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Competition, Information, and Quality: Evidence from Nursing Homes

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Abstract

Economic theory suggests that competition and information disclosure can both be important for quality improvement, yet evidence on how they may interact to affect quality is sparse. This paper estimates the impact of nursing homes competition on their quality and how this impact varies as consumers have better access to quality information. To identify the effect of competition on quality, I exploit exogenous variation in nursing homes' geographical proximity to their potential consumers, using an Instrumental Variable (IV) derived from the estimation of demand as a function of travel distances. The change in information is captured by the recent launch of the Five-Star Quality Rating System, which increased information transparency by adding easy-to-understand star ratings to the multi-dimensional clinical quality measures. I find that while the effect of competition on nursing home quality is generally rather limited, this effect becomes significantly stronger with increased information transparency. The results suggest that regulations regarding quality rating and market structure are policy complements and should be considered jointly to best improve quality.

JEL Codes: I10, L10, L22

Key Words: Quality of care, competition, information, nursing homes, discrete choice model

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1 Introduction

To promote the quality of products and services, policy makers often rely on regulations to enhance competition. Basic microeconomic theory suggests that competition unambiguously leads to better quality when price is administratively set above marginal cost (Gaynor and Town 2011). When price is fixed, firms compete on quality to attract consumers. Additional competitors increase the elasticity of market shares with respect to quality, thus providing more incentives for investment in quality. Despite the clear prediction from economic theory, the empirical evidence is mixed in the literature of fixed-price health care markets. For example, by examining nursing home residents or Medicare patients with heart diseases, some studies establish a positive relationship between competition and quality (Castle et al., 2007; Kessler and McClellan, 2000; Cooper et al., 2011), whereas others draw the opposite conclusion (Grabowski, 2004; Forder and Allan,2014; Gowrisankaran and Town, 2003; Propper et al., 2010).

The effectiveness of competition in promoting quality can be limited by the lack of understandable information on provider quality. Transparent information is essential for raising consumers' sensitivity toward quality and providing firms with incentives to select higher quality in competition. Though promising, this interaction between competition and information to improve quality has not been systematically tested. In this paper, I estimate the effect of competition on nursing home quality, and explore how the effect varies when consumers have better access to quality information.

The first challenge in studying how competition and information may interact to affect quality is to establish the causality between competition and quality. A major concern is the endogeneity arising from the simultaneity between competition and quality: when the market structure drives the choice of quality, the latter shapes the distribution of demand and thus affects the former as well. To address the endogeneity problem, I use an Instrumental Variable (IV) derived from the estimation of a partial demand function which is dependent on travel distances between nursing homes and their potential consumers. Travel distance is valid because it has an impact on individuals' choice of the provider, but depends neither on unobserved characteristics of patients nor on unobserved determinants of facility quality

(Kessler and McClellan, 2000; Mehta, 2007). The idea of this IV strategy is to identify the effect of market competitiveness using exogenous variation in nursing homes' geographical proximity to their potential consumers. In addition to the IV approach, I employ panel estimation with facility fixed effects to control for time-invariant unobservable factors that may affect both the nursing home performance and the market structure.

To study the role of information transparency, I exploit a recent change in quality reporting in nursing homes. Before 2009, the quality of a nursing home was known to the public as 18 distinctive clinical measures that were difficult to interpret. In 2009, Centers for Medicare and Medicaid Services (CMS) launched the Five-Star Quality Rating System to provide easy-to-understand quality information. The new rating system added overall star ratings to the existing multi-dimensional clinical measures, which reduced consumers' learning costs and encouraged the use of CMS's quality reporting.[1] The consistent availability of the clinical measures allows me to estimate the effects of competition on quality both before and after 2009. The pre-post difference in the effects is the primary interest and captures the interaction effect of competition and information on quality.

Analysis of this paper uses panel data from 2006-2010, spanning the introduction of the Five-Star Rating System. The data are pulled together from three main sources: Nursing Home Compare (NHC); the Health Care Information System (HCIS); and the American Community Survey (ACS). The NHC provides nursing home quality (both the clinical measures and the star ratings) and a rich set of nursing home characteristics at the facility level. The HCIS data include information on annual patient flows of nursing homes. From the ACS, I derivedAflowstiof characteristict of potentiof consumere.

disappear once I replace the outcome variables with non-simplified quality measures [2], suggesting an important role played by the information simplification. Second, demand shifts toward the high-quality nursing homes after the release of star ratings, suggesting that consumers are actually aware of the new rating system and are taking advantage of it. I subject the analysis to extensive robustness tests over different covariates and on various subsamples. All results support the hypothesis that the improvement in information delivery is driving a more positive effect of competition on quality.

