Congestion-Quality Tradeoff: Evidence from Japanese Long-Term Care Facilities*

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Abstract

Directing consumers to higher-quality service providers has been considered an effective policy to improve service outcomes and consumer welfare in various contexts. However, higher-quality providers may tend to be more congested, and congestion may be detrimental to outcomes and welfare. We study this *congestion-quality tradeoff* and discuss its policy implications in the context of Japanese nursing facilities. We find evidence that (1) *within nursing facilities*, higher occupancy leads to poorer care outcomes but (2) *between nursing facilities*, occupancy and outcome-based quality measures are positively correlated. To evaluate the welfare impact of patient reallocation policy, we then develop and estimate a model of demand for nursing facility care where choice set is potentially constrained in an unobserved manner by providers' rationing behavior. We find that nursing facilities are less likely to admit patients at higher occupancy but no evidence that patients dislike congestion. Simulation of a reallocation policy suggests a potential gain from occupancy smoothing even though the policy sends patients to lower-quality care providers on average.

Keywords: congestion, value added, long-term care, demand estimation, choice constraint, consideration set

JEL Codes: I11, I18.

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1 Introduction

Researchers and policymakers have taken great interest in outcome-based measures of institutional quality in various contexts, such as schools, teachers, hospitals, doctors and nursing facilities. They have documented substantial heterogeneity in quality in these settings,[1] and have suggested that moving service consumers (e.g., students, patients) from a low-quality institution to a high-quality institution will improve outcomes and welfare.[2] Informational interventions have been discussed as a policy tool to achieve such reallocation of consumers and to improve outcomes and welfare.

In many markets with supply constraints, another important determinant of consumer outcomes and welfare is congestion. Higher degree of congestion can increase the likelihood of adverse events such as hospital admission and mortality (Hoe, 2022; Gutierrez and Rubli, 2021), and it can also lead to long wait times for services, which will lower consumer welfare.[3] Moreover, congestion and quality considerations may conflict each other: higher-quality service providers may be more congested, which affects outcomes and welfare negatively.

This paper evaluates such a tradeoff, which we refer to as *a congestion-quality tradeoff*, in the context of Japanese nursing facilities.[4] As in the US skilled nursing facilities, Japanese nursing facilities are typically highly crowded due to regulations on capital investments along with increasing demand due to rapid aging. Universal long-term care insurance with provider reimbursement adjusted to patient[5] severity enables us to focus on congestion-quality tradeoff and omit other concerns such as patient cherry-picking (Gandhi, 2023) from our analysis.

Our research proceeds in three steps. In the first step, we document the effect of conges-

[1]See, for example, Kane and Staiger (2008); Chetty et al. (2014a,b) for quality measures for teachers, Deming (2014); Angrist et al. (2017) for schools, Geweke et al. (2003); Chandra et al. (2016); Hull (2020); Chandra et al. (2023) for hospitals, Einav et al. (2022) for nursing facilities, Abaluck et al. (2021) for health insurance plans, and Chetty and Hendren (2018) for counties.

[2]For example, Einav et al. (2022) document substantial variation in nursing facility value added even within geographic markets and conclude that their finding "points to the potential for substantial gains from within-market reallocation of patients" (p5). Chetty et al. (2014b) illustrate the magnitude of their estimates of teacher quality by evaluating the policy counterfactual of replacing teachers in the bottom 5 percent of the distribution of teacher quality with average teachers.

[3]See Leshno (2022) for a conceptual framework for allocation mechanisms via waiting lists, and Fréchette et al. (2019); Buchholz et al. (2020); Castillo (2022) for empirical evidence for consumers' distaste for waiting. Waiting times also serve as a key allocation mechanism in fixed-price healthcare markets such as the English National Health Service (Moscelli et al., 2021) and the US Veterans Health Administration (Yee et al., 2022).

[4]Below, we refer to nursing facilities simply as "providers."

[5]In this article, we refer to the user of nursing facilities as "patients" rather than "residents."

tion on care outcomes. A key challenge is that bed occupancy (which we use as a measure of congestion) may be endogenous because larger patient volume in more congested facilities may be due to higher quality for producing desirable care outcomes. To address this problem, we exploit variation in the volume of short-stay patients as an exogenous shifter of occupancy faced by long-stay patients. Providers in our setting serve both short-stay patients for respite services and long-stay patients for long-term care using the same capacity, so variation in the volume of the former shifts congestion faced by the latter. Also, short stays typically begin with temporary unavailability of family caregivers or other reasons plausibly unrelated to outcomes of long-stay patients, and end within around 2 weeks, so their fluctuations are unlikely to be directly related to outcomes of long-stay patients. We show evidence that variation in short-stay flows is not systematically related to characteristics and length of stay of long-stay patients. Our baseline results suggest that a 1pp decline in congestion (occupancy) during an episode of stay leads to a 1.3pp (3.8% of baseline) increase in the probability of discharge to home, which is considered a desirable outcome of nursing facility care (Einav et al., 2022), and a 3.1pp (8.3% of baseline) decrease in the probability of hospitalization. The large effects may arise from rehabilitation and procedural delays, as well as potential deterioration of health conditions due to insufficient treatment.[6]

In the second step, we examine the measure of provider quality and its correlation to occupancy. We show that our quality measures unbiasedly predict the outcomes of patients who are admitted to a high-quality vs. low-quality providers due to random geographic proximity, which implies that our measure is not systematically biased by nonrandom patient sorting. Furthermore, we show that our quality measure is positively correlated to occupancy, which suggests the existence of the congestion-quality tradeoff.

In the final step, to evaluate welfare impacts of congestion and counterfactual policies of patient reallocation, we estimate patients' preferences for nursing care providers and providers' admission rule. A challenge is that availability of providers for an admission is not fully observable, which can lead to under-estimates of the preference for provider quality. To deal with this difficulty, we assume that short-run fluctuations in occupancy affect a provider's admission rules but do not affect patient preferences, conditional on the

[6] We are currently exploring a potential bias in the estimates due to heterogeneity across occupancy levels.

provider's average occupancy over a time period and other provider characteristics. We also formalize identification of our demand model with such (one-way) exclusion restrictions. In estimation, we address the endogeneity of occupancy using the approximate version of the approach of Berry et al. (1995, henceforth BLP), as proposed by Lee and Seo (2015). The approximate BLP approach relaxes the market-share constraints while updating parameters, which is convenient for estimating demand models with limited consideration. Our estimates imply that a nursing care provider is more likely to offer an admission if the applicant lives in the same city as the provider, is female, or is of low care level (severity), or if the congested provider becomes less occupied. Patients prefer providers which are close to their (former) home and which have higher quality for facilitating home discharge. However, we do not find evidence that they have distaste for congestion. Simulation of patient reallocation to smooth occupancy between the most congested and least congested providers within each area suggests that occupancy smoothing can yield a net positive effect on patient outcomes, at least for some areas, even though such reallocation sends patients to lower-quality providers on average. For patient welfare (preference), our result suggests that such reallocation makes marginal patients worse off.

This paper relates to the literature on the effect of congestion on healthcare outcomes and provider behavior. Hoe (2022) and Gutierrez and Rubli (2021) use admission shocks to find that hospital crowding increases unplanned readmission and in-hospital mortality, respectively. Relative to these studies, we study longer-term care outcomes (home discharge, hospitalization and mortality outcomes of an episode of length up to 365 days).[7] Previous studies have exploited short-run occupancy fluctuations to study patient selection in the context of long-term care (Gandhi, 2023; He and Konetzka, 2015; Hackmann et al., 2023) and hospital care (Freedman, 2016; Sharma et al., 2008; Bachner et al., 2023). An advantage of the setting of Japanese nursing facilities is that there is a universal insurance system where reimbursement rate is adjusted to patient severity, which mitigates selection incentives and allows us to focus on the issue of congestion management rather than dynamic incentives for

[7] In the context of India, Andrew and Vera-Hernández (2022) study a large cash-transfer program which incentivizes women to give birth in a health facility and find evidence that congestion induced by the program led to higher perinatal mortality in low-capacity districts, and find suggestive evidence that such effects may have persisted up to five to ten years.

patient selection. Also, unlike many previous studies, we use an instrumental variable for occupancy and show that it can make a difference conditional on fixed effects.

This paper also relates to the vast literature on outcome-based institutional quality, often referred to as value added; see footnote 1 for examples. Researchers have estimated institutional quality and further investigated its implications on choice and competition for schools (Neilson, 2013; Allende, 2019; Abdulkadiroğlu et al., 2020; Beuermann et al., 2022; Ainsworth et al., 2023) and hospitals (Gaynor et al., 2016; Chandra et al., 2016). By contrast, value-added measures for nursing facilities have not been studied extensively, with a few exceptions (Einav et al., 2022; Olenski and Sacher, 2022; Bär et al., 2022; Cheng, 2023). These papers examine relatively short-run outcomes such as 30-day mortality and home discharge, whereas we study patient outcomes on a longer horizon, up to one year.[8]

Finally, this paper relates to the literature on demand estimation under choice constraints. Choice sets of service providers from which consumers can choose are often restricted, for various reasons such as limited attention (Goeree, 2008; Ho et al., 2017; Abaluck and Adams-Prassl, 2021; Heiss et al., 2021), search frictions (De Los Santos et al., 2012; Honka, 2014), stockouts (Conlon and Mortimer, 2013; Kawaguchi et al., 2021), institutional reasons (Gaynor et al., 2016) and supply-side behavior (Dubois and Sæthre, 2020; Gandhi, 2023; Agarwal and Somaini, 2022). Agarwal and Somaini (2022) provide general identification results for many of these models using two-sided exclusion restrictions, i.e., a variable affecting consumer preference but not choice sets and another variable affecting choice sets but not consumer preference. We contribute to this literature by formalizing identification of a (frequently used) subset of the choice-constraint models using one-sided exclusion restrictions: we assume that some variable affects choice constraints without shifting utility, but not that another variable shifts utility without affecting choice constraints.[9] Relaxing two-sided exclusion restrictions is important in our setting, as well as in other settings where "consideration" or "acceptance" is the decision by an economic agent whose incentive de-

[8]Olenski (2022) uses quality-of-care violations, rather than an outcome-based quality measure, to study the long-run impacts on nursing home patients through provider exits and patient reallocation.

[9]In the context of choice under risk, Barseghyan et al. (2021) propose identification of a consideration set model using preference shifters which are excluded from consideration, together with an "identification-at-infinity" type assumption. Abaluck and Adams-Prassl (2021) do not use exclusion restrictions and instead exploit symmetry of demand analogous to the Slutsky symmetry to identify consideration set models.

pends on the benefit and cost of acceptance. In our empirical setting, providers may prefer admission of patients from their own city, so the commonly used distance instrument may be invalid. Our estimate confirms this conjecture.

