Quantifying the Impacts of Limited Supply:

The Case of Nursing Homes[!]

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Abstract:

In the U.S. nursing home industry, supply is restricted by the certificate-of-need laws and Medicaid reimbursement rates are usually set lower than the private-pay prices. As a result, the nursing home industry has been thought to face two main problems: limited access/rationing and low quality. In this paper, we develop an empirical demand model and an estimation strategy that can account for excess demand, and the unobserved component of nursing home quality. Our methodology allows us to quantify the extent of rationing and the potential welfare gain by removing capacity constraints. We apply our framework to study the Wisconsin nursing home market in 1999. The estimated model suggests that nearly 18% of elderly who qualified for Medicaid were rationed out, and around 27% of Medicaid nursing home patients could not enter their first-choice nursing homes. However, the net social welfare gain of removing capacity constraints maybe small, mainly because the welfare gain to Medicaid patients could be largely offset by the increase in Medicaid expenditures.

Keywords: rationing, excess demand, capacity constraints, demand estimation, nursing homes, unobserved quality

JEL Classification: C15, C35, D45, I11, I18

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1. Introduction

With the substantial growth of the elderly population, it has become increasingly more important to understand the workings of the nursing home market. This market is widely thought to face some serious problems. One such problem is access to care: some potential patients who qualify for Medicaid have difficulty finding a nursing home nearby with available beds (e.g., Gruenberg and Willemain 1982; Norton 1992; Ettner 1993). Another problem is quality of care: in many cases the quality of care has been perceived to be low.[1] These problems are likely related to government regulations. The industry is heavily regulated in two important ways. First, many state governments restrict supply so that a certificate of need (CON) is necessary for new nursing homes to enter the market, or even for the existing ones to increase the number of beds. Second, state governments regulate the price that they pay for a large percentage of nursing home care through Medicaid programs.

These regulations have led to a large body of work that studied their impacts on the nursing home market.[2] One group of studies focused on the effect of Medicaid reimbursement, such as how the level of Medicaid reimbursement rates affects nursing home quality of care and whether the difference of reimbursement method—prospective or cost-based payment—affects nursing home outcomes (e.g., Nyman 1985, 1998a, 1994; Gertler 1989, 1992; GAO 1990; Cohen and Spector 1996; Grabowski 2001). Another group of studies investigated the effects of the CON laws. Because the CON laws can potentially create excess demand in the market and allow existing nursing homes to establish and preserve market power, some of the studies aim at examining the empirical relationship between excess demand/market concentration and market outcomes (e.g., Lee et al. 1983; Nyman 1988a, 1988b, 1994; Gertler 1989, 1992; Cohen and Spector 1996; Spector et al. 1998).

These studies argued that excess demand plays an important role in the industry. More specifically, they argued that excess demand does not only cause access problems, but also change the effects of other policies. For example, they argue that raising Medicaid reimbursement rates would likely improve the

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[1] See the report to Congress made by Health Care Financing Administration in July 2000.
[2] Norton (2000) provides an excellent survey on this topic.

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quality of care in counties where excess demand is not an issue, but the same policy would likely reduce the quality of care in counties where excess demand exists. Excess demand in the nursing home market was first explicitly modeled in Scanlon (1980). Following Scanlon's theory, studies that utilized data in the 1970s and early 1980s found empirical evidence of excess demand (e.g., Nyman 1985, 1988a, 1988b, 1989, 1994; Gertler 1989, 1992). The studies that utilized more recent data, however, suggest that excess demand may become less prevalent (e.g., Cohen and Spector 1996; Grabowski 2001; Grabowski and Angelelli 2004).

We have learned much from the previous works; however, there remain some important questions that they cannot answer, due to their reduced-form modeling approach. In general, they suffer three limitations. First, many previous studies have used market tightness as a proxy for excess demand. However, a tight market does not always imply that the market has excess demand; rather, it could be consistent with nursing homes being nearly fully occupied at equilibrium. More importantly, their approach cannot quantify the extent of rationing because it does not measure the number of patients who prefer to live in a particular nursing home but cannot enter. Second, when measuring quality provided by a nursing home, most of the previous studies used either input-based or outcome-based method, which did not take into account factors that are unobserved to the econometrician (e.g., reputation). Unobserved factors are potentially important. They may adjust between the actual quality the nursing home provides and the average quality that can be produced with the staffing intensity the nursing home uses. Unobserved factors can also lead to endogeneity problem of price if one ignores their presence in estimation. Third, as it is well-known, the reduced-form approach cannot measure patient welfare, and hence cannot evaluate the welfare impact of counterfactual experiments.

In light of these shortcomings in the previous literature, the goal of this paper is to develop a structural demand model and a new estimation strategy that enables us to account for excess demand and the unobserved component of nursing home quality. After obtaining the structural parameters of the model, our modeling framework allows us to quantify the extent of rationing and the potential welfare gain if we remove nursing homes' capacity constraints. Motivated by several institutional features of the nursing

home industry, our model assumes that (i) some nursing homes may face excess demand from Medicaid patients; (ii) nursing homes are free to admit private-pay patients first, who typically pay more than the Medicaid reimbursement rate; (iii) the potential number of private-pay patients is not large enough for them to face the capacity constraints problem; and (iv) both private-pay and Medicaid patients rank nursing home quality similarly. The key idea of our identification strategy is that we need to observe the demand for one group of patients who do not face the rationing problem (in this case, the private-pay patients), and hence we can use the revealed preference argument to recover the quality of nursing homes based on their observed demand. By further assuming that both Medicaid and private-pay patients share similar preferences for nursing home quality (i.e., the nursing homes' qualities recovered by private-pay patients' demand also apply to Medicaid patients), we can then use our model to infer the true demand for each nursing home, and measure the extent of rationing. Our modeling assumptions, together with our data set, allow us to extend the estimation approach developed by Berry (1994), Berry et al. (1995), and Petrin (2002) to obtain the structural parameters of the model, when we only have access to market share data. Taking this approach allows us to measure quality of care from patient demand—this quality measure can potentially lessen the problem of input-based or outcome-based quality measure, and allow us to address the potential endogeneity problem of private-pay price.[3]

To estimate our model, we use the 1999 Wisconsin Annual Survey of Nursing Homes, which contains each nursing home's characteristics and some statistics of its patients. We also supplement it with the Special Tabulation on Aging from the 2000 Census and the 1999 Wisconsin Health Survey. We study the nursing home market in 1999 because excess demand for nursing homes was believed to be common back then, but the limitations of data and previous empirical methods were not able to quantify the extent of rationing. Therefore, this environment should serve as a useful place to illustrate our proposed empirical framework for investigating excess demand.

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[3] The empirical framework proposed in this paper can potentially be extended to other markets where firms' capacity constraints would often bind, and are very costly to expand, e.g., hospitals, hotels, airlines, etc. It should be noted that markets such as hotel and airlines often admit full-fare customers at the expense of overbooking their rooms or seats. In those settings, full-fare customers, similar to our private-pay patients, would hardly face capacity constraints. Moreover, to a large extent, consumers tend to agree on how to rank the quality of rooms/seats and services provided by the staffs, which hardly discriminate consumers based on the fare class they paid.

Our estimation results suggest that excess demand is still prevalent in Wisconsin in late 90s. Approximately half of nursing homes used for this study are estimated to face binding capacity constraints; about 27 percent of the Medicaid nursing home patients could not enter their first-choice nursing homes; and about 18 percent of potential patients qualified for Medicaid are rationed out for nursing home care (i.e., they would have chosen to enter nursing homes if the capacity constraints do not exist). However, we also find evidence that the net social welfare gain of removing the capacity constraints may be small, because it is expensive for the state government to cover the additional nursing home care. By using the estimated qualities of care by nursing homes, we re-examine some of the issues that the previous literature studied. Consistent with the previous findings, we find evidence that nursing homes that receive higher Medicaid reimbursement rates generally do not provide higher quality of care, but higher private-pay prices are usually associated with higher quality of care. We also find that nursing homes tend to provide lower quality of care in counties with tight supply.

The rest of the paper is organized as follows. Section 2 summarizes some important regulations in Wisconsin. Section 3 presents the demand model. Section 4 details the data and section 5 presents the estimation procedure. Parameter estimates and their implications are provided in section 6. Finally, section 7 concludes.

2. Background—Regulations in Wisconsin

This section summarizes the regulations in Wisconsin, which affect key institutional features of the nursing home industry.

Medicaid Reimbursement

In Wisconsin, a prospective payment method is used for setting Medicaid reimbursement, based on a facility-specific rate. A facility-specific rate for the 1999 fiscal year is based on the facility's actual allowable expense in 1998 and other factors such as inflation, its case-mix and its own occupancy rate. The actual allowable expenses are divided into seven categories: (1) direct care, (2) support services, (3) administration, (4) fuel and utilities, (5) property tax, (6) property costs, and (7) over-the-counter drugs. The

expense of each category is calculated separately. When the facility's actual allowable expense in 1998 exceeds the maximum set by the state, which is adjusted regionally, the facility specific rate is calculated based on the state-set maximum. Wisconsin does not allow these rates to be adjusted during a fiscal year.

