2 Incidence and Covariates of Clustering

(a) Distribution of clustering conduct by chain size

Number of sibling units	Quartile 1	Quartile 2	Quartile 3	Quartile 4
0	578	511	432	284
1	284	239	217	183
2	95	121	102	131
3	34	56	62	80
4	14	39	46	58
5	10	29	18	48
6	0	16	16	47
7	0	7	6	31
8	0	6	15	16
9	0	11	3	23
10	0	3	4	12
11–20 units	0	3	26	42
21–25 units	0	0	18	14
Total unbranded units	1,015	1,041	965	981
One or more siblings (%)	43	51	55	71
Two or more siblings (%)	15	28	33	52
Three or more siblings (%)	6	16	22	39

(b) Covariates of clustering conduct

	Unclustered	Clustered	Difference	*p*-value
Demographics				
Rural	0.27	0.08	0.19	[0.000]
Registered nurses per elderly	0.03	0.04	−0.01	[0.000]
Tax, legal and regulatory				
Property tax	1.52	1.45	0.07	[0.000]
High-litigation states	0.15	0.10	0.05	[0.000]
CON law states	0.67	0.64	0.03	[0.017]

Notes. Panel (a) shows the extent of geographic clustering of all nursing home chains by quartile of chain size (where size is defined as the number of nursing homes owned by the chain). Sibling units within 25 miles of a given unit is listed on the vertical. The data allow us to say, for example, that 578 of the nursing homes owned by the chains in the lowest quartile of size have no sibling units within 25 miles. Panel (b) documents covariates of clustered and unclustered chain units. We find that chains are less likely to cluster nursing homes in rural areas and areas with less skilled nursing. In addition, clustering also covaries negatively with (1) property tax rates, (2) litigation risk, and (3) CON laws that impede entry and thereby increase the cost of forming a cluster.

be difficult to cluster nursing homes in rural areas, whereas it may be more likely to find clustering in growing areas. Similarly, prior research indicates that nursing home chains avoid high litigation states (Brickley et al. 2011), which would preclude their clustering nursing homes in such states. In Table 2(b), we find that clustered nursing homes are more likely to exist in areas with more registered nurses and less likely to be found in rural areas, areas with higher property taxes, high-litigation states, and states that restrict the building of nursing homes (CON law states). Each of these partial correlations is consistent with an informal theory of their partial effects. Although we cannot ascribe causation without a well-specified regression approach, there appear to be exogenous factors that limit the extent of clustering, helping to explain why clustering is not ubiquitous despite its apparent advantages.

3.2. Quality Measures

Our empirical analysis focuses on a specific indicator of noncontractible, operational performance: deficiency citations. Each year, an inspection team randomly conducts a health inspection in each nursing home, using a checklist of approximately 190 quality dimensions. When a particular dimension of quality does not satisfy minimum requirements, a deficiency citation is issued. An extensive body of prior research uses deficiency citations as a measure of nursing home performance (Nyman 1985, Grabowski et al. 2004, O'Neil et al. 2003, Lu 2012). In addition, the Centers for Medicare and Medicaid Services (CMS) uses aggregate deficiency citations as its main criterion to rank nursing homes, using a "five-star" ranking system. CMS refers to deficiency citations as a proxy for overall "quality of care."[13] Given their use by CMS, deficiency citations are an important component of a nursing home's public reputation.

Inspectors assign deficiencies into one of four severity levels: minor harm, potential harm, actual harm and jeopardy. For example, extreme violations likely resulting in death give rise to a jeopardy citation (e.g., losing track of the location of an elderly patient). Alternatively, less significant errors, such as misplacement of a medication container, will give rise to a minor harm citation. For some of our analyses, we classify deficiency citations into two groups based on their severity levels: a minor/potential harm (MPH) group and a jeopardy/actual harm (JAH) group. Although regulators provide (arguably unbiased) assessments of both dimensions, we argue that it is more difficult to accurately measure and therefore contract upon minor or potential harm deficiencies. This is because such violations are harder to detect and can be observed only through close monitoring.

We stress that even citations assigned to the minor/potential harm grouping have a material impact on a nursing home's reputation and value. First, the vast majority of all deficiency citations are assigned to the MPH group (see Table 3). Second, citations in this group may be symptomatic of more significant operational problems. For this reason, responsible risk management should focus on minimizing these citations. Third, many of the citations in this grouping "count" in the five-star rankings of nursing homes devised by CMS. Table 3(a) provides some summary data on our quality measure by quartile of chain size. Table 3(a) indicates that MPH deficiency citations are

[13] See CMS (2010, p. 16), where the text provides an interpretation of its methodology and uses the terms "quality of care" and "deficiency citations" interchangeably.

Table 3 **Summary Statistics and Cross Tabulations of Deficiency Citations**

(a) Summary statistics of quality measures by chain size

	All chains			
Chain size	Frequency	Total citations	Minor/ potential harm	Jeopardy/ actual harm
Quartile 1	1,015	6.5	6.2	0.3
Quartile 2	1,041	6.6	6.3	0.3
Quartile 3	965	6.5	6.3	0.2
Quartile 4	981	6.4	6.1	0.3
Total	4,002	6.5	6.2	0.3

(b) Cross tabulation of clustering and deficiency citations: Large chains

	Top 12 national chains			
Number of sibling units	Frequency	Total citations	Minor/ potential harm	Jeopardy/ actual harm
0	384	6.5	6.2	0.3
1	233	6.7	6.3	0.4
2	155	5.9	5.6	0.3
3	92	5.5	5.3	0.2
4	58	5.6	5.3	0.3
5–10 units	187	5.9	5.6	0.3
11 or more units	70	5.5	5.2	0.3

Notes. Panel (a) provides summary statistics of our quality measures by quartile of chain size. Three quality measures are listed horizontally across the top of the page, whereas quartiles are listed on the vertical. This table indicates that minor/potential harm deficiency citations are more common than jeopardy/actual harm citations and that, overall, chains average about 6–7 citations per inspection, regardless of chain size. Panel (b) provides a simple cross tabulation of deficiency citations and the amount of nursing home clustering for a sample of 12 large national chains. The vertical column indicates the amount of clustering (i.e., nearby sibling units) for a given nursing home, whereas the type of deficiency citation is listed across the horizontal. Each cell lists the mean number of citations for a given clustering level and deficiency type.

much more common than JAH citations and that, overall, nursing homes average about six citations per inspection.

In the appendix, we also provide some empirical evidence of the relation between nursing home reputation and deficiency citations. Following a methodology described in McDevitt (2011), we investigate the simple relationship between a nursing home's lagged citations and its likelihood of either changing its name (a proxy for declines in its reputation) or, more significantly, exiting from the market.[14] Consistent with our discussion above, we find that both MPH and JAH citations (individually) predict both name changes and market exit. Finally, we note that in a simple cross tabulation of the top 12 chain's data, given in Table 3(b), there appears to be a modest negative correlation between clustering and both total and MPH citations and no apparent correlation between clustering and JAH citations. Of course, such results do not demonstrate causality. Presently, we consider a methodology to uncover the causal relationship between citations and clustering.