The rest of this paper proceeds as follows. Section 2 describes institutional background and data. In Section 3, we present our empirical framework for and results of the effect of congestion on patient outcomes. Section 4 presents analysis of the quality measures of nursing facilities. Section 5 presents our demand model, and Section 6 provides an identification result and estimation approach. Estimation and simulation results of our demand model are presented in Section 7. Section 8 concludes. Additional results and proofs are found in the Appendix.

2 Institutional Background and Data

2.1 Nursing Home Industry in Japan

Japanese nursing home industry features its public, universal long-term care insurance (LTCI). People who are over 65 years old, and are certified as in need of long-term care (LTC) services, are eligible for LTCI benefits. The eligibility is determined by in-person health examination, which evaluates the applicant's physical and mental disability and yields a measure of the degree of their disability, called a health score. Applicants are eligible for LTCI benefits if their health score exceeds a threshold. Beneficiaries can use both home care and institutional care, typically with 10 or 20% coinsurance rates. Due to the rapid population aging, Japanese public expenditures on LTCI have been increasing. The annual cost of LTCI was 12.7 trillion JPY (127 billion USD) in 2021, accounting for 2.3% of Japanese GDP. The cost of institutional care, including nursing facilities studied in this paper, accounts for half of the total cost.

We focus on a type of nursing facilities called a Geriatric Health Services Facility (GHSF), which we simply refer to as "provider" or "facility" below.[10] GHSF is a non-profit organization aimed at providing high-quality inpatient rehabilitation services and restoring the

[10]GHSF is also known as "Kaigo Roujin Hoken Shisetsu" or "Rouken" for short in Japanese.

physical capabilities of users so that they can live in their home or community.[11] Establishment of GHSF is restricted, requiring an approval by the prefectural governor. As of April 2019, approximately 360,000 patients were admitted in one of 4,337 GHSFs nationwide.

Various healthcare workers, such as physicians, nurses and social workers, stay at GHSFs to provide patients with high-quality rehabilitation and nursing care. Due to the rapidly aging population, inflexible wage setting and harsh working conditions, GHSFs and other nursing homes are constantly facing labor shortages. The survey by Care Work Foundation (2016) indicates that 62.6% of facilities were understaffed and that 73.1% of such facilities responded that the primary cause of labor shortage is hiring difficulties, due to factors such as low wages[12] (57.3%) and demanding jobs (49.6%).

2.2 Admission and Discharge Processes

Admission process is initiated by LTCI beneficiaries' application for admission to the facility. Recipients consult with physicians and social workers in the application process. After the application is received by a facility, it conducts an interview with the applicant to evaluate their physical conditions and service necessity. Admission decision is based on the interview and supplementary documents. Once they are admitted in a GHSF, patients receive rehabilitation services following their care plan, which is made in advance by care managers.

Once a patient is on track to be discharged, the facility initiates the discharge process together with the patient and their family, to secure post-discharge LTC and living arrangement. Patients may be discharged to their home; alternatively, they may move to another nursing home, with an intention to stay there forever. If a patient's health condition deteriorates and requires acute care, they may be transferred to a hospital. Some patients move to another GHSF to continue rehabilitation.

Patients stay in a GHSF for various objectives. Our analysis focuses on long-stay patients, who are institutionalized to receive rehabilitation care and restore their physical capabilities necessary to return to their community. Other patients use the facilities for short-run ser-

[11]The slogan of Japan Association of Geriatric Health Services Facilities (2015) is to "improve the user's function to enable them to return home."

[12]Flexible wage setting is difficult due to the revenue cap implied by publicly set reimbursement rates.

vices. These short-stay patients enter facilities with the aim of receiving temporary services, typically for a respite or temporary unavailability of family caregivers. LTCI only covers up to 30 consecutive days of such short stays, and over 70% of the short stays end within two weeks of admission (Ministry of Health, Labor and Welfare, 2017). Moreover, GHSFs serve both short-stay patients and long-stay patients using the same capacity. Therefore, while fluctuations in short stays are likely exogenous to the health condition of long-stay patients, they create variation in the occupancy faced by long-stay patients. These features motivate us to exploit short-stay fluctuations to construct an instrument for occupancy below.

2.3 Reimbursement

GHSF reimbursement consists of per-diem fixed payment and fee-for-service (FFS) payment. The per-diem payment is adjusted to patients' severity of disability, based on a severity measure called care levels. Care levels classify LTCI beneficiaries into seven groups: support levels 1–2 and care levels 1–5, in ascending order of severity.[13] The classification is based on the health score mentioned in Section 2.1. In principle, only patients with care level 1 or above are eligible for institutional care in GHSFs. The nursing care burden is reflected in reimbursement by setting higher rates of fixed payment for higher care levels. By contrast, FFS payment is paid to providers for certain medical procedures, such as short-term intensive rehabilitation, dementia care, and terminal care, regardless of care levels.

Table 1 shows per-diem and FFS payment in our sample, by care levels.[14] As Table 1 suggests, over 90% of reimbursement consists of per-diem payment.

2.4 Data Sources and Sample Selection

Our main data source is LTCI claims data. The claims provide information on each LTCI recipient's LTC service utilization at the monthly level, as well as patient characteristics such as age, sex, care level, and coinsurance rate. We obtain claims from April 2011 to March 2017.[15] We complement the claims data with the Survey of Long-Term Care Service

[13] Table A1 in Appendix A describes general functional status for each support level and care level.

[14] Because our data contain information on FFS payment only at the monthly level, we compute the per-diem FFS payment by dividing the patient's monthly FFS payment by the length of stay in the month.

[15] Japanese fiscal year begins on April 1 and ends on March 31.

Table 1: Per-diem Reimbursement

	Fixed payment (USD) (1)	FFS payment (USD) (2)	Fraction of fixed payment (3)
Care level 1	78.2	6.4	92.5%
Care level 2	83.4	6.6	92.6%
Care level 3	89.7	7.1	92.7%
Care level 4	95.3	7.1	93.1%
Care level 5	101.3	6.9	93.6%

Notes: This table presents per-diem reimbursement rate by care levels, together with fee-for-service components, which are computed from the claims data.

Facilities, which contain information on each GHSF's characteristics such as the number of beds at the annual level.

Our sample consists of episodes of stays in a GHSF. For each episode, the claims contain information on the identity of the provider, admission and discharge dates, and discharge destination. The information, together with information on capacity, allows us to compute occupancy rates at the provider-daily level, which we can then aggregate to average occupancy rate of each episode. We can similarly compute the average characteristics of peer patients during each episode, which are to be used as controls below.

We present summary statistics at the patient level in Table 2. The average age of at admission is 85 and 69% of patients are female. The average length of stay (LOS) is 339 days, which is calculated based on patients who were discharged in the sample period. The LOS varied widely among patients, with the 25th percentile being 60 days but the 75th percentile being 390 days. In the analysis below, we focus on episodes of admissions in a facility with LOS between 14 and 365 days.

Table 2: Summary Statistics (Patients)

	Mean (1)	SD (2)	p25 (3)	p50 (4)	p75 (5)	Obs. (6)
Age	85.07	8.13	81	86	91	1,105,046
Female	0.69	0.46	0	1	1	1,105,046
Length of stay (days)	339	519	60	139	390	1,105,046
Care level 1	323	524	58	126	358	122,751
Care level 2	344	520	61	136	394	207,679
Care level 3	353	525	64	146	411	264,722
Care level 4	332	499	60	142	385	301,078
Care level 5	338	536	52	136	382	208,807

Notes: The table presents summary statistics at the patient (strictly speaking, episode) level, before restricting the sample for patient outcome analysis. Columns (3), (4) and (5) present 25th, 50th and 75th percentile, respectively. The length of stay is calculated based on patients who were discharged during the sample period.

3 Effect of Occupancy on Patient Outcomes

This section discusses our approach to estimating the effect of occupancy on patient outcomes and presents results. Section 3.1 introduces our econometric model. Section 3.2 discusses our identification strategy. We then present our empirical specificaion in Section 3.3 and present results in Section 3.4 .

3.1 Econometric Model

We model the care outcome of patient i if she is admitted to provider j in period $\tau(=\tau_i)$ as

$$Y_{ij\tau} = \mu_j + \beta n_{j\tau} + x'_{ij\tau}\gamma + \varepsilon_{ij\tau} \tag{1}$$

where $Y_{ij\tau}$ denotes an outcome, μ_j is the provider fixed effect (FE), $n_{j\tau}$ denotes the average occupancy of provider j in period τ, and $x_{ij\tau}$ denotes controls, including the length of stay and other FEs. As outcomes, we use indicators of whether a given episode of stay in the provider ends with (i) discharge to home, (ii) hospitalization, or (iii) death. Given the goal of providers noted in Section 2, home discharge is considered a good outcome, whereas hospitalization and death represent bad outcomes.[16] So far, μ_j only represents the average tendency of provider j to produce a specific outcome, which may include differences in case mix as well as the causal effect of the provider; we discuss its causal interpretation in Sections 4.1 and 4.2.

Model (1) yields the following regression model:

$$Y_{i\tau} = \mu_i + \beta n_{i\tau} + x'_{i\tau}\gamma + \varepsilon_{i\tau} \tag{2}$$

where $Y_{i\tau} = \sum_j Y_{ij\tau} I(j_i = j)$ denotes the realized outcome (with j_i denoting the provider to which i is admitted), and other variables are defined analogously.

[16] Similarly, the literature on nursing facility quality has examined community discharge (Einav et al., 2022), hospitalization (Rahman et al., 2016), and death (Cheng, 2023).

3.2 Identification of the Effect of Occupancy

An identification concern for Eq.(2) is that occupancy rates may be correlated to unobserved determinants of patient outcomes, $\varepsilon_{i\tau}$, in which case the ordinary least squares estimate (OLSE) of β will be a biased estimate of the causal effect of occupancy on patient outcomes. Two major sources of such endogeneity are (i) patient composition which varies with occupancy and (ii) unobserved provider quality. Endogeneity via patient composition arises if providers facing high occupancy admit/discharge patients that are systematically different from those admitted/discharged when the providers face low occupancy. Endogeneity via unobserved provider quality occurs if providers which are of unobservedly better attract more patients.

We mitigate the concern about patient composition by including rich controls. We control for the patient's age, sex, indicator of high coinsurance rate (a proxy for the income of the patient), indicator of terminal care utilization, and care level (severity measure) dummies. In addition, we control for the averages of these variables among patients within the same provider and same time period. We also control for the length of stay of the focal patient. Moreover, we include provider FEs, discharge-date FEs and discharge year-month by medical area[17] FEs to control for provider- and time-specific shocks and regional trends in care outcomes, which will capture some portion of provider quality in addition to patient composition. Finally, We control for local hospital capacity, which may affect the choice of discharge destination.

