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Quantifying the Impacts of Limited Supply: The Case of Nursing Homes[*][†]

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Abstract

This paper develops a new estimation method that accounts for excess demand and the unobserved component of product quality. We apply our method to study the Wisconsin nursing home market in 1999, and find that nearly 20% of elderly qualified for Medicaid were rationed out. However, our counterfactual experiment shows that the net welfare gain of fulfilling all nursing home demands may be small, because the welfare gain to Medicaid patients could be largely offset by the increase in Medicaid expenditures. We also find that a 1% increase in quality would crowd out 3.2% Medicaid patients in binding nursing homes.

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

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

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1. Introduction

Products or services with limited supply are prevalent in our economy. Examples include hotels, schools, public housing, hospitals, nursing homes, etc. Due to the stickiness of prices or government regulations, these services commonly experience excess demand from time to time. When demand exceeds supply, consumers would either need to wait in line or choose their second best options. This poses a challenge to researchers who are interested in recovering consumer preferences from market shares/sales data available to them – in general, one cannot use such data alone to infer true underlying consumer preferences. In particular, without properly taking the extent of rationing into account, the preference parameters and product quality obtained from the standard estimation procedure could be very misleading. In this paper, we develop an estimation strategy that accounts for excess demand and the unobserved component of product quality. Our methodology is motivated by the institutional details of the nursing home market. It allows us to quantify the extent of rationing, price and quality elasticities of demand, and shed light on the potential welfare gain/loss if we try to fulfill all rationed demand. We apply our framework to study the Wisconsin nursing home market in 1999, which has been thought to face two main problems: limited access/rationing and low quality (e.g., Gruenberg and Willemain 1982; Norton 1992; Ettner 1993).[2]

Besides being a market which commonly experiences excess demand, the nursing home market is important on its own because of the substantial growth of the elderly population. To control for the expenditures on nursing home care, most state governments regulate the industry 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 existing ones to increase their number of beds. Second, state governments regulate the price that they pay for a large percentage of nursing home care through Medicaid

[2] See the report to Congress made by the Health Care Financing Administration in July 2000 (Health Care Financing Administration, 2000). It is also worth pointing out that a nursing home shortage is a public concern even today. See "The coming nursing home shortage", the Fiscal Times (2012) http://www.thefiscaltimes.com/Articles/2012/01/26/The-Coming-Nursing-Home-Shortage, accessed on Feb 17, 2014.

programs. These regulations have led to two groups of studies.[3] 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 in 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 have aimed 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). Extending Scanlon's (1980) pioneering work, studies that used data in the 1970s and early 1980s found evidence of excess demand (e.g., Nyman 1985, 1988a, 1988b, 1989, 1994; Gertler 1989, 1992). Studies that used 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 previous work; however, due to the reduced-form modeling approach, there remain some important questions that this work cannot answer. In general, there are three limitations. First, many previous studies 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 which they cannot enter. Second, when measuring quality provided by a nursing home, most of the previous studies used either input-based or outcome-based methods, 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 used by the nursing home. Unobserved factors can also lead to an

[3] Norton (2000) provides an excellent survey on this topic.

endogeneity problem of price if one ignores their presence in estimation. Third, as is well-known, the reduced-form approach cannot measure patient welfare under 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, we can quantify the extent of rationing and the potential welfare gain/loss if we try to fulfill all the rationed demand at prevailing private-pay prices, Medicaid reimbursement rates, and nursing homes qualities. 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 by 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 from 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 by constructing a "quality index", which can potentially lessen the problem of input-based or outcome-based quality measure, and address the endogeneity problem of private-pay prices.[4]

[4] Unlike our approach, Geyer and Sieg (2013) make use of *individual* level data on exit rate and an equilibrium model to infer the unobserved waiting list in public housing. Our paper is also closely related to Conlon and Mortimer (2013), who propose an estimation approach that applies to a situation where all types of consumers could face stock-out problems.

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 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.

Our estimation results suggest that excess demand was still prevalent in Wisconsin in the late 90s. Approximately half of the nursing homes used for this study is estimated to face binding capacity constraints; about 20 percent of potential patients who qualified for Medicaid are rationed out for nursing home care (i.e., they would have chosen to enter nursing homes if the capacity constraints did not exist); and about 26 percent of the Medicaid nursing home patients could not enter their first-choice nursing homes. 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 additional nursing home care. Our estimation results show that the unobserved component of quality accounts for 40% of the quality index, and plays an important role in explaining market shares. Moreover, our estimated quality index suggests that nursing homes tend to provide lower quality of care in counties with tight supply. Interestingly, it also implies that not-for-profit nursing homes tend to provide better quality than for-profit nursing homes, which is consistent with what the health service literature finds.

The rest of the paper is organized as follows. Section 2 summarizes some important nursing home regulations in Wisconsin. Section 3 presents the demand model. Section 4 details the data and section 5

However, their approach is computationally very challenging to implement when there are many products experiencing stock-out, because it needs to integrate out all possible unobserved orders of stock-out to obtain the likelihood. Our proposed approach completely avoids this computational problem, given the crucial assumptions we made. Our paper is also related to the marketing literature which focuses on the out-of-stock situation: Bruno and Vilcassim (2008), Che, Chen and Chen (2012), Musalem, et al. (2010). These papers rely on using proxies to indicate which products experience out-of-stock.

presents the estimation procedure. Estimation results, their implications and limitations are provided in section 6. Finally, section 7 concludes.

2. Background—Regulations in Wisconsin

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

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. 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. These rates cannot be adjusted during a fiscal year.

Certificate-of-Need

Wisconsin has used a CON law for nursing homes since 1980. The review criteria and standards for CON applications include a need for additional beds in the health planning area, sufficient funds availability, and satisfactory quality care to be provided. 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. The state also 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. 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 homes opened in two counties (Price and Washington) in 1999.

TABLE 1[5]: 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, have minimum staffing requirements for the number of nurse hours per bed (Black, et al. 2003). Moreover, due to a 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 2014). 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. State regulation prohibits discriminatory treatment based on 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.

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

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.[6] 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 will provide beds to private-pay patients first, then fill Medicaid patients as residuals.[7,8] As a result, a Medicaid patient may not be able to enter their most preferred nursing homes which face binding capacity constraints. In that situation, we assume Medicaid patients will choose one of the remaining nursing homes with available beds to maximize their utility. In

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[6] Many studies on nursing homes adopt the same assumption, e.g., Gertler (1992), and Cohen and Spector (1996). In addition, it is practical to provide services of the same quality across patients because most of these services, such as daily care and dietary, enjoy considerable economies of joint production (Gertler, 1992).

[7] Note that even a not-for-profit or government nursing home has an incentive to admit private-pay patients first, and use the extra revenue to provide higher quality of service, which in turn can benefit Medicaid patients. We have tested the hypothesis that not-for-profit/government nursing homes give priority to Medicaid patients (perhaps due to altruism). But we do not find evidence to support such a hypothesis (see appendix D).

[8] The same model implications were used in Nyman (1985, 1988a, 1994) who also analyzed data from Wisconsin, which does *not* have a regulation that requires nursing homes to offer beds on a first-come, first-served basis.

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.[9] 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 may 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.[10]

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:

[9] In our model, we refer "patient" to any consumers who consider nursing home care, even if he/she ends up choosing the outside option.

[10] 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. Conceivably, before patients enter nursing homes, they may live with their sons/daughters, who may have strong preferences for nursing homes that are nearby, as it would be more convenient for them to visit their parents.

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

with

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

where Q_j, p_j, and D_{ij} are quality, price paid by private-pay patients, and distance to nursing home j from patient i's residence, respectively.[11] 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 0 otherwise.[12] z_{ir} is patient i's observed characteristic r, such as age, sex, and payment type. The variable ε_{ij} captures the unobserved 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,

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[11] 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, and charge identical private-pay price and Medicaid reimbursement rate regardless of patients' severity.