[14] Following the methodology described in McDevitt (2011), we control for both firm and market characteristics in predicting both name change and market exit. Total citations and minor/potential harm citations predict both name change as well as exit. Jeopardy/actual harm citations are a predictor of exit. Additional detail is provided in the appendix.

4. Empirical Results

4.1. Impact of Clustering on Operational Efficiency

We conduct tests of the monitoring hypothesis, which states that (a) clustering improves operational efficiency and (b) the effect is not due to local experience. We test this hypothesis by estimating the effects of clustering on nursing home quality, controlling for inputs and other factors. We conduct these tests using our measures of deficiency citations described in §3.2.

4.1.1. Methods. We assume that nursing homes produce quality (measured as the opposite of deficiency citations) with a set of inputs that include labor and materials as well as the resident's initial health stock (i.e., patient health is treated as an input). We define maximum quality as that level of quality which would occur in the absence of managerial agency costs or other frictions; agency costs take the nursing home away from its efficient frontier. In this heuristic, clustering is a tool that enables a nursing home unit to approach its production frontier. Finally, we also assume that observed quality is affected by random factors (i.e., white noise) that may include measurement error.

Under these assumptions, observed quality may be modeled using a stochastic frontier model (Wang and Schmidt 2002, Kumbhaker and Tsionas 2006). According to this model, observed quality is an additive function of inputs, a nonpositive term, $(-\mu)$, that represents productive inefficiency (due to, for example, agency costs) as well as a white noise term, v.

Formally,

$$Y = \alpha + \beta X - \mu + v, \tag{1}$$

where Y is a (positive) measure of quality, X is a vector of productive inputs, and β is a vector of parameters that measures the marginal effects of inputs such as labor, materials, and patient health status on quality.

To complete the model, we also assume that μ is equal to the sum of a term, γZ, that captures systematic drivers of efficiency (including clustering and other efficiency drivers), as well as a random term ε. The random term ε is bounded in such a way that $(-\mu)$ is always negative, consistent with the frontier model. Formally,

$$\mu = \gamma Z + \varepsilon, \tag{2}$$

where $\min(\varepsilon) \geq -(\gamma Z)$.

We employ a linear, instrumental variables model that does not impose parametric assumptions on ε.[15] To derive this model, define $\varepsilon^* = \varepsilon - E(\varepsilon/Z)$. Then, consistent with the model described above, we can write the following:

$$Y = \alpha + \beta X - \gamma Z - E(\varepsilon/Z) + \psi, \tag{3}$$

where $\psi = \nu - \varepsilon^*$. Note that $E(\psi) = 0$ (although ψ has an asymmetric distribution).[16] Note further that $E(Z \cdot E(\varepsilon/Z)) \neq 0$. For this reason, an ordinary least squares (OLS) regression of quality (Y) on the X and Z (clustering) may result in biased estimates of the γ. Clustering (an element of Z) may be correlated with $E(\varepsilon/Z)$ because chains may select clustering conditional on the value of ε. For example, chains may choose to cluster more where their efficiency is low to improve efficiency. Alternatively, chains may tend to put additional units in a geographic area where, for unmeasured reasons, they are able to attain high efficiency, resulting in a "coincidental" clustering.[17] The net result, in either case, is a bias (that may run in either direction).

To obtain consistent estimates, we instrument for clustering by utilizing an instrumental variable (IV) that correlates with clustering conduct but not with the unmeasured dimensions of the chain's efficiency level. For these purposes, we use the number of elderly above 65 years old within 25 miles, *Elderly* (65+), as the IV for clustering. We reason that chains tend to open more units in areas with a higher elderly population, but that this fact is independent of whether a nursing home has above-average deficiency citations.[18]

We present estimates of Equation (3). We use deficiency citations as the dependent variable. Our set of factor "input" variables (the X vector) includes total staffing (number of nursing hours) and patient characteristics, including a measure of the patient's activity limitations, whether the patient is bedridden, a pain index, and a patient restraint index. Our controls for systematic determinants of efficiency (the Z vector) include our instrumented values of clustering and other nursing home characteristics, including percentage of Medicaid patients, total beds, whether the nursing home is hospital based, and whether it has a family committee. We also include chain-level fixed effects to control for the overall efficiency level of the chain, as well as state fixed effects.[19] Finally, we also include the market's HHI competition index to control for any effects of market structure,[20] as well as a set of local demographic controls interacted with chain dummies to control for the chain's preferences for markets with specific demographic profiles.

According to the derivation of Equation (3), the coefficient for clustering has a positive predicted sign, provided that quality is defined as a positive measure, where quality is measured as a negative (e.g., total deficiency citations) predicted coefficients reverse sign so that the predicted effect of clustering becomes negative.

4.1.2. Main Results. Tables 4 and 5 present our main regressions of nursing home quality (total deficiency citations) on nursing home clustering and other controls. In Table 4, two separate specifications are estimated (Models 1 and 2) using both OLS and 2SLS estimators. The specifications differ only by whether market demographics are included in the specification. This table also provides the first-stage results of the 2SLS estimation.

It is important to note that our first-stage IV results indicate a positive and significant coefficient of the elderly population on clustering. Furthermore, the Anderson canonical correlation test shows that the minimum eigenvalue statistic is significantly larger than the critical value of 16.38, thus allowing us to reject the null hypothesis of a "weak" instrument.

Turning to the results in Table 4, we find clear support for the hypothesis that clustering improves quality. Both models indicate a negative relationship between a unit's number of nearby siblings and deficiency citations. In Model 1, the marginal effect of

[15] Battese and Coelli (1995) propose a one-step estimator to estimate the model's parameters (β, γ). They point out that two-step approaches (i.e., estimating the frontier model first without the Zs and then regressing the fitted "inefficiencies" on the Zs) are theoretically inconsistent. However, we note that the Battese and Coelli (1995) approach has two potential limitations. First, the Battese and Coelli (1995) model makes strong parametric assumptions about the distribution of ε. The authors not only assume that ε is distributed normally, but also that the normal is truncated at $-(\gamma Z)$. This is a more restrictive assumption than $\min(\varepsilon) \geq -(\gamma Z)$. Second, this method does not address the case where elements of Z may be selected endogenously in a way that correlates with other drivers of the firm's inefficiency. For example, we argue that chains may choose the degree of clustering differently for nursing home units that are systematically more or less efficient than average.

[16] We rely on the asymptotic properties of 2SLS estimators to argue that ψ's limiting distribution is normal.

[17] That is, clustering occurs in this case because the chain wishes to take advantage of its higher level of efficiency in a given geographic area and not because of a deliberate strategy to cluster to achieve a clustering efficiency.

[18] To address the concern that our instrument, number of elderly, may correlate with vigorous state regulation over nursing home quality, we also include state dummies in all of our regressions.

[19] Another reason that we include a control for state effects is that deficiency citations are issued by state inspectors. State dummies allow us to control for heterogeneous inspector behavior across states.