Certificate-of-Need

Wisconsin has used a CON law for nursing homes since 1980. The purpose of this policy in Wisconsin is clearly written in the state statutes, "*it exists* in order to enable the state to budget accurately for medical assistance and to allocate fiscal resources most appropriately,..." (Wisconsin Statutes Chapter 150). Wisconsin has a statewide bed limit, which was 51,795 in 1999. Although there are no countywide bed limits, the state limits the number of beds in each county by allowing only nursing homes within a county to redistribute beds as a result of a nursing home closure within that county. The review criteria and standards for applications include a need for additional beds in the health planning area, sufficient funds availability, and satisfactory quality care to be provided. As shown in Table 1, occupancy rates vary from county to county. Although the occupancy rate in some counties is close to 100 percent, there were only two new nursing home opened in two counties (Price and Washington) in 1999.

TABLE 1[4]: County Level Occupancy Rate in 1999

County Level Occupancy Rate	Number of Counties
95-100%	8
90-95%	18
85-90%	22
80-85%	16
<80%	7
Total	71

Quality of Care

Many states, including Wisconsin, has minimum staffing requirements for number of nurse hours per bed (Black et al. 2003). Moreover, due to shortage of nurses (Bureau of Health Profession 2002; Nevidjon and Erickson 2001), it is difficult for nursing homes to improve their quality of care by hiring more nurses (Lin

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[4] The calculation is based on the 390 nursing homes used in this study. Section 4 explains the sample selection criteria.

2012). Another interesting feature of this market is that nursing homes are required to offer the same quality of care to all patients regardless of the source of a patient's payment or amount of payment. The state regulation prohibits discriminatory treatment based on the payment sources (Wisconsin Administration Code Chapter HFS 132).

3. Model

3.1 Basic Assumptions

Following Berry (1994), Berry et al. (1995), our demand system is obtained by aggregating a discrete choice model of patients. To account for institutional features of this industry, we make assumptions specific to the nursing home market.

First, there are two types of patients: one is private-pay and the other is Medicaid. Since private-pay patients have to pay the price of the nursing home by themselves, their preferences are affected by prices. On the other hand, Medicaid patients do not pay for themselves; the government pays for them. Therefore, nursing home prices have no effect on their preferences.

Second, quality of care is assumed to be common for both types of patients in a given nursing home. This is a regulatory requirement in many states, including Wisconsin, as mentioned above. Results of a recent study have also validated this assumption by using individual level data from seven states (Grabowski et al. 2008). Quality depends on a variety of factors, such as staff intensity, services provided, and technology used by a nursing home. To simplify the model, we assume that each patient evaluates nursing home quality by constructing a quality index from these factors and that the function they use to construct the quality index is common to all patients. This implies that all patients have the same quality index for a given nursing home.

Lastly, we assume each nursing home has a capacity constraint, that is, the bed supply in each nursing home is fixed in the model. This is motivated by the CON law, which restricts entry of new nursing homes, and the number of beds in existing nursing homes. This assumption affects both demand and supply behaviors. Since freely determined private-pay prices are usually higher than Medicaid reimbursement rates

which are set by the government in advance, and the quality of care is required to be common to all patients in any given nursing home, a profit-maximizing nursing home should provide beds to private-pay patients first, then fills Medicaid patients as residuals.[5] A Medicaid patient who seeks care from a nursing home may face a binding capacity constraint, and consequently, would not be able to enter it. In that situation, we assume Medicaid patients will choose one of the remaining nursing homes with available beds to maximize their utility. In section 3.4, we develop a computational algorithm to obtain aggregate Medicaid demand under this environment.

3.2 Utility specification

The patient's utility of choosing a nursing home is defined over nursing home price, quality, and distance between the patient's residence and the nursing home.[6] We allow the coefficients of our multinomial logit model to vary across patient's characteristics in age, sex, distance to nursing home, and payment type. These patient characteristics can be important determinants in the choice of a nursing home. For instance, male patients may be more price-sensitive than female patients, because it is more likely that their partners can take care of them (wives are usually younger than husbands; female also live longer than male on average). As another example, private-pay patients could be more quality-sensitive than Medicaid patients because private-pay patients are wealthier, and consequently, they may also have better resource to find out the quality of nursing homes. Although complete patient-level data is unavailable to us, our data set contains statistics on each nursing home's patients that are categorized by patient characteristics, such as age, sex, payment type, and which county patients resided prior to entering the nursing home. These data allow us to construct moments to identify how patient's preferences varies with age, sex, payment types, as well as distance between his/her residence and a nursing home.[7]

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[5] The same assumption was made in Nyman (1985, 1988a, 1994) who also analyzed data from Wisconsin. Wisconsin does _not_ have a regulation that requires nursing homes to offer beds on a first-come, first-served basis.
[6] In our model, we refer "patient" to any consumers who consider nursing home care, even if he/she ends up choosing the outside option.
[7] Gaynor and Vogt (2003) show that distance is an important determinant of the demand for hospital. Distance is likely to be important for nursing home choice too, as it plays an important role for family members who need to visit their parents.

Private-pay patient i's utility of care from nursing home j is defined as:

$$u_{ij}^p = \gamma_i + \alpha_i p_j + Q_j + \lambda D_{ij} + \varepsilon_{ij}, \tag{1}$$

and Medicaid patient i's utility of care from nursing home j is defined as:

$$u_{ij}^m = \gamma_i + \kappa Q_j + \lambda D_{ij} + \varepsilon_{ij}, \tag{2}$$

with

$$\alpha_i = \bar{\alpha} + \sum_r \alpha_r z_{ir}, \text{ and } \gamma_i = \bar{\gamma} + \sum_r \gamma_r z_{ir}, \tag{3}$$

where Q_j, P_j, and D_{ij} are quality, price paid by private-pay patients, and distance to the nursing home from patient i's residence, respectively.[8] Quality is defined later in this section. We normalize private-pay patients' coefficient for Q_j to be 1, but allow Medicaid patients to have a different coefficient for Q_j, as captured by κ. In our specification, measure of distance takes the form of a dummy variable that equals to 1 if nursing home j is located in the same county as patient i, and zero otherwise.[9] z_{ir} is patient i's observable characteristic r, such as age, sex, and payment type. The variable ε_{ij} captures the unobservable matching value between patients and nursing homes, which is assumed to follow *i.i.d.* type I extreme value distribution.

The demand system is completed by defining an "outside option" for each patient, which is "staying at home". This includes having relatives to take care of him/her, or using private home care. Utility from choosing this option is

$$u_{i0} = \xi_0 + \varepsilon_{i0} \tag{4}$$

where ξ_0 is the mean utility from not going to any nursing home. For identification reasons, ξ_0 is normalized to be zero.

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[8] Prices vary in a nursing home according to the patients' severity. To simplify the model, however, we assume a nursing home provides identical services to patients regardless of patients' severity.

[9] We have tried other more flexible specifications for distance, and find that the results remains qualitatively unchanged. According to the data, about 80 percent of patients in a nursing home previously lived in the same county where the nursing home is located. Therefore, it appears that our distance dummy is able to capture the first-order impact of distance.

We assume in specification (1) and (2) that the whole state of Wisconsin is an integrated market for nursing home services, and patients consider all nursing homes within the states as their potential choice alternatives. This assumption is justified by the fact that 95% of the patients in Wisconsin nursing homes come from the same state. We do not model counties as independent markets because, on average, 18% of the patients of a given nursing home come from other counties (but in the same state), suggesting that substitution between nursing homes across county border cannot be totally ignored. However, individuals do prefer a nursing home within the same county as his residence (since 77% of the patients choose to do so in the data), and this feature will be captured by the parameter of disutility to distance (λ) in the model.

3.3. Quality

Quality is measured by nursing home observable characteristics as well as an unobservable characteristic.[10] Nursing home observable characteristics include input variables, such as nurse intensity and other staff intensity. As discussed earlier, unlike unskilled labor, nursing homes may not be able to fully control nurse inputs because (i) many states (including Wisconsin) impose minimum staffing requirements (Black et al. 2003), and (ii) it takes time to train someone to become nurses, and their shortage has been a problem since the 90s (Bureau of Health Profession 2002; Nevidjon and Erickson 2001). Other observable characteristics are ownership type, facility size, specific services provided by the nursing home, and nursing home location. These characteristics are even harder for nursing homes to change after they have entered the market.

Incorporating an unobservable characteristic along with these observable characteristics could lessen the problems of the quality measures used in the previous literature. Two types of quality measures have been commonly used. One is input-based measure that refers to the inputs used in the provision of care. The other is outcome-based measure that infers quality from patient health outcomes, such as mortality, functional change, presence of bedsore, and so on. Input-based measures cannot distinguish if more resource intensity translates to high quality of care, or if it is due to an inefficient use of resource. Outcome-based measures should be adjusted to reflect the patient's risk factor properly, and this requires more

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[10] The term "unobservable characteristic" refers to the characteristic that is unobserved to econometricians, but observed to patients. The term "observable characteristics" refers to characteristics that are observed by both patients and econometricians.

detailed patient-level information (e.g., Gowrisankaran and Town 1999; Geweke, Gowrisankaran and Town 2003). The unobservable characteristic can also capture a nursing home's reputation resulting from the average health/satisfaction of the patients.[11]

Quality is assumed to be evaluated by all patients as follows.

$$Q_j = X_j \beta + \xi_j,\tag{5}$$

where X_j, is a vector of nursing home j's observable characteristics excluding price and distance, and ξ_j is an unobservable characteristic. Based on our discussion above, we further assume that X_j is mean independent of ξ_j.[12]