This paper relates to three strands of literature. The first has investigated the impacts of quality reporting on patient choices and quality itself (Mukamel et al., 2008; Werner et al., 2009, 2012; Grabowski and Town, 2011; Culter et al., 2004; Dafny and Dranove, 2008; Bundorf et al., 2009). Results in this paper echo the recent finding that consumers respond to quality report cards. One unique contribution of this article is a more rigorous design of identification, which allows me to provide direct and solid evidence that public reporting improves quality through inducing informed choices and rewarding high-quality services. The findings also emphasizes that the understandability of the information is important in quality reporting. This confirms the conjecture in the literature that confusing information leads to ineffective public reporting of quality (Marshall et al., 2000), and helps to explain why only minimal consumer response is found to the public reporting of the multi-dimensional nursing home quality in 2002 (Werner et al., 2012; Grabowski and Town, 2011).

Second, this paper adds to the literature on the relationship between market concentration and quality in the health care markets. Previous research has studied how the relationship is influenced by other factors such as managed care penetration (Kessler and McClellan, 2000) and patient valuation (Kessler and Geppert, 2005). This current study brings attention to information transparency. Observing how the positive competition-quality relationship can be recovered by transparent information is desirable, for it provides a possible way to reconcile the inconsistent findings in the literature. Moreover, it suggest that for markets where competition may lead to lower quality, a better solution is to provide understand-

[2] Only a subset of the clinical quality measures are selected to form star ratings. The unselected ones are defined as non-simplified quality measures.

able information rather than to limit competition itself. Knowing this would prevent the states from implementing Certificate of Need (CON) laws that aimed to enhance quality by restricting the entry of facilities. Not surprisingly, CON policies turned out to be unsuccessful and have been removed in some states.[3]

Lastly, this study pertains to demand estimation in the nursing home industry. To my best knowledge, Mehta (2006) is the only work that investigate how nursing home demand is affected by consumer preference over location. While she restricts her study sample to private pay patients in Wisconsin in 2002, I offer an extension by targeting the majority of nursing home residents (the Medicaid/Medicare beneficiaries) nationwide for a longer period of time. Furthermore, the scope of my data allows me to test whether consumer preference differs based on regulatory environment, i.e., the difference across states in Medicaid regulations or the change over time in information regimes.

The paper proceeds as follows. Section 2 provides the background information on the nursing home industry and the reform in quality reporting. Section 3 describes the data and the construction of key variables. Section 4 proposes the estimation methodology. Section 5 presents the results. Section 6 shows the extensions and the robustness checks. Section 7 discusses the limitations and the future work.

2 Backgrounds

2.1 The Nursing Home Industry

Nursing homes remain the largest and the most expensive component of long-term care in the United States, despite the rapid growth in other long-term care services (Kaye, Harrington, and LaPlante, 2010). In the U.S., more than 16,000 nursing homes are providing services to over 1.5 million residents, with an annual expenditure of over $100 billion (2004 National Nursing Home Survey). The services include skilled nursing and rehabilitation that have a wide impact on populations especially the adults aged 65 years and older. The health, function, and quality life of senior citizens are important and are listed as one of

[3] Improving Health Care: A Dose of Competition, A Report by the Federal Trade Commission and the Department of Justice, July 2004

the major objectives of Healthy People 2020 (Department of Health and Human Services, 2010). Not only because older adults are among the fastest growing age group as "baby boomers" approach 70s, but also because they are at high risk for developing chronic illnesses and related disabilities that are the leading causes of death (Kramarow E, Lubitz J, Lentzner H, et al., 2005).

The industry is characterized by strict price regulations. Most nursing homes receive the majority of their revenues from Medicaid and Medicare enrollees, whose coverage and payment are administrated at the federal or state levels. Medicaid pays for the nursing services of more than 68 percent of all nursing home residents, and Medicare pays for additional 12 percent (Lin 2014). Medicaid beneficiaries are not charged for basic services in nursing homes. Additionally, most states employ the prospective payment system (PPS) so that the reimbursement rate is predetermined and is not based on current services provided.

Given the above background, the nursing home industry is ideal for estimating the interaction effect of competition and information simplification on quality. First, the strict price regulation offers the prerequisite for providers to compete in quality. Second, as the primary users of nursing homes, the elderly are potentially less able to understand complicated information about quality. Therefore, the fact that the quality reporting on nursing homes was initially confusing and later improved makes it meaningful and possible to study the effect of information simplification.