[20] We also estimate regressions with the number of nursing homes in the county as an alternative proxy for competition. The results are robust to this alternative specification.

Table 4 Effects of Clustering on Nursing Home Quality: Full Sample Results

	Model 1			Model 2		
		2SLS			2SLS	
Variables	OLS	First	Second	OLS	First	Second
Siblings	−0.058		−0.296***	−0.082*		−0.432***
	(0.035)		(0.081)	(0.037)		(0.088)
Nursing home inputs						
Staffing	−0.073	0.022	−0.068	−0.072	0.021	−0.065
	(0.041)	(0.017)	(0.038)	(0.041)	(0.017)	(0.038)
Market characteristics						
HHI_zip	−0.243	−0.247*	−0.334	−0.209	−0.255**	−0.346
	(0.232)	(0.099)	(0.218)	(0.232)	(0.099)	(0.220)
Nursing home characteristics						
Medicaid	1.621**	0.621**	1.732***	1.420**	0.679**	1.654**
	(0.526)	(0.224)	(0.491)	(0.542)	(0.231)	(0.511)
Beds	0.017***	−0.0002	0.018***	0.017***	−0.001	0.017***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Hospital based	2.864*	−0.458	2.799*	2.814*	−0.422	2.749*
	(1.226)	(0.521)	(1.142)	(1.223)	(0.521)	(1.147)
Family committee	−0.318	0.145	−0.285	−0.286	0.153*	−0.229
	(0.180)	(0.077)	(0.168)	(0.180)	(0.076)	(0.169)
Constant	5.077***	−0.400	8.179***	−2.545	−5.660***	−5.251
	(1.094)	(0.465)	(2.313)	(3.888)	(1.687)	(4.389)
Instrument						
Elderly (65+)		0.073***			0.070***	
		(0.003)			(0.003)	
State fixed effects	Y	Y	Y	Y	Y	Y
Chain fixed effects	Y	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y	Y
Market demographics	N	N	N	Y	Y	Y
R-squared	0.34	0.64	0.33	0.35	0.64	0.33
N	4,002	4,002	4,002	4,002	4,002	4,002
H0: Instruments are weak			Anderson canonical correlation test			
Min eigenvalue stat (F)		739.8			625.8	
Prob > F		0.000			0.000	

Notes. This table presents regressions of total nursing home deficiency citations on measures of nursing home clustering (*Siblings*), patient characteristics, market characteristics, nursing home characteristics, and local market demographics. We present both OLS and IV regression results, as well as the first-stage results of the IV regressions in which *Siblings* is regressed on the model's other variables as well as our instrument, population over 65. Our clustering measure is defined as the number of sibling units within 25 miles of the nursing home. Other variable definitions are provided in Table 1. Standard errors are in parentheses.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

an additional sibling on reducing deficiency citations increases as we move from OLS (−0.058) to 2SLS (−0.296) estimators, with both estimates statistically significant. In Model 2, the coefficients are (−0.082) for OLS and (−0.432) for 2SLS, also statistically significant. The increased magnitude of the 2SLS results indicates an OLS bias toward zero, which would occur, for example, if chains increased clustering of their units in cases where they expected quality to be low, otherwise. Judged in terms of magnitude, the Model 2 2SLS results imply that the addition of a sibling to a nursing home's local market area reduces its expected level of nursing home citations by about 6.6% at the mean level of deficiency citations (6.6% = −0.432/6.7).

We also note that other controls take on their expected signs in cases where they are statistically significant. Nursing home staffing and family committees reduce citations while percentage of patients in pain and restraints, as well as Medicaid dependence, total nursing home beds, and being a hospital-based nursing home increase expected citations.

In Table 5 we present results where we divide the dependent variable into MPH versus JAH citations. In the first two columns of results, we show both OLS and 2SLS results for JAH citations, using the full sample. In the final six columns we show results using MPH citations as the dependent variable, and we also show how the results vary as we divide the sample at the median of total units owned.

Table 5 Effects of Clustering on Nursing Home Quality: Divided Sample Results

	Jeopardy/actual harm		Minor/potential harm					
	All chains		All chains		Small chains		Big chains	
Variables	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	OLS (7)	2SLS (8)
Siblings	0.004	−0.005	−0.095**	−0.398***	−0.126	−1.194***	−0.067	−0.271**
	(0.006)	(0.014)	(0.035)	(0.083)	(0.104)	(0.328)	(0.039)	(0.086)
Nursing home inputs								
Staffing	−0.003	−0.003	−0.071	−0.064	−0.027	−0.026	−0.100	−0.095
	(0.007)	(0.006)	(0.038)	(0.036)	(0.057)	(0.051)	(0.053)	(0.052)
Market characteristics								
HHI_zip	0.032	0.029	−0.212	−0.331	−0.190	−0.515	−0.206	−0.301
	(0.038)	(0.036)	(0.219)	(0.207)	(0.323)	(0.303)	(0.304)	(0.300)
Nursing home characteristics								
Medicaid	0.072	0.078	1.207**	1.410**	2.216**	2.244***	0.541	0.753
	(0.089)	(0.083)	(0.512)	(0.482)	(0.761)	(0.679)	(0.707)	(0.697)
Beds	0.001*	0.001*	0.015***	0.015***	0.012***	0.013***	0.016***	0.017***
	(0.0003)	(0.0003)	(0.002)	(0.002)	(0.0030)	(0.0030)	(0.003)	(0.003)
Hospital based	−0.007	−0.009	2.749*	2.693*	1.630	1.364	4.441*	4.463*
	(0.201)	(0.186)	(1.155)	(1.080)	(1.517)	(1.355)	(1.837)	(1.800)
Family committee	−0.024	−0.023	−0.268	−0.219	0.031	0.040	−0.463*	−0.410
	(0.029)	(0.027)	(0.170)	(0.159)	(0.262)	(0.233)	(0.227)	(0.223)
Constant	0.700	0.754	−1.702	−5.719	−2.685	−5.370	−1.038	1.557
	(0.638)	(0.711)	(3.671)	(4.135)	(5.873)	(5.712)	(4.888)	(7.042)
State fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Chain fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Market demographics	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.20	0.20	0.36	0.35	0.47	0.43	0.27	0.26
N	4,002	4,002	4,002	4,002	2,056	2,056	1,946	1,946

Notes. This table presents regressions of total nursing home deficiency citations on measures of nursing home clustering (*Siblings*), patient characteristics, market characteristics, nursing home characteristics, and local market demographics. We present results where we divide the dependent variable into MPH versus JAH citations. In the first two columns, we show both OLS and 2SLS results for JAH citations using the full sample. In the final six columns, we show results using MPH citations as the dependent variable, and we also show how the results vary as we divide the sample into small and big chains using the median of total units as the cutoff. Variable definitions are provided in Table 1. Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

As discussed previously, given that MPH citations are arguably more difficult to observe and less likely to be used to set managerial compensation, we hypothesize that clustering has a stronger effect on reducing these deficiencies. This is, in fact, what we observe in Table 5, where clustering has a significant negative effect on MPH citations but an insignificant effect on JAH citations. As in Table 4, other controls take on their expected signs, where they are statistically significant. Within the category of MPH citations, our 2SLS results indicate that clustering improves performance for both large and small chains, but that the effect is approximately three times larger in the small chain sample. It may be that monitoring is a more important control device in small chains, which may lack complementary tools for quality production (e.g., training programs) that are available to larger chains.