3.4. Demand

As mentioned earlier, nursing homes have a financial incentive to provide beds to private-pay patients first and then to fill the remaining beds with Medicaid patients. In the model, we assume that private-pay patients enter a nursing home first, and then Medicaid patients can choose a nursing home which has beds available. More specifically, we assume that private-pay patients do not face capacity constraints. This is justified by the fact that the demand for private-pay patients alone is far from enough to fill up any nursing home.[13] In this demand framework, aggregate private-pay demand can be easily obtained. First, private-pay patient i's probability of choosing nursing home j is given by:

$$\text{Prob}_{ij}^{p} = \frac{\exp(\gamma_i + \alpha_i p_j + Q_j + \lambda D_{ij})}{1 + \sum_{k \in J} \exp(\gamma_i + \alpha_i p_k + Q_k + \lambda D_{ik})},\tag{6}$$

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[11] The unobservable characteristic can also be viewed as the deviation from the actual nursing home quality and the average quality produced by the staff intensities used and services provided by the nursing home.
[12] Although our discussion cannot completely rule out that nurse inputs could be correlated with the unobservable characteristic, they imply that nursing homes do not have complete freedom to choose the amount of staff inputs. We therefore feel that relative to p_j, the endogeneity problem of nurse inputs should be of second order importance in the short run, which is the focus of our analysis here. We therefore decide not to address this issue, and leave it for future research. But we will address the potential endogeneity problem of p_j.
[13] At most private-pay patients occupy 66% of beds of a nursing home, 90 percent of the nursing homes have less than 38% of their beds occupied by private-pay patients, and on average 21% of beds are occupied by private-pay patients. As a comparison, the 90 percentile of the occupancy rate for Medicaid patients is 68%, and the average is 54%.

where J denotes the set of nursing homes in the market. It follows that the aggregate private-pay demand for nursing home j can be expressed as,

$$n_j^p = M^p \int_i \text{Prob}_{ij}^p dF_i^p , \tag{7}$$

where F_i^p is the CDF distribution and M^p is the market size of private-pay patients.

Medicaid demand is not as simple as the private-pay demand, because Medicaid patients could face rationing. That is, a Medicaid patient may not be able to enter the nursing home that give him/her the highest utility. If that is the case, he/she must look for another nursing home in which beds are still available. Following Leslie (2004), we assume that potential Medicaid patients are randomly ordered to choose a nursing home among those still have beds available. The first Medicaid patient chosen at random will enter the nursing home that gives her the highest utility from all nursing homes. After the first Medicaid patient has entered the nursing home or has chosen an outside alternative, the second Medicaid patient chosen randomly will enter a nursing home that gives her the highest utility from all nursing homes with available beds, and so on and so forth. This means that if a Medicaid patient took a nursing home's last bed, no subsequent Medicaid patients will be able to enter that nursing home even if it would give them the highest utility. This process continues until either all potential Medicaid patients make their choices, or there is no nursing home left with empty beds.

The logit closed form of choice probability and the assumption of randomly ordered Medicaid patients, make Medicaid demand computation easier. The Medicaid population can be partitioned into R groups, $\{ M_1^m, M_2^m, \ldots, M_R^m \}$. Within each group, the distribution of patients is identical to the entire Medicaid population. The groups are divided such that after each group of Medicaid patients make their decisions, exactly one additional nursing home will just reach its capacity constraints, subject to $M_r^m < M^m - \sum_{l=1}^{r-1} M_l^m$. Specifically, M_1^m is the maximum measure of the population who can enter any nursing home. M_2^m is the maximum measure of the population who can enter any nursing homes other than

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the one with its last bed taken by the first group, M_1^m. M_r^m is the maximum measure of the population who can enter any nursing homes other than the r-1 nursing homes which are already fully occupied by the previous r-1 groups.[14] Therefore, the aggregate Medicaid demand is calculated as:

$$n_j^m = \sum_r M_r^m \int_i \text{Prob}_{ij,r}^m dF_i^m, \tag{8}$$

where $\text{Prob}_{ij,r}^m$ is the probability that patient i who is in group r enters nursing home j, and F_i^m is the distribution of Medicaid patients. Let J_r be the set of nursing homes whose beds are available when people in group r make a decision. If nursing home j has some beds available when patient i belonging to group r chooses, i.e., $j \in J_r$, the probability can be written as:

$$\text{Prob}_{ij,r}^m = \frac{\exp(\gamma_i + \kappa Q_j + \lambda D_{ij})}{1 + \sum_{k \in J_r} \exp(\gamma_i + \kappa Q_k + \lambda D_{ik})}, \tag{9}$$

If nursing home j has no beds left, i.e., $j \notin J_r$, the probability of choosing it is zero.

$$\text{Prob}_{ij,r}^m = 0 \tag{10}$$

4. Data

Three major data sources are used for this study—the 1999 Wisconsin Annual Survey of Nursing Homes, the 1999 Wisconsin Health Survey, and the 2000 Census of Population and Housing: Special Tabulation on Aging. It is believed that many nursing homes faced excess demand (and hence provided low quality of care) in late 90s. But as we mentioned earlier, the limitations of data and previous empirical methods were not able to quantify the extent of rationing. Therefore, the nursing home environment in 1999 should be suitable for illustrating our proposed empirical framework.[15]

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[14] The only exception is M_R^m. This last group of population may not be large enough to fill up any nursing homes left.

[15] The use of this data from Special Tabulation on Aging is very important for us to calibrate the potential number of patients

The state of Wisconsin requires nursing homes to complete this Annual Survey as part of the annual requirements for Medicaid re-certification. Therefore, the Annual Survey contains information from all 465 Wisconsin licensed nursing homes. Since the paper focuses on the demand by the elderly population, forty-eight nursing homes for the developmentally disabled and those with mental disease are excluded (note that most of the patients in these nursing homes are fairly young). Thirteen nursing homes which specialize in Medicare patients are also excluded. Moreover, we also drop one nursing home for veterans, one for young patients, and one with missing value in private-pay price. Finally, we exclude eleven nursing homes with zero number of private-pay patients because our estimation algorithm requires us to observe non-zero market share of private-pay patients for each nursing home. In the end, there are 390 nursing homes in our final sample. We use information of private-pay and Medicaid patients aged 65 or over who reside in these 390 nursing homes.

The Wisconsin Annual Survey of Nursing Homes provides characteristics of each nursing home in Wisconsin, such as staff intensities, ownership, facility size, certificate level, location, provided services, and so on. For prices, it reports per diem rate for different methods of payment by level of care, including intensive skilled care, skilled care, intermediate care, limited care, personal care, and residential care. Since people using skilled care represent nearly 80% of both private-pay and Medicaid patients in the data, we choose the per diem rate for skilled care service as our measure of price.[16] In addition, the dataset also provides patient information for each nursing home. Within a nursing home, we observe the number of patients by payment type-sex pair, age-gender pair, and the number of patients by their former residence (at the county level). This information allows us to control for patient heterogeneity by constructing micro moments. Consequently, we can estimate the coefficients for interaction terms between nursing home observable characteristics and patient's characteristics, and more flexible intercept terms.

Table 2 presents a description of the average characteristics of nursing homes. The average private-

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by sex, age and payment type. But it also imposes a constraint on which year we can apply our empirical framework since Census is conducted once every 10 years. Although Census 2010 is now available, the Wisconsin Annual Survey of Nursing Homes has stopped after 2006.

[16] There are two nursing homes with missing value in skilled care price. In this case, we take the per diem rate for intermediate care as the price measure.

pay price is around $129, which is about $30 higher than the average Medicaid reimbursement rate. On average, the nursing home employees categorized nursing services, therapeutic services and other services, spend around 20, 0.5, and 13 hours weekly per bed, respectively. The average facility size is 108 beds. The average occupancy rate is slightly higher than 89 percent, with 76 percent by elderly (65 or over) who are either private-pay or Medicaid patients. Occupancy rate by private-pay patients is less than half of that by Medicaid patients; occupancy rate by male patients is less than half of that by female patients. Male patients tend to be younger than female patients. Majority of patients in a nursing home come from same the county as the nursing home. Moreover, there are around 14 percent of nursing homes that are government owned facilities, 38 percent are not-for-profit facilities, and 12 percent are located in Milwaukee County.

TABLE 2: Average Nursing Home Characteristics in Wisconsin

	Mean	Std. Dev.	Min	Max
Price Private-pay	128.7	21.4	88.0	205.0
Medicaid	97.4	8.8	61.3	145.0
Nursing Services Weekly Hours per Bed	20.3	4.0	9.3	36.8
Registered Nurses	4.0	1.4	0.7	9.3
Licensed Practical Nurses	2.6	1.1	0.0	8.4
Nurse Assistants/Aids	13.5	3.2	4.8	28.3
Certified Medication Aides	0.1	0.4	0.0	2.4
Therapeutic Services Weekly Hours per Beds	0.5	0.9	0.0	4.4
Other Services Weekly Hours per Beds	13.2	4.3	3.7	34.7
Capacity (Number of Beds)	108	64	18	457
Occupancy Rate	89.4%	9.6%	36.9%	100.0%
Private-pay or Medicaid 65 years old or over	75.5%	13.2%	17.8%	100.0%
Private-Pay Male	6.1%	3.9%	0.0%	21.9%
Private-Pay Female	15.2%	9.9%	0.0%	52.1%
Medicaid Male	14.0%	6.2%	0.0%	37.7%
Medicaid Female	40.1%	10.8%	6.9%	80.0%
Male 65-84 years old	11.3%	5.0%	0.0%	28.3%
Male 85 years old or over	8.8%	3.9%	0.0%	22.3%
Female 65-84 years old	21.9%	6.1%	3.2%	54.8%
Female 85 years old or over	33.4%	12.2%	3.5%	82.0%
Patients from the same county as the nursing home	82.9%	16.4%	0.0%	100.0%
Ownership				
Government	0.14	n.a.	n.a.	n.a.
Not-for-profit	0.38	n.a.	n.a.	n.a.
Location (county)				
Milwaukee	0.12	n.a.	n.a.	n.a.