Nursing homes provide a high level of medical care, compared to other senior housing facilities such as retirement communities [4]. They are equipped with registered nurses and nursing aides, who have received training to deal with various medical needs of nursing home residents. Usually 24 hours a day, the staff are supposed to interact with the residents to provide basic care services and to assist people with special needs such as Alzheimer patients. The provision of intensive medical care makes the quality of nursing home care particularly important for the U.S. long-term care.

Persistent poor quality of the industry, despite substantial investment and regulations from the government, has drawn increasing attention from policy makers and researchers. About 1/3 of U.S. nursing facilities are penalized for violations of Federal regulations in

[4]For example, http://www.rlcommunities.com/).

inspections. I focus on stars of clinical outcomes, primarily because they are not subject to gaming or manipulation as other quality dimensions. Staffing, for instance, can be easily manipulated within a short periods of time before inspection and data collection (Williams et al., 2010). The stars are formed by collapsing a subset of the initial quality measures. The subset is selected based on "their validity and reliability, the extent to which the measure is under the facility's control, statistical performance, and importance" [6].

The new rating system has lowers consumers' learning costs and improved their searching experience. First, it enables consumers to easily target a few high performance nursing

the measure of competition[7]

I obtain a list of all urbanized areas and urban clusters from a national 2010 urban area file

used in the previous literature to assess quality of care. The first is the number of deficiency citations, which is viewed as a proxy of nursing home quality (Grabowski, 2004). Deficiencies indicate failure to meet certain federal requirements during an on-site inspection that examine the health and safety environment of the facilities. Allowing deficiencies to enter the analysis would control for the facilities' management efficiency on nursing home quality and consumer choice.

Other supply-side controls comprise the number of beds, the nonprofit indicator, the chain affiliation, and the rate of Medicaid patients. The total number of certified beds controls for the facility size and rules out the effect of economies of scale. The nonprofit indicator captures the difference in the value of quality caused by ownership status. The chain membership deals with any impact of care standardization on quality. Last, the rate of Medicaid patients is included to ensure that quality is compared among health providers with similar structure of payer-mix. This addresses the concern that quality might be disproportionately low in nursing homes that have high ratio of Medicaid beneficiaries, because Medicaid reimburses at lower rates than Medicare or private insurances.

The demand-side controls are mainly census tract characteristics including average household income, population over age 65, and average travel time to work. These demographic variables are used in the first stage demand estimation. Income controls for the potential influence of wealth on nursing home preferences. Commute time implies consumers' tolerance for long-distance travel. The inclusion of these d-side contao4irof car1ouse-

competition and calls for an appropriate IV to address the problem.

4 Estimation Methodology

4.1 Constructing IV in the First Stage

In establishing the causality between competition and quality, I construct an IV in steps to address the endogeneity problem. First, a random utility logit model is used to estimate the demand for nursing home care. The main purpose is to structurally predict market shares from exogenous travel distance and other characteristics of nursing homes and census tracts. The predicted market shares are then transformed to a negative log of HHI for each county, which serves as an IV for the degree of competition.

Figure 5 illustrates the idea of estimating nursing home demand from travel distance. The solid black circle indicates a county or a market, in which nursing homes (the black dots) compete for potential consumers from all census tracts (the dashed red circles). For each census tract, I assume there is a representative consumer locating in the center (the black square). The probability that a representative consumer chooses a certain nursing home depends on the distance between them, nursing home characteristics, and the consumer's taste. I then aggregate the individual choices from each census tract to infer the demand for nursing homes. On the other hand, the actual demand is calculated by dividing the number of nursing home residents by the potential consumers in the market. The coefficients of demand are derived by minimizing the differences between the inferred market shares and the actual market shares.

I follow Berry (1994) and Berry, Levinsohn and Pakes (1995) to estimate demand, primarily because their estimation methodology only requires aggregate data. Assume the utility of a representative consumer i choosing nursing home j at time t is:

$$u_{ijt} = \gamma \quad dist_{ij} + X_{it} \bullet A + Y_{j(t)} \bullet B + \quad _{ijt} \tag{1}$$

where $dist_{ij}$ denotes the distance, the vector X_{it} includes the time-varying census tract controls, and $Y_{j(t)}$ contains the characteristics of providers. This specification allows consumer

heterogeneity to enter the model through demographics variables as well as the random shocks. The benefit is to eliminate the typical problem of unrealistic substitution patterns arising from the multinomial logit model. To facilitate comparisons across predictors, I create z-scores for all of the independent variables.