4.1.3. Tests to Rule Out Local Learning as an Explanation for Our Findings. In Table 6 we provide regressions of quality on measures of local organizational learning in an attempt to rule out local learning as a competing explanation for our findings. For these purposes, we define "local learning" as the aggregate local experience that the nursing home and its siblings have in the local market (Darr et al. 1995, Baum and Ingram 1998, Kalnins and Mayer 2004).

There are several reasons to expect, a priori, that a local learning hypothesis will fail to account for our clustering results. First, anecdotally, several chains report that they apply chain-level models to achieve unit quality (through training programs, etc.), so that it is likely that clustering primarily assists with monitoring and supervising the chain quality model instead of promoting local learning.[21]

[21] For example, SunBridge "uses an exciting training method called Sun University that provides the underpinnings for most of its education and training . . . [for] dietary professionals, occupational therapists and administrators. SunBridge supports new leadership and encourages them to be successful with the company's processes and systems through divisional and regional on-boarding." (See http://

Table 6 Effects of Clustering and Learning on Nursing Home Quality

	Model 1 OLS	Model 2 2SLS	Model 3 OLS	Model 4 2SLS	Model 5 2SLS	Model 6 2SLS
Learning (*T*-*t*)	−0.057	0.041	−0.024	0.150*	5.049	
	(0.046)	(0.342)	(0.050)	(0.067)	(3.177)	
Siblings			−0.075	−0.471***	−1.725	−0.303
			(0.039)	(0.107)	(0.931)	(0.161)
Residual learning (*L*-*S*)						5.049
						(3.177)
State fixed effects	Y	Y	Y	Y	Y	Y
Chain fixed effects	Y	Y	Y	Y	Y	Y
Nursing home inputs	Y	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y	Y
Nursing home characteristics	Y	Y	Y	Y	Y	Y
Market characteristics/demos	Y	Y	Y	Y	Y	Y
R-squared	0.35	0.35	0.35	0.33	.	.
N	3,983	3,983	3,983	3,983	3,983	3,983

Notes. This table presents regressions of nursing home deficiency citations on measures of nursing home clustering, local learning, patient characteristics, market characteristics, nursing home characteristics, and local market demographics. We present both OLS and IV regression results. Our clustering measure (*Siblings*) is defined as the number of sibling units within 25 miles of the nursing home. Our learning measure is defined as the aggregate (collective summed) number of years that the nursing home and its sibling have been active in the local market. Other variable definitions are provided in Table 1. Standard errors are in parentheses.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Moreover, Wong (2004) report that distant ("distal") processes may impede local learning so that, to the extent that the chain is imposing its own quality of care processes, this may impede any local learning that would otherwise occur. Second, we report evidence below (in §4.3), indicating that major chains try to locate their units close to corporate headquarters whenever possible, also consistent with the goal of monitoring and supervision as opposed to a reliance on local learning (locating units close to headquarters may serve a function similar to that of clustering). Third, operational quality, unlike strategic choice of location, has no defining local characteristic (quality in one market is achieved in the same way as in another), so it seems less likely that local learning will matter in this context. In summary, available evidence indicates that chains have chain-level quality models that they try to apply uniformly. In this context, clustering is a natural means to achieve monitoring and supervision of the business model.

However, it is conceivable that local learning may assist with quality even if this is not chains' avowed purpose for clustering. For this reason, we provide a formal test of the null hypothesis that local learning (as proxied by local experience) does not explain our findings. Tests of local learning are complicated by the fact that learning and clustering measures are positively correlated in our data (Pearson partial correlation of raw measures equals (0.4)). Regressions in which learning measures are entered alone may pick up the omitted effects of clustering and monitoring. Likewise, regression estimates in which both measures are entered may suffer problems of multicollinearity, resulting in imprecise estimates. In spite of these potential problems, we are able to obtain useful estimates from both types of regressions. We argue that results in which the local learning measure alone is statistically insignificant and regressions in which clustering is significant and local learning insignificant provide evidence that our main effects are not due to local learning. Table 6 provides several specifications that test the null hypothesis that local learning effects do not lead to operational improvements in clustered nursing home markets.[22] The first two specifications in Table 6 include local learning measures alone (with no controls for clustering). The first model uses OLS, whereas the second model uses 2SLS. The 2SLS specification uses the date of entry of the chain's

www.sunbridgehealthcare.com/Working_at_SunBridge/Current_Employees/Sun_University.aspx.) Likewise, apropos of monitoring and supervision efforts, Five Star "conducts routine surveys and intensive inspections, covering all departments, at every Five Star community. For dining and nutrition alone, [they] evaluate 130 separate checkpoints. [Their] healthcare specialists track resident experience with health and wellness goals, such as safe mobility and nutrition, to measure progress." (See http://fivestarseniorliving.com/active-retirement-senior-living.php, accessed February 2011.)

[22] The local experience measure reported in Table 6 discounts years of experience by *T*-*t*. We also try other discount rates and the results are robust. In addition, we also try other measures of local experience based on total nursing homes beds and total historical nursing days supplied within the cluster and obtain similar results (available from the authors upon request). The methodological approach of using total prior quantity supplied to measure *service* learning is also employed in Lapré and Tsikriktsis (2006), who note that this measure works as an effective proxy for learning in the case of airline satisfaction.

first nursing home in the market as the instrument for local learning (this variable is found to be a powerful instrument.) Turning to the results, we are unable to reject the null hypothesis that local learning has no effect on operational improvements, because the learning measure is statistically insignificant in both regressions. Specifications 3-6 include both clustering and local learning measures. In Model 3 we use OLS. We instrument for clustering (only) in Model 4 and instrument for both measures in Model 5. Finally, in Model 6 we subtract the clustering measure from the learning measure and include the resulting residual as well as clustering.[23] This is done to address the collinearity issue. In this case, we again instrument for both measures. Turning to the results, we again fail to reject the null hypothesis that local learning does not improve operations. However, we are able to reject the null hypothesis that clustering does not improve operations in Model 4 and at the 10% confidence level in Models 3, 5, and 6. In the instrumental variables regressions, the study variables (instrumented values) are even more collinear than in the OLS regressions (correlations exceed (0.8)). As a result, some of the coefficients in Models 4–6 are an order of magnitude larger and have significantly higher standard errors than in regressions where either variable is entered by itself. However, in all cases the clustering measure remains negative while the local learning measure remains insignificant (or, in one case positive and significant). Finally, we repeat these analyses using modified definitions of local experience based on total historical volume of business and beds, and we obtain similar results. In summary, these results are consistent with the idea that the benefits of clustering occur by facilitating monitoring and supervision of the unit as opposed to facilitating local learning within units of the cluster.