Number of Nursing Homes = 390

The Special Tabulation on Aging from the 2000 Census reports the joint distribution of population by county, gender, age group, and income categories.[17] Payment method depends on individual's income. We assume that patients earning less than 2 times of the poverty line pay their nursing home stays through Medicaid reimbursement, while patients earning more than 2 times of poverty line pay out of their own pockets. [18,19]

TABLE 3: Nursing Home Utilization Rates in Wisconsin in 1999

	Overall	Poor/Fair Health Condition
Total (65 years old or over)	4.7	16.8
Male 65-84 years old	1.8	6.2
Male 85 years old or over	15.2	53.2
Female 65-84 years old	2.7	10.1
Female 85 years old or over	25.6	95.6
Male Medicaid	4.7	16.5
Male Private-pay	1.6	5.4
Female Medicaid	7.5	28.0
Female Private-pay	3.6	13.5

Based on authors' calculation by combining three data sources

Column 1 of Table 3 shows the nursing home utilization rates per 100 people in Wisconsin. Approximately, 4.7 percent of the total number of elderly aged 65 or over reside in nursing homes. The utilization rates are much higher for older patients (above 85) and for females. Also, the payment type affects the utilization rate: utilization rates per 100 Medicaid eligible population is much higher than that of private-pay population for both sexes. In column 2, we reduce the population base by focusing on senior people with poor/fair health status, as reported in 2000 Wisconsin Family Health Survey.[20] We use this

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[17] The related age groups in this study are: 60-64, 65-74, 75-84, and >85. Income categories is defined according to "Ratio of Income to Poverty", i.e., income divided by the poverty threshold: 1.00, 1-1.24, 1.25-1.49, 1.5-1.99, 2-2.49, 2.5-2.99, >3.
[18] In 2000, the poverty threshold for households with 1 person is an annual income of $ 8,259; for 2 persons is $10,419. For details, refer to http://www.census.gov/hhes/www/poverty/index.html.
[19] Although whether patients are eligible for Medicaid or not depends on the state policies, all states are required to offer Medicaid to Supplemental Security Income (SSI) recipients. Most states supplement the basic SSI payments made to individuals by the federal government. States can further broaden eligibility for Medicaid via the medically needy classification, which includes persons whose medical bills are large enough to reduce their disposable income to the SSI level. We therefore feel that 2 times of the poverty line is a reasonable starting point for calibrating the set of potential patients who are eligible for Medicaid.
[20] 2000 Wisconsin Family Health Survey reports the population estimates by age, gender, and self-reported health status

sub-population of senior people as our potential size of the market, because these are the people who are much more likely to demand for nursing home care than those in good/excellent health conditions.

5. Estimation

We use Generalized Method of Moments (GMM) proposed by Hansen (1982) to estimate our model. Our basic estimation strategy follows Berry et al. (1995) and Petrin (2002), although ours does not include supply-side equations in GMM. Similar to Petrin (2002), three sets of moment restrictions are imposed. One is related to market share, another one is related to micro moments, and the last one is related to nursing homes' unobservable characteristics.

We set the baseline patient group to be private-pay male patients whose age is between 65 and 85 years old. The set of parameters, θ, can be divided into three groups: the first group $\theta_1 = (\alpha_{female}, \gamma_{male\_>85}, \gamma_{female\_65-85}, \gamma_{female\_>85}, \lambda)$ captures the heterogeneity that affect the utility of *both* private-pay patients and Medicaid patients; the second group $\theta_2 = (\kappa, \gamma_{medicaid}, \gamma_{medicaid,rural}, \gamma_{medicaid,for-profit}, \gamma_{medicaid,not-for-profit})$ captures the heterogeneity for the Medicaid patients; and the third group $\theta_3 = (\overline{\alpha}, \overline{\gamma}, \beta)$ captures the parameters for the baseline patients, including those for the quality index.

Private-pay market share

Most of the previous work matches the model's market share predictions to observed market share. In this study, however, since nursing home markets have two different demands and Medicaid demand may exceed observed supply, only market shares for private-pay patients can be used to match the model predictions.

More specifically, for any θ_1, we require the predicted market shares for private-pay patients, $s_j^p (Q(\theta_1), \theta_1)$, to match with their observed counterparts, $s_j^p = n_j^p / M^P$, where M^P is the private-pay market size. The restrictions can be written as,

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(poor/fair vs. good/excellent). For people older than 65, the proportion of having a poor/fair health status is 30% for males and 28% for females. We assume that this proportion by gender is constant across income groups and counties.

$$s_j^p - s_j^p (Q(\theta_1), \ \theta_1) = 0, \quad j = 1,..., J \tag{11}$$

This moment matching is equivalent to solving for each nursing home's quality index $Q_j(\theta_1)$ because

$Q(\theta_1) = (Q_1(\theta_1),...,Q_J(\theta_1))$ is exactly identified based on these J restrictions. To solve for $Q(\theta_1)$, we

use the successive approximation procedure proposed by Berry et al. (1995). The details are described in

Appendix A. We should highlight that this set of moment conditions is crucial for recovering the

unobserved component of nursing home quality. If we cannot observe the market shares for a subgroup of

consumers who do not face rationing, we will not be able to use Eq(11) to obtain $Q(\theta_1)$.

Micro moments

The second set of restrictions relates to micro moments (i.e., moments related to patient

characteristics). Given θ_1, θ_2, and $Q(\theta_1)$, Medicaid demand is calculated according to the procedure

explained in section 3.4. That is, it considers the possibility that some nursing homes face a binding

capacity constraint, and hence some Medicaid patients may be rationed out.

In the estimation, we choose θ_1 and θ_2 to match the four sets of micro moments, which are

constructed from each nursing home's patient information. The first set matches the number of patients

characterized by age-sex pair (4 moments), the second set matches the number of patients characterized by

payment type-sex pair (3 moments),[21] the third set matches the number of patients characterized by county

of residence—whether they came from the same county of the nursing home or not (2 moments), the fourth

set matches the number of Medicaid patients within rural, for-profit, and not-for-profit nursing homes (3

moments).[22] For example, we define the error, $\varsigma_{female,j}^p$, as the difference between the realized number of

private-pay female patients and the model prediction given θ_1 and θ_2,

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[21] These three categories are private-pay female, private-pay male, and Medicaid patients.

[22] There are certain implicit restrictions making some of the micro moments redundant. For example, the sum of number of female private-pay patients and number of male private-pay patients is equal to the number of private-pay patients, which is matched exactly in equation (11). In our implementation, we use 9 micro moments involving the number of patients with the following characteristics: (1) female age between 65 and 85, (2) female age above 85, (3) male age above 85, (4) private-pay female, (5) patients from different county of the nursing home, (6) Medicaid patients, (7) Medicaid patients in nursing homes located in rural area, (8) Medicaid patients in not-for-profit nursing homes, and (9) Medicaid patients in for-profit nursing homes.

$$\varsigma_{female,j}^{p}(\theta_1, \theta_2) = n_{female,j}^{p} - n_{female,j}^{p}(\theta_1, \theta_2),$$ (12)

At the true parameter value, $\theta^0 = (\theta_1^0, \theta_2^0, \theta_3^0)$,

$$E[\varsigma_{female,j}^{p}(\theta_1^0, \theta_2^0)] = 0.$$ (13)

Moments related to unobserved nursing home characteristics and potential endogeneity problem in private-pay price

As a standard issue in the demand estimation, private-pay price is determined by each nursing home, therefore may be correlated with nursing home unobservable characteristics, $\xi_j(\theta_1, \theta_3)$. Take reputation as an example, if a more "well-known" nursing home tends to attract more patients and charge higher price, then the magnitude of the price coefficient will be biased downwards.

To deal with this endogeniety problem, we define a set of instrumental variables,

$$Z_j = [p_j^m \quad X_j]$$

where p_j^m denote Medicaid reimbursement rate in nursing home j and serves as the instrumental variable (IV) for private-pay price, p_j, and other nursing home characteristics serve as instruments for themselves based on our assumption that X_j is mean independent of ξ_j. Under the true parameters, the following orthogonality condition should be satisfied:

$$E[Z_j'\xi_j(\theta_1^0, \theta_3^0)] = 0.$$ (14)

We provide three justifications for using p_j^m as an IV for p_j. First, for nursing homes that have binding capacity constraints, Nyman (1994) argued that a nursing home's pricing decision depends on its Medicaid reimbursement rate because it basically acts like the opportunity costs of admitting a private-pay patient. Second, even for nursing homes that do not face binding capacity constraints, Medicaid reimbursement rate should still be correlated with private-pay price because both of them depend on some major cost factors. As mentioned earlier, the facility specific Medicaid reimbursement rate in Wisconsin depends on a nursing home's previous year expenses in: (1) direct care, (2) support services, (3)

administration, (4) fuel and utilities, (5) property tax, (6) property costs, and (7) over-the-counter (OTC) drugs. Since it is unlikely for these costs factors to change much within a year, the allowable expenses at $t-1$ should also be correlated with a nursing home's pricing decision at t via its profit-maximizing behavior.