Based on the utility function, I calculate the probability that representative consumer i chooses nursing home j at time t, s_{ijt}.

$$s_{ijt} = \frac{\exp(\gamma \quad dist_{ij} + X_{it} \bullet A + Y_{jt} \bullet B)}{}$$

(Equation (4)) and actual market shares (the proportion of the admitted patients to the po-

markets pre-2009, and coefficient β_{4k} captures the difference in the growth rate before and after the reform for areas with low competition. Coefficient β_{5k} absorbs the abrupt change in quality assessment in 2011.

5 Estimation Results

Table 3 column (1) summarizes the estimates of demand in the first stage. Most coefficients have anticipated signs. First, longer travel distance reduces the likelihood of patronage. Second, serving a high proportion of Medicaid residents hurts the attractiveness of a nursing home while being a for-profit facility raises it. These observations are consistent with previous findings that quality of nursing homes is negatively associated with the proportion of Medicaid residents but positively with the for-profit ownership (Harrington and Swan, 2004; Lau et al., 2004). Other nursing home characteristics– the number of deficiencies, the number of certified bed, and chain affiliation– are insignificant in determining consumers' taste. It is surprising, since previous studies found that chain affiliation and smaller bed size often predict higher nursing home quality (Zimmerman et al., 2002; Harrington and Swan, 2003). One possible explanation would be lack of rationality among consumers.

The F-statistics on the instrument is 26.35 (not reported in the table), confirming that the IV is a good predictor of the competition measure. In addition, a Durbin–Wu–Hausman test (Hausman 1978) is performed for the competition measure in each quality estimation (Equation (6)) to determine if exogeneity could be rejected. The null hypothesis is rejected in all cases. Specifically, the p-values of Durbin-Wu-Hausman tests for competition are 0.000, 0.018, 0.000, 0.007, 0.039, and 0.043 of the six quality regressions, respectively. Rejection of the null hypothesis suggests that the IV estimates should be preferred to the OLS estimates.

Table 3 column (2)-(4) and column (5)-(7) exhibit estimation results for two quality indicators–PRE and UTI [9]– using three models (OLS, IV, and IV with nursing home fixed effects). The model specification with both IV and fixed effects (column (4) and (7)) pro-

[9] Pressure ulcers and UTI are considered the most important chronic-care quality indicators by CMS (Morriset et al., 2003; Konetzka et al., 2008).

the quality measure or the data limitation. The failure to find meaningful effects on PAI is attributed to a potential weakness regarding this quality measure. It is clinically ambiguous whether higher value is consistently associated with better or worse quality. PHY has low

In the second test, I explore how demand varies with quality star ratings before and after 2009. An immediate challenge is that star ratings did not exist before 2009. To overcome this data limitation, I first predict pre-2009 star ratings from an array of clinical quality measures using a non-parametric estimation called the kth-nearest-neighbor (KNN) discriminant analysis. The main idea of KNN is to find the k closest examples of a particular object in the multidimensional feature space, list the categories to which each of the k examples belongs, and assign the object to the category that encompass most of the k neighbor examples. In the current nursing home case, the multidimensional feature space consist of 9 quality measures and the categories are the five-star ratings. It is known that the five star ratings are generated from which quality measures, but the specific formula remains unclear to researchers. Therefore it is more appropriate and convenient to use KNN than a simple linear regression, for KNN can recover the mapping without a specific functional form.

Overall, the KNN model does a good job of predicting in sample. Figure 6 compares the distribution of actual star ratings and that of the predicted star ratings after 2009 as an evaluation of the non-parametric fitting. Panel A illustrates the kernel density of both the actual and the predicted star ratings. The KNN model successfully classifies most nursing homes to their actual quality bins, with a slight over-assignment to the middle level and under-assignment to the two extreme levels. Figure 6 panel B provides the confusion matrix. Numbers on the diagonal reveal the percentage of correct predictions at each star levels. For example, nursing homes that are predicted as a 5-star facility turn out to be an actual 5-star facility with probability 61%. The stars are predicted correctly at least 45% of the time and are neither systematically overestimated nor underestimated. Together, the two panels in Figure 6 reveal the validity and the accuracy of the methodology to recover quality star ratings.