4.2. Robustness Checks

We also conduct a series of other robustness checks of our main results. These additional tests focus on three areas: (1) establishing the robustness of our findings to alternative definitions of clustering; (2) performing tests to rule out "gaming behavior" and alternative explanations for our findings; and (3) expanding our sample to include branded nursing homes to test whether our clustering results hold across an expanded sample of nursing homes.[24]

4.2.1. Alternative Definitions of Clustering. We reestimate our main specification using alternative measures of clustering to test the robustness of our results. Our theoretical discussion (see §2.2) suggests that clustering helps to reduce the costs of monitoring and supervision. However, different mechanisms of cost reduction may imply different clustering definitions. For example, using distance to measure clustering (as in Tables 4–6) implies that some combination of travel time and travel cost (e.g., fuel charges) determine the level of monitoring. On the other hand, if travel time is the sole or primary cost element of monitoring, then a pure measure of travel time between nursing homes may be the best clustering measure. Finally, it is also possible that clustering should be defined using different distances in urban versus rural areas. That is, consider the hypothesis that when chains set monitoring intensity, they decide that a rural nursing home cluster that is, say, 50 miles apart should receive the same intensity of monitoring as an urban cluster where the nursing homes are 15 miles within one another. This would imply that the definition of clustering should vary across urban and rural areas. Finally, note that the threshold distances (or travel times) used to define clustering may be varied as well.

We start by creating the alternative time-based clustering measure. We use the number of sibling units within 45 minutes travel time as an alternative clustering measure in this case.[25] This measure effectively reduces the effects of population density on clustering. For example, it may take 45 minutes to travel no more than 15 miles in a dense metropolitan area (MSA), whereas possibly less time to travel more than 30 miles in rural areas. In the time-based clustering measure, the rural area appears to be relatively more clustered compared to our distance-based clustering measure. We note that this measure is created using Google Map by applying a computationally intensive algorithm.[26]

[23] The R-square of Models 5 and 6 is missing. "Missing R-square, negative R-square, and negative model sum of squares are all the same issue.... Whether a negative R-square should be reported or simply suppressed is a matter of taste. At any rate, the R-square really has no statistical meaning in the context of 2SLS/IV" (Sribney et al. 2005).

[24] We do not present the results that include branded nursing homes. One apparent difference from the unbranded sample results is that clustering also appears to reduce JAH citations in the branded sample (but, again, by a much smaller magnitude than the effect of clustering on MPH citations). Chains may be more attentive to reducing major violations among their branded units because major violations may have a large spillover effect on the reputation of branded units. Results are available from the authors upon request.

[25] We also tried 30- and 60-minute travel times. The results are robust to these alternatives as well.

[26] There are 5,982 chain nursing homes in our sample, of which 4,002 nursing homes are unbranded. To create the measure, we are theoretically required to search Google Map 17,892,162 times ($= 5{,}982 \cdot 5{,}982/2$). Because of daily limits in the use of Google Map (about 15,000 times a day, maximum), we first reduce the scope of our task by calculating the physical distance between any two nursing homes and restricting our travel time searches to those

Next, to define the relative clustering measure, we simply define clustering in three different ways, for MSA, urban, and rural areas, using clustering distances of 15, 25, and 50 miles, respectively. The resulting clustering measures are then entered as a single variable in the main specification. We note that the instrumental variable is also adjusted to the corresponding radius in this case.

Table 7 provides a summary of our robustness tests using alternative definitions of clustering. Table 7(a) summarizes our results using the travel time and relative distance definitions of clustering. Table 7(b) shows how the results change when we vary the threshold distances for defining clustering. In each of these regressions, we use the base specification from Table 4 apart from the alternative definition of clustering.

Turning to the results in Table 7(a), we find that the clustering effects are quite robust to these alternative definitions. In the case of the travel-time measure, both total and MPH citations are reduced by time-based clustering whereas JAH citations are unaffected. Moreover, the clustering-effect magnitudes are roughly twice those obtained using geographic distance to measure clustering (note that the scale of the clustering measure is the same in both cases, based on "counts" of clustered nursing homes). One interpretation is that a pure measure of travel cost has a larger impact on monitoring intensity than other dimensions of monitoring cost tied to distance.[27] Regressions employing the relative clustering measure also provide robust findings, with magnitudes similar to our base results.

Table 7(b) summarizes a series of other robustness checks where we vary the geographic radius used for counting siblings (25 or 50 miles) combined with defining clustering as a binary measure (any siblings within the radius) versus using a continuous measure of clustering (number of siblings within the radius). Along the vertical axis, we show how results for these definitions of clustering vary as we also vary the specification (whether or not learning is included as a control) and the instrument employed.[28] The results in Table 7(b) indicate that our main results are robust to each of these permutations.

nursing home pairs whose physical distance is within the range of 5 to 50 miles. This reduces the required searches to just over 200,000. We then process the search using a Python program, which is available from the authors upon request.

[27] This does not, however, imply that travel cost alone determines monitoring intensity. It is conceivable that some weighted average of travel time and distance should be used, to the extent that travel costs other than time also influence the extent of monitoring.

[28] We use total residents who use nursing homes with a radius as the alternative IV.

4.2.2. Ruling Out "Gaming" Behavior. We also take steps to rule out the possibilities that (a) clustered nursing homes can "game" the inspection process by having a member of a cluster "tip off" other members of the cluster that an inspection team is in the area and that inspections are imminent; and/or (b) inspectors are somehow less diligent when inspecting several nursing homes in a cluster, and spend less time inspecting each individual nursing home (that is, they may target a fixed amount of time to be spent on an entire cluster as opposed to each nursing home, resulting in a less diligent inspection of each nursing home in a cluster).

To show that our results are not driven by these alternative explanations, we first provide institutional detail on the inspection process that suggests that the process is random and uniform. Inspections are carried out by state agencies under guidelines put forth by the CMS. CMS guidelines specifically state that dates of inspection for each nursing home are to be determined individually and randomly. As an example of how this policy is implemented by the states, consider the case of Illinois.[29] In Illinois, a single nursing home is selected at the beginning of each week and assigned at random to 1 of 40 inspection teams, with the resulting inspection taking three to four days. Teams are assigned to individual nursing homes and not clusters, contrary to the notion that they may rush through a multiple nursing home assignment.

Consistent with this discussion, we are able to show that the inspection dates for clustered units are selected as randomly as for those of other nursing homes. For these purposes, we make simple comparisons of the standard deviation of the inspection week for clustered and nonclustered units in a local area. The results show no difference between clustered and nonclustered units. We are able to conclude from this result that clustered nursing homes possess no relative advantage in inferring the likely date of inspection.

Finally, we directly test the "tip off" hypothesis, which states that nursing homes that are inspected after the first inspection in a cluster will have fewer deficiencies because they are tipped off by the first nursing home inspected in the cluster. We rerun our base specification and now add an interaction with our clustering variable to indicate that the nursing home was not inspected first. If the tipping off hypothesis is correct, then the interaction term should be negative, indicating that the order of inspection makes a difference in deficiency citations. The results,

[29] The details of the Illinois policies are based on extended interviews conducted by one of the authors.

