Picking Your Patients:

Selective Admissions in the Nursing Home Industry

Ashvin Gandhi*

UCLA Anderson

Draft Date: September 13, 2019

Click here for the latest version.

Abstract

Do healthcare providers pick their patients? This paper uses patient-level administrative data on skilled nursing facilities in California to estimate a structural model of selective admission practices in the nursing home industry. I exploit within-facility covariation between occupancy and admitted patient characteristics to distinguish admission patterns attributable to selective admission practices from those attributable to heterogeneous patient preferences. In spite of anti-discrimination laws, I find strong evidence of selective admission practices that disproportionately harm Medicaid-eligible patients with lengthy anticipated stays. Counterfactual simulations show that enforcing a prohibition on selective admissions would increase access for these residents at the cost of crowding out short-stay non-Medicaid patients from their preferred facilities. I simulate two additional policies intended to mitigate selective admissions: raising the Medicaid reimbursement rate and expanding capacity. I find the latter to be less costly and more effective than the former.

*I thank my Ph.D. advisers, Ariel Pakes, David Cutler, Robin Lee, and Elie Tamer. I am also grateful to David Grabowski, Mark Shepard, Myrto Kalouptsidi, Pierre Dubois, Alex MacKay, Nathan Hipsman, Sam Antill, Xiaosheng Mu, Prabhava Upadrashta, David Zhang, Frank Pinter, Jeff Miron, Vincent Mor, Kevin He, Shoshana Vasserman, and the many seminar participants who provided helpful feedback. I thank The Lab for Economic Applications and Policy and The Institute for Quantitative Social Science for funding data acquisition. Additionally, funding from the National Institute on Aging, through Grant Number T32-AG000186 to the National Bureau of Economic Research, is gratefully acknowledged.

Electronic copy available at: https://ssrn.com/abstract=3613950

1 Introduction

Policymakers and academics have long been concerned with inequality in access to quality healthcare. Even with equal geographic access, inequality can persist when providers can pick their patients. In particular, providers facing capacity constraints or increasing marginal costs may choose to treat more profitable patients while turning away less profitable ones.

This paper uses patient-level administrative data on residents of skilled nursing facilities (SNFs) to study the role of selective admission practices in the nursing home industry.[1] The United States has more than 15,000 nursing homes with approximately 1.4 million residents at any given time (National Center for Health Statistics, 2017). The quality of these facilities varies substantially (Castle and Ferguson, 2010), and patients may not all have access to the same quality of care. Patients' rights activists (Carlson, 2005), policymakers (Senate, 1984; Wright, 2002), and academics (Gruenberg and Willemain, 1982; Ettner, 1993; Uili, 1995; Ching et al., 2015) have often accused SNFs of discriminating against patients who are poorer or sicker in admissions. If true, these practices have important implications for the health outcomes of these patients and may violate federal and state laws prohibiting Medicaid and disability discrimination.[2]

A number of factors incentivize selective admission practices in the nursing home industry. First, reimbursement rates can vary substantially depending on the payment source.[3] For example, while facilities are legally obligated to offer the same type and quality of care to their Medicaid and private-pay residents, private-pay rates are nearly 30% higher than Medicaid rates on average. Second, since private and Medicaid reimbursements are typically fixed per-diems, SNFs are not fully compensated for the additional care requirements of high-needs patients. Third, capacity constraints imply an opportunity cost to admissions.[4] These opportunity costs can be substantial since some residents are expected to remain at the facility for years, during which time their beds cannot be allocated to admit more profitable patients.