[12] 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. Note that we only observe the total number of patients coming from different counties by nursing homes (i.e., it is not broken down by payment type). Therefore, we have decided to restrict the sensitivity to distance to be the same for both private-pay and Medicaid patients.

(4) $$u_{i0} = \xi_0 + \varepsilon_{i0},$$

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

We assume in specifications (1) and (2) that the whole state of Wisconsin is an integrated market for nursing home services, and that 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 observed characteristics (observed to both patients and econometricians) as well as an unobserved characteristic (unobserved to econometricians, but observed to patients). Nursing home observed characteristics include input variables, such as nurse intensity and other staff intensities. 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 during the 90s (Bureau of Health Profession 2002; Nevidjon and Erickson 2001). Other observed characteristics are ownership type, facility size, specific services provided by the nursing home, and nursing home location (e.g., urban vs. rural). These characteristics are even harder for nursing homes to change after they have entered the market.

Incorporating an unobserved characteristic along with these observed 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 whether 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 detailed patient-level information (e.g., Gowrisankaran and Town 1999; Geweke, Gowrisankaran and Town 2003). The unobserved characteristic can 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. It can also capture a nursing home's reputation resulting from the average health/satisfaction of its patients.

To capture these ideas, quality is assumed to be evaluated by all patients as follows.

(5) $$Q_j = X_j\beta + \xi_j ,$$

where X_j is a vector of nursing home *j*'s observed characteristics excluding price and distance, and ξ_j is an unobserved characteristic. Based on our discussion above, we further assume that X_j is mean independent of ξ_j.[13]

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

[13] Although our discussion cannot completely rule out that nurse inputs could be correlated with the unobserved characteristic, they imply that nursing homes do not have complete freedom to choose the nurse inputs. This suggests that relative to p_j, the endogeneity problem of nurse inputs may 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.

justified by the fact that the demand for private-pay patients alone is far from enough to fill up any nursing home.[14] 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:

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

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

$$\text{(7)} \qquad n_j^p = M^p \int_i \mathrm{Prob}_{\mathrm{ij}}^{\mathrm{p}} dF_i^p ,$$

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.

[14] On average 21% of beds are occupied by private-pay patients, 90 percent of the nursing homes have less than 38% of their beds occupied by private-pay patients, and private-pay patients occupy at most 66% of beds of a nursing home. As a comparison, the 90 percentile of the occupancy rate for Medicaid patients is 68%, and the average is 54%.

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. Specifically, M_1^m is the maximum measure of the Medicaid population who can enter any nursing home. M_2^m is the maximum measure of the Medicaid population who can enter any nursing homes other than the one with its last bed taken by the first group, M_1^m. M_r^m is the maximum measure of the Medicaid 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.[15] Therefore, the aggregate Medicaid demand is calculated as:

(8) $$n_j^m = \sum_r M_r^m \int_i \mathrm{Prob}_{\mathrm{ij,r}}^{\mathrm{m}} dF_i^m ,$$

where $\mathrm{Prob}_{\mathrm{ij,r}}^{\mathrm{m}}$ 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:

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

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

(10) $$\mathrm{Prob}_{\mathrm{ij,r}}^{\mathrm{m}} = 0.$$

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

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 provided low quality of care) in the late 90s. But as we mentioned earlier, the limitations of 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.[16]

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. Because our study 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. We also drop three more nursing homes: one specializes to care for veterans, one for young patients, and one with missing values for the private-pay price. Finally, we exclude eleven nursing homes with no private-pay patients because our estimation algorithm requires us to observe a non-zero market share of private-pay patients for each nursing home.[17] In the end, there are 390 nursing homes in our final sample.

[16] The use of this data from Special Tabulation on Aging is very important for us to calibrate the potential number of patients by sex, age and payment type. But it also imposes a constraint on which year we can apply our empirical framework since a Census is conducted once every 10 years. Although Census 2010 is now available, the Wisconsin Annual Survey of Nursing Homes stopped after 2006.

[17] Among these 11 nursing homes, one home exited the market during the year; one was a "transitional care" unit (which only provides temporary care); three were very small (they only took less than 30 Medicaid patients each); two did not have any private-pay or Medicaid elderly patients (they only took younger patients who were either covered by Medicare or had a disability). We suspect that the two nursing homes with zero patients were set up just before the survey was carried out (i.e., near the end of 1999). For the rest of the four nursing homes, they altogether took 296 Medicaid patients. However, the

The Wisconsin Annual Survey of Nursing Homes provides characteristics of each nursing home in Wisconsin, such as staff intensity, ownership, facility size, certificate level, location, services provided, and so on. For prices, the survey reports per diem rates 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 patients using skilled care represent nearly 90% 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.[18] In addition, the dataset 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 observed characteristics and patient characteristics, and more flexible intercept terms.

Table 2 presents a description of the average characteristics of nursing homes. The average private-pay price is around \$129, which is about \$30 higher than the average Medicaid reimbursement rate. Nursing home employees are classified into three categories: (i) nursing services, (ii) therapeutic services and (iii) other services, and on average they 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. The majority of patients in a nursing home comes from the same county as the nursing home. Moreover, around 14 percent of nursing homes are government owned facilities, 38 percent are not-for-profit facilities, and 12

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proportion of the younger patients (age below 65) among these homes (ranges from 25% to 40%) is much higher than the average in our sample (13%). Therefore, we believe that excluding these 11 nursing homes should not have any material impacts on our results.

[18] 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.

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 a joint distribution of the population by county, gender, age group, and income categories.[19] Payment method depends on an individual's income. We assume that patients earning less than two times the poverty line pay their nursing home stays through Medicaid reimbursement, while patients earning more than two times the poverty line pay out of their own pockets.[20,21]

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

[19] The related age groups in this study are: 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, and >3.

[20] In 2000, the poverty threshold for households with one person is an annual income of $ 8,259; for two persons is $10,419. For details, refer to http://www.census.gov/hhes/www/poverty/index.html (accessed on May 8, 2014).

[21] Although Medicaid eligibility 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. Thus, two times the poverty line seems to be a reasonable starting point for calibrating the potential market size of Medicaid patients.

matters: the utilization rates of the 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 elderly people with poor/fair health status, as reported in the 2000 Wisconsin Family Health Survey.[22] We use this sub-population of elderly people as our potential size of the market, because these are the people who are much more likely to demand 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 types of moment restrictions are imposed. The first type is related to market share, the second type is related to micro moments, and the third one is related to nursing homes' unobserved 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 affects 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.

5.1. Private-pay market share

Most of the previous work matches the model's market share predictions to observed market shares. In this study, however, since nursing home markets have two different types of patients, and the Medicaid patients'

[22] The 2000 Wisconsin Family Health Survey reports the population estimates by age, gender, and self-reported health status (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.

demand may exceed the actual 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, $\mathrm{s}_\mathrm{j}^\mathrm{p} = \mathrm{n}_\mathrm{j}^\mathrm{p} / M^P$, where M^P is the private-pay market size. The restrictions can be written as,

$$\mathrm{s}_\mathrm{j}^\mathrm{p} - s_j^P(Q(\theta_1),\ \theta_1) = 0, \qquad j = 1, \ldots, J \tag{11}$$

This moment matching is equivalent to solving for each nursing home's quality index $Q_j(\theta_1)$ because $Q(\theta_1) = (Q_1(\theta_1), \ldots, Q_J(\theta_1))$ 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 equation (11) to obtain $Q(\theta_1)$.

5.2. 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),[23] 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), and the fourth set matches the number of Medicaid patients within rural, for-profit, and not-for-profit nursing

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

homes (3 moments).[24] For example, we define the error, $\varsigma^{p}_{female,j}$, as the difference between the realized number of private-pay female patients and the model prediction given θ_1 and θ_2,

(12) $$\varsigma^{p}_{female,j}(\theta_1,\theta_2) = \mathrm{n}^{\mathrm{p}}_{\mathrm{female,j}} - n^{p}_{female,j}(\theta_1,\theta_2),$$

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

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

5.3. Moments related to unobserved characteristics and potential endogeneity problem of price

As a standard issue in the demand estimation, private-pay price is determined by each nursing home, and therefore it may be correlated with the nursing home's unobserved 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 endogeneity 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:

[24] 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 aged between 65 and 85, (2) female aged above 85, (3) male aged 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.