We address the concern about residual unobserved quality by instrumenting occupancy with the number of short-stay discharges (and admissions), to study the outcome of long-stay patients. The idea is that demand for short-stay care is unrelated to the quality for long-term care but affects congestion faced by long-stay patients. For exogeneity, we note that demand for short-stay services typically arises from temporary unavailability of family caregivers or intentions to receive short-run rehabilitation training. These stays typically end within 2 weeks of admission, as noted in Section 2. Thus, short-stay admissions and

[17] More specifically, we use the secondary medical area. The market concept segments Japan into about 350 areas and is defined so that general inpatient treatments are expected to be completed within the area. In this sense, our (secondary) medical area is smaller than the hospital referral region in the US, which segments the US into about 300 regions and represents regional markets for tertiary medical are.

discharges are likely arranged independently of the shocks to long-stay patients' outcomes. Although one may worry that some shocks may affect both the number/share of short stays and the composition among long-stay patients, we show in Section 3.4 that characteristics of long-stay patients do not vary much with the number of short-stay (admissions or) discharges.

For relevance, providers we study use the same bed and staff capacity to serve both short-stay and long-stay patients, and adjusting the capacity in response to such short-run fluctuations is difficult due to capital investment regulation and inflexible labor market. Consequently, fluctuations in short stays affect occupancy faced by long-stay patients. One caveat, however, is that the sign of the effect of increased short-stay admissions on the average occupancy faced by long-stay patients may be heterogeneous. Specifically, in congested facilities, short stays may *decrease* occupancy, because short-stay patients will substitute long-stay patients, the latter of whom would occupy beds for longer periods. By contrast, in less congested facilities, an increase in short-stay admissions may increase occupancy, because short-stay patients will not crowd out long stays. Such heterogeneity may lead to overestimates of the effect of congestion, by making the first-stage coefficient on the short-stay admissions small. In the empirical analysis below, we use short-stay discharges as a main instrument.[18]

Previous studies on the effect of health facilities' occupancy on care outcomes or provider behavior (Gandhi, 2023; Hackmann et al., 2023; Freedman, 2016; Hoe, 2022) similarly motivate the exogeneity assumption on their occupancy measures by noting that short-run fluctuations are perceived exogenous to the outcome of interest. One difference of our work from theirs is that we only exploit variation in short-stay admissions and discharges for identification, whereas previous studies use occupancy variation which arises from both short-stay and long-stay patients, although both of these studies control for rich fixed effects to mitigate endogeneity concerns. In Section 3.4, we show that our two-stage least squares estimates are quite different from OLSEs, which suggests that instrumenting occupancy may be important even conditional on rich controls.

[18]We are currently investigating the heterogeneity in the first stage.

3.3 Empirical Specification

The above model (2) will not fit all types of patients. On one hand, a short period of an exposure to congestion will not affect patient outcomes. On the other hand, some patients utilize a provider with intention to stay there for life. To focus on patients to whom congestion is most relevant, our analysis focuses on patients who stay with a provider for 14 to 365 days with a service code identified with a long stay. We also exclude episodes which occur at a provider with a dementia care unit; for such providers, we cannot observe whether a patient is admitted to the regular unit or a dementia unit, making it hard to identify relevant congestion level. Finally, we exclude providers which are in the bottom 20 percentile or top 5 percentile in the distribution of provider's maximum occupancy during the sample period. The former restriction is intended to exclude providers which are always empty, and to mitigate concerns about missing data.[19] The latter restriction aims to eliminate outliers of occupancy, which may reflect measurement errors.[20]

We estimate Eq.(2) using two specifications of instruments which are constructed using short-stay discharges. As an instrument for the average occupancy during episode, our benchmark analysis uses (i) the average number of discharges of short-stay patients from the provider in which the focal patient stays, where average is taken over days during the episode. To mitigate the concern that short-stay fluctuations directly correlate to long-stay outcomes, we also show regression results which use (ii) the average number of discharges of short-stay patients from the provider, during the 14 days *prior to the start date of the episode, controlling for average short-stay discharges during episode*. We also define analogues using short-stay admissions.

We normalize provider fixed effects to have mean zero. Further, we apply the empirical Bayes shrinkage (Morris, 1983; Chandra et al., 2016) to reduce the noise in their estimates.

[19]Some researchers of Japanese long-term care are worried that low occupancy reflects under-reporting of claims by the municipality to the central government.

[20]Relaxing the trimming criteria does not alter qualitative results.

3.4 Results of the Effect of Occupancy

We begin by checking covariate balance across different values of our baseline instrument (episode mean of short-stay discharges) by regressing covariates on the instrument and other controls. We examine patients' age, sex, an indicator of high cost sharing (an income measure), and care level at admission, as well as an indicator of receiving terminal care during the episode and the length of stay. Table 3 shows the results of the regression. It shows that our instrument is not systematically related to patients' cost sharing, care level, terminal-care status, or length of stay. Although the instrument is correlated to age and sex, the correlation is weak. Table A2 similarly shows that correlation between short-stay admissions and patient characteristics are weak, if any.

Table 3: Covariate Balance

	(1) Age	(2) Female	(3) High cost sharing	(4) Care level	(5) Receiving terminal care	(6) Length of stay
Short-stay discharge in pp	0.1135*	0.00928**	0.00154	-0.00920	0.000976	-0.1556
	(0.06617)	(0.00376)	(0.00146)	(0.01059)	(0.000761)	(0.8773)
Mean outcome	85.11	0.6752	0.0342	3.21	0.0109	121.61
N	599,946	599,946	599,946	599,946	599,946	599,946

*** p<0.01, **p<0.05, *p<0.1

Note: This table presents the result of regression of patient characteristic (indicated by each column) on our instrument (average number of short-stay discharges during episode, expressed as a percentage of capacity) and controls other than the dependent variable. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

Table 4 presents the results of the instrumental variable regression of patient outcomes on occupancy. The first-stage result reported in Column (1) shows that a 1pp increase in the number of short-stay discharges leads to a 0.76pp decrease in average occupancy. The pp change in occupancy is less than the pp change in short-stay discharges, likely because providers increase admissions in response to an occupancy reduction induced by short-stay discharges.

Table 4: Instrumental Variable Regression of Patient Outcomes on Occupancy

	(1) First Occupancy	(2) Second Home Discharge	(3) Second Hospitalization	(4) Second Death
Occupancy in pp		-0.01309** (0.00618)	0.03072*** (0.00742)	0.00146 (0.00223)
Short-stay discharge in pp	-0.760*** (0.121)			
Mean outcome	0.8913	0.3452	0.3718	0.0654
N	599,946	599,946	599,946	599,946

*** p<0.01, **p<0.05, *p<0.1

Note: This table presents the results of instrumental variable regressions of patient outcomes on occupancy and other controls, using average short-stay discharges during the episode as an instrument. Column (1) displays the first-stage coefficient on the instrument and Columns (2)-(4) display the second-stage coefficients on occupancy. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

Columns (2)-(4) report the IV estimates of the coefficient on occupancy. The results imply that a 1pp increase in occupancy during the episode leads to a 1.3pp decline in the probability of home discharge (3.8% of baseline) and a 3.1pp increase in the probability of hospitalization (8.3% of baseline). These estimates may reflect rehabilitation and procedural delays, in addition to potential health deterioration due to insufficient treatment. Although occupancy is also estimated to increase the likelihood of dead discharge, the estimate is not statistically significant.

Table 5 shows regression results using as an instrument average short-stay discharges in the 14 days preceding admission, while controlling for average short-stay discharges during episode. The effects of occupancy on hospitalization and death probability are close to the estimates reported in Table 4. Although the effect of occupancy on home discharge is again negative and statistically significant, the magnitude is three times larger than our estimates with baseline instrument (episode mean of short-stay discharges).

Tables A3 and A4 in Appendix A present the results of the regressions of patient out-

Table 5: Instrumental Variable Regression of Patient Outcomes on Occupancy (Before-Episode Discharge IV)

	(1) First Occupancy	(2) Second Home Discharge	(3) Second Hospitalization	(4) Second Death
Occupancy in pp		-0.03722*** (0.00601)	0.03017*** (0.00535)	0.00203 (0.00218)
Short-stay discharge in pp (before admission)	-0.456*** (0.0323)			
Mean outcome	0.8913	0.3452	0.3718	0.0654
N	593,518	593,518	593,518	593,518

*** p<0.01, **p<0.05, *p<0.1

Note: This table presents the results of instrumental variable regressions of patient outcomes on occupancy and other controls, using average short-stay discharges in the 14 days preceding admission as an instrument, controlling for average short-stay discharges during the episode. Column (1) displays the first-stage coefficient on the instrument and Columns (2)-(4) display the second-stage coefficients on occupancy. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

comes using short-stay admissions as instruments. The estimates for home discharge and hospitalization using the episode mean of short-stay admissions are remarkably similar to those using the episode mean of short-stay discharges. Results using short-stay admissions before admission as an instrument are also qualitatively similar to those using short-stay discharges before admission as an instrument.

Finally, to compare with our main results, Table A5 of Appendix A presents the results of OLSE of Eq.(2). In contrast to the IV estimates, we do not find economically or statistically significant relationship between occupancy and patient outcomes. This is consistent with a hypothesis that the negative causal effect of occupancy on patient outcomes is offset by the between-provider positive correlation of occupancy and quality.

4 Outcome-Based Quality of Nursing Homes

This section presents our framework for studying provider quality. In Section 4.1, we introduce a method to test whether the provider fixed effects obtained from regression (2) can be interpreted as a causal effect of the provider on patient outcomes. We implement the test and report the result in Section 4.2. Using validated quality measures, we then provide evidence for congestion-quality tradeoff in Section 4.3.

4.1 Validating Value Added as Causal Quality

One concern about using value-added measures as institutional quality is that the measures may be systematically biased due to consumer sorting. For example, patients admitted to provider A may be systematically better in their health status than those admitted to provider B, even conditional on observables. In such a case, the value-added measure overstates the quality of provider A relative to that of provider B, because it conflates the true causal effect with differences in patient mix. Although instrumenting provider choice may be an effective solution in theory, finding strong instruments which induce sufficient variation in the choice among a large number of providers will prove difficult in practice. Instead of using J instruments to estimate J value added measures, we follow the validation method adopted in the literature (Chetty et al., 2014a; Abaluck et al., 2021). The method only requires a single instrument to estimate a single parameter, called a forecast coefficient, which informs us of the degree of systematic bias in value added measures.