Table 6 demonstrates the estimation results of consumers' responses to star ratings. Three measures of demand (log of the patient count, log of the market share, and log of the total number of patients discharged) are regressed against star ratings, the post-reform dummy, and their interactions. The coefficients on star2 to star5 reveal consumer's attitude to better nursing homes pre-2009. The coefficients on the interaction terms capture the pre-post differences in consumers' preference for higher-quality nursing homes relative to 1-star

they are less able to increase sale by raising quality even if the market is sensitive to quality. To test the above "ceiling effect" hypothesis, I run the main specification separately for nursing homes with occupancy rates above and below the sample mean. Table 8 exhibits the estimation results, with the top panel reporting highly occupied nursing homes and the bottom panel the less occupied. Consistent with the hypothesis, the effects of competition and information are larger for nursing homes with less concern about reaching capacity limit.

7 Discussions

In the health care industry all over the world, policy makers rely heavily on competition or public quality reporting to promote quality and efficiency (Cooper et al. 2011). This paper assesses the impact of competition on care quality, and more interestingly how quality is affected by the interaction between competition and information transparency. Using the nursing home industry as a case study, I find that competition has a limited effect on clinical quality measures, but the effect becomes significantly stronger as consumers have better access to quality information. One policy implication is that public reporting and competition regulation should be considered jointly to beset promote quality. The result that the information simplification further improves quality suggests the limitation of quality rating in certain markets and prompts necessary supplementary initiatives to mitigate market imperfections.

Several observations are noteworthy. First, results in this paper suggest a multi-task-agency effect. In other words, measuring and rewarding quality in some areas may harm quality in other areas. In this study, I find evidence that health providers are substituting resources away from non-simplified quality measures (e.g. vaccinations) to simplified ones (e.g. pressure ulcers). The reallocation of resources parallels the previous finding that unreported components of quality were adversely affected by quality reporting (Lu 2012). However, the effect should not raise too much concern in this paper. First, non-simplified quality measures are still collected and reported. Their continuous availability to the public puts a cap on the transfer of resources. What is more, the switching of resources itself may

be beneficial. After all, the simplified quality measures are selected for a reason: more reliable, more manageable, and more important. For example, treating pressure ulcers costs the U.S. $11 billion annually (Institute for Healthcare Improvement, 2007), suggesting a $100 million savings from better management of pressure ulcers found in this paper. While on the other hand, influenza vaccination has been proved not cost effective for healthy people between ages 65 and 74 years (Allsup et al., 2004). On balance, the savings would outweigh the costs due to the switching of focus.

Second, the positive yet small effect of information simplification on quality calls for a further optimization in public reporting of provider quality. One important direction is to incorporate consumer satisfaction information into the rating system. In the U.S., quality information of long-term care is gathered only through provider self-assessments and inspections, although perspective of users are often used as a supplement in European counties including Sweden and Finland (Rodrigues et al. 2014). It might be beneficial to collect and post quality measures that are from the residents' point of view. Adding consumer evaluation helps to align the health providers' objective with consumer welfare. It also has the potential to suppress the inflation in current self-reported quality measures, which has already aroused suspicion from the public. Consumer-reported outcomes and reviews, through either public reporting or online feedback mechanism, can potentially complement provider-reported quality indicators regarding clinical care.

This study has some limitations, despite the high number of robustness/specification checks performed. First, due to the data limitation, I treat census tracts as representative consumers to study choice of nursing homes. The underlying assumption is that all individuals over the age of 65 within a census tract are identical. Lacking data on the distribution of socioeconomic characteristics within a census tract, it is difficult to evaluate the credibility of this assumption. However, the fact that the study sample is restricted to rural areas helps to alleviate the concern, because population in rural communities are found more homogeneous than their urban counterpart in social, racial and psychological traits [13].

Another limitation pertains to the test of over-identification. The test is often performed

to assess whether the IV affects the outcome variable only via its impact on the instrumented variables. In this study, over-identification cannot be tested because the equation estimated is exactly identified, i.e., the number of instruments and the number of the instrumented variables are the same. However, the main results are unlikely to be undermined, for there is no evidence suggesting that the competition predicted from travel distance (the IV) would affect the quality (the outcome) through channels other than driving the actual competition (the instrumented variable). Future work is required to find more instruments to complete the test.

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4) Physical Restraint (PHY)

This quality measure reflects the percent of residents in the nursing home who were not physically restrained daily during the 7-day assessment period. There are various types of physical restraints. For example, chairs with lap trays, lap belts, and special types of vests. Physical restraints are supposed to only be used as a part of a resident's medical condition, not for punishing a resident or for making a staff's life easier.