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

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 actual allowable expenses in the previous year: (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 allowable expenses to change much within a year, the allowable expenses at *t-1* should be correlated with a nursing home's pricing decision at *t* via its profit-maximizing behavior.

Third, p_j^m should be largely uncorrelated with ξ_j, which 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 controls for three of them: direct care, 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.). Two factors which we do not control for -- fuel & utilities and OTC drugs expenses -- seems unlikely to matter much to patients. But the last two factors that we have left out -- property tax and property costs -- could be some omitted variables that patients indirectly care about because these factors may reflect the location, size and the newness of the facility. Since we do not control for these two 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. Altogether, these three arguments suggest that p_j^m should be correlated with private-pay price, and largely uncorrelated with ξ_j.[25]

It is worth discussing why we do not use the standard instruments in the demand estimation literature proposed by Berry (1994) and Berry, et al. (1995) (BLP), i.e., the observable characteristics of other nursing homes, X_{-j}. 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 takes into account other nursing homes' characteristics when setting its price. In standard oligopolistic markets, the latter is a natural assumption to make. But the nursing home market is regulated by the CON law, which impedes competition by restricting new entry, and potentially led to excess demand in many counties during the 90s.[26] Therefore, compared with p_j^m , we expect that X_{-j} would likely be weaker instruments here.[27]

5.4. 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

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

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[25] By regressing p_j on p_j^m and controlling for nursing home characteristics, the coefficient of p_j^m is 0.642 and significant at 1% level.

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

[27] In appendix B, we re-estimate our model using BLP instruments. Our estimation results remain largely robust.

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 appendix A, we provide more details about how to implement our estimation procedure.

TABLE 4: Estimation Results

	Parameters	Estimates	SE	Significance
Price (α)	Base	-4.008	(0.846)	***
Price (α_*female*)	Female	0.323	(0.060)	***
Quality (κ)	Medicaid (multiplier)	0.558	(0.059)	***
Distance (λ)	Different County	-5.837	(0.156)	***
Base constant ($\bar{\gamma}$)	Private-pay, Male 65-85, govt. owned	-8.094	(0.647)	***
Dummies (γ_r)	Female >85	5.572	(0.570)	***
	Female 65-85	0.112	(0.040)	***
	Male >85	2.754	(0.067)	***
	Medicaid	-3.794	(0.083)	***
	Medicaid x Rural	0.496	(0.139)	***
	Medicaid x Not-for-profit	-0.227	(0.093)	**
	Medicaid x For-Profit	-0.252	(0.094)	***
Quality (β)	Registered Nurse Hours per Bed	0.127	(0.042)	***
	Licensed Practical Nurse Hours per Bed	0.075	(0.047)	
	Nurse Assistant Hours per Bed	0.073	(0.015)	***
	Certified Medication Aid Hours per Bed	0.163	(0.123)	
	Therapeutic Service Staff Hours per Bed	0.130	(0.049)	***
	Other Service Staff Hours per Bed	0.014	(0.011)	
	Log(#Beds)	1.186	(0.147)	***
	Milwaukee	-1.709	(0.170)	***
	Rural	0.744	(0.142)	***
	Not-for-profit	0.448	(0.144)	***
	For-profit	0.191	(0.146)	
	Wand (utilizes formal wandering precautions)	-0.043	(0.158)	
	CBRF (community-based residential facility)	0.168	(0.120)	
	Hospital (operated with a hospital)	-0.275	(0.154)	*
	JCAHO (Joint Commission on Accreditation of Health Care Organizations)	0.153	(0.125)	
	HMO (operated with a HMO)	0.255	(0.109)	**
	Lock (has a lock unit)	-0.137	(0.187)	
	Hospice (offers hospice services)	0.020	(0.089)	

Alzheimer (units for Alzheimer patients)	-0.025	(0.098)	
Percentage of Patients younger than 65	-3.149	(0.584)	***

Notes:
* - t-statistics > 1.65; ** - t-statistics > 1.96; *** - t-statistics > 2.58

6. Results

As pointed out by Nyman (1988a, p.82), even with excess demand, normal turnover means that most homes have some empty beds regardless of demand conditions. Moreover, nursing homes may prefer to reserve some empty beds for private-pay patients. Therefore, instead of using 100% of existing beds as the capacity constraint, we follow Gertler (1992, p.339), and assume that nursing homes with more than 95% occupancy rates face excess demand. If the actual observed demand is above 95%, we will attribute it to the error term in the moment conditions.[28] In appendix C, we also estimate the model with alternative cutoffs: 91%, 93%, 97%, and 99% (Table C1). The results are quite similar to those using the 95% cutoff. In fact, the model with the 95% cutoff produces slightly better fit compared with others based on the mean absolute percentage error (MAPE) (see Table C2).

6.1. Parameter Estimates

The estimation results are presented in table 4. 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 observable characteristics, such as age, sex, and payment type. Recall that the base intercept term, $\bar{\gamma}$, corresponds to private-pay male patients aged 65-85. As expected, patients older than 85 tend to value nursing home care more than patients aged 65-85. Male 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 male younger patients have relatively better health conditions than other groups of patients.

[28] Specifically, in our estimation algorithm, we assume that a nursing home will stop admitting Medicaid patients once its occupancy rate reaches 95%.

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 females 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 the fact that elderly men are more likely 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 care 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 0.56. 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, suggesting that patients prefer living in a larger nursing home. This may be because a larger nursing home can provide more activities, or give patients more opportunities to make friends. Quality varies by location and by ownership type. The quality of nursing homes in Milwaukee County tends to be lower, while that in rural counties tends to be higher. 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; and nursing homes focusing more on patients younger than 65 generate less utility for older patients.

6.1.1. Goodness-of-fit

Although our model is quite parsimonious, it fits the data reasonably 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. As mentioned above, when simulating the predicted demand, we assume that the capacity constraint is binding when the occupancy rate reaches 95%. Column (1) reports the mean value of micro-moments across nursing homes; column (2) shows the mean value of predicted moments; column (3) reports the differences between columns (1) & (2); column (4) calculates the correlation coefficients between 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 fits these micro-moments fairly well 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	33.63	-0.01	0.82
Female 65-85	23.05	22.97	-0.08	0.85
Male >85	8.53	8.51	-0.02	0.76
Private-Pay, Female	15.12	15.12	0.00	0.98
Medicaid	57.83	57.68	-0.15	0.93
Different County	13.16	13.14	-0.02	0.39
Medicaid, Rural	36.86	36.75	-0.11	0.96
Medicaid, Not-for-profit	21.61	21.54	-0.08	0.99
Medicaid, For-profit	25.56	25.49	-0.07	0.95
Occupancy Rate	0.87	0.87	0.00	0.49

Our model predicts the number of nursing home patients to be 22,495, which is very close to the actual number, 22,555. If we count nursing homes with more than 95% occupancy rate to face binding capacity constraints, our model correctly predicts close to 70 percent of nursing homes with binding constraints in the data. In total, 207 nursing homes are predicted to be binding, and they are distributed across 52 counties. This implies that around 73.2 percent of the 71 counties in Wisconsin have at least one binding nursing home. Moreover, 41 counties have more than 50 percent of nursing homes that are binding; 10 counties have 25 to 50 percent of nursing homes binding; and 20 counties have less than 25 percent of nursing homes binding.

6.1.2. External Validation

There are a number of studies which have found evidence that for-profit nursing homes provide lower quality of care than not-for-profit nursing homes (Hillmer, et al. 2005). To check if our results lead to sensible quality measures, we compare our estimated Q_j of for-profit, not-for-profit and government owned nursing homes.