Table 7 Robustness Checks Using Alternative Clustering Measures

(a) Alternative clustering definitions

	Total citations		Minor/potential harm		Jeopardy/actual harm	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Siblings	-0.085^{*}	-0.802^{***}	-0.092^{**}	-0.773^{***}	0.003	-0.022
(*45 min. travel*)	(0.036)	(0.150)	(0.034)	(0.142)	(0.006)	(0.023)
Siblings	-0.089^{*}	-0.383^{***}	-0.100^{*}	-0.376^{***}	0.001	-0.002
(*different radius*)	(0.044)	(0.101)	(0.041)	(0.096)	(0.007)	(0.017)
State fixed effects	Y	Y	Y	Y	Y	Y
Chain fixed effects	Y	Y	Y	Y	Y	Y
Market characteristics	Y	Y	Y	Y	Y	Y
Patient characteristics	Y	Y	Y	Y	Y	Y
NH characteristics	Y	Y	Y	Y	Y	Y
R-squared	0.350	0.270	0.360	0.290	0.200	0.200
N	4,002	4,002	4,002	4,002	4,002	4,002

(b) Robustness check using alternative distances for the clustering radii

	Radii	Within 25 miles		Within 50 miles	
Dependent variables:	*Models*	*Siblings*	*Clustering*	*Siblings*	*Clustering*
Total citations	2SLS	-0.432^{***}	-4.094^{***}	-0.298^{***}	-4.405^{***}
		(0.088)	(0.930)	(0.084)	(1.261)
	2SLS	-0.471^{***}	-4.148^{***}	-0.301^{***}	-4.473^{***}
	(Learning)	(0.107)	(0.947)	(0.086)	(1.295)
	2SLS	-0.412^{***}	-4.139^{***}	-0.291^{***}	-4.778^{***}
	(New IV)	(0.095)	(0.986)	(0.083)	(1.403)

Notes. Panel (a) shows the results of robustness checks of our main results using alternative clustering definitions. We employ alternative definitions based on (i) travel time between nursing homes (instead of distance), and (ii) using different distance measures to define clustering in urban versus rural areas. Our travel time measures were constructed using Google Map. Our different distance measure defines the clustering radius as 15, 25, and 50 miles for MSA, urban, and rural areas, respectively. Our principle finding is that our main results are robust to the use of these alternative clustering definitions. Compared to our main findings, the clustering effects using the travel time measure are roughly double in magnitude. Clustering effects using alternative distances for urban and rural areas are similar to those in Table 4. Panel (b) presents robustness checks using both 25- and 50-mile radii to define clustering (our main results use the 25-mile radius). We present three sets of results, using (i) our main specification (from Table 4), (ii) our specification including a learning measure control, and (iii) our main specification but now employing an alternative instrument for clustering. In addition, we define clustering as both a continuous (*Siblings*) and binary (*Clustering*) variable. In all cases, the estimated effects of the clustering measure are significant. Standard errors are in parentheses.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

however, support the null hypothesis that no such effect exists, because the estimated interaction terms are not statistically different from zero.[30]

4.3. Endogenous Clustering

As a final analysis, we conduct tests of endogenous clustering. We hypothesize that if clustering is intrinsically valuable, as our results indicate, then clustering should be pursued as an endogenous firm strategy. Support for this hypothesis adds validity to our operational results and helps to assure us that they are not a statistical artifact. If clustering were costless, it would logically be ubiquitous across markets. This does not appear to be the case. One impediment to clustering may lie in the fact that firms use specific business formats that are suited to particular market settings. A reasonable clustering hypothesis is that chains will regard nearby, preexisting units as a positive factor in deciding whether to bid upon or build a unit in a given location. However, market characteristics matter as well. For example, the degree of similarity of a market with the demographics of the chain's other markets should also be a factor in the entry decision.

We select a sample of 69 cases in which an unbranded nursing home unit changes ownership between 2005 and 2006 and is subsequently acquired

[30] These results are available from the authors upon request.

by 1 of the 12 largest for-profit chains.[31] Our dependent variable is an indicator of which chain makes the acquisition. We regress this measure on the extent of prior clustering, as well as a set of other controls. In selecting the set of other controls, we are most concerned that clustering may be correlated with omitted effects that measure the attractiveness of a given region to a chain (e.g., proximity of the region to corporate headquarters). Therefore, our list of controls includes a measure of proximity of the target to the nursing home chain's headquarters as well as interactions of the market's demographics with chain dummies (to control for the chain's preferences for certain types of markets). Consistent with our discussion of the role of market homogeneity on the chains' tendency to cluster, we also include three measures of how similar the target's market demographics are to the demographics of the other markets in which the chain has nursing homes. We use a conditional discrete-choice model to obtain our estimates. Turning to the results in Table 8, we find strong evidence that prior clustering increases the likelihood that a nursing home will acquire a given target conditional on our various controls. In Model 5, our most complete specification, an additional sibling unit increases the likelihood that a given chain will acquire a given target by about 2% on average.[32] Furthermore, our controls for distance to corporate headquarters as well as similarity of the target market to the chain's other markets are statistically significant in the expected direction. These findings are consistent with other findings in the literature, suggesting that chains pursue clustering as an endogenous strategy. They are also logically consistent with the results presented in §4.

Table 8 **Regressions of Market Entry on Presence of Sibling Units**

	(1)	(2)	(3)	(4)	(5)
Siblings (*number*)	0.287***	0.144	0.236*	0.450*	0.383*
	(0.070)	(0.084)	(0.113)	(0.180)	(0.184)
Distance to headquarters		−0.005*	−0.006**	−0.010***	−0.010***
		(0.002)	(0.002)	(0.003)	(0.003)
Preexisting unit		0.744*	0.877*	0.782	0.962
		(0.356)	(0.405)	(0.540)	(0.557)
Chain dummies	N	N	Y	Y	Y
Market characteristics $(Z) * \text{Chain}$	N	N	N	Y	Y
Similarity measures (X)	N	N	N	N	Y
LR χ^2	17.27	23.01	88.72	98.47	39.37
N	828	828	828	828	828

Notes. This table presents conditional discrete-choice regressions of market entry on the presence of sibling units in a given market. The dependent variable is an indicator of which for-profit chain acquired a nursing home in a given market between 2005 and 2006. The explanatory variables includes the number of sibling units in the market prior to the sale of the unit, plus a set of controls that includes (1) the distance from the new unit to the headquarters of each chain; (2) an indicator for the presence of at least one sibling prior to entry; (3) measures of market dissimilarity relative to the chain's other markets; (4) chain dummies; and (5) interactions of the chain dummy with a set of market characteristics including per capita income, market HHI, and percentage of black population. Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

5. Discussion

Previous research supports the hypothesis that horizontally integrated organizations, including chains and franchises, pursue clustering as an endogenous strategy (Kalnins and LaFontaine 2004, Baum et al. 2000).