Third, we argue that p_j^m should be largely uncorrelated with ξ_j. ξ_j includes a nursing home's reputation and some other demand-related characteristics that are omitted in our demand model. Among all the expense factors that Medicaid considers, our demand model has controlled for direct care and support services (correspond to major nurse and staff inputs), and administration expenses (correspond to nursing home characteristics such as Wand, Hospice services, Lock unit, HMO, etc.). It seems unlikely that patients care about fuel and utilities, and OTC drugs expenses. But property tax and costs could be some omitted variables that patients indirectly care about because they may reflect the location, size and the newness of the facility. Since we do not control for these factors, they would be included in ξ_j. Fortunately, property tax and costs only account for around 8% of the reimbursement rate on average (see Table 3.2 in Chapter 3 of Von Mosch et al. 1997). Therefore, we believe that ξ_j should mainly consist of reputation of a nursing home, which p_j^m does not depend on. By combining all these three points, it suggests that p_j^m should be correlated with private-pay price, and largely uncorrelated with ξ_j.[23]

It is worth discussing why we do not use the standard instruments in the demand estimation literature, i.e., the observable characteristics of other nursing homes, X_{-j} (Berry 1994; Berry et al. 1995). To justify using p_j^m as an IV for p_j, we only need to assume that nursing home j cares about its own characteristics. But to justify using X_{-j} as IVs for p_j, we need to make a stronger assumption that each nursing home also take other nursing homes' characteristics into account when setting its price. In standard oligopolistic

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[23] In table B1 in appendix B, we estimate a simple logit demand model for private-pay patients, using both OLS (column 1) and 2SLS estimation when p_j is instrumented by p_j^m (column 2). The coefficient on price has a much higher magnitude in column 2 than column 1, which suggests that it would be biased downward if one fails to take the endogeneity problem into account. Column 3 reports the first stage regression results: regressing p_j on p_j^m delivers a significant coefficient of 0.64, suggesting that p_j^m is potentially a strong instrument for p_j.

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markets, the latter is a natural assumption to make. But the nursing home market is regulated by the CON law, which impeded competition by restricting new entry, and potentially led to excess demand in many counties during the 90s.[24] Therefore, compared with p_j^m, we feel that X_{-j} would likely be weaker instruments here.

GMM criterion function

Following Petrin (2002), two sets of moments enter the GMM criterion function. $g_1(\theta)$ is the moments associated with the market disturbances (see Eq(14)), and $g_2(\theta)$ is the micro moments (see Eq(13)). At the true parameter value, θ^0, the moment conditions are assumed to be zero, or

$$E[g(\theta^0)] = E\begin{bmatrix} g_1(\theta^0) \\ g_2(\theta^0) \end{bmatrix} = 0. \tag{15}$$

Following Hansen (1982), the criterion function to be minimized is defined by $[\hat{g}(\theta)' A^{-1} \hat{g}(\theta)]$, where $\hat{g}(\cdot)$ is the sample analogue to $g(\cdot)$, and A is the asymptotic covariance matrix of the vector sample moments $\hat{g}(\theta)$. In the appendix, we provide more details about how to implement our estimation procedure.

Remarks about implementing the estimation procedure

We find that simply applying this procedure leads to unsatisfactory estimation results. The main problem is that we allow nursing homes with low occupancy rates to potentially face capacity constraints. When applying GMM, the criterion function penalizes more on parameter vectors that 'under' predicts demand (i.e., when the estimated demand is smaller than the observed demand) relative to those that 'over' predicts demand (i.e., the estimated demand is greater than the observed demand). Note that the parameter vectors that 'over' estimate demand will only receive limited penalty because we essentially put an upper bound on the difference between the predicted demand (which cannot exceed the capacity constraint) and the observed demand. As a result, we obtain parameter estimates that predict many "low-demand" nursing

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[24] Grabowski and Town (2011) provide indirect evidence to support the lack of competition in many nursing home markets from 1999 to 2005.

homes face binding capacity constraints. We therefore modify our procedure when implementing it. We further assume that capacity constraints do not apply to nursing homes with occupancy rates below a certain threshold level. We have experimented different threshold levels of occupancy rate. The results (judged by the goodness-of-fit) are quite reasonable when we assume the threshold occupancy rate to be 80 percent.

Another modification of the procedure is necessary to capture the actual capacity constraints faced by nursing homes. Because nursing homes are not required to admit patients on a first-come first-serve basis and private-pay patients are more profitable, it is possible that they reserve some beds in case private-pay patients may come.[25] Moreover, turnover of patients also happens regularly. Thus, even if a nursing home faces excess demand from Medicaid patients, its observed occupancy rate may be below 100 percent in the data. Therefore, we decide to set a tighter constraint in our estimation algorithm, and use 91 percent occupancy rate as the capacity constraint. Our choice of 91 percent is motivated by the fact that Wisconsin sets the minimum standard occupancy rate at 91 percent. If a nursing home does not meet this cutoff, the state will reduce its Medicaid reimbursement rate based on its occupancy rate. Therefore, it seems unlikely that a nursing home will reserve too many beds for private-pay patients such that it is below 91 percent occupancy rate. We find these two modifications of the algorithm lead to parameter estimates that produce much better goodness-of-fit with respect to occupancy rates.[26]

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[25] This is another motivation that justifies why private-pay patients would *unlikely* face rationing.
[26] One caveat is that a nursing home with low observed occupancy rate may have predicted demand higher than its capacity constraint at the parameter estimates. This happens at 25 such nursing homes (out of 97) in our estimation results.

TABLE 4: Results of Demand-Side Equations

	Parameters	Estimates	SE	Significance
Price (α)	Base	-4.00	(0.85)	***
Price (α_female)	Female	0.32	(0.06)	***
Quality (κ)	Medicaid (multiplier)	0.69	(0.08)	***
Distance (λ)	Different County	-5.83	(0.34)	***
Base constant ($\bar{\gamma}$)	Private-pay, Male 65-85	-8.09	(0.65)	***
Dummies (γ_r)	Female >85	5.53	(0.61)	***
	Female 65-85	0.11	(0.04)	**
	Male >85	2.74	(0.07)	***
	Medicaid	-3.66	(0.22)	***
	Medicaid x Rural	0.39	(0.27)	
	Medicaid x Not-for-profit	-0.4	(0.29)	
	Medicaid x For-Profit	-0.28	(0.32)	
Quality (β)	Registered Nurse Hours per Bed	0.13	(0.04)	***
	Licensed Practical Nurse Hours per Bed	0.08	(0.05)	
	Nurse Assistant Hours per Bed	0.07	(0.01)	***
	Certified Medication Aid Hours per Bed	0.16	(0.12)	
	Therapeutic Service Staff Hours per Bed	0.13	(0.05)	***
	Other Service Staff Hours per Bed	0.01	(0.01)	
	Log(#Beds)	1.19	(0.15)	***
	Milwaukee	-1.71	(0.17)	***
	Rural	0.74	(0.14)	***
	Not-for-profit	0.45	(0.14)	***
	For-profit	0.19	(0.15)	
	Wand (utilizes formal wandering precautions)	-0.04	(0.16)	
	CBRF (community-based residential facility)	0.17	(0.12)	
	Hospital (operated with a hospital)	-0.27	(0.15)	*
	JCAHO (Joint Commission on Accreditation of Health Care Organizations)	0.15	(0.12)	
	HMO (operated with a HMO)	0.25	(0.11)	**
	Lock (has a lock unit)	-0.14	(0.19)	
	Hospice (offers hospice services)	0.02	(0.09)	
	Alzheimer (units for Alzheimer patients)	-0.03	(0.10)	
	Percentage of Patients younger than 65	-3.15	(0.58)	***

Notes:
* - t-statistics > 1
** - t-statistics > 2

6. Results

6.1. Parameter Estimates

The results of estimating the demand-side equations are presented in table 4 (on the previous page). The signs of the coefficient estimates for the utility function are as expected. The coefficient on the impact of distance on nursing home choice is negative and significantly different from zero. The base coefficient on price is also negative and significantly different from zero. We allow the intercept term to vary according to patient's observable characteristics, such as age, sex, and payment type. Recall that the base intercept term, $\bar{\gamma}$, corresponds to private-pay male 65-85 patients. As expected, patients older than 85 tend to value nursing home care more than patients with 65-85 do. Female younger patients tend to value nursing home care the least, while female patients older than 85 tend to value it the most. This may be because female younger patients have relatively better health conditions than other groups of patients.

It is also worth pointing out how preferences vary by gender. Within the same age group, female patients tend to value nursing homes higher than male patients. The interaction between female and price is positive, indicating that female patients are less price sensitive than male patients. Consistent with our previous discussion, these two patterns seem to reflect that it is more likely for elderly men to receive care from their wives (because women are usually younger than their husbands, and they also live longer than men).

Interestingly, the Medicaid dummy is negative. This suggests that Medicaid patients may value nursing home less than private-pay patients. Because Medicaid patients potentially face rationing, this may reflect the costs of waiting, or not being able to select their most preferred nursing home.

The coefficient on quality for private-pay patients is normalized to 1 and that for Medicaid patients is estimated to be 0.69. As expected, Medicaid patients' responsiveness for quality is less than that of private-pay patients. The signs of the estimated parameters for the quality function (β's) are also expected. All of the staffing variables are positive and significant. The coefficient for log(#beds) is positive. This may reflect that patients prefer living in a larger nursing home so that they have a better chance to make friends. Quality varies by location and by ownership type: Quality of nursing homes in Milwaukee County

tends to be lower, while that in rural counties tends to be higher; Not-for profit nursing homes tend to provide higher quality than for-profit or government-owned nursing homes. Various services offered by nursing homes also influence quality: Nursing homes jointly operating with a Health Maintenance Organization (HMO) but not with a hospital tend to have higher quality; nursing homes focusing more on patients younger than 65 generate less utility for the older patients.