The idea behind such forecast regressions is simple: if the value added measures are unbiased estimates of true causal effects, then they should provide unbiased predictions of the outcome of consumers who are (quasi-)randomly assigned to institutions. Following Abaluck et al. (2021), we can evaluate the bias of our value-added estimates $(\hat{\mu}_j)_j$ by the regression

$$Y_{i\tau} = \lambda \hat{\mu}_i + \beta n_{i\tau} + x_{i\tau}' \gamma + \varepsilon_{i\tau} \tag{3}$$

using an instrument for $\hat{\mu}_i$. An unbiased measure $(\hat{\mu}_j)_j$ of provider quality will yield $\lambda = 1$.

$1-\lambda$ can be interpreted as the degree of bias of the value added as a causal quality measure.

Because we cannot include provider FEs to Eq.(3) (as they are collinear with μ_j), estimating (3) may not yield a consistent estimate of λ. Instead, we regress $Y_{i\tau} - \hat{\beta} n_{i\tau}$ on $\hat{\mu}_i$ and $x_{i\tau}$, instrumenting the former by an exogenous variable $W_{i\tau}$.[21] As an instrument $W_{i\tau}$ for realized value added, we use the value added of the provider which is closest to the focal patient's home. The idea is that (i) the value added of the patient's closest provider is likely correlated to realized (assigned) quality, because patients tend to choose a provider in their vicinity,[22] whereas (ii) it is uncorrelated to health shocks because patients' location relative to quality providers is conditionally random.

4.2 Result of Quality Validation

Table 6 presents the results of forecast regressions for value-added measures from the regression (3). We take the specification with the episode mean of short-stay discharges as an instrument for occupancy: value-added estimates from other specifications of instruments are validated similarly. For all outcomes, the value added unbiasedly predicts the outcome of patients who are assigned to providers due to (arguably random) geographic proximity.

[21] Under reasonable assumptions, an IV regression of Eq.(2) yields a consistent estimate of β even if $(\hat{\mu}_j)_j$ are biased.

[22] In our sample, 35% of patients are admitted to the closest provider. Because the majority of patients enter a non-closest provider, the first-stage coefficients in Table 6 are far below 1, which suggests that our result is not due to the realized quality being almost identical to the closest provider's quality.

Table 6: Forecast Regression to Validate Value-Added Measure

	(1)	(2)	(3)	(4)	(5)	(6)
	First	Second	First	Second	First	Second
	Home Discharge	Home Discharge	Hospitalization	Hospitalization	Death	Death
	Value Added		Value Added		Value Added	
Value Added		1.079***		1.025***		1.036***
		(0.0149)		(0.0108)		(0.0363)
Value Added of the Nearest Provider	0.295***		0.271***		0.161***	
	(0.00365)		(0.00387)		(0.00315)	
Control	Y	Y	Y	Y	Y	Y
N	419,709	419,709	419,709	419,709	419,709	419,709

*** $p<0.01$, **$p<0.05$, *$p<0.1$

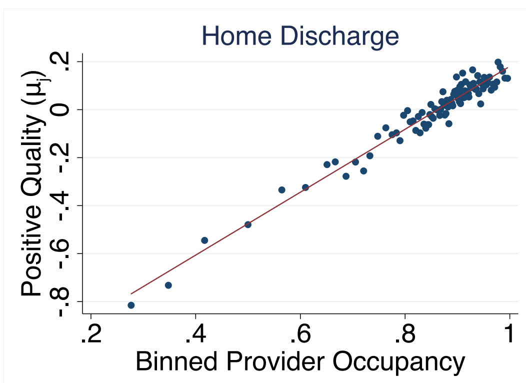
Note: This table presents the results of instrumental variable regressions of patient outcomes (residualized by the occupancy term) on the value-added measure and other controls, using the value added of the focal patient's closest provider as an excluded instrument. Columns (1), (3) and (5) display the first-stage coefficients on the excluded instrument and Columns (2), (4) and (6) display the second-stage coefficients on the value added. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

4.3 Congestion-Quality Tradeoff

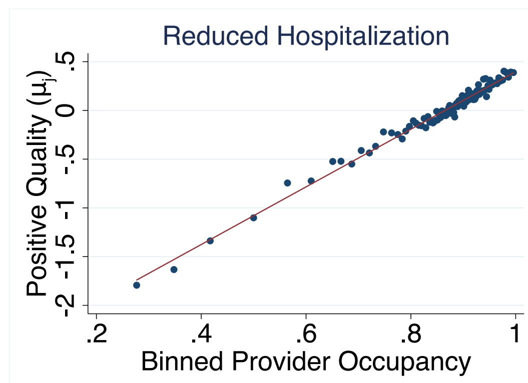
Figure 1 displays the scatter plot of provider-level value-added measures (fixed effects from Eq.(2) against provider-specific average occupancy rate. Value-added measures for home discharge (Panel (a)) and reduced hospitalization (Panel(b)) exhibit strong positive correlation with provider occupancy. This suggests a *congestion-quality tradeoff*: moving patients to a higher-quality provider tends to exacerbate the congestion faced by the patients, which might substantially offset the benefit of better quality.

Figure 1: Congestion and Quality

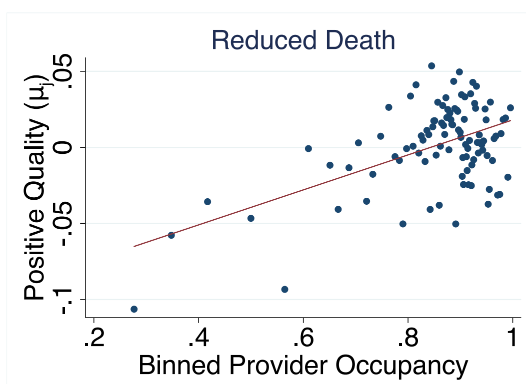
(a) Congestion and Home Discharge



(b) Congestion and Reduced hospitalization



(c) Congestion and Reduced Death



Note: This figure plots provider-level positive quality measure (fixed effects from Eq.(2) signed so that larger values imply the higher likelihood of a desirable outcome) against provider-level average occupancy rate. We use estimates of regressions with episode averages of discharges as instruments.

A caveat about the quality measure μ_j is that it measures *occupancy-adjusted productivity*:

it measures productivity of each provider holding observed production factors constant. While covariate-adjusted productivity is a common measure of value added used in the literature, it may overstate quality differences between providers which take substantially different values of covariates. Thus, our quality measure is likely more reliable to compare the quality of providers which are similar in occupancy.[23]

5 Demand Model with Choice Constraint

Having observed that higher occupancy may lead to poorer patient outcomes, we now introduce and estimate a model of demand for nursing care. Estimating patient preferences is crucial for policy evaluation for two reasons. First, patients may value provider characteristics other than quality (e.g., distance from their previous home), in which case reallocation to smooth occupancy may be harmful to their welfare. Second, if patients dislike congestion, then they will (partially) internalize the congestion externalities, which may reduce the need for policy interventions. To address these issues, we build and estimate a model of patients' demand for nursing facility admission and providers' admission decisions.

Timing. Patients (denoted by i) arrive sequentially to some market $t = t_i$. Upon patient i's arrival, admission is realized via the following decisions.

- Each provider $j \in \mathcal{J}_t$ decides whether to offer i an admission.
- Patient i chooses which offer to accept.

An advantage of this (seemingly simplistic) assumption is that it leads to a familiar demand model with choice set constraints, commonly referred to as a consideration set model (Goeree, 2008). In our model, the consideration sets (i.e., restricted choice sets) are induced by providers' acceptance/rejection decisions.

[23] Note, however, that the congestion-quality tradeoff is not a mechanical result. Under the validity of our instruments, we find that occupancy affects patient outcomes negatively. If providers at different occupancy levels are not systematically different in their quality, then we will observe a negative correlation between occupancy and patient outcomes. In actual data, this is not the case: recall that the OLSE of the coefficient on occupancy is statistically insignificant. Therefore, these patterns inform us that congested providers are better in unobserved terms.

Moreover, under additional assumptions, the above timing assumption yields the same choice outcome as the following, possibly more realistic, alternative:

- Upon arrival, i applies for facilities in order of preference.
- Upon receiving an application, provider j decides whether to accept the application.
- Patient i is matched to the best facility which accepts her application.

In either case, patient i is matched to her most preferred provider which accepts her application.

Payoffs. Provider j offers patient i an admission according to the following admission rule:[24]

$$O_{ijt} = I\left(\tilde{v}_{ijt} > 0\right) \tag{4}$$

$$\tilde{v}_{ijt} = v_j\left(x_{ijt}, n_{ijt}\right) - \eta_{ijt} \tag{5}$$

where $O_{ijt} = 1$ indicates that provider j offers an admission to patient i who arrives at market t. The "admission desirability" of patient i for provider j, $\tilde{v}_{ijt}$ (which we simply call provider's "utility"), depends on observed patient-provider characteristics $x_{ijt} \in \mathcal{X}_j$, episode-level occupancy $n_{ijt} \in \mathcal{N}_j = \left(\underline{n}_j, \bar{n}_j\right)$ and an unobserved variable $\eta_{ijt} \sim F_{\eta_{jt}|x_{ijt}}$ which admits a density function.

Patient i's utility from admission to provider j is $u_{ijt} = u\left(x_{ijt}, \xi_{jt}\right) + \varepsilon_{ijt}$, where ξ_{jt} denotes unobserved demand shocks to provider j and ε_{ijt} denotes an idiosyncratic shock with a distribution function G. As discussed below, we allow x_{ijt} to include the average occupancy at the provider-market level.

Other modelling issues. We omit discharge decisions. We also omit dynamic considerations of occupancy management, which is less of a concern because patients in our empirical setting are likely relatively homogeneous in their profitability compared to the US setting. Finally, an outside option contains nursing facilities of other types (private or public). We

[24]For simplicity, in the empirical analysis below, we assume v is common across j, and de-mean n_{ijt} by j-specific averages to account for baseline heterogeneity in occupancy.

will normalize the systematic component of the utility of the outside option to zero, instead of accounting for their quality and occupancy.

Equilibrium. Let $C_i \subseteq \mathcal{J}_t$ be the subset of "inside" facilities that offer i an admission. Outside option is always available. The "equilibrium" of this model is the strategy profile which satisfies the following conditions: for each i and j,

1. patient i chooses provider j iff $j \in C_i \cup \{0\}$ and $u_{ijt} \geq u_{ij't}$ for all $j' \in C_i \cup \{0\}$.

2. provider $j \neq 0$ offers patient i an admission iff $v_{ijt} \geq 0$. Thus, $C_i = \{j \in \mathcal{J}_t : v_{ijt} \geq 0\}$.