Figure 1. Distribution of Quality Index by Nursing Home Ownership

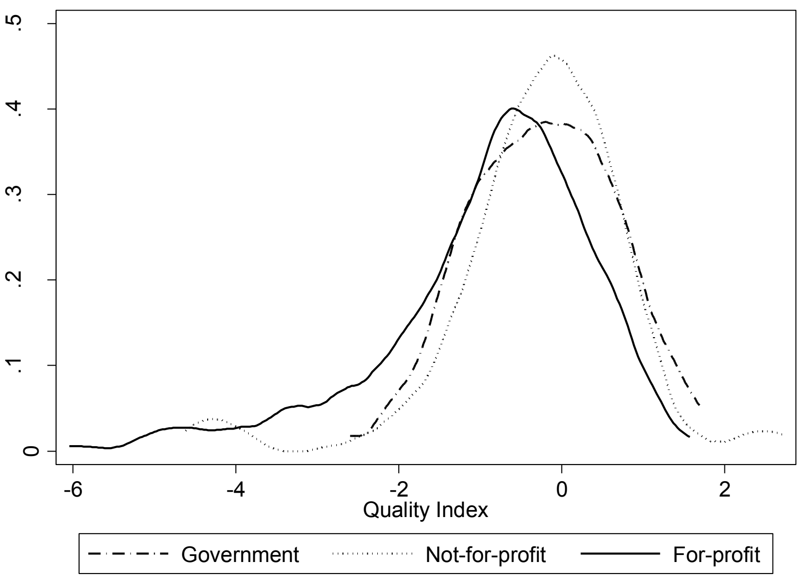


Figure 1 shows that the mode of the distribution of Q_j of for-profit nursing homes is on the left side of those of not-for-profit and government owned nursing homes. On average, Q_j's of for-profit nursing homes are lower than those for not-for-profit and government owned nursing homes. This is consistent with the findings from the health service research literature.[29]

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 would be the potential welfare gain if all the rationed demand were fulfilled at prevailing prices, Medicaid reimbursement rates and qualities in 1999? What role does the unobserved component of quality play in explaining the market demand? How is excess demand correlated with market outcomes, such as price and quality? How do price and quality changes affect private-pay demand and

[29] Another way to provide external validation is to compare our estimated quality ranking with the ranking published by government agencies. Unfortunately, we cannot find publicly available nursing home rankings (or quality disclosure information) back in the late 1990s or early 2000s.

Medicaid demand?

6.2.1. The extent of rationing, and potential welfare impacts due to capacity constraints

To quantify the extent of rationing at *prevailing private-pay prices and qualities*, we simulate the model by assuming that there is no capacity constraint for nursing homes. Under this environment, our estimated model predicts that 27,844 Medicaid patients would demand nursing home care. Given that the actual number of Medicaid patients residing in nursing homes is 22,555 in 1999, this implies that 19.2 percent of patients qualified for Medicaid eventually chose the outside option because their preferred nursing homes reached their capacity constraints. Our simulation result also reveals that 7,186 Medicaid patients were not able to enter their first-choice nursing homes, which is about 25.8 percent of the Medicaid patients who wanted to enter nursing homes.

The next question we ask is what the potential welfare gain would be if all nursing home demand were fulfilled at prevailing private-pay prices, Medicaid reimbursement rate, and qualities in 1999. In order to answer this question, we compute the consumer surplus under the actual environment, and the counterfactual environment where nursing homes have no capacity constraints. For each consumer, we use the closed form formula in McFadden (1981) and Small and Rosen (1981) to compute consumer surplus. Under the counterfactual environment, the consumer surplus for each consumer is,

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

where

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

The total consumer surplus can be expressed as,

(18) $$E[TCS^m] = M^m \int_i E[CS_i^m] dF_i^m$$

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

Under the actual 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/her consumer surplus is,

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

The total consumer surplus is,

(20)
$$E[TCS_R^m] = \sum_r M_r^m \int_i E[CS_{i,r}^m]dF_i^m$$

where M_r^m is defined in section 3.4.

If we assume that 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 $1.23 million per day or $470 million per year. On the other hand, in order to cover more Medicaid patients in the counterfactual experiment, the total government expenditure would need to increase by $203(=1,014-811) million, at the existing Medicaid reimbursement rates.[30] Therefore, this exercise suggests that the net welfare gain of this policy experiment would be $267(=470-203) 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 quite unlikely because Medicaid patients should have much lower income than private-pay patients. Since Medicaid patients do not pay at all for nursing home care, we are not able to estimate their price coefficients. But we can still interpret the net welfare gain calculated above as an upper bound (assuming that Medicaid patients are more price-sensitive). In fact, removing the capacity constraints could result in net welfare loss. If the Medicaid patient's marginal utility of income is twice of the private-pay patient's, the net welfare gain under this counterfactual experiment would only be $32(=470/2-203) million per year. If the Medicaid patient's marginal utility of income is three times of the private-pay patient's, we would have net welfare *loss* of $46(=203-470/3) million per year. Obviously, we

[30] In the actual environment, the total annual government expenditures on nursing homes is $881 million in Wisconsin; in the counterfactual environment, the total annual expenditures would increase to $1,014 million.

cannot use our estimation results to pinpoint the welfare consequence of removing capacity constraints. But if future research can uncover the marginal utility of income for Medicaid patients, it could be combined with our model to provide better guidance on welfare implications.

It should be noted that our analysis above assumes that all structural parameters of consumer preferences remain unchanged when patients are allowed to enter nursing homes freely at the prevailing prices and quality of care. But recall that the Medicaid dummy for utility intercept is estimated to be negative, and this could reflect inconvenient costs due to rationing (or the psychological costs due to 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.

Another potential shortcoming is that patients may prefer a nursing home where their friends live. The perceived quality estimate may include this network effect because it is not being explicitly modeled here. Therefore, under the counterfactual environment, it is possible that the quality measure may also change (if some people belonging to friends' networks were rationed out in the actual environment). However, it is worth reiterating that most of the nursing home patients are above 85, and there is evidence which suggests older nursing homes patients (above 65) tend to suffer social isolation (British Columbia Ministry of Health, 2004). As a result, the nursing home patients focused in our study may not value friendship as much as the younger population.

Besides the two limitations mentioned above, it is clear that the analysis conducted here is a partial equilibrium analysis. If the capacity constraints were removed, nursing homes may choose to provide different quality of care, and change their prices accordingly. If one wants to conduct a general equilibrium analysis, it is important to model the supply side explicitly. Modeling the supply side for the nursing home market is very challenging. Allowing quality and price to be endogenous would mean that we need to know the cost function in terms of quality as well. Even if we are willing to pick a functional form and estimate such a marginal cost function, it should be noted that the parameters of this marginal cost function may not be stable under the counterfactual experiment. When there is no capacity constraint, it is likely that more patients would choose to use nursing home care. Recall that we model Q_j as a function of different types of nurse inputs, and there are minimum nurse input requirements. Hence, to keep up the quality, nursing homes would likely need to hire more nurses. Due to the shortage in the supply of nurses, this would probably drive up their wages, and hence change the structure of the marginal cost function.

Even if we assume that Q_j's are fixed, and only consider prices to be endogenous (e.g., Bertrand equilibrium), we still encounter a complication that some nursing homes face binding capacity constraints, and hence marginal cost does not appear in their first order conditions (FOCs) for price – instead, it is the Medicaid reimbursement rate that enters it (Gertler, 1992). Therefore, we cannot use the FOCs to obtain the marginal costs for nursing homes that face excess demand. Without knowing the marginal costs for a subset of nursing homes, we will not be able to simulate the new equilibrium prices and private-pay demand.[31]

6.2.2. The Importance of Unobserved Quality

Our approach allows us to separate observed quality component ($X_j\beta$) from the unobserved quality component (ξ_j). The unobserved quality accounts for almost 40% of the variation in Q_j, which suggests that the unobserved component of quality can play an important role in explaining patients' demand. To further investigate this, we simulate the demand by excluding ξ_j. The results are reported in table 6.