To date, some researchers have argued that the effects of clustering on local experience and learning provide a strategic rationale for this conduct (Kalnins and Mayer 2004). An alternative explanation is that clustering may be used to improve operational performance through the mechanism of improved monitoring and supervision of managers. Support for this hypothesis would be significant, for it implies that clustering may be used to address one of the main weaknesses of the organizational model of horizontal integration, managerial agency costs.

Showing that clustering improves operational performance is arguably straightforward. However, demonstrating that the mechanism for such improvements is reduced managerial agency costs and enhanced supervision is more difficult because it is impossible to observe managerial effort directly. Testing hypotheses such as this, where direct measurement is impossible, must appeal to the institutional details of the relevant setting as well as the type of evidence that can be provided (Hubbard 2004). Our goal in this paper is to provide both an industry setting and a preponderance of evidence to indicate that monitoring and supervision is the most plausible explanation for our findings.

We build our "case" that clustering reduces agency costs and increases supervision with five independent arguments: (1) we focus on an industry (nursing homes) where managerial agency issues are likely to be acute and where contractual and ownership solutions are difficult; (2) we focus on (analyze) a measure, quality, that is directly implicated in managerial effort; (3) we provide anecdotal, institutional

[31] We limit our sample to the 12 largest chains that added new units between 2005 and 2006 because the conditional discrete-choice model does not perform well as the number of choices increases. We also try other subsamples using the top 8 and top 10 chains. The results are robust.

[32] We calculate the average marginal own-effect of one more sibling unit on the likelihood of acquiring a new unit. Therefore, we obtain 12 own-effects. The reported number is the average own-effect of the 12 chains.

evidence that at least one chain views clustering as a means to improve *operational* (i.e., not strategic) performance; (4) we provide statistical evidence that clustering improves quality and that improvements are especially pronounced in operational areas that are presumably harder to observe without close monitoring, as reflected in minor violations; and (5) we provide statistical evidence that the effect is not due to generally accepted measures of local experience and learning.

Finally, we provide evidence that helps us to rule out explanations for quality improvements based on competition, scale economies, or other explanations. Regarding competition, we argue that this explanation is contradicted by the robustness of our findings to the inclusion of various controls for competition. Furthermore, an explanation based on scale economies in quality production is inconsistent with our finding that improvements are concentrated in the area of less severe violations as well as the observation that scale economies are driven by the size of the market and not clustering per se. Our paper thus provides some of the first evidence that clustering improves operational performance, most plausibly by improving monitoring and supervision.

Future research in this area may address several questions that are suggested by our findings. From the perspective of organizational design, if clustering improves operational performances, then why would chains not adopt this strategy for all of their units? Similarly, if clustering confers a significant operational advantage and mitigates managerial agency costs, then would chain ownership be ubiquitous? Are the factors that impede chain clustering an effective barrier to chain entry into local markets? Conversely, can clustering of chain units impede the entry of independent owners? Future work on these and related questions may improve our understanding of the horizontal integration of industries.

Acknowledgments
The authors are grateful to James Brickley, Carolina Caetano, David Dranove, Ryan McDevitt, Jerry Zimmerman, three anonymous referees, session participants at the 2011 9th International Industrial Organization Conference and the 2011 Academy of Management Annual meetings, and seminar participants at the University of Rochester for useful comments and suggestions.

Appendix. Regressions of Name Changes and Market Exit on Deficiency Citations

In this appendix, we provide regression evidence relating both major and minor deficiency citations to two key dimensions of nursing home performance: (1) the likelihood of the nursing home changing its name (a proxy for diminished reputation); and (2) the likelihood of the nursing home exiting the market. The specification for these regressions is drawn from McDevitt (2011), who considered the economics of reputation and name changes.[33] Although these two dependent variables do not comprise all dimensions of nursing home performance, the tests meet our objective of demonstrating that both major and minor deficiency citations are important determinants of nursing home outcomes, especially those tied to reputation.

The multinomial probit specification used in McDevitt (2011) is

$$Outcome_{i,t} = \alpha_0 + \alpha_1 \cdot Q_{i,t-1} + \alpha_2 \cdot X_{i,t-1} + \varepsilon_{i,t} \qquad (4)$$

Here, i indexes each firm, t indexes year, and *Outcome* is the categorical variable.

The explanatory variable Q refers to "quality performance" and is lagged one year (and two years in some regressions). It is assumed that in each period consumers form expectations and make purchase decisions using the level of quality provided by a firm in the previous period as a signal of the quality that they can expect in the next period.

One methodological concern is that nursing homes anticipating a near-term name change or exit may endogenously reduce quality because they have little incentive to maintain their reputation. If this is the case, our estimates may be biased and reflect reverse causality. We address this concern in two ways. First, Tadelis (1999, 2002) noted that firms changing their names have an incentive to maintain their reputation because such names are frequently sold. Similarly, if the nursing home's name links it to the larger chain, the firm will wish to maintain its reputation in the face of name change or exit, because its reputation is linked to the reputation of the larger chain. Moreover, to the extent that these arguments do not apply (i.e., the nursing does not sell its name or worry about the larger chain's reputation), our use of a *lagged* quality performance measure should suffice, because it is unlikely that a firm would deliberately diminish its quality a full year prior to changing its name or exiting a market. To address any remaining concerns about reverse causality, we also present some results for a two-year lag of quality performance. (In the latter case we expect a weaker finding, but in the trade-off, we gain greater confidence that our results are not affected by reverse causality.)

We construct a sample of all for-profit nursing homes from 2001 to 2006 to estimate Equation (4). Table A.1 provides the results of these regressions where we lag deficiency citations counts both one and two years. The set of controls (X vector in Equation (4)) includes both year and state dummies, as well as a set of firm and patient characteristics that include nursing home age, total nursing home beds, percentage of revenues from Medicaid, staffing measures, and patient health status. Standard errors are clustered at the nursing home level.

Turning to the results, we note that both JAH and MPH citations (individually) influence the likelihoods of both

[33] McDevitt (2011) used a multinomial logit model to estimate the impact of consumer complaints on firm reputational behavior. In his model, the dependent variable is a categorical variable indicating three types of firm behavior (keep name, change name, or exit), and the explanatory variable set includes lagged values of consumer complaints as well as firm and market characteristics.