6 Identification and Estimation of the Demand Model

6.1 Identification

In our empirical analysis below, we assume that the distribution of $(\eta_{ijt}, \varepsilon_{ijt})$ is known and estimate the parameterized version of u and v using observations on $x_{it} = (x_{ijt})_{j \in \mathcal{J}_t}$, $n_{it} = (n_{ijt})_{j \in \mathcal{J}_t}$ and choice j_i. There are two challenges with our empiricala analysis:

1. Offers C_i are unobserved.

2. Occupancy n_{ijt} may be correlated to current and past demand unobservables $\xi^t \equiv (\xi_{j\tau})_{j \in \mathcal{J}_\tau, \tau \leq t}$.

Failing to address the first problem leads to biased parameter estimates, hence biased welfare conclusions. To illustrate this, suppose patients value quality x_{jt} of providers and providers' acceptance policy is decreasing in occupancy n_{ijt}. Then higher-quality providers are more likely to be excluded from the choice set C_i, as they attract more applications from patients. If we estimate patient preferences assuming that all options are available, then we will underestimate patients' valuation of the quality, because they will be admitted to providers which are on average of lower quality than they would choose were it not for choice constraints. The second problem implies that occupancy is not excluded from patients' choice probabilities conditional on other observables.

In this section, we explain how we address the above problems, in two steps. First, we show that consideration probabilities and choice probabilities are separately identified from observed data, if we tentatively assume that occupancy rate n_{ijt} is independent of $(\xi_{jt})_{j\in\mathcal{J}_t}$. We then discuss how to restore the independence assumption using a control function. We omit market subscript t for notational simplicity.

6.1.1 Identification of Choice and Consideration Probabilities

We show that offer probabilities $\Pr(j \text{ offers } i \text{ an admission}|x_{ij}, n_{ij}) = F_{\eta_j|x_{ij}}(v_j(x_{ij}, n_{ij}))$ and the choice probability $\Pr(i \text{ chooses } j|C_i = C, x_i)$ are separately identified, using an exclusion restriction that n_{ij} shifts offer probability but not choice probability.

More specifically, we impose Assumptions 1 and 2.

Assumption 1

(i) η_{ij} *is independent across* j *conditional on* $x_i = (x_{ij})_{j\in\mathcal{J}}$ *and* $n_i = (n_{ij})_{j\in\mathcal{J}}$.

(ii) $\varepsilon_i = (\varepsilon_{ij})_{j\in\mathcal{J}}$, $\xi = (\xi_j)_{j\in\mathcal{J}}$, $\eta_i = (\eta_{ij})_{j\in\mathcal{J}}$ *and* n_i *are mutually independent conditional on* x_i.

(iii) For each j *and* x_{ij}, $\lim_{n_{ij}\to\underline{n}_j} F_{\eta_j|x_{ij}}(v_j(x_{ij}, n_{ij})) = 1$.[25]

Assumption 1(i) yields an "alternative specific consideration model" (Abaluck and Adams-Prassl, 2021), where the probabilities of a consideration set can be written as a product of independent consideration probabilities of each alternative. Assumption 1(ii) excludes n_i from choice probabilities conditional on x_i and C_i. Assumption 1(iii) is an "identification-at-infinity" assumption which has been imposed in most previous studies to fix the location parameter.

The above assumptions are different from those proposed by Agarwal and Somaini (2022) for identification of general demand models with choice set constraints. On the one hand, their identification result is applicable to a wider class of models, as they do not impose independent consideration (Assumption 1(i)). On the other hand, they impose two-way

[25] We can slightly relax this assumption to accommodate, e.g., $v(x, n) = \alpha + \beta x \cdot \left(\frac{1}{n} - 2\right)$, $n \in (0, 1)$.

exclusion restrictions, i.e., that some variable affects choice set without affecting preference and another variable affects preference without affecting choice set.

We also need a rank condition:

Assumption 2 *Let*

$$\begin{aligned} F(C; x_i, n_i) &= \Pr(C_i = C \mid x_i, n_i) \\ &= \prod_{k \in C} F_{\eta_k | x_{ik}}(v_k(x_{ik}, n_{ik})) \prod_{l \in J \setminus C} \left[1 - F_{\eta_l | x_{il}}(v_l(x_{il}, n_{il}))\right] \end{aligned}$$

denote the conditional probability of consideration set C. For each j, let $\mathcal{C}(j) = \{C \subseteq \mathcal{J} : j \in C\} \equiv \left\{C_1^j, \ldots, C_K^j\right\}$ denote the set of all consideration sets which contain j. Then, for each j and x_i, there exist $n^{1,j}, \ldots, n^{R,j}$ such that the matrix

$$F^j(x_i, \mathbf{n^j}) = \begin{bmatrix} F\left(C_1^j; x_i, n^{1,j}\right) & \cdots & F\left(C_K^j; x_i, n^{1,j}\right) \\ \vdots & \ddots & \vdots \\ F\left(C_1^j; x_i, n^{R,j}\right) & \cdots & F\left(C_K^j; x_i, n^{R,j}\right) \end{bmatrix}$$

has rank K.

We then obtain an identification result for choice and consideration probabilities.

Proposition 1 *Suppose that Assumptions 1 and 2 hold. Then the offer probability*

$$\Pr(j \textit{ offers } i \textit{ an admission} | x_{ij}, n_{ij}) = F_{\eta_j | x_{ij}}(v_j(x_{ij}, n_{ij}))$$

and the choice probability

$$\Pr(i \textit{ chooses } j | C_i = C, x_i)$$

are identified for all (j, x_i, n_i, C).

Proof. See Appendix B.

As discussed above, an advantage of the above result relative to that of Agarwal and

Somaini (2022) is that our result only requires an exclusion of some choice set shifter from patient preference. Also, beyond independence and exclusion, our result imposes few properties on choice probabilities, so it can be used as a basis for testing some properties.[26]

6.1.2 Identification of Admission Rule and Preference

Identification of choice and consideration probabilities does not imply identification of preference u and admission parameter v. Identification of the primitives is required, for example, to examine the convexity of the admission cost captured by $-v$: if v is identified only up to some monotonic transformation, then we cannot tell whether the true $-v$ is convex in occupancy.

Conditions for the identification of u and v are available in the literature (e.g., Matzkin 1992). These conditions typically assume the existence of some large-support variable which enters the function linearly. However, in our case, we may be interested in investigating whether occupancy (the large-support variable) enters the negative provider utility in a convex manner. Therefore, in Appendix B, we develop an identification result which requires that some variable, not necessarily with a large support, enters the cost function linearly. Intuitively, such a variable allows us to identify the derivatives of v, which together with a location normalization yields v.[27]

For identification of patient preferences, we invoke existing results (Berry and Haile, 2016, 2022), conditional on identification of choice probabilities.

6.1.3 Addressing Endogeneity of Occupancy

Proposition 1 is based on the conditional independence of n_i and ξ. This may fail, however, because current occupancy is partly the result of past demand shocks and demand shocks are serially correlated. Specifically, we will have $n_{ijt} = n_{ijt}\left(\xi^{t-1}, x^{t-1}\right)$ where $\xi^t = \left(\xi_{j\tau}\right)_{j \in \mathcal{J}_\tau, \tau \leq t}$, etc.

[26] For example, we can test whether the choice probabilities satisfy Slutsky-like symmetry (Abaluck and Adams-Prassl, 2021) or the random utility axioms (Falmagne, 1978).

[27] The assumption requires that the provider utility be continuously differentiable with respect to occupancy. In the empirical analysis below, we specify v as a piecewise linear function of occupancy, so the identification assumption does not hold exactly.

To address this problem, we make some assumptions. Recall that the occupancy rate varies even within market, defined by medical area-quarter in the empirical analysis below, because occupancy fluctuates at the daily level. Let n_{ijt} denote the occupancy rate at the beginning of episode i at provider j in market t.[28] Also, let n^e_{jt} denote provider-quarter average of occupancy. Define the residualized occupancy as $\tilde{n}_{ijt} = n_{ijt} - n^e_{jt}$.

Assumption 3

(i) Patients only care about provider-quarter average occupancy n^e_{jt}.

(ii) $\tilde{n}_{ijt}$ *is independent of* $(\xi_{j\tau})_{j,\tau \leq t}$ *conditional on* n^e_{jt} *and other observables.*

Assumption 3(i) means that patients who arrive on different days in market t use the same expected occupancy to make an application decision.[29] Assumption 3(ii) suggests that the occupancy fluctuations around its market-provider-specific average is independent of demand shocks and is excluded from choice probability, conditional on n^e_{jt}. Therefore, n^e_{jt} serves as a control function to restore independence between (residualized) occupancy and demand. Specifically, by controlling for n^e_{jt} both in choice and consideration probabilities, the residual variation in occupancy becomes excluded from demand, which enables us to apply Proposition 1 for identification. This assumption is violated if, for example, there is a serially correlated demand shock which varies at the daily level.

Conditional on the average occupancy n^e_{jt}, residual fluctuations in occupancy come from unexpected patient inflows/outflows such as emergency admissions and patient deaths. Although these factors may be correlated to provider quality (hence ξ_{jt}) in the long run, the precise timing of emergencies to family caregivers and deaths is likely random.

Because n^e_{jt} is endogenous to demand, we need to instrument for it. Motivated by the analysis in Section 3, we use the number of short-stay discharges in the previous quarter as an IV. Note that our approach yields patients' preference over average occupancy n^e_{jt}, which will be of interest for evaluating welfare effects of policies.

[28] We assume this is what the provider cares about. Alternative assumptions are possible.

[29] With additional complexity, we can allow the occupancy in patients' information set to be patient-specific.

6.2 Empirical Specification

We adopt simple specifications for provider and patient utility functions as follows:[30]

$$
\begin{aligned}
v_{ijt} &= \alpha_{n1} n_{ijt} + \alpha_{n2} n_{ijt} I\left(n_{ijt} \geq K\right) + \alpha_{e1} n_{jt}^{e} + y_{ijt}^{f\prime} \alpha_y - \eta_{ijt} \\
u_{ijt} &= \underbrace{w_{jt}^{\prime} \beta_w + \beta_{e1} n_{jt}^{e} + \xi_{jt}}_{\equiv \delta_{jt}} + y_{ijt}^{p\prime} \gamma_y + \varepsilon_{ijt} \\
u_{i0t} &= \varepsilon_{i0t}
\end{aligned}
$$

where y_{ijt}^{f} denotes a vector of patient characteristics which affect facility j's decision to accept or reject an application from patient i (hence a superscript f), y_{ijt}^{p} is a vector of patient-provider characteristics which affect patients' preferences, and w_{jt} is a vector of facility characteristics. K denotes a threshold value of daily occupancy, which we set to the average occupancy in sample. The portion of patient utility which varies at the provider-market level is denoted by δ_{jt}. We normalize $\delta_{0t} + y_{ijt}^{p\prime}\gamma_y = 0$. η_{ijt} follows i.i.d. logistic distribution, and ε_{ijt} follows i.i.d. Type-I Extreme Value distribution.