Goodness-of-fit

Our model fits the data well. Table 5 presents the goodness-of-fit based on micro-moments. We use the algorithm described in section 3.4 to calculate the expected demand for each nursing home. We assume that the default capacity constraint is 91 percent of the occupancy rate, except for the nursing homes which are observed to have higher occupancy rates. For these nursing homes, we use their observed occupancy rates as their capacity constraints. Column (1) reports the mean value of the micro-moments across nursing homes; column (2) shows the mean value of the predicted moments; column (3) reports the differences between columns (1) & (2); column (4) calculates the correlation coefficients between the real and predicted moments across nursing homes. On average, our model matches the average of micro-moments (which served as the basis in our GMM objective function) very well. The strong correlation shown in column (4) indicates that our model also fit these micro-moments even at the individual nursing home level.

TABLE 5: Goodness-of-Fit of the Micro Moments

Moments	Data (1)	Prediction (2)	Difference (3)	Correlation (4)
Female >85	33.65	33.53	-0.11	0.85
Female 65-85	23.05	22.45	-0.59	0.82
Male >85	8.53	8.37	-0.16	0.76
Private-Pay, Female	15.12	15.12	0.00	0.98
Medicaid	57.83	56.63	-1.21	0.92
Different County	13.16	13.15	-0.01	0.41
Medicaid, Rural	36.86	36.24	-0.62	0.97
Medicaid, Not-for-profit	21.61	21.32	-0.30	0.98
Medicaid, For-profit	25.56	24.70	-0.86	0.95
Occupancy Rate	0.87	0.86	-0.02	0.60

Our model predicts the number of nursing home patients to be 22,085, which is very close to the actual number, 22,555. If we count nursing homes with more than 91 percent occupancy rate to face binding capacity constraint, our model correctly predicts 80 percent of those nursing homes with binding constraints in the data. In total, 197 nursing homes are predicted to have binding constraints by the model. They are distributed across 60 counties, which implies that 84.5 percent of the 71 counties in Wisconsin have at least one nursing home with a binding capacity constraint. Moreover, 41 counties have more than 50 percent of nursing homes facing binding capacity constraints; 15 counties have 25 to 50 percent of nursing homes facing a binding capacity constraint; and 15 counties have less than 25 percent of nursing homes facing a binding capacity constraint.

6.2. Implications of the Parameter Estimates

This subsection discusses implications of the estimation results by answering the following questions: What is the extent of rationing? What is the potential welfare gain if we remove the capacity constraints for nursing homes? How is excess demand or a binding capacity constraint correlated with market outcomes, such as price and quality? Do nursing homes receive higher Medicaid reimbursement rates also provide higher quality of care? How do price and quality changes affect private-pay demand and Medicaid demand?

6.2.1. The extent of rationing

To quantify the extent of rationing, we conduct a counterfactual experiment by removing the capacity constraints for nursing homes. Under this environment, our estimated model predicts that there will be 27,419 Medicaid patients who will demand for nursing home care. Given that the actual number of Medicaid patients resided in nursing homes is 22,555 in 1999, this implies that there are approximately 17.7 percent of Medicaid patients who wanted to enter nursing homes, but eventually chose the outside option because their preferred nursing homes were full. Our counterfactual experiment also reveals that 7,519 Medicaid patients were not able to enter their first-choice nursing homes, which is about 27.4 percent of the Medicaid patients who wanted to enter nursing homes.

It should be noted that our analysis above assume that all the structural parameters remain unchanged under this counterfactual experiment. But recall that the Medicaid dummy for utility intercept is estimated to be negative, and this could reflect the inconvenient costs due to rationing (or not being able to choose the most preferred nursing homes). Hence, once the capacity constraints are removed, the value of the Medicaid dummy may increase, and that would lead to even more Medicaid consumers who would choose to enter nursing homes. Therefore, the extent of rationing that we have estimated here should probably be viewed as a lower bound.

6.2.2. Potential Welfare Gain of Removing Capacity Constraints

The next question we ask is what the potential welfare gain is if the capacity constraints were removed. In order to answer this question, we compute the consumer surplus under the current environment, and the counterfactual environment where nursing homes have no capacity constraints. For each consumer, we follow McFadden (1981) and Small and Rosen (1981), and used their closed form formula for computing consumer surplus. Under the no constraints environment, the consumer surplus for each consumer is,

$$E[CS_i^m] = \frac{1}{\alpha_i^m} E\big[\max(u_{ij}^m)\big] = \frac{1}{\alpha_i^m} \log\left(\sum_{j \in J} \exp(\bar{u}_j^m)\right) \tag{16}$$

where
$$\bar{u}_j^m = u_{ij}^m - \varepsilon_{ij}. \tag{17}$$

The total consumer surplus can be expressed as,

$$E[TCS^m] = M^m \int_i E[CS_i^m] dF_i^m \tag{18}$$

where M^m is total potential size of the Medicaid patients.

Under the current environment, some nursing homes may not be available for all patients to choose from. For patient i who faces a restricted choice set, J_r (defined in section 3.4), his consumer surplus is,

$$E[CS_{i,r}^m] = \frac{1}{\alpha_i^m} \log\left(\sum_{j \in J_r} \exp(\bar{u}_j^m)\right) \tag{19}$$

The total consumer surplus is,

$$E[TCS_R^m] = \sum_r M_r^m \int_i E[CS_{i,r}^m] dF_i^m$$

(20)

where M_r^m is defined in section 3.4.

If we assume that the Medicaid patients and private-pay patients share the same marginal utility of income (i.e., if their price coefficients are the same), then the total consumer surplus under the counterfactual experiment would increase by $1.28 million per day or $468 million per year. On the other hand, in order to cover more Medicaid patients in the counterfactual experiment, the total government expenditure will need to increase by $205(=999-794) million.[27] Therefore, this exercise suggests that the net welfare gain of this policy experiment would be $263(=468-205) million per year.

One caveat of the above analysis is that we assume Medicaid patients and private-pay patients share the same marginal utility of income. This is unlikely to be the case because Medicaid patients should have much lower income than private-pay patients. Unfortunately, since Medicaid patients do not pay for the nursing care at all, we are not able to estimate their price coefficients. But we believe the net welfare gain calculated above should be viewed as an upper bound. In fact, removing the capacity constraints could result in net welfare loss. Suppose that the marginal utility of income for Medicaid patients is twice of that for private-pay patients. Then the net welfare gain under this policy experiment would only be $29(=468/2-205) million per year. If the marginal utility of income for Medicaid patients is three times of that for private-pay patients, we would have net welfare *loss* of $49 (=205-468/3) million per year.

6.2.3. The effects of binding capacity constraint on quality and price

The relationship between a binding capacity constraint and market outcomes has been studied in nursing homes for a long time. Several previous studies argued that the prevalence of excess demand gives nursing homes incentives to provide low quality and high price (Nyman 1988a, 1994, Gertler 1989). However,

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[27] In the current environment, the total annual government expenditures on nursing homes is $794 million in Wisconsin; in the counterfactual environment, the total annual expenditures would increase to $999 million.

previous studies ignored the unobserved component of quality. They also cannot tell which nursing homes face excess demand. Having estimated our model, we are able to shed more light on the relationship between a binding capacity constraint and market outcomes.
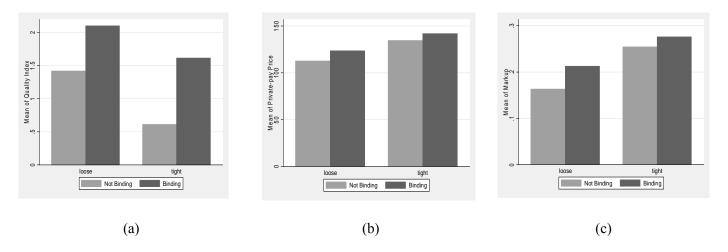
Figure 1. Comparison between Nursing Homes with and without Binding Constraints

(a)   (b)   (c)

In Figure 1, we group counties according to their bed intensities: A "tight" county is a county where the number of beds per 100 potential patients in the county is less than 20;[28] The remaining counties are loose counties. Within each county, we identify nursing homes with occupancy rate higher than 91% predicted by the model as the "binding" nursing homes; while those with occupancy rate lower than 91% as the "non-binding" nursing homes. In total, there are 111 binding nursing homes and 95 non-binding nursing homes among the 35 tight counties; there are 88 binding nursing homes and 96 non-binding nursing homes among the 36 loose counties. The subfigures show comparison results for quality index, private-pay price, and markup, respectively. Following Nyman (1994), we define markup of nursing home j as,

$$Markup_j = \frac{p_j - p_j^m}{p_j^m},$$

(21)

where p_j is the private-pay price, and p_j^m is the Medicaid reimbursement rate. Two trends are noticeable. First, nursing homes in the tight counties tend to provide lower quality, charge higher private-pay price, and

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[28] The 50th percentile cutoff is 20 beds per 100 potential patients.

earn higher markups than nursing homes in the loose counties. Second, within each type of counties, binding nursing home provide higher quality, charge higher private-pay price, and earn higher markups than the non-binding nursing homes. All of these comparisons are statistically significant at 5% levels, except the markup comparison between binding and non-binding nursing home. Our findings are consistent with the previous studies which argue that nursing homes have incentives to provide low quality and high prices when the supply of nursing home is limited. However, it should be noted that the prices in tight counties are only slightly higher than those in loose counties.