In order to measure the prevalence and impacts of selective admission practices, I estimate a structural model of admissions in the nursing home industry that incorporates both residents' preferences and facilities' admission policies. Specifically, I model nursing homes as multiproduct firms (Sullivan, 2017; Wollmann, 2018) facing capacity constraints (Ryan, 2012; Ching et al., 2015; Kalouptsidi, 2014, 2018) that dynamically adjust the types of patients they are willing to admit. Each facility considers each arriving patient and decides whether to offer her admission based on her characteristics, the facility's current census of residents,

[1] The terms "skilled nursing facility," "nursing facility," and "nursing home" carry various meanings in different contexts. I use these interchangeably to refer to facilities certified by the Centers for Medicare & Medicaid Services to provide skilled nursing and related services (see 42 U.S.C. §1395i and §1396r). Importantly, these do not include assisted living facilities, which do not provide the same degree of health care services but are sometimes referred to as nursing homes in the vernacular.

[2] Being unable to access facilities that perform well on quality metrics such as staffing ratios and deficiencies is expected to result in worse health outcomes along a number of dimensions, including rates of mortality, infection, and re-hospitalization (Schnelle et al., 2004; Backhaus et al., 2014; Lin, 2014; Foster and Lee, 2015; Friedrich and Hackmann, 2017).

[3] One form of selection on payment source is a provider's decision about which insurance plans to accept. Recent literature has explored the relationship between networks, plan choice, and negotiated rates (Ho, 2006, 2009; Shepard, 2015; Ho and Lee, 2018). The vast majority of SNFs, however, accept all three primary payers: Medicare, Medicaid, and out-of-pocket. This paper examines selective admissions in the context of patients whose reimbursements are nominally accepted by the provider.

[4] The median facility occupancy in my sample is 88%, and my estimates suggest many facilities would quickly reach capacity if they admitted all applicants. Firms may also face increasing marginal costs due to challenges in adjusting staffing levels and other inputs. Such diseconomies of scale would raise the effective cost of admitting residents similarly to capacity constraints.

Electronic copy available at: https://ssrn.com/abstract=3613950

and the facility's beliefs about prospective residents that will arrive in the future.[5] Patients then choose and are admitted to their preferred facility offering admission.

The primary empirical challenge to estimating this model is that only realized admissions are observed. Since realized admissions are determined by both facilities' admission policies and patients' preferences, it is difficult to distinguish admission patterns attributable to selective admissions from those attributable to heterogeneous patient preferences. For example, though dual-eligibles—i.e., residents eligible for Medicaid in addition to Medicare—are admitted to lower quality facilities (Rahman et al., 2014a,b), this does not necessarily imply Medicaid discrimination since the disparity could be also be explained by dual-eligibles having weaker preferences for quality metrics. Prior work incorporating selective admissions has typically done so by assuming that dual-eligibles can only choose from facilities with capacity remaining after all other patients have been admitted (Nyman, 1985; Gertler, 1992; Ching et al., 2015).[6]

My model incorporates selective admissions as a source of variation in residents' choice sets that is unobserved when estimating demand. Unlike many other settings with availability variation (Hickman and Mortimer, 2016), the set of facilities willing to admit a patient is never observed, and facilities' willingness to admit particular patients is plausibly correlated with those patients' preferences.[7] Agarwal (2015) addresses a similar issue in estimating a model of the medical residency match using only data on observed matches. While the dynamic and decentralized nature of admissions in the nursing home industry precludes the methods in Agarwal (2015), it also provides an alternative source of identification: facilities facing capacity constraints or increasing marginal costs are expected to increase the selectivity of their admission practices as their census of residents increases (Greenlees et al., 1982). I therefore exploit within-facility covariation between facility census and admitted resident characteristics to identify selective admission practices.

I first provide evidence that the composition of residents that facilities admit covaries with facility occupancy. I find that as facilities become more full, their newly admitted residents are less likely to be Medicaid-eligible, have long anticipated stays, or require uncompensated care. This evidence suggests that admission policies discriminate against residents with these characteristics. I then use machine learning methods to aggregate residents' many observable characteristics into a univariate desirability score for each resident. Finally, I estimate the structural model of admissions in two stages. In the first stage, I estimate resident preference parameters and facilities' admission policies via maximum likelihood, where admission policies determine residents' choice sets, and resident preferences determine the realized admissions from within those sets.[8] In the second stage, I estimate the structural profitability parameters underlying facili-

[5] A facility's census is its set of current residents.