In our empirical analysis, y_{ijt}^{f} includes a constant, an indicator of at least 75 years of age, a female indicator, an indicator of care level being 3 or higher (on a scale of 1-5), and an indicator of whether the patient is from the same city of the provider. As y_{ijt}^{p}, we use the distance between patient i's former residence and provider j. w_{jt} includes a constant and the value added for home discharge.

Similarly to the analysis of patient outcomes in Section 3, we prefer to assume that our instrument is exogenous only after eliminating systematic differences across providers. To do so, we apply within-provider transformation to our occupancy variables.[31]

Finally, we restrict the sample for the structural analysis. We focus on patients who are at age 65 or older at admission; those who access long-term care below this age may have special care needs and choose providers differently. Also, due to computational cost, we focus on observations in the Tokyo prefecture.

[30] Although not ideal, we assume that controlling for the linear term of n_{jt}^{e} eliminates the relevant portion of correlation between occupancy and demand shocks.

[31] In the result below, we do not apply within-provider transformation to other variables, such as quality. Using within-transformed quality measures which varies over time is a future extension.

6.3 Estimation

We aim to estimate $\tilde{\theta} = (\theta, \beta)$ where $\theta \equiv \left(\alpha_{n1}, \alpha_{n2}, \alpha_{e1}, \alpha_y', \gamma_y'\right)'$ collects parameters commonly called *nonlinear parameters* in the IO literature, and $\beta = (\beta_w', \beta_{e1})'$ denotes so-called *linear parameters*.

An estimation challenge is to deal with the correlation between average occupancy n_{jt}^e and unobserved demand shocks ξ_{jt} in the nonlinear setting. A common approach to this problem is the contraction mapping of Berry et al. (1995). In this approach, estimation proceeds in a loop structure where in the inner loop given a trial parameter value, they find a "mean utility" vector δ which equates the predicted market share to the empirical market share. They provide a contraction mapping algorithm to solve for δ. Besides its potentially slow convergence, applying their approach to models with choice set constraints involves an additional difficulty: for some parameter value θ, there may not exist $\delta = \delta(\theta)$ that solves the market-share equation. If, for example, the parameter value is such that the acceptance probability of option j is at most 0.5, then no vector δ can rationalize its empirical market share of 0.6.[32] Therefore, an estimation approach which relaxes the market share constraint is desired. Although there are alternative estimation approaches which do not (always) impose market share equations during parameter search (Dubé et al., 2012; Grieco et al., 2023), they involve optimization over a large number of parameters, which may be difficult in complex models with choice set constraints.

We therefore adapt an approximate BLP method (Lee and Seo, 2015) to our setting with choice set constraints and microdata. With "just identification" (meaning that the number of endogenous variables is the same as that of excluded instruments), our approach can further be simplified, yielding the following iterative procedure:

1. Given an initial value δ^0, we update parameter in the h-th iteration by

$$\theta^h = \arg \max_{\theta \in \Theta_{NL}} \ln L\left(\theta; \delta^{h-1}\right)$$

where $\ln L\,(\theta; \delta)$ denotes the log-likelihood of the patient-level sample and Θ_{NL} denotes

[32] Strictly speaking, this example contradicts the identification-at-infinity assumption above. However, the intuition will remain valid if the acceptance probability approaches one only infrequently.

the support of the nonlinear parameters θ.

2. Update δ by

$$\begin{aligned}\delta^{h} &= \delta\left(\theta^{h}, \delta^{h-1}\right) \\ &\equiv \delta^{h-1} + \left[\nabla_{\delta'} \ln s\left(\delta^{h-1}; \theta^{h}\right)\right]^{-1}\left[\ln S - \ln s\left(\delta^{h-1}; \theta^{h}\right)\right]\end{aligned}$$

where S denotes the vector of empirical market share and $s(\delta; \theta)$ is the vector of predicted market share.

3. Upon convergence, we obtain estimates $(\hat{\theta}, \hat{\delta})$. We then estimate β by

$$\hat{\beta} = \left[Z'X\right]^{-1} Z'\hat{\delta}$$

where X and Z are a matrix of provider characteristics and that of instruments, respectively.

This approach avoids imposing market share equations at implausible parameters. Instead of obtaining $\delta(\theta)$ which solves $\ln S = \ln s(\delta; \theta)$, we update δ based on the Taylor approximation of this log market share equation. Although we have not investigated formal properties of convergence, the update of δ alone follows a Newton-Raphson step, so we conjecture that similar convergence property may hold if we also update θ. The convergent point $\hat{\delta}$ solves the market share equation.[33]

Note also that this approach exploits the separability of the micro and macro objective functions conditional on δ (Grieco et al., 2023). Specifically, given δ, the micro likelihood function is devoted to pinning down parameters governing patient heterogeneity, whereas standard macro moments are devoted to addressing the provider-level endogeneity problem. The estimation approach becomes slightly more complicated if the number of excluded instruments is strictly larger than that of endogenous variables, because the choice of θ will have to account for macro moments in addition to micro likelihood.

[33] We are also working on an alternative estimator suggested by Grieco et al. (2023), which does not involve the concern about convergence.

The likelihood for patient i admitted to provider j is

$$
\begin{aligned}
l_{ij}\left(x_{it}, n_{it}\right) &= \sum_{C \subseteq \mathcal{J}} \prod_{k \in C} \frac{\exp\left(\bar{v}_{ikt}\right)}{1+\exp\left(\bar{v}_{ikt}\right)} \prod_{l \in \mathcal{J} \setminus C} \frac{1}{1+\exp\left(\bar{v}_{ilt}\right)} \frac{I\left(j \in C\right)\exp\left(\bar{u}_{ijt}\right)}{1+\sum_{j' \in C}\exp\left(\bar{u}_{ij't}\right)} \\
&\equiv \sum_{C \subseteq \mathcal{J}} \prod_{k \in C} F_{ikt}(\theta^f) \prod_{l \in \mathcal{J} \setminus C} \left(1 - F_{ilt}(\theta^f)\right) P_{ijt}(C;\theta^p) \\
&\equiv \sum_{C \subseteq \mathcal{J}} Q_{it}(C;\theta^f) P_{ijt}(C;\theta^p).
\end{aligned}
$$

Instead of evaluating this, we simulate the likelihood by drawing consideration sets, with importance sampling to smooth the objective function. Details are described in Appendix C.

7 Estimation and Simulation Results

7.1 Estimation Results

Table 7 shows the estimates of provider parameters. Providers are more likely to accept an application if the applicant lived in the same city as the provider, is female, is of lower care level (lower severity), or if the occupancy rate is low relative to high baseline occupancy. To facilitate interpretation, Table 7 also displays the marginal effect of each characteristic for the acceptance probability of a single provider, evaluated at the mean value of characteristics. For example, acceptance probability is 4.4 pp higher if the applicant is from the same city.

Table 8 similarly presents estimates of patient parameters and implied marginal effects. We isolate the marginal effect on conditional choice probability (from effect on consideration) by presenting the marginal effect of a characteristic on the probability that an alternative is chosen over an outside alternative, from the binary choice set which contains these two options. Patients prefer providers with higher value added for home discharge and dislike distant providers. The coefficient on provider-quarter-specific average occupancy is imprecisely estimated, which may indicate that patients do not take congestion into account when choosing a provider.

Table 7: Estimates of Provider Parameters

Parameter	Estimate	SE	Marginal Effect
Constant	0.0115	0.0144	0.0029
Same City	0.1767	0.0074	0.0441
Old	0.0109	0.0120	0.0027
Female	0.0144	0.0075	0.0036
High Care Level	-0.0261	0.0084	-0.0065
Occupancy	0.0890	0.1325	0.0222
Occupancy$\times$ I(Occupancy > Mean)	-0.3100	0.1752	-0.0774

Note: This table presents the estimates of provider parameters. Rows indicate the coefficient on the constant term, the indicator of whether the patient's home is in the same city as the provider, indicator of whether the patient is 75 years old or older, female indicator, indicator of care level 3 or above (indicating relatively severe disability), de-meaned (by provider-specific average) daily occupancy, and de-meaned occupancy interacted by an indicator of the occupancy above mean (zero by construction). The column "Marginal Effect" displays the marginal effect of each characteristic on the offer probability of a single provider, evaluated at the mean value of characteristics. Estimate of the coefficient on the control covariate (provider-quarter-specific average occupancy) is omitted. Occupancy is denoted by the absolute number (1=100pp).

7.2 Simulation Results

To illustrate the effect of reallocation, we simulate a simple policy of smoothing occupancy. Instead of considering a complicated procedure to smooth occupancy across different episodes, we treat each year-quarter as consisting of homogeneous episodes and predict how the probability of home discharge changes with the policy, using the estimate of the coefficient on occupancy and provider quality estimates (using the specification with episode average of short-stay discharges as an instrument, as reported in Table 4).

More specifically, we assume that the occupancy rate is constant within provider-year-quarter bin (at the average within the bin). This generates a hypothetical set of homogeneous episodes, each lasting from the beginning of the year-quarter to the end of it. We then consider reallocating patients from the most congested provider to the least congested provider within each market (medical area-year-quarter) to equalize their average occupancy in the year-quarter. We ignore changes in variables other than occupancy and quality, and

Table 8: Estimates of Patient Parameters

Parameter	Estimate	SE	Marginal Effect with Binary Choice
Constant	0.8531	0.0317	0.0981
Value Added for Home Discharge	1.2406	0.1363	0.1426
Occupancy	5.5632	7.0981	0.6395
Distance (km)	-0.4856	0.0018	-0.0558

Note: This table presents the estimates of patient parameters. Rows indicate the coefficient on the constant term, the value added for home discharge, provider-quarter-specific average occupancy, and distance from (former) home to the provider. The column "Marginal Effect with Binary Choice" displays the marginal effect of each characteristic on the probability that an option with mean characteristics is chosen over an outside option, from the binary choice set. Occupancy is denoted by the absolute number (1=100pp).

decompose the effect of reallocation on patient i's outcome as follows:

$$\begin{aligned}\Delta_i &= E\left[Y_{ij_i^{\text{post}}} \mid n_j^{\text{post}}\right] - E\left[Y_{ij_i^{\text{pre}}} \mid n_j^{\text{pre}}\right] \\ &= \underbrace{\beta\left(n_{ij_i^{\text{post}}} - n_{ij_i^{\text{pre}}}\right)}_{\text{occupancy}-\text{smoothing effect}} + \underbrace{\mu_{j_i^{\text{post}}} - \mu_{j_i^{\text{pre}}}}_{\text{quality effect}} \equiv \Delta_i^o + \Delta_i^q \end{aligned} \tag{6}$$

where β is the coefficient on average occupancy in Eq.(2) and j_i^{post} (j_i^{pre}) is the facility to which patient i is assigned after (before) reallocation. The first term of Eq.(6) is an occupancy-smoothing effect, due to changing occupancy. Let h (l) denotes the provider with the higher (lower) occupancy. For home discharge ($\beta < 0$), we have $\Delta_i^o > 0$ if $j_i^{\text{pre}} = h$ and $\Delta_i^o < 0$ if $j_i^{\text{pre}} = l$, and the net occupancy-smoothing effect within each pair of providers, $\sum_{i:j_i^{\text{pre}} \in \{h,l\}} \Delta_i^o$, is *always* non-negative.[34] On the other hand, with congestion-quality tradeoff, we expect $\sum_{i:j_i^{\text{pre}} \in \{h,l\}} \Delta_i^q$ to be negative. We report the result for aggregate home discharges at the market level.