6.2.4. Medicaid reimbursement rate and quality

How Medicaid reimbursement rates affect quality of care has been a hotly debated topic. Some studies have concluded that raising reimbursement rates may lower the quality of care in markets with "excess demand" (Nyman 1985, 1988a, 1988b; Gertler 1989, 1992). These studies used data in the 1970s or early 1980s. Studies using more recent information have concluded that reducing Medicaid reimbursement rates appears to reduce quality (Cohen and Spector 1996; Grabowski 2001; Grabowski and Angelelli 2004).

Our model cannot address how nursing homes would react to higher reimbursement rates. However, we can examine whether Medicaid reimbursement rate and quality of care are positively correlated. That is, we can check whether nursing homes receive higher Medicaid reimbursement rate tend to provide higher quality of care or not. Our quality index function (equation 5) can be rewritten in the following way.

$$Q_j = X_{1j}\beta_1 + X_{2j}\beta_2 + \xi_j, \tag{5'}$$

where X_{1j} includes staffing intensity, that is various types of staff hours per bed, X_{2j} includes dummy variables that indicates the nursing home's ownership and location characteristics and services provided by the nursing home, and ξ_j is an unobservable characteristic. Let us refer $X_{1j}\beta_1$ to input-based quality, and $X_{2j}\beta_2$ to service-based quality. Table 6 summarizes the Pearson correlation coefficients between Medicaid reimbursement rate and various quality measures.

TABLE 6: Correlation between Medicaid Reimbursement Rate and Various Quality Measures[29]

	All		Tight		Loose	
Quality Index (Q_j)	-0.03	0.58	0.02	0.82	0.11	0.15
Input-based ($X_{1j}\beta_1$)	0.00	0.95	-0.04	0.55	0.14*	0.05
Service-based ($X_{2j}\beta_2$)	-0.19**	0.00	-0.09	0.18	-0.04	0.61
Unobserved (ξ_j)	0.00	1.00	0.05	0.46	-0.04	0.61

Notes: ( ) - p-value
* - p-value < 0.05
** - p-value < 0.01

We find that in general the reimbursement rate is not correlated with the quality index. Input-based quality is significantly positively correlated with Medicaid reimbursement rate only in loose counties at 10% level. To provide a point of comparison, Table 7 shows Pearson correlation coefficients between private-pay price and various quality measures. In contrast to Medicaid reimbursement rate, private-pay price is significantly positively correlated with quality index in all types of counties at 10% level. Price appears to better reflect quality evaluated by consumers than Medicaid reimbursement rate.

TABLE 7: Correlation between Private-Pay Price and Various Quality Measures

	All		Tight		Loose	
Quality Index (Q)	0.16**	0.00	0.21**	0.00	0.62**	0.00
Input-based	0.14**	0.01	0.14**	0.04	0.33**	0.00
Service-based	-0.43**	0.00	-0.38**	0.00	-0.09	0.24
Unobserved	0.36**	0.00	0.39**	0.00	0.52**	0.00

Notes: ( ) - p-value
* - p-value < 0.05
** - p-value < 0.01

6.2.5. Price and quality elasticity of demand

Table 8 presents the effects of price changes on private-pay demand. In column 1, the average own-price elasticity of private-pay demand and of private-pay demand by age-sex groups are reported. For the overall sample, the model estimates imply that 1 percent increase in the private-pay price would lead to about 4.5 percent fall in private-pay demand for the nursing home. Female patients are more likely to stay

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[29] The zero correlation between ξ_j and p_j^m is due the fact that we are using the latter as the instrument for p_j and the moment condition requires p_j^m to be orthogonal to ξ_j in the quality index.

in the same nursing homes than male patients when facing a price increase.

TABLE 8: Effects of Price Changes on Private-Pay Demand

	Own Price Elasticity		Among all patients leaving due to price increase, % of them go to			
			other NHs in the same state		other NHs in the same county	
All	-4.55	(0.77)	42.5%	(5.30%)	25.4%	(9.60%)
Male 65-85	-5.00	(0.81)	3.6%	(1.26%)	2.4%	(1.31%)
Male >85	-4.86	(0.85)	34.7%	(7.60%)	22.2%	(9.15%)
Female 65-85	-4.60	(0.75)	5.9%	(1.89%)	4.0%	(2.05%)
Female >85	-4.26	(0.82)	91.9%	(2.65%)	52.9%	(17.43%)

Note:
Standard deviation across nursing homes in bracket.

Our results are in line with the prediction of the standard model of nursing homes, e.g., Nyman (1994). In Nyman's model, when nursing homes set price optimally, the price elasticity of demand would satisfy:

$$\eta_{jj} = \frac{p_j}{p_j - p_j^m}, \tag{22}$$

where p_j is the private-pay price, and p_j^m is the Medicaid reimbursement rate. Given the sample mean of private-pay price ($128.7) and Medicaid reimbursement rate ($97.4), the above formula implies a price elasticity of 4.11, which is quite close to the estimates based on our model.

The second column of table 8 shows that among all the patients who leave their nursing home due to its price increase, on average 43 percent of them will choose some other nursing homes, instead of staying at home. The substitution patterns vary by age-sex groups: comparing with the younger age group, the elderly patients (65-85) are less likely to choose the outside option; comparing with male patients, female patients are more likely to move to another nursing home instead of choosing the outside option. These patterns are consistent with the fact that the elderly patients, in particular, if they are female, are more likely to have need for nursing home care.

The last column of table 8 shows that about 25.4 percent of the private-pay who leave their nursing

home due to price increase would move to one of the nursing homes in the same county. This implies

approximately 60 percent (25.4/42.5) of switchers choose nursing homes within the same county.

The effects of quality changes on the number of Medicaid patients in nursing homes are shown in

table 9. Because in the model Medicaid patients cannot enter nursing homes if the beds are fully occupied

by private-pay patients and other Medicaid patients, the effects greatly depend on whether the nursing home

faces a binding capacity constraint or not. All columns present the average percent changes in the number

of Medicaid patients of the nursing home whose quality increases by 1 percent. The first column shows the

average of all nursing homes, the second column shows the average among nursing homes without binding

capacity constraints, and the third column shows the average among nursing homes with binding capacity

constraints. Not surprisingly, the percentage change in the number of Medicaid patients in nursing homes

with binding capacity constraints is negative and that in nursing homes without binding capacity constraints

is positive. When a nursing home raises its quality, more private-pay patients would enter the nursing home.

If the nursing home faces a binding capacity constraint, the number of Medicaid patients in the nursing

home needs to be reduced as a result of more private-pay patients. If the nursing home does not face a

constraint, then the number of Medicaid patients can also increase.

Overall, the crowding out effects of the private-pay patients on Medicaid patients are strong as

shown by column (1). This suggests that simply asking nursing homes to improve their service quality

might not be a good policy if one wants to improve the welfare of the Medicaid patients.

TABLE 9: Effects of Quality Changes on the Number of Medicaid Patients

	Own		NHs without constraints		NHs with constraints	
All	-1.58	(3.23)	0.76	(0.92)	-3.49	(3.19)
Male 65-85	-1.90	(3.39)	0.69	(0.96)	-4.00	(3.19)
Male >85	-1.32	(3.15)	0.83	(0.89)	-3.06	(3.25)
Female 65-85	-1.66	(3.30)	0.76	(0.92)	-3.62	(3.23)
Female >85	-1.31	(3.14)	0.83	(0.89)	-3.04	(3.25)

Notes: ( ) standard deviations.

7. Conclusion

In this paper, we offered an alternative approach to analyze nursing home markets. We have developed a discrete-choice demand-side model that takes into account a possible binding capacity constraint and other key features of the nursing home industry. The estimated model enables us to answer some of the questions that previous studies cannot tackle with. In particular, the model enables us to identify which nursing homes face a binding capacity constraint and to quantify the extent of rationing, which is not feasible with a reduced-form modeling approach. We also examined the relationship between a binding capacity constraint and market outcomes and between Medicaid reimbursement rate and quality of care.

The results suggest that (i) nearly 18 percent of Medicaid consumers are rationed out; and (ii) about 27.4 percent of Medicaid nursing home patients did not enter their first-choice nursing homes (but most of those patients likely have entered their second-choice or less preferred nursing homes). Compared with previous studies, our structural model uncovers that excess demand is a more common phenomenon. However, it is not clear if removing capacity constraints would necessarily improve social welfare because providing extra nursing home care can dramatically increase Medicaid expenditures, and hence put significant burden on the state budget. We also find evidence that for nursing homes that receive higher Medicaid reimbursement rates, they generally do not provide higher quality of care. On the contrary, higher quality of care is usually associated with higher private-pay prices. We have also demonstrated that our demand model can be used to investigate the price and quality elasticities of demand. In particular, we show that one can use our model to quantify the extent of crowding-out Medicaid patients when a nursing home raises its quality.

As mentioned before, our study assumes that nursing home quality to be exogeneous in the short run due to high adjustment costs. Although we believe this assumption is reasonable for our research purpose, which is to develop an empirical framework to quantify the extent of rationing at a given point of time, it is certainly a limitation if one is interested in understanding the long run equilibrium. To understand any long-run market outcomes, it is important to explicitly model quality choice taking adjustment costs

into account. Lin (2012) has taken a first step towards this research direction by developing a dynamic oligopoly structural model. However, such a model is very computationally intensive, and therefore she needs to abstract away the potential rationing problem on the demand side, and simply use a reduced form profit functions for nursing homes. In the future, an important research topic is to combine our demand model with a dynamic oligopoly supply side model of quality choice, in order to study the long term impact of government regulations.