[31] But if we are willing to assume Q_j's and Medicaid reimbursement rates are fixed, our counterfactual welfare analysis would still be valid because the demand of Medicaid patients is independent of p_j's under the counterfactual environment.

Table 6a. Baseline vs. Model without Unobservable Quality (ξ): Fitness of Micro-moments

	Baseline		Without ξ	
	Correlation	MAPE*	Correlation	MAPE*
	(1)	(2)	(3)	(4)
Female >85	0.82	0.35	0.76	0.43
Female 65-85	0.85	0.28	0.81	0.36
Male >85	0.76	0.43	0.71	0.50
Private-Pay, Female	0.98	0.16	0.66	0.62
Medicaid	0.93	0.15	0.94	0.16
Different County	0.39	1.35	0.36	1.37
Medicaid, Rural	0.96	0.09	0.97	0.10
Medicaid, Not-for-profit	0.99	0.04	0.99	0.04
Medicaid, For-profit	0.95	0.09	0.96	0.10
Occupancy Rate	0.49	0.05	0.09	0.09
Private-pay Patients	1.00	0.00	0.67	0.59

* Mean absolute percentage error (MAPE) for micro moment t is calculated as $MAPE_t = \frac{1}{J}\sum_j \left|\frac{\mathbf{n}_{t,j} - n_{t,j}(\theta)}{\mathbf{n}_{t,j}}\right|$, where $\mathbf{n}_{t,j}$ is the actual number of type t patients in nursing home j, and $n_{t,j}(\theta)$ is the predicted number of type t patients in nursing home j, given the set of parameter estimates θ.

Table 6b. Baseline vs. Model without Unobservable Quality (ξ): Aggregate Demand

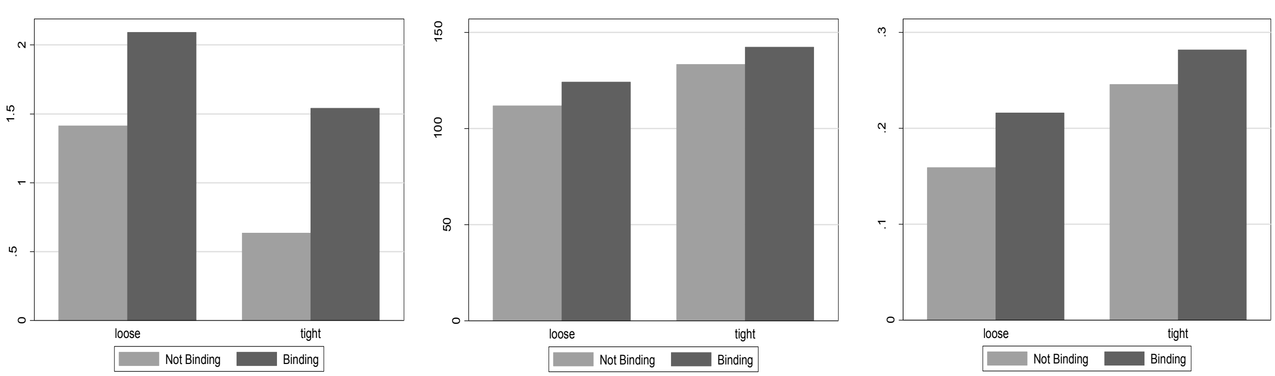
Row		Baseline	Without ξ
		(1)	(2)
1	Total # of Private-pay patients in the data	8607	8607
2	Total # of Private-pay patients predicted by the model	8607	8310
3	Total # of Medicaid patients in the data	22555	22555
4	Total # of Medicaid patients predicted by the model	22495	23123
5	Total # of Medicaid if there is no constraint	27844	26930
6	Percentage of Medicaid patients who got rationed out (row 5- row 4)/row 5	19.20%	14.41%
7	# of Medicaid patients who cannot enter their first choice nursing homes	7186	4981
8	Percentage of MCD patients who cannot enter their first choice nursing homes (row 7/row 5)	25.80%	18.50%

The model without ξ generates a worse fit than the baseline model (Table 6a), and underestimates the extent of excess demand (14.4% vs. 19.2%, Row 6 of Table 6b). It is worth pointing out that without ξ, the model predicts that there would be slightly more Medicaid patients (23,123 vs. 22,495). This is because (i) the quality ranking has changed, and some patients would choose to enter nursing homes which used to have large excess capacity; and (ii) the private-pay demand drops and it frees up some beds for Medicaid patients. In particular, the number of Medicaid patients who cannot enter their first choice nursing homes drops from 7,186 to 4,981. These results indicate that the unobserved quality component is playing a crucial role and excluding it could lead to very misleading inferences.

6.2.3. Quality, Price and Excess Demand

The relationship between excess demand 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, previous studies ignored the unobserved component of quality. Moreover, our approach could allow us to better identify which nursing homes face excess demand. Having estimated our model, we are able to shed more light on the relationship between excess demand and market outcomes.[32]

Figure 2. Comparison between Nursing Homes with and without Binding Constraints



(a) (b) (c)

[32] It is important to highlight that we are only showing correlation here. But we hope these patterns will be useful for future research to model the market outcomes in the nursing home industry.

In Figure 2, we group counties according to their bed supply: A "tight" county is a county where the number of beds per 100 potential patients in the county is less than 20;[33] the remaining counties are loose counties. Within each county, we refer nursing homes with predicted occupancy rates higher than 95% to "binding nursing homes", and the rest to "non-binding nursing homes." Among the 35 tight counties, there are 117 binding nursing homes and 89 non-binding nursing homes; among the 36 loose counties, there are 90 binding nursing homes and 94 non-binding nursing homes. 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,

$$Markup_j = \frac{p_j - p_j^m}{p_j^m}, \tag{21}$$

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 earn higher markups than nursing homes in the loose counties. Second, within each type of counties, binding nursing homes provide higher quality of care, charge higher private-pay price, and earn higher markups than the non-binding nursing homes. All of these comparisons are statistically significant at the 5% level. Our findings are consistent with previous studies which argue that nursing homes have incentives to provide low quality of care and high prices when the supply of nursing homes 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. Price and quality elasticity of demand

Table 7 presents the effects of price changes on private-pay demand. In column 1, the average own-price elasticities of private-pay demand are reported. For the overall sample, the model estimates imply that a 1 percent increase in the private-pay price would lead to about a 4.5 percent fall in private-pay demand for the nursing home. Moreover, female patients are more likely to stay in the same nursing homes than male patients when facing a price increase.

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

TABLE 7: 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	-4.56	(0.77)	43.4%	(5.39%)	25.9%	(9.80%)
Male 65-85	-5.01	(0.82)	3.6%	(1.25%)	2.4%	(1.31%)
Male >85	-4.86	(0.85)	35.0%	(7.65%)	22.4%	(9.21%)
Female 65-85	-4.60	(0.75)	5.9%	(1.88%)	4.0%	(2.05%)
Female >85	-4.26	(0.82)	92.2%	(2.59%)	53.0%	(17.51%)

Note:
Standard deviation across nursing homes reported in brackets.

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

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

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 7 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 (65-85), the elderly patients 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 7 shows that about 25.9 percent of private-pay patients who leave their nursing home due to a price increase would move to one of the nursing homes within the same county. This implies approximately 60 percent (25.9/43.4) 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 8. 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 would need to be reduced as a result of more private-pay patients (because private-pay patients are admitted first). 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 in 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 Medicaid patients.

TABLE 8: Effects of Quality Changes on the Number of Medicaid Patients

	Own		NHs without constraints		NHs with constraints	
All	-1.81	(3.62)	0.51	(0.79)	-3.20	(3.93)
Male 65-85	-2.11	(3.72)	0.44	(0.84)	-3.64	(3.93)
Male >85	-1.55	(3.57)	0.57	(0.75)	-2.82	(3.97)
Female 65-85	-1.88	(3.67)	0.51	(0.79)	-3.31	(3.97)
Female >85	-1.54	(3.57)	0.58	(0.75)	-2.80	(3.97)

Note:

Standard deviation across nursing homes reported in brackets.