Table A.1 Reputational Consequence of Deficiency Citations

	Model 1		Model 2		Model 3	
Variables	Name change (1)	Exit (2)	Name change (3)	Exit (4)	Name change (5)	Exit (6)
Total citations	0.030*** (0.003)	0.026*** (0.005)				
Minor/potential harm			0.025*** (0.004)	0.020*** (0.006)	0.029*** (0.005)	0.016* (0.007)
Jeopardy/actual harm			0.061*** (0.016)	0.067*** (0.023)	0.002 (0.023)	0.076** (0.025)
Firm characteristics	Y	Y	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y	Y	Y
State dummies	Y	Y	Y	Y	Y	Y
Observations	51,706	51,706	51,706	51,706	40,556	40,556

Notes. This sample includes profit-maximizing nursing homes from 2001 to 2006. Following McDevitt's (2011) name and reputation analysis, we utilize the same estimation strategy using our nursing home panel data. Models 1 and 2 use one-year lagged citation measures, whereas Model 3 uses two-year lagged citation measures. This table shows that more total deficiency citations lead to name change or exit. Moreover, more minor/potential harm citations increase the probabilities of both name change and exit, whereas more jeopardy/actual harm citations cause exit. This table suggests that there are reputational consequences. Huber–White standard errors clustered by nurisng homes are in parentheses.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

name changes and exit. For example, in the regressions where citations are lagged for one year, a nursing home with a record of minor deficiency citations one standard deviation above the mean is 10.5% more likely to change its name. We note also that in Model 3, using the two-year lagged citation measures, that the effects of MPH citations remain statistically significant and of a similar magnitude. Both types of citations continue to show an effect on the likelihood of exit.

References

Battese GE, Coelli TJ (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Econom.* 20(2):325–332.

Baum JAC (1999) The rise of chain nursing homes in Ontario, 1971–1996. *Soc. Forces* 78(2):543–583.

Baum JAC, Ingram P (1998) Survival-enhancing learning in the Manhattan hotel industry, 1898–1980. *Management Sci.* 44(7):996–1016.

Baum JAC, Li SX, Usher JM (2000) Making the next move: How experiential and vicarious learning shape the locations of chains' acquisitions. *Admin. Sci. Quart.* 45(4):766–801.

Blair RD, Lafontaine F (1999) Will *Khan* foster or hinder franchising? An economic analysis of maximum resale price maintenance. *J. Public Policy Marketing* 18(1):25–36.

Brickley JA, Linck JS, Smith CW (2003) Boundaries of the firm: Evidence from the banking industry. *J. Financial Econom.* 70(3):351–383.

Brickley JA, Lu SF, Wedig GJ (2011) Horizontal ownership and brand affiliation in service industries: Evidence from nursing homes. Working paper, Univeristy of Rochester, Rochester, NY.

Centers for Medicare and Medicaid Services (CMS) (2010) Design for nursing home compare five-star quality rating system: Technical users guide. CMS, Baltimore.

Cohen WM, Levinthal DA (1990) Absorptive-capacity—A new perspective on learning and innovation. *Admin. Sci. Quart.* 35(1):128–152.

Darr ED, Argote L, Epple D (1995) The acquisition, transfer, and depreciation of knowledge in service organizations: Productivity in franchises. *Management Sci.* 41(11):1750–1762.

Feder J, Scanlon W (1980) Regulating the bed supply in nursing-homes. *Milbank Memorial Fund Quart.-Health Soc.* 58(1):54–88.

Giacalone JA, Duetsch LL (2001) *The U.S. Nursing Home Industry* (M.E. Sharpe, Armonk, NY).

Glaeser EL, Shleifer A (2001) Not-for-profit entrepreneurs. *J. Public Econom.* 81(1):99–115.

Grabowski DC, Angelelli JJ, Mor V (2004) Medicaid payment and risk-adjusted nursing home quality measures. *Health Affairs* 23(5):243–252.

Harrington C, Swan JH, Nyman JA, Carrillo H (1997) The effect of certificate of need and moratoria policy on change in nursing home beds in the United States. *Medical Care* 35(6):574–588.

Holmstrom B, Milgrom P (1991) Multitask principal agent analyses—Incentive contracts, asset ownership, and job design. *J. Law Econom. Organ.* 7(Special issue):24–52.

Hubbard TN (2004) Affiliation, integration, and information: Ownership incentives and industry structure. *J. Indust. Econom.* 52(2):201–227.

Hubbard TN (2008) Viewpoint: Empirical research on firms' boundaries. *Canadian J. Econom.* 41(2):341–359.

Ingram P, Baum JAC (1997) Chain affiliation and the failure of Manhattan hotel, 1898–1980. *Admin. Sci. Quart.* 42(1):68–102.

Jin GZ, Leslie P (2009) Reputational incentives for restaurant hygiene. *Amer. Econom. J.-Microeconomics* 1(1):237–267.

Kalnins A (2004) An empirical analysis of territorial encroachment within franchised and company-owned branded chains. *Marketing Sci.* 23(4):476–489.

Kalnins A, Lafontaine F (2004) Multi-unit ownership in franchising: Evidence from the fast-food industry in Texas. *RAND J. Econom.* 35(4):747–761.

Kalnins A, Mayer KJ (2004) Franchising, ownership, and experience: A study of pizza restaurant survival. *Management Sci.* 50(12):1716–1728.

Kumbhakar SC, Tsionas EG (2006) Estimation of stochastic frontier production functions with input-oriented technical efficiency. *J. Econometrics* 133(1):71–96.

Lafontaine F, Slade M (2007) Vertical integration and firm boundaries: The evidence. *J. Econom. Literature* 45(3):629–685.

Lapré MA, Tsikriktsis N (2006) Organizational learning curves for customer dissatisfaction: Heterogeneity across airlines. *Management Sci.* 52(3):352–366.

Lu SF (2012) Information disclosure, multitasking and product quality: Evidence from nursing homes. *J. Econom. Management Strategy* 21(3):673–705.

McDevitt R (2011) Name and reputation: An empirical analysis. *Amer. Econom. J.: Microeconomics* 3(3):193–209.

Nyman JA (1985) Prospective and cost-plus medicaid reimbursement, excess medicaid demand, and the quality of nursing-home care. *J. Health Econom.* 4(3):237–259.

O'Neill C, Harrington C, Kitchener M, Saliba D (2003) Quality of care in nursing homes—An analysis of relationships among profit, quality, and ownership. *Medical Care* 41(12):1318–1330.

Rosenfeld J (2009) What's in a name? Are large nursing home chains intentionally attempting to deceive the public when it comes to corporate ownership? *Nursing Homes Abuse Blog* (August 19), http://www.nursinghomesabuseblog.com/national-nursing-home-issues/manorcare/whats-in-a-name-are-large-nursing-home-chains-intentionally-attempting-to-deceive-the-public-when-it-comes-to-corporate-ownership/.

Shepard A (1993) Contractual form, retail price, and asset characteristics in gasoline retailing. *RAND J. Econom.* 24(1):58–77.

Sribney W, Wiggins V, Drucker D (2005) Negative and missing *R*-squared for 2SLS/IV. *Stata J. Stata Corp.* Accessed November 2010, http://www.stata.com/support/faqs/statistics/two-stage-least-squares/.

Tadelis S (1999) What's in a name? Reputation as a tradable asset. *Amer. Econom. Rev.* 89(3):548–563.

Tadelis S (2002) The market for reputations as an incentive mechanism. *J. Political Economy* 110(4):854–882.

Wang HJ, Schmidt P (2002) One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *J. Productivity Anal.* 18(2):129–144.

Wong SS (2004) Distal and local group learning: Performance tradeoffs and tensions. *Organ. Sci.* 15(6):645–656.