We also hope that the empirical framework developed here can be extended to study other markets where capacity constraints are hard to expand, and hence firms may face excess demand, e.g., hotels, airlines, etc. In these markets, it is common for firms to offer different fare (or price) classes. They set quota for discounted fare, but not for full-fare. The consumers who are willing to pay full fare correspond to the private-pay patients in our study. If researchers can observe the data on market shares for full-fare consumers (and the standard market share data), it may be possible to extend our framework to estimate the true demand in these markets as well.

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A   Appendix: Estimation

Following the notation in the text, denote $\theta_1 = (\alpha_{female}, \gamma_{male\_>85}, \gamma_{female\_65-85}, \gamma_{female\_>85}, \lambda)$, $\theta_2 = (\kappa, \gamma_{medicaid}, \gamma_{medicaid,rural}, \gamma_{medicaid,for-profit}, \gamma_{medicaid,not-for-profit})$, and $\theta_3 = (\overline{\alpha}, \overline{\gamma}, \beta)$. The GMM criterion function has to be evaluated at many different values of $\theta = (\theta_1, \theta_2, \theta_3) \in \Theta$ to locate the minimum. The following steps describe this iterative process.

A.1   BLP moments $E(Z'\xi) = 0$

Define the mean utility from going to nursing home j as

$$\delta_j = \overline{\gamma} + \overline{\alpha}p_j + Q_j = \overline{\gamma} + \overline{\alpha}p_j + X_j\beta + \xi_j \tag{1}$$

For any given θ_1, we use a contraction mapping to find δ_j such that $s_j^p(\delta_j, \theta_1) = \mathbf{s}_j^p$, where $\mathbf{s}_j^p$ is a vector of observed market shares in the private-pay market, and $s_j^p(.)$ is a vector of predicted market shares in the private-pay market.[1] Following Berry et al (1995), we use the following contraction mapping function,

$$f(\delta_j) = \delta_j + \ln \mathbf{s}_j^p - \ln s_j^p(\delta_j, \theta_1). \tag{2}$$

This allows us to start with any initial guess, δ_j^0, and use the method of successive approximation to obtain $\delta_j(\theta_1)$.

Denote $\mathbf{1}$ as a vector of 1 with dimension of J. Define $X_p = (\mathbf{1}, p, X)$ and $Z = (\mathbf{1}, p^m, X)$, where we use medicaid price (p^m) as instrument for private-pay price (p), while other characteristics (X) serve as instruments for themselves. Following Nevo (2000), $\widehat{\theta}_3$ can be expressed as a function of θ_1,

$$\widehat{\theta}_3 = (X_p'Z\Phi^{-1}Z'X_p)^{-1}X_p'Z\Phi^{-1}Z'\delta_j(\theta_1), \tag{3}$$

where Φ is the weighting matrix.[2] Estimate of ξ can be expressed as,

$$\widehat{\xi}(\widehat{\theta}_3(\theta_1), \delta_j(\theta_1)) = \delta_j(\theta_1) - X_p\widehat{\theta}_3(\theta_1), \tag{4}$$

and BLP moments are calculated as,

$$g_1(\theta_1) = Z'\widehat{\xi}(\widehat{\theta}_3(\theta_1), \delta_j(\theta_1)) \tag{5}$$

A.2   Micromoments $E(\mathbf{n}_j^m - n_j^m(\theta)) = 0$

We use $t \in (1, ..., T)$ to index consumer types (in terms of age, gender, and payment combinations). The predicted number of type t patients entering nursing home j is given by,

$$n_{t,j}(\theta) = M^p \int_{i \in t} \text{Prob}_{ij}^p dF_{i \in t} \tag{6}$$

---

[1] Refer to equation (6) and (7) in Section 3 for the formulas of predicting private-pay market share.

[2] In practice, we use the covariance vector sample moment $\widehat{g}_1(\theta)$ defined in equation (5) as the weighting matrix. Refer to Appendix A.3 for its calculation.

if they pay out of their own pockets, or

$$n_{t,j}(\theta) = \sum_{r=1}^{R} M_r^m \int_{i \in t} \text{Prob}_{ij,r}^m dF_{i \in t} \tag{7}$$

if they are covered by Medicaid reimbursement. The micromoments are constructed as,

$$g_2(\theta) = \frac{1}{J} \sum_j [\mathbf{n}_{t,j} - n_{t,j}(\theta)], \tag{8}$$

where J is the number of nursing homes, $\mathbf{n}_j = (\mathbf{n}_{1,j}, ..., \mathbf{n}_{T,j})$ is the vector of the observed number of patients of different types in nursing home j, and $n_j(\theta) = (n_{1,j}(\theta), ..., n_{T,j}(\theta))$. It should be highlighted that $g_2(.)$ depends on all the parameters.

A.3   GMM estimator

Collect all moments

$$g(\theta) = \begin{bmatrix} g_1(\theta_1) \\ g_2(\theta) \end{bmatrix}. \tag{9}$$

In order to obtain the *feasible optimal-GMM*, we proceed in two steps:

Step 1. Using an arbitrary positive definite weighting matrix (e.g., the identity matrix) we obtain a consistent GMM estimator $\widehat{\theta}^{(1)}$,

$$\widehat{\theta}^{(1)} = \arg\min_{\theta \in \Theta} g(\theta)'g(\theta). \tag{10}$$

Step 2. Given $\widehat{\theta}^{(1)}$, we obtain a consistent estimator of the covariance matrix of the vector sample moment $\widehat{g}(\theta)$ as follows,

$$\widehat{\Omega} = \frac{1}{J} \sum_{i=1}^{J} g^j(\widehat{\theta}^{(1)})g^j(\widehat{\theta}^{(1)})', \tag{11}$$

where $g^j(.)$ is the vector of sample moments for nursing home j. Then, we obtain the optimal GMM estimator as:

$$\widehat{\theta} = \arg\min_{\theta \in \Theta} g(\theta)'\widehat{\Omega}^{-1}g(\theta). \tag{12}$$

2

Appendix B

Table B1. Logit Regression for Private-pay Patients

	OLS	2SLS 2nd stage	2SLS. 1st stage
	(1)	(2)	(3)
Private-pay Price	-0.222	-1.502	
	[0.190]	[0.669]**	
Medicaid Price			0.642
			[0.106]***
Hours per Bed			
Registered Nurse Hours per Bed	0.082	0.119	0.018
	[0.026]***	[0.033]***	[0.007]***
Licensed Practical Nurse Hours per Bed	0.032	0.073	0.025
	[0.030]	[0.037]*	[0.008]***
Nurse Assistant Hours per Bed	0.046	0.052	0.005
	[0.011]***	[0.012]***	[0.003]
Certified Medication Aid Hours per Bed	0.035	0.125	0.059
	[0.082]	[0.097]	[0.021]***
Therapeutic Service Staff Hours per Bed	0.117	0.124	0.007
	[0.037]***	[0.039]***	[0.010]
Other Service Staff Hours per Bed	0.009	0.009	-0.001
	[0.008]	[0.008]	[0.002]
Log(Beds)	0.927	1.098	0.124
	[0.074]***	[0.116]***	[0.018]***
Milwaukee	-0.598	-0.46	0.073
	[0.109]***	[0.134]***	[0.029]**
Rural	-0.179	-0.331	-0.093
	[0.079]**	[0.113]***	[0.020]***
Not-for-profit	0.335	0.371	0.035
	[0.106]***	[0.114]***	[0.028]
For-profit	0.051	0.104	0.079
	[0.106]	[0.115]	[0.028]***
Wand (utilizes formal wandering precautions)	-0.052	-0.034	0.009
	[0.118]	[0.125]	[0.031]
CBRF (community-based residential facility)	0.211	0.228	0.007
	[0.089]**	[0.095]**	[0.023]
Hospital (operated with a hospital)	-0.292	-0.35	-0.049
	[0.111]***	[0.121]***	[0.029]*
JCAHO (Joint Commission on Accreditation of Health Care Organizations)	0.046	0.088	0.038
	[0.091]	[0.099]	[0.024]
HMO (operated with a HMO)	0.071	0.155	0.064
	[0.071]	[0.086]*	[0.018]***

	(1)	(2)	(3)
Lock (has a lock unit)	-0.296	-0.255	0.034
	[0.139]**	[0.148]*	[0.036]
Hospice (offers hospice services)	0.114	0.1	-0.012
	[0.066]*	[0.070]	[0.017]
Alzheimer (units for Alzheimer patients)	-0.017	-0.058	-0.023
	[0.071]	[0.078]	[0.019]
Percentage of patients younger than 65	-3.219	-2.975	0.197
	[0.420]***	[0.462]***	[0.109]*
Constant	-13.202	-12.697	-0.148
	[0.421]***	[0.512]***	[0.140]
Obs	390	390	390
R-square	0.53	0.47	0.56

Notes:

The dependent variable in column (1) and (2) is $\log(s_j^p) - \log(s_0^p)$, where s_j^p is the market share of private-pay patients in nursing home j, and s_0^p is the proportion of private-pay patients staying at home. In column (2), private-pay price is instrumented by the Medicaid reimbursement rate. The dependent variable in column (3) is p, i.e., the private-pay price in nursing home j.

Standard errors are in [ ].

* significant at the 10 percent level.
** significant at the 5 percent level.
*** significant at the 1 percent level.