6.3. Other limitations

It should be pointed out that some private-pay patients may eventually become Medicaid patients as they use up their savings. Therefore, the distinction between private-pay patients and Medicaid patients may not be as clear cut as our model suggests, and some Medicaid patients observed in our data set may initially be admitted as private-pay patients. This raises the question whether we are using the "right" patient-mix to estimate the model. If the probability that private-pay patients become Medicaid patients is homogeneous across nursing homes, then the quality index inferred from our data set should remain robust, although the intercept term for private-pay patients would likely be biased downwards (and the intercept for Medicaid patients would likely be biased upwards).

To our knowledge, nursing homes are allowed to ask for information about income and savings of applicants.[34] It is conceivable that nursing homes may use this information to help determine who to admit first. In particular, based on income information, a nursing home can predict approximately how long a patient can remain as private-pay. If they expect a patient to become eligible for Medicaid soon, they can choose to put them on the wait list (or ration them out). Interestingly, as Ettner (1993, p.272) argues, "low-income persons who do not yet have Medicaid coverage are likely to have poor access to nursing home care if nursing home operators plan ahead and are reluctant to admit patients who will quickly spend down to Medicaid. … This 'transition group' may even have poorer access to care than persons on Medicaid, if the nursing home operators are afraid that these patients will run out of money before Medicaid benefits begin." Note that even not-for-profit and government nursing homes are required to recover costs. Hence, it seems plausible that most nursing homes would take this factor into account. This could help alleviate the concern that the observed patient-mix may not accurately represent the one faced by nursing homes when they decide admission.

The argument above by no means rules out the potential significance of the transition group. If we do observe market shares for other types of patients who were admitted as private-pay and then became

[34] http://www.delaneylawoffices.com/PracticeAreas/NursingHomeContracts.aspx, accessed on May 8, 2014.

Medicaid within a short window, we can introduce another type of "semi-private-pay" patients who also care about price, and these would be given second priority with respect to being admitted by nursing homes. It is theoretically straightforward to extend our model to take extra types of consumers into account.[35]

Our model also abstracts away the possibility that nursing homes may select patients based on the level of care expected, and hence capacity constraints may bind differentially for different levels of care. Since the Medicaid reimbursement rate is fixed, a nursing home may be able to earn higher profits by admitting a relatively healthier patient.[36] To address this, we would need to observe the distribution of finer health status in the population by county, and those admitted into nursing homes. Unfortunately, we are only able to observe two types of health status in the population by county: (i) good/excellent, (ii) fair/poor. Moreover, we do not observe the distribution of health for patients who received skilled care (which is the most common category). If these finer levels of data are available, it is possible to extend our model to take them into account. On the other hand, if the health status is fairly homogeneous for the population who requires skilled care, then this type of nursing home's behavior may not be a serious concern.

7. Conclusion

In this paper, we offer an alternative approach to estimate consumer preference parameters when excess demand is common for many products. We apply our approach to analyze the nursing home market. The estimated model enables us to answer some of the questions that previous studies cannot tackle. 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 examine the relationship between excess demand and market outcomes.

[35] We do need to set their order of admission a priori, based on their income level. Using Census information we can calibrate the potential size of each type of consumer.

[36] Interestingly, using data in North Carolina, Weissert and Cready (1988) find *no* evidence that nursing homes select patients for admission based on the level of care expected.

The results suggest that (i) nearly 20 percent of potential patients who qualified for Medicaid are rationed out for nursing home care; and (ii) about 26 percent of Medicaid nursing home patients did not enter their first-choice nursing homes (but most of those patients likely 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 place a significant burden on the state budget. We also demonstrate 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 binding nursing home raises its quality.

As mentioned before, our study assumes nursing home quality to be exogenous 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 in time, it is certainly a limitation if one is interested in understanding the long run equilibrium. To understand any long-term market outcomes, it is important to explicitly model quality choice taking adjustment costs into account. Lin (2014) has taken a first step towards this research direction by developing a dynamic oligopoly structural model. However, such a model is very computationally intensive to solve, and therefore she abstracts away the potential rationing problem on the demand side, and simply uses a reduced form profit function 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, and use it to study the long-term impact of government regulations.

We hope that the identification strategy proposed here can be extended to study other markets where capacity constraints are hard to expand in the short run, and hence excess demand may exist, e.g., condo, school, concerts, hospitals, etc. We should highlight that three key ideas of our identification argument are: (i) one needs to observe different types of consumers for which the firms give different orders of priority in selling their products or providing their services; (ii) at least one type of consumer does not face rationing; and (iii) there exists vertical differentiation in terms of quality. For school admission, we often see that students with the strongest scores are admitted first. The top students can essentially choose to enter their first choice, but the next tier of students may end up at their second or third choice. For many sought-after events in music, theatre, or dining, some preferred customers are able to purchase tickets and reserve seats before these events go on sale to the general public.[37] For condo purchases, some VIP real estate agents are able to access new condos before they are made available to the general public. For hospitals, the most severely ill patients would also tend to have priority for admission. These markets share some similarities to the nursing home market analyzed here. It is clear that some important modifications would have to be made in order to extend our identification strategy to other markets. We hope future research will explore this research direction further.

[37] For example, American Express card holders can enjoy their "Front of the Line" privilege.

Appendix

A. Estimation

Following the notation in the text, denote:

$$\theta_1 = (\alpha_{female}, \gamma_{male\_>85}, \gamma_{female\_65\text{-}85}, \gamma_{female\_>85}, \lambda),$$

$$\theta_2 = (\kappa, \gamma_{\text{medicaid}}, \gamma_{medicaid,\ \text{rural}}, \gamma_{\text{medicaid},for-profit}, \gamma_{medicaid,not-for-profit}),\ \text{and}$$

$$\theta_3 = (\overline{\alpha}, \overline{\gamma}, \beta).$$

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

(A1) $$\delta_j = \overline{\gamma} + \overline{\alpha} p_j + Q_j = \overline{\gamma} + \overline{\alpha} p_j + X_j \beta + \xi_j.$$

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 $s_j^p(\cdot)$ is a vector of predicted market shares in the private-pay market.[38] Following Berry, et al (1995), we use the following contraction mapping function,

(A2) $$f(\delta_j) = \delta_j + \ln \mathbf{s}_j^p - \ln s_j^p(\delta_j, \theta_1).$$

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 1 as 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), $\hat{\theta}_3$ can be expressed as a function of θ_1,

[38] Refer to equation (6) and (7) in Section 3.4 for the formulas of predicting private-pay market share.

(A3) $$\hat{\theta}_3 = (X'_p Z\Phi^{-1}Z'X_p)^{-1} X'_p Z\Phi^{-1}Z'\delta_j(\theta_1),$$

where Φ is the weighting matrix.[39] Estimate of ξ can be expressed as,

(A4) $$\hat{\xi}(\hat{\theta}_3(\theta_1), \delta_j(\theta_1)) = \delta_j(\theta_1) - X_p\hat{\theta}_3(\theta_1),$$

and BLP moments are calculated as,

(A5) $$g_1(\theta_1) = Z'\hat{\xi}(\hat{\theta}_3(\theta_1), \delta_j(\theta_1)).$$

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

We use $t \in (1,\ldots,T)$ 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,

(A6) $$n_{t,j}(\theta) = M^p \int_{i\in t} \text{Prob}_{ij}^p dF_{i\in t}$$

for private-pay patients, and

(A7) $$n_{t,j}(\theta) = \sum_{r=1}^{R} M_r^m \int_{i\in t} \text{prob}_{ij,r}^m dF_{i\in t}$$

for Medicaid patients. The micromoments are constructed as follows,

(A8) $$g_2(\theta) = \frac{1}{J}\sum_j [\mathbf{n}_{t,j} - n_{t,j}(\theta)],$$

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

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

A.3. GMM estimator

Collect all moments

(A9) $$g(\theta)=\begin{bmatrix} g_1(\theta_1) \\ g_2(\theta) \end{bmatrix} .$$

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 $\hat{\theta}^{(1)}$

(A10) $$\hat{\theta}^{(1)}=\arg\min_{\theta\in\Theta} g(\theta)' g(\theta) \ .$$

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

(A11) $$\hat{\Omega}=\frac{1}{J}\sum_{i=1}^{J} g^{j}(\hat{\theta}^{(1)}) g^{j}(\hat{\theta}^{(1)})' ,$$