5) Indwelling Catheter (CAT)

This quality measure reports the percent of residents who did not have a catheter inserted and left in their bladder for a period of time during the 14-day assessment period. Inserted catheters may cause urinary tract infections, physical injury, or skin problems. Thus a catheter should only be used when medically necessary, not for the staff's convenience.

6) Urinary Tract Infection (UTI)

This quality measures reflects the percent of residents who did not have an infection in their urinary tract anytime during the 30 days before their most recent assessment. An untreated UTI can spread to other parts such as the bladder and kidney and cause more infections. The most effective way to prevent UTI is to make sure the residents are having good hygiene. It requires nursing home staff to keep the area clean, empty residents' bladder regularly, and provide sufficient drinking fluid.

A2: Number of Nursing Homes by State and Year

Figure A1: Number of Nursing Homes by State and Year

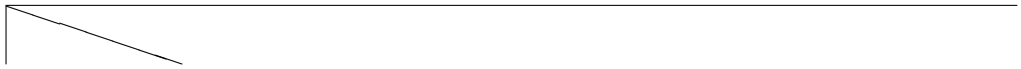
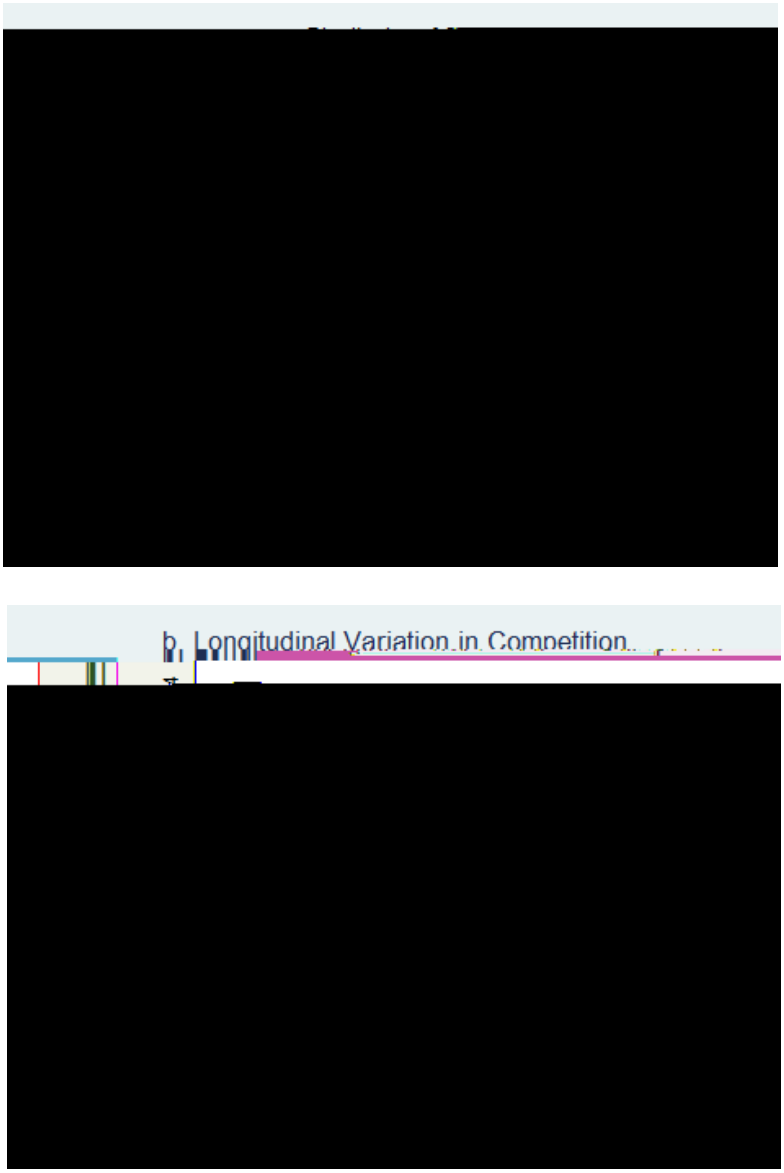


Figure 3: Variation in Nursing Home Competition



Source: the Health Care Information System (HCIS) Data File.
NLHHI = NLHHI_rual = average negative log of HHI in rural markets; NLHHI_all = average negative log of HHI in all markets; NH_rural = average number of nursing homes in rural markets; NH_all = average number of nursing homes in all markets.