We also compute changes in the utility of patients, measured relative to the disutility from distance.

Table 9 shows simulation results. Panel (a) shows that occupancy-smoothing effect is positive but quality effect is typically negative, as reallocation transfers patients to a lower-

[34] Proof is omitted. Roughly, this is because there are more patients who enjoy an occupancy reduction than those who suffer an occupancy increase.

quality provider on average. The total effect is negative on average; however, the median effect is positive, so there are more winner markets than there are loser markets. Panel (b) shows that the welfare is negatively affected by reallocation, with average disutility equivalent to an increase in distance of 7.3km.

Table 9: Simulated Effect of Occupancy Smoothing on Patient Outcomes and Welfare

	Mean (1)	Std. Dev. (2)	Median (3)	Obs. (4)
(a) Change in Per-Patient Likelihood of Discharge to Home				
Occupancy-smoothing (pp)	0.273	4.117	0.287	262
Quality (pp)	-0.918	1.870	-0.074	262
Total (pp)	-0.646	4.082	0.159	262
(b) Change in Utility				
Total (relative to dist. coef)	-7.30	2.06	-8.04	1,416

Notes: This table presents changes in discharge to home and patient utility following reallocation. The row "Occupancy-smoothing (pp)" in panel (a) shows the per-patient net occupancy-smoothing effect (sum of Δ_i^o in Eq. (6) within each medical area-quarter, divided by the number of affected patients), in percentage points. Similarly, the row "Quality (pp)" shows the net quality effect (sum of Δ_i^q in Eq. (6) within each medical area-quarter) and the row "Total (pp)" shows the net total effect (sum of Δ_i in Eq. (6) within each medical area-quarter), both on per-patient basis and represented in pp. The row "Total (relative to dist. coef)" in panel (b) shows changes in patient utility, divided by the absolute value of distance coefficient.

However, this analysis is preliminary because we only consider marginal (affected by reallocation) patients, and it is partly driven by noisy estimates of utility parameters. Other limitations of the current simulation exercise are mentioned in Section 8.

8 Conclusion

Researchers and policymakers have documented substantial heterogeneity in outcome-based quality measures across institutions, and suggested possible gains from steering consumers to higher-quality institutions. This paper suggests that under capacity constraint, we may need to consider another factor, congestion, which may involve a tradeoff with quality. Using short-run fluctuations in occupancy as instruments, we find that a 1pp decrease in average occupancy (congestion) during an episode of nursing-home stay leads to 1.3pp higher likelihood of home discharge and 3.1pp lower likelihood of hospitalization. On the other hand, higher-quality providers also tend to be more congested, which generates a *congestion-quality tradeoff* in producing patient outcomes. The net effect of occupancy smoothing on the home discharge outcome can be positive for at least some cities participating in the simulated reallocation policy.

Our finding has implications on policies which aim to steer consumers toward high-quality institutions. Informational interventions to steer more consumers to better institutions may backfire if it generates excessive congestion. This tradeoff between negative externality of congestion and improved choice is reminiscent of the finding of Handel (2013), who suggests that improving choice by eliminating inertia may have unintended consequences due to adverse selection. Beyond informational interventions, our findings have implications for capacity policies, such as entry regulations. Whereas provider exits may improve the quality of surviving providers (Olenski, 2022), there may emerge an offsetting effect of congestion. Thus, the policymaker may need to pay attention to congestion along with the quality of operating institutions.

This paper leaves some issues up to future research. First, the effect of congestion may be heterogeneous; more specifically, it may be stronger for high-occupancy episodes. We are currently investigating effect heterogeneity and how it may affect our conclusions on congestion-quality tradeoff. Second, we have only considered the welfare impact of reallocation on the patients who are transferred to a different provider. Third, we have not discussed whether the current allocation of patients is efficient. Discussions of spatial misallocation will require us to take stance on the "right" preference and what causes deviation of occupancy distribution from the efficient one. Finally, we have not investigated what policy can lead to efficient outcomes (relative to the current or an alternative benchmark). We will consider these extensions in the future updates of this paper.

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A Additional Figures and Tables

Table A1: Functional Status of Each Support and Care Level

Support level 1-2	The patient is able to perform most of the basic activities of daily living on her own, but some nursing care is required for complex daily activities.
Care level 1	The patient's ability to perform complex daily activities has declined further from the state of Support level.
Care level 2	In addition to the condition of care level 1, the patient requires nursing care for basic daily activities.
Care level 3	Compared to the state of care level 2, there is a significant decline in terms of both basic and complex daily activities, and almost total nursing care is required.
Care level 4	In addition to the condition of care level 3, the patient's ability to move is further reduced and it becomes difficult for her to carry out daily living without nursing care.
Care level 5	The patient's ability to perform daily activities is even worse than the state of care level 4, and it is almost impossible for the patient to carry out daily living without nursing care.

Notes: This table describes physical status of patients in each category of support levels and care levels.

Table A2: Covariate Balance (Admission Instrument)

	(1) Age	(2) Female	(3) High cost sharing	(4) Care level	(5) Receiving terminal care	(6) Length of stay
Short-stay admission in pp	0.09056	0.00937**	0.00120	-0.00226	0.000598	1.578*
	(0.06669)	(0.00380)	(0.00148)	(0.01069)	(0.000769)	(0.8861)
Mean outcome	85.11	0.6752	0.0342	3.21	0.0109	121.61
N	599,946	599,946	599,946	599,946	599,946	599,946

*** p<0.01, **p<0.05, *p<0.1

Note: This table presents the result of regression of patient characteristic (indicated by each column) on our instrument (average number of short-stay admissions during episode, expressed as a percentage of capacity) and controls other than the dependent variable. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

Table A3: Instrumental Variable Regression of Patient Outcomes on Occupancy (Admissions IV)

	(1) First Occupancy	(2) Second Home Discharge	(3) Second Hospitalization	(4) Second Death
Occupancy in pp		-0.01371** (0.00668)	0.03157*** (0.00803)	0.00278 (0.00243)
Short-stay admission in pp	-0.714*** (0.122)			
Mean outcome	0.8913	0.3452	0.3718	0.0654
N	599,946	599,946	599,946	599,946

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table presents the results of instrumental variable regressions of patient outcomes on occupancy and other controls, using average short-stay admissions during the episode as an instrument. Column (1) displays the first-stage coefficient on the instrument and Columns (2)-(4) display the second-stage coefficients on occupancy. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

Table A4: Instrumental Variable Regression of Patient Outcomes on Occupancy (Before-Episode Admission IV)

	(1) First Occupancy	(2) Second Home Discharge	(3) Second Hospitalization	(4) Second Death
Occupancy in pp		-0.01802***	0.02157***	-0.00299
		(0.00643)	(0.00606)	(0.00255)
Short-stay admission in pp (before admission)	-0.410***			
	(0.0334)			
Mean outcome	0.8913	0.3452	0.3718	0.0654
N	593,518	593,518	593,518	593,518

*** p<0.01, **p<0.05, *p<0.1

Note: This table presents the results of instrumental variable regressions of patient outcomes on occupancy and other controls, using average short-stay admissions in the 14 days preceding admission as an instrument, controlling for average short-stay admissions during the episode. Column (1) displays the first-stage coefficient on the instrument and Columns (2)-(4) display the second-stage coefficients on occupancy. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

Table A5: OLS Estimates of the coefficient on Occupancy

	(1) Home Discharge	(2) Hospitalization	(3) Death
Occupancy	-0.0000853	0.00000176	-0.0000197
in pp	(0.000136)	(0.000141)	(0.0000688)
Control	Y	Y	Y
Mean outcome	0.3452	0.3718	0.0654
N	599,946	599,946	599,946

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table presents the results of OLS regressions of patient outcomes on occupancy and other controls. Controls included are: age, female indicator, indicator of high cost sharing, care level, indicator of receiving terminal care, average of these variables at the provider during the episode, length of stay, local hospital capacity, discharge date fixed effects and medical area by discharge year-month fixed effects.

B Proofs and Additional Results

B.1 Proof of Proposition 1.

By Assumption 1(i)(ii), the probability that i is admitted to j can be written as

$$\begin{aligned}
l_{ij}(x_i, n_i) &= \Pr\left(j_i = j | x_i, n_i\right) \\
&= \sum_{C \subseteq \mathcal{J}} \Pr\left(C_i = C | x_i, n_i\right) \Pr\left(j_i = j | C_i = C, x_i\right) \\
&= \sum_{C \subseteq \mathcal{C}(j)} \prod_{k \in C} F_{\eta_k | x_{ik}}\left(v_k(x_{ik}, n_{ik})\right) \prod_{l \in \mathcal{J} \setminus C} \left[1 - F_{\eta_l | x_{il}}\left(v_l(x_{il}, n_{il})\right)\right] \Pr\left(j | C, x_i\right) \\
&= F_{\eta_j | x_{ij}}\left(v_j(x_{ij}, n_{ij})\right) \\
&\quad \times \sum_{C \subseteq \mathcal{C}(j)} \prod_{k \in C \setminus \{j\}} F_{\eta_k | x_{ik}}\left(v_k(x_{ik}, n_{ik})\right) \prod_{l \in \mathcal{J} \setminus C} \left[1 - F_{\eta_l | x_{il}}\left(v_l(x_{il}, n_{il})\right)\right] \Pr\left(j | C, x_i\right)
\end{aligned}$$

where the third equality holds because of independence between η_i and ε_i and independence of η_{ij} across j, with $\mathcal{C}(j)$ denoting the collection of subsets of $\mathcal{J}$ that contain j.