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

(A12) $$\hat{\theta}=\arg\min_{\theta\in\Theta} g(\theta)'\hat{\Omega}^{-1} g(\theta) \ .$$

B. Sensitivity Analysis Using Alternative Instruments

In this appendix section, we compare our baseline model using Medicaid reimbursement rate as instrument with the one using instruments suggested by Berry, Levinsohn, and Pakes (1995) (BLP). BLP (1995) propose to use the mean observable characteristics of competitors (X_{-j}) as the instruments for price. Here, we assume that only nursing homes in the same county are considered to be the *close* competitors (justified by their higher cross-price elasticities). More specifically, the BLP instruments are constructed as follows:

$$X_{-j,c} = \frac{1}{K_c} \sum_{k \in J^c, k \neq j} X_{k,c} \,, \tag{B1}$$

where c denotes counties; $J^c = \{1, \ldots, K_c\}$ is the set of nursing homes in county c.

Table B1 reports the comparison results. BLP instruments in our context include average competitors' nurse hours inputs and the nursing home attributes that are statistically significant in Table 4. The coefficients on private-pay price ($\overline{\alpha}$) are significantly negative in all specifications. However, the model that treats private-pay price as exogeneous (column 1) shows the smallest magnitude (-1.637). When using the BLP instruments, the magnitude of the price coefficient increases to -3.884. When using Medicaid reimbursement rate as an instrument, the price coefficient further increases to -4.008. Therefore, the results reported in our paper remains largely robust even if we switch to BLP instruments.

Table B1. Comparison Using Different Instruments: Full Model

Choice of Cutoffs	No IV			Baseline IV: P^m			BLP IV: X_{-j}		
	(1)			(2)			(3)		
Parameters	Est.	SE		Est.	SE		Est.	SE	
Price (α)	-1.637	(0.233)	***	-4.008	(0.846)	***	-3.884	(0.675)	***
Price (α_female)	0.362	(0.048)	***	0.323	(0.060)	***	0.321	(0.056)	***
Medicaid (multiplier, κ)	1.183	(0.085)	***	0.558	(0.059)	***	0.620	(0.041)	***
Different County (λ)	-6.397	(0.677)	***	-5.837	(0.156)	***	-5.796	(0.169)	***
Private-pay, Male 65-85	-8.906	(0.515)	***	-8.094	(0.647)	***	-8.146	(0.608)	***
Constant (γ_r)									
Female Old	6.779	(0.490)	***	5.572	(0.570)	***	5.371	(0.456)	***
Female Young	0.117	(0.040)	***	0.112	(0.040)	***	0.111	(0.038)	***
Male Old	3.228	(0.060)	***	2.754	(0.067)	***	2.711	(0.064)	***
Medicaid	6.550	(0.173)	***	-3.794	(0.083)	***	-3.606	(0.091)	***
Medicaid x Rural	-1.696	(0.432)	***	0.496	(0.139)	***	0.421	(0.143)	***
Medicaid x Not-profit	-5.353	(0.725)	***	-0.227	(0.093)	**	-0.238	(0.097)	**
Medicaid x Profit	-4.906	(0.775)	***	-0.252	(0.094)	***	-0.196	(0.109)	*
Quality (β)									
Registered Nurse Hours per Bed	0.046	(0.032)		0.127	(0.042)	***	0.124	(0.039)	***
Licensed Practical Nurse Hours per Bed	-0.007	(0.036)		0.075	(0.047)		0.072	(0.044)	
Nurse Assistant Hours per Bed	0.065	(0.013)	***	0.073	(0.015)	***	0.072	(0.015)	***
Certified Medication Aid Hours per Bed	-0.035	(0.100)		0.163	(0.123)		0.158	(0.116)	
Therapeutic Service Staff Hours per Bed	0.120	(0.045)	***	0.130	(0.049)	***	0.129	(0.049)	***
Other Service Staff Hours per Bed	0.015	(0.010)		0.014	(0.011)		0.014	(0.010)	
Log(Beds)	0.820	(0.091)	***	1.186	(0.147)	***	1.174	(0.129)	***
Milwaukee	-2.087	(0.134)	***	-1.709	(0.170)	***	-1.709	(0.159)	***
Rural	1.165	(0.097)	***	0.744	(0.142)	***	0.749	(0.128)	***
Not-for-profit	0.392	(0.130)	***	0.448	(0.144)	***	0.444	(0.141)	***
For-profit	0.092	(0.130)		0.191	(0.146)		0.186	(0.142)	
Wand (utilizes formal wandering precautions)	-0.077	(0.145)		-0.043	(0.158)		-0.045	(0.156)	
CBRF (community-based residential facility)	0.122	(0.110)		0.168	(0.120)		0.168	(0.118)	
Hospital (operated with a hospital)	-0.143	(0.136)		-0.275	(0.154)	*	-0.270	(0.150)	*
JCAHO (Joint Commission on Accreditation of Health Care Organizations)	0.065	(0.112)		0.153	(0.125)		0.150	(0.122)	
HMO (operated with a HMO)	0.099	(0.087)		0.255	(0.109)	**	0.247	(0.102)	**
Lock (has a lock unit)	-0.192	(0.170)		-0.137	(0.187)		-0.143	(0.184)	

Hospice (offers hospice services)	0.041	(0.081)		0.020	(0.089)		0.022	(0.088)	
Alzheimer (units for Alzheimer patients)	0.074	(0.087)		-0.025	(0.098)		-0.023	(0.096)	
Percentage of Young Patients	-3.731	(0.515)	***	-3.149	(0.584)	***	-3.163	(0.568)	***

Notes:

Column (1) reports the OLS results using no instrument. Column (2) uses Medicaid reimbursement rate to instrument the private-pay price. Column (3) uses the characteristics of competing nursing homes (X_{-j}) to instrument the private-pay price. In column (3), the X_{-j} contains all nursing hours measures plus the characteristics that are significant in our full structural model (see Table 4).

Standard errors are in ( ). * significant at the 10 percent level. ** significant at the 5 percent level.*** significant at the 1 percent level.

C. Sensitivity Analysis Using Different Cutoff Occupancy Rates to Define Capacity Constraints

Table C1. Parameter Estimates Using Different Cutoffs to Define Capacity Constraints