Figure 4: Distribution of Market Shares by Star Quality Ratings: Pre- and Post-2009

Figure 5

Figure 6

Figure 7: Histogram of Nursing Home Characteristics – Rural Versus Non-rural Markets

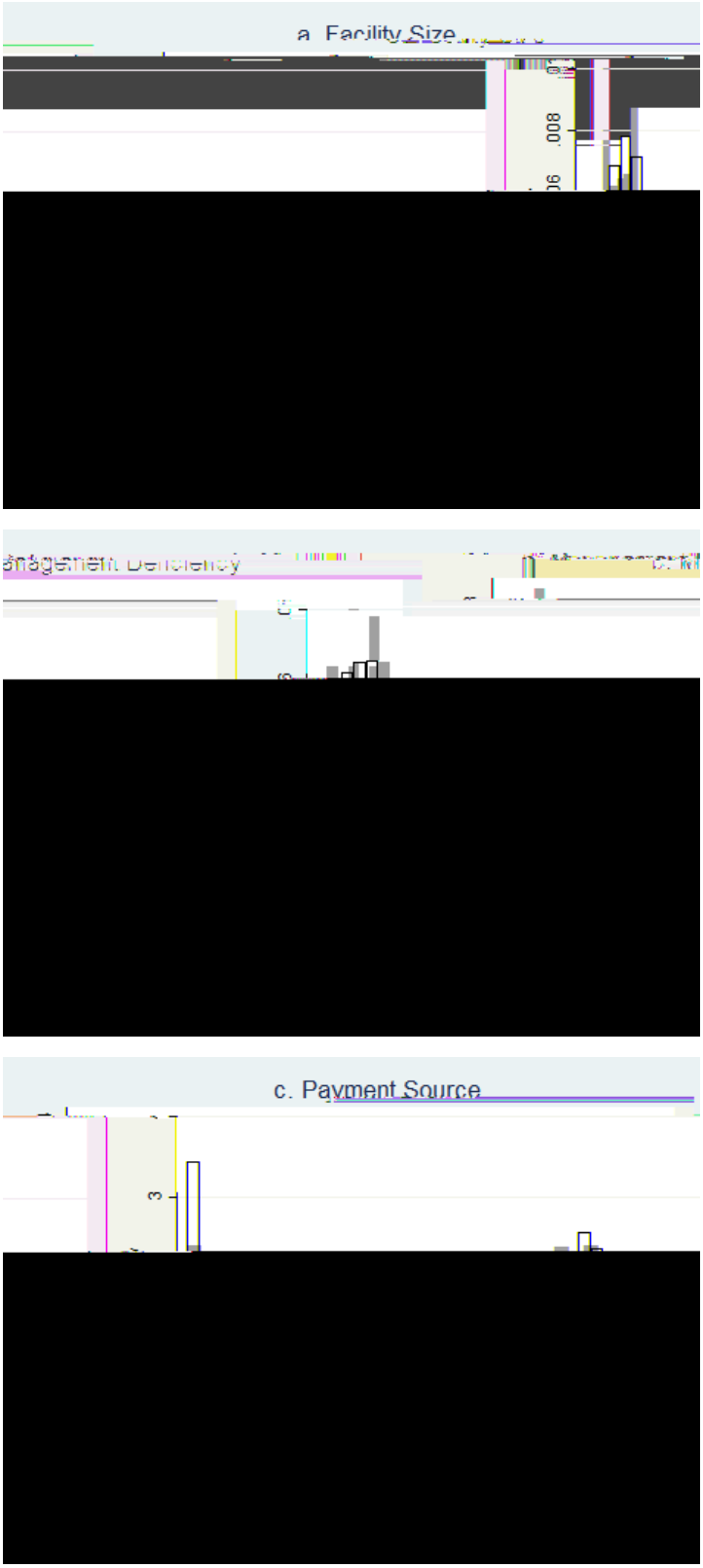


Table 1: Cross-correlations of the Quality Measures

Quality	PRE	UTI	CAT	ADL	PAI	PHY
PRE	1.00					
UTI	0.20	1.00				
CAT	0.20	0.22	1.00			
ADL	0.01	0.08	-0.01	1.00		
PAI	-0.09	0.03	0.02	0.08	1.00	
PHY	0.09	0.05	-0.01	0.04	-0.01	1.00