Below, we proceed by slightly relaxing Assumption 1(iii):

Assumption 1(iii-b) *For each j, (i) we know x_{ij}^0 such that $\lim_{n_{ij} \to \underline{n}_j} F_{\eta_j | x_{ij}^0}\left(v_j(x_{ij}^0, n_{ij})\right) = 1$. (ii) we know n_j^0 such that $\lim_{n_{ij} \to n_j^0} F_{\eta_j | x_{ij}}\left(v_j(x_{ij}, n_{ij})\right) > 0$ does not depend on x_{ij}.*

This assumption slightly relaxes Assumption 1(iii). For example, with $v(x, n) = \alpha + \beta x \cdot \left(\frac{1}{n} - 2\right)$, $n \in (0, 1)$, $\beta > 0$ and $F_{\eta_j | x_{ij}} = F_{\eta_j}$, Assumption 1(iii) does not hold at $x = 0$ but Assumption 1(iii-b) still holds with $x^0 = 1$ and $n^0 = 0.5$.

Fix j. Let $n = (n_1, \ldots, n_J)$ and $n' = \left(n_1, \ldots, n_{j-1}, n_j', n_{j+1}, \ldots, n_J\right)$ be any two vectors of daily occupancy which only differ in j's occupancy. We then have $\frac{l_{ij}(x_i, n)}{l_{ij}(x_i, n')} = \frac{F_{\eta_j | x_{ij}}(v_j(x_{ij}, n_j))}{F_{\eta_j | x_{ij}}\left(v_j(x_{ij}, n_j')\right)}$. Therefore, by Assumption 1(iii-b), at $x_i = x_i^0 = (x_{i1}^0, \ldots, x_{iJ}^0)$,

$$F_{\eta_j | x_{ij}^0}\left(v_j(x_i^0, n_j)\right) = \lim_{n_{j'} \to \underline{n}_j} \frac{F_{\eta_j | x_{ij}^0}\left(v_j(x_i^0, n_j)\right)}{F_{\eta_j | x_{ij}^0}\left(v_j(x_i^0, n_j')\right)} = \lim_{n_{j'} \to \underline{n}_j} \frac{l_{ij}(x_i^0, n)}{l_{ij}(x_i^0, n')}$$

is identified at all n_j.

Next, at any (x_{ij}, n_j),

$$F_{\eta_j|x_{ij}}\left(v_j(x_{ij}, n_j)\right) = \lim_{n'_j \to n^0_j} \frac{F_{\eta_j|x_{ij}}\left(v_j(x_{ij}, n_j)\right)}{F_{\eta_j|x_{ij}}\left(v_j(x_{ij}, n'_j)\right)} F_{\eta_j|x_{ij}}\left(v_j(x_{ij}, n'_j)\right)$$
$$= \lim_{n'_j \to n^0_j} \frac{l_{ij}(x_i, n)}{l_{ij}(x_i, n')} \lim_{n'_j \to n^0_j} F_{\eta_j|x^0_{ij}}\left(v_j(x^0_{ij}, n'_j)\right),$$

is identified. Repeating this argument, we identify $F_{\eta_{j'}|x_{ij'}}\left(v_{j'}(x_{ij'}, n_{j'})\right)$ for all j', $x_{ij'}$ and $n_{j'}$.

Now, pick any x_i and $n^{1,j}, \ldots, n^{R,j}$ that satisfies Assumption 2. Stack the above equations at this value in a vector

$$L_j(x_i, \mathbf{n^j}) \equiv \begin{bmatrix} l_{ij}(x_i, n^{1,j}) \\ \\ l_{ij}(x_i, n^{R,j}) \end{bmatrix}$$
$$= \begin{bmatrix} F\left(C^j_1; x_i, n^{1,j}\right) & \cdots & F\left(C^j_K; x_i, n^{1,j}\right) \\ \vdots & \ddots & \vdots \\ F\left(C^j_1; x_i, n^{R,j}\right) & \cdots & F\left(C^j_K; x_i, n^{R,j}\right) \end{bmatrix} \begin{bmatrix} \Pr\left(j_i = j | C_i = C^j_1, x_i\right) \\ \\ \Pr\left(j_i = j | C_i = C^j_K, x_i\right) \end{bmatrix}$$
$$= F^j(x_i, \mathbf{n^j}) P_j(x_i)$$

and stack the matrices further as

$$L(x_i, \mathbf{n}) \equiv \begin{bmatrix} L_1(x_i, \mathbf{n^1}) \\ \\ L_J(x_i, \mathbf{n^J}) \end{bmatrix} = \begin{bmatrix} F_1(x_i, \mathbf{n^1}) & & 0 \\ & \ddots & \\ 0 & & F_J(x_i, \mathbf{n^J}) \end{bmatrix} \begin{bmatrix} P_1(x_i) \\ \\ P_J(x_i) \end{bmatrix}$$
$$\equiv F(x_i, \mathbf{n}) P(x_i).$$

We then identify the choice probabilities as $P(x_i) = \left[F(x_i, \mathbf{n})^\top F(x_i, \mathbf{n})\right]^{-1} F(x_i, \mathbf{n})^\top L(x_i)$. We can repeat this for all x_i. ■

B.2 Identification of Admission Parameters

We discuss identification of providers' utility function v and distribution of idiosyncratic cost, $F_{\eta_j|x_{ij}}$.

Assumption 4 *For each j,*

(i) the utility of not offering i an admission is normalized to zero.

(ii) $F_{\eta_j|x_{ij}}$ is strictly increasing and differentiable, and v_j is continuously differentiable in n_j and some element $x_{ij}^{(s)}$ with a finite derivative.

(iii) $\frac{\partial v_j(x_{ij},n_j)}{\partial x_{ij}^{(s)}} \overset{restrict}{=} \beta_s \overset{normalize}{=} 1$.

(iv) $F_{\eta_j|x_{ij}}$ does not depend on $x_{ij}^{(s)}$.

(v) the τ-th quantile of $\eta_j|x_{ij}$ is known. For each x_{ij}, we observe n_j such that $F_{\eta_j|x_{ij}}(v_j(x_{ij},n_j)) = \tau$.

Assumption 4(i) is standard normalization. Assumptions 4(ii), (iii) and (iv) together allow us to identify the derivative of v_j with respect to n_j. Note that we do not assume $x_{ij}^{(s)}$ has a large support. Finally, Assumption 4(v) fixes the location. It holds if, e.g., for all x_{ij}, $F_{\eta_j|x_{ij}}(\cdot)$ and $v_j(x_{ij},\cdot)$ are continuous, $v_j(x_{ij},\cdot)$ is decreasing and $F_{\eta_j|x_{ij}}(v_j(x_{ij},\bar{n}_j)) < \tau < F_{\eta_j|x_{ij}}\big(v_j(x_{ij},\underline{n}_j)\big)$. A more specific example is that $\eta_j|x_{ij}$ has conditional median zero, and that $F_{\eta_j|x_{ij}}(v_j(x_{ij},n_j)) = 0.5$ for some n_j.

Proposition 2 *Suppose that Assumption 4 holds and we observe $F_{\eta_j|x_{ij}}(v_j(x_i,n_j))$ for all (j,x_{ij},n_j). Then $v_j(x_{ij},n_j)$ is identified for all (j,x_{ij},n_j). Moreover, $F_{\eta_j|x_{ij}}$, $x_{ij}\in\mathcal{X}_j$, is identified on $v_j(\mathcal{X}_j,\mathcal{N}_j)$, where $\mathcal{X}_j$ and $\mathcal{N}_j$ denote the support of x_{ij} and n_j, respectively.*

Proof. By Assumptions 4(ii)(iii)(iv),

$$\frac{\frac{\partial F_{\eta_j|x_{ij}}(v_j(x_{ij},n_j))}{\partial n_j}}{\frac{\partial F_{\eta_j|x_{ij}}(v_j(x_{ij},n_j))}{\partial x_{ij}^{(s)}}} = \frac{\frac{\partial v_j(x_{ij},n_j)}{\partial n_j}}{\frac{\partial v_j(x_{ij},n_j)}{\partial x_{ij}^{(s)}}} = \frac{\partial v_j(x_{ij},n_j)}{\partial n_j}.$$

is identified for all (x_{ij}, n_j). Take any x_{ij}. We observe some $n_j(x_{ij})$ such that $v_j(x_{ij}, n_j(x_{ij})) = q_j^\tau(x_{ij})$, where $q_j^\tau(x_{ij})$ is the known τ-th quantile of $\eta_j|x_{ij}$. Therefore,

$$v_j(x_{ij}, n_j) = q_j^\tau(x_{ij}) + \int_{n_j(x_{ij})}^{n_j} \frac{\partial v_j(x_{ij}, n_j')}{\partial n_j'} dF_j(n_j'),$$

where $F_j(n_j)$ is the distribution function of n_j, is identified. Thus, at any $(x_{ij}, n_j) \in \mathcal{X}_j \times \mathcal{N}_j$, $F_{\eta_j|x_{ij}}(v_j(x_{ij}, n_j))$ is identified. ■

C Estimation Details

Note the individual likelihood can be rewritten as

$$\begin{aligned}
l_{ij} &= \sum_{C \subseteq \mathcal{J}} \prod_{k \in C} F_{ikt}(\theta^f) \prod_{l \in \mathcal{J} \setminus C} \left(1 - F_{ilt}(\theta^f)\right) P_{ijt}(C; \theta^p) \\
&= \sum_{C \subseteq \mathcal{J}} Q_{it}(C; \theta^f) P_{ijt}(C; \theta^p) \\
&= \sum_{C \subseteq \mathcal{J}} \left\{ \frac{Q_{it}(C; \theta^f)}{Q_{it}(C; \theta_0^f)} P_{ijt}(C; \theta^p) \right\} Q_{it}(C; \theta_0^f)
\end{aligned}$$

where θ_0 is an initial value. This suggests the following simulation algorithm:

1. Draw $U_{ijt}^r \sim U[0,1]$, $r = 1, \ldots, R$, for each i and j.
2. Obtain $C_{it}^r = \left\{ j \in \mathcal{J}_t : F_{ijt}\left(\theta_0^f\right) \geq U_{ijt}^r \right\}$ for each i and r.
3. Calculate $P_{ijt}(C_{it}^r; \theta^p) = I(j \in C_{it}^r) \frac{\exp(\bar{u}_{ijt})}{1 + \sum_{j' \in C_{it}^r} \exp\left(\bar{u}_{ij't}\right)}$.
4. Calculate $\hat{l}_{ijt} = \frac{1}{R} \sum_{r=1}^R \frac{Q_{it}\left(C_{it}^r; \theta^f\right)}{Q_{it}\left(C_{it}^r; \theta_0^f\right)} P_{ij}(C_{it}^r; \theta^p)$.

The simulated likelihood is smooth in parameters. Moreover, we can hold simulated consideration sets fixed throughout estimation.