[6] Hackmann (2018) does so by interacting an indicator for high occupancy with payer source in the utility model.

[7] Prior work on product availability has primarily focused on assortment variation (Tenn and Yun, 2008; Bruno and Vilcassim, 2008; Draganska and Klapper, 2011; Shah et al., 2015; Musalem, 2015; Crawford et al., 2017) and stock-outs (Anupindi et al., 1998; Musalem et al., 2010; Conlon and Mortimer, 2013) in retail settings.

[8] Since admission policies are not observed, I parameterize them as a function of resident characteristics, unobserved resident profitability, facility characteristics, and current facility census. I then compute the likelihood of each admission by integrating over the probabilistic distribution of choice sets available to the resident. Sovinsky Goeree (2008) and Dubois and Saethre (2018) apply similar methods, respectively parameterizing unobserved choice sets using observed advertising levels and markups.

Electronic copy available at: https://ssrn.com/abstract=3613950

ties' admission policies by matching moments in the data to those implied by optimal admission policies.[9] These second-stage estimates allow me to compute facilities' optimal admission policies in counterfactual simulations. As in the reduced form, selective admission practices in the structural model are identified from the relationship between facilities' censuses and realized admissions.

My structural estimates indicate that 19% of California's SNF residents are not admitted to their first-choice facility and that 40% of care-days are spent at facilities other than the resident's first choice.[10] Medicaid-eligible residents with very long anticipated stays fare particularly poorly and are denied admission to their most-preferred facility nearly 50% of the time. While this suggests significant admissions discrimination against Medicaid-eligible residents, I also find that Medicaid-eligible residents have weaker preferences for facility staffing levels, meaning that heterogeneous preferences also contribute to admission disparities. However, this preference disparity is much smaller than when demand is estimated under the assumption that selective admissions do not occur. Therefore, failing to account for selective admission practices leads the econometrician to significantly misestimate both demand elasticities and welfare measures.

I use my estimated model to simulate the effects of three policies intended to improve access to high-quality facilities: mandating that facilities practice "first come, first served" (FCFS) admissions, raising the Medicaid reimbursement rate, and increasing capacity at facilities with excess demand from Medicaid-eligible residents. Each of these relates to policies that have been considered or implemented in various states.[11] My simulations indicate that FCFS admissions would lead to welfare gains that residents value equivalently to .20 hours (1.1 standard deviations) of registered nurse (RN) care per day on average. These gains accrue primarily to Medicaid-eligible residents with lengthy anticipated stays, who experience increased access under FCFS, and come partially at the expense of non-Medicaid short-stay patients, who are sometimes crowded out of their preferred facilities under FCFS. Raising the Medicaid reimbursement rate has similar distributional effects: access for Medicaid-eligible residents improves slightly but does so largely at the expense of non-Medicaid residents.[12] Targeted capacity increases, on the other hand, benefit both groups. I find that adding 800 beds (an 11% increase) to facilities with excess demand in the San Diego area leads to welfare gains for both Medicaid (.13 RN hours per day) and non-Medicaid residents (.06 RN hours per day) and is substantially more cost-effective than raising the Medicaid reimbursement rate.

While this paper specifically examines nursing homes, concerns about providers picking their patients

[9] While the admission policies in the first stage approximate facilities' optimal admission policies, they are not computed as the solutions to facilities' optimal control problems. Therefore, the first-stage estimates cannot be used to simulate facilities' optimal admission policies under counterfactual government policies. Computing optimal admission policies in the second stage requires solving facilities' Bellman equations at each step in the GMM minimization (Rust, 1987) since common conditional choice probability methods (Hotz and Miller, 1993; Hotz et al., 1994; Pakes et al., 2007; Bajari et al