Table 2: Summary Statistics of Key Variables and Other Controls

Variable	Mean	Std. Dev.	N
Key Variables			
HHI	0.02	0.12	2336
NLHHI	7.03	1.57	2336
PRE	89.21	4.56	1736
UTI	90.81	3.87	2120
CAT	94.60	3.23	2110
ADL	83.89	5.40	2045
PAI	94.62	3.61	2097
PHY	96.19	4.41	2126
Distance	19.20	74.53	58431
Nursing Home Characteristics			
Deficiencies	9.70	5.21	2336
Beds	97.03	57.86	2336
Medicaid	0.59	0.22	2336
Nonprofit	0.26	0.41	2336
Chain	0.51	0.43	2336
Nurse hours	4.58	5.62	2336
Charges	314.29	69.28	2307
Government-owned	0.07	0.25	2336
Census Tract Characteristics			
Time2work	25.56	6.15	6967
Income	73409.51	35897.44	6935
Population65	607.77	399.35	6967
Market Controls			
Pop65_county	127361.61	305511.58	812
Income_county	58353.57	13996.43	812
Poverty	15.59	6.39	812
Medicaid payment	5291.99	1180.92	859

Table 3: Effects of Market Structure on Nursing Home Quality: PRE and UTI

Table 4: Effects of Market Structure on Nursing Home Quality: All Measures

A.Basic Specification						
	(1)	(2)	(3)	(4)	(5)	(6)
	PRE	UTI	CAT	ADL	PAI	PHY
NLHHI	1.10	0.54	-0.05	0.73	-0.11	0.20
	(0.73)	(0.30)	(0.20)	(0.46)	(0.32)	(0.27)
NLHHI*after	0.06	0.07	0.03	-0.00	0.01	-0.03
	(0.03)	(0.02)	(0.01)	(0.04)	(0.03)	(0.02)
N	8373	10985	10892	10473	10731	10998
B.Market Controls						
	(1)	(2)	(3)	(4)	(5)	(6)
	PRE	UTI	CAT	ADL	PAI	PHY
NLHHI	1.01	0.33	0.01	0.82	-0.09	0.20
	(0.74)	(0.30)	(0.19)	(0.50)	(0.34)	(0.29)
NLHHI after	0.05	0.05	0.02	0.03	0.00	-0.03
	(0.03)	(0.02)	(0.01)	(0.04)	(0.03)	(0.02)
N	8164	10580	10501	10128	10353	10590
C.Market Controls and State-year FE						
NLHHI	0.82	0.07	0.02	0.17	0.20	0.19
	(0.63)	(0.26)	(0.17)	(0.44)	(0.30)	(0.25)
NLHHI after	0.30	-0.01	0.04	-0.21	-0.18	-0.05
	(0.17)	(0.12)	(0.08)	(0.20)	(0.14)	(0.12)
N	8164	10580	10501	10128	10353	10590

Standard errors in parentheses

$^{\square}$ $p < 0.10$, $^{\square\square}$ $p < 0.05$, $^{\square\square\square}$ $p < 0.01$

All regressions use IV and nursing home fixed effects. The basic specification is the same as in Table 3.

Market controls consist of county population, median household income, percentage below poverty line, and state Medicaid reimbursement rate. Complete estimation results are available upon requests.

Table 5:

Table 6: Consumer Response to Quality Star Ratings: Pre- and Post-2009

	(1)	(2)	(3)
	log patient count	log market share	log patient discharged

Table 8: Effect of Market Structure on Nursing Home Quality – High-occupancy Versus Low-occupancy

High Occupancy						
	(1)	(2)	(3)	(4)	(5)	(6)
	PRE	UTI	CAT	ADL	PAI	PHY
NLHHI	0.32	0.65	0.27	0.64	-0.86	0.60
	(0.65)	(0.44)	(0.28)	(0.70)	(0.53)	(0.44)
NLHHI after	0.01	0.05	0.02	-0.01	0.01	-0.01
	(0.04)	(0.03)	(0.02)	(0.05)	(0.04)	(0.03)
N	4923	5829	5802	5687	5751	5834
Low Occupancy						
NLHHI	3.64	0.79	-0.30	0.44	0.49	-0.18
	(2.82)	(0.47)	(0.32)	(0.74)	(0.49)	(0.41)
NLHHI after	0.19	0.08	0.05	0.01	0.01	-0.07
	(0.10)	(0.04)	(0.02)	(0.06)	(0.04)	(0.03)
N	3450	5156	5090	4786	4980	5164

Standard errors in parentheses

$^{\square}$ $p < 0.10$, $^{\square\square}$ $p < 0.05$, $^{\square\square\square}$ $p < 0.01$

Each regression is estimated using IV with facility fixed effects, time trend, and other controls as in Table 3.