Cutoffs	OR = 99%			OR = 97%			OR = 95%			OR = 93%			OR = 91%		
	Est.	SE		Est.	SE		Est.	SE		Est.	SE		Est.	SE	
Price (α)	-4.007	(0.845)	***	-4.006	(0.845)	***	-4.008	(0.846)	***	-4.013	(0.846)	***	-4.130	(0.861)	***
Price (α_female)	0.323	(0.056)	***	0.323	(0.057)	***	0.323	(0.060)	***	0.322	(0.057)	***	0.351	(0.053)	***
Medicaid (multiplier, κ)	0.641	(0.050)	***	0.602	(0.052)	***	0.558	(0.059)	***	0.505	(0.062)	***	0.457	(0.077)	***
Different County (λ)	-5.836	(0.165)	***	-5.835	(0.182)	***	-5.837	(0.156)	***	-5.845	(0.183)	***	-5.996	(0.294)	***
Private-pay, Male 65-85 (γ_bar)	-8.092	(0.647)	***	-8.094	(0.647)	***	-8.094	(0.647)	***	-8.092	(0.648)	***	-8.041	(0.659)	***
Constant (γ_r)															
Female Old	5.546	(0.490)	***	5.556	(0.492)	***	5.572	(0.570)	***	5.613	(0.499)	***	6.161	(0.538)	***
Female Young	0.112	(0.037)	***	0.112	(0.037)	***	0.112	(0.040)	***	0.113	(0.036)	***	0.116	(0.036)	***
Male Old	2.744	(0.061)	***	2.748	(0.061)	***	2.754	(0.067)	***	2.767	(0.061)	***	3.055	(0.070)	***
Medicaid	-3.753	(0.079)	***	-3.770	(0.091)	***	-3.794	(0.083)	***	-3.842	(0.097)	***	-4.217	(0.148)	***
Medicaid x Rural	0.420	(0.144)	***	0.455	(0.158)	***	0.496	(0.139)	***	0.564	(0.168)	***	0.744	(0.275)	***
Medicaid x Not-profit	-0.312	(0.091)	***	-0.276	(0.098)	***	-0.227	(0.093)	**	-0.128	(0.126)		1.993	(0.477)	***
Medicaid x Profit	-0.213	(0.097)	**	-0.230	(0.096)	**	-0.252	(0.094)	***	-0.284	(0.112)	**	-0.336	(0.126)	***
Quality (β)															
Registered Nurse Hours per Bed	0.127	(0.042)	***	0.127	(0.042)	***	0.127	(0.042)	***	0.127	(0.042)	***	0.126	(0.043)	***
Licensed Practical Nurse Hours per Bed	0.075	(0.047)		0.075	(0.047)		0.075	(0.047)		0.075	(0.047)		0.077	(0.048)	
Nurse Assistant Hours per Bed	0.073	(0.015)	***	0.073	(0.015)	***	0.073	(0.015)	***	0.073	(0.015)	***	0.074	(0.015)	***
Certified Medication Aid Hours per Bed	0.164	(0.123)		0.163	(0.123)		0.163	(0.123)		0.163	(0.123)		0.159	(0.125)	
Therapeutic Service Staff Hours per Bed	0.130	(0.049)	***	0.130	(0.049)	***	0.130	(0.049)	***	0.130	(0.049)	***	0.132	(0.050)	***

Other Service Staff Hours per Bed	0.014	(0.011)		0.014	(0.011)		0.014	(0.011)		0.014	(0.011)		0.015	(0.011)	
Log(Beds)	1.186	(0.147)	***	1.186	(0.147)	***	1.186	(0.147)	***	1.186	(0.147)	***	1.185	(0.149)	***
Milwaukee	-1.708	(0.170)	***	-1.709	(0.170)	***	-1.709	(0.170)	***	-1.712	(0.170)	***	-1.746	(0.173)	***
Rural	0.744	(0.142)	***	0.744	(0.142)	***	0.744	(0.142)	***	0.746	(0.143)	***	0.772	(0.145)	***
Not-for-profit	0.448	(0.144)	***	0.448	(0.144)	***	0.448	(0.144)	***	0.449	(0.144)	***	0.456	(0.147)	***
For-profit	0.191	(0.146)		0.191	(0.146)		0.191	(0.146)		0.191	(0.146)		0.195	(0.149)	
Wand (utilizes formal wandering precautions)	-0.043	(0.158)		-0.043	(0.158)		-0.043	(0.158)		-0.043	(0.159)		-0.041	(0.161)	
CBRF (community-based residential facility)	0.168	(0.120)		0.168	(0.120)		0.168	(0.120)		0.168	(0.120)		0.165	(0.123)	
Hospital (operated with a hospital)	-0.274	(0.154)	*	-0.274	(0.154)	*	-0.275	(0.154)	*	-0.274	(0.154)	*	-0.274	(0.156)	*
JCAHO (Joint Commission on Accreditation of Health Care Organizations)	0.153	(0.125)		0.153	(0.125)		0.153	(0.125)		0.153	(0.125)		0.153	(0.127)	
HMO (operated with a HMO)	0.255	(0.109)	**	0.255	(0.109)	**	0.255	(0.109)	**	0.255	(0.109)	**	0.262	(0.111)	**
Lock (has a lock unit)	-0.137	(0.187)		-0.137	(0.187)		-0.137	(0.187)		-0.136	(0.188)		-0.127	(0.191)	
Hospice (offers hospice services)	0.020	(0.089)		0.020	(0.089)		0.020	(0.089)		0.020	(0.089)		0.018	(0.091)	
Alzheimer (units for Alzheimer patients)	-0.025	(0.098)		-0.025	(0.098)		-0.025	(0.098)		-0.025	(0.098)		-0.021	(0.100)	
Percentage of Young Patients	-3.149	(0.583)	***	-3.149	(0.583)	***	-3.149	(0.584)	***	-3.150	(0.584)	***	-3.166	(0.594)	***

Note:
Standard errors are in brackets . * significant at the 10 percent level. ** significant at the 5 percent level.*** significant at the 1 percent level

Table C2. MAPE* of Micro-moments Using Estimates from Different Cutoffs

Cutoffs	99%	97%	95%	93%	91%
Female >85	0.327	0.337	0.346	0.359	0.498
Female 65-85	0.299	0.292	0.284	0.279	0.353
Male >85	0.433	0.431	0.432	0.432	0.447
Private-Pay, Female	0.157	0.157	0.157	0.157	0.158
Medicaid	0.171	0.159	0.148	0.144	0.146
Different County	1.355	1.351	1.352	1.355	1.365
Medicaid, Rural	0.109	0.101	0.094	0.090	0.088
Medicaid, Not-for-profit	0.051	0.046	0.043	0.042	0.046
Medicaid, For-profit	0.095	0.090	0.086	0.085	0.084
Occupancy Rate	0.059	0.054	0.050	0.048	0.048
Overall	0.306	0.302	0.299	0.299	0.323

*Mean absolute percentage error (MAPE) for micro moment t is calculated as $MAPE_t = \frac{1}{J}\sum_j \left| \frac{\mathbf{n}_{t,j} - n_{t,j}(\theta)}{\mathbf{n}_{t,j}} \right|$, where $\mathbf{n}_{t,j}$ is the actual number of type t patients in nursing home j, and $n_{t,j}(\theta)$ is the predicted number of type t patients in nursing home j, given the set of parameter estimates θ.

D. Payment Type Composition by Nursing Home Ownership

Table D1. Regression of Payment Type Composition on Nursing Home Ownership

Dependent variable:	Number of Medicaid Patients	Number of Private-pay Patients	Percentage of Medicaid Patients	Number of Medicaid Patients	Number of Private-pay Patients	Percentage of Medicaid Patients
	(1)	(2)	(3)	(4)	(5)	(6)
Government	-0.28	-0.566	0.005	0.295	-2.953	0.028
	[3.525]	[2.074]	[0.022]	[4.157]	[2.327]	[0.025]
Not-for-profit	-5.873**	7.462***	-0.056***	-5.971*	7.638***	-0.049**
	[2.667]	[1.569]	[0.017]	[3.147]	[1.762]	[0.019]
NH Characteristics	Y	Y	Y	Y	Y	Y
County FE	N	N	N	Y	Y	Y
R-squared	0.75	0.58	0.36	0.78	0.66	0.46

Note: Other than the ownership dummies, all regression control for the same set of nursing home characteristics as in Table 4. Column (4) to (6) add in county fixed effect as well. Standard errors are in brackets. * significant at the 10 percent level. ** significant at the 5 percent level.*** significant at the 1 percent level.

Columns (3) and (6) show that, government-run nursing homes' patient-mix is similar to for-profit nursing homes'. Moreover, not-for-profit nursing homes actually admit significantly less Medicaid patients, and more private-pay patients compared with for-profit nursing homes. Therefore, while it is plausible that not-for-profit or government nursing homes may have a preference for taking Medicaid patients, we do not find evidence to support this hypothesis. But the results are consistent with our finding that on average not-for-profit nursing homes provide higher quality of care (compared with the for-profit ones), and private-pay patients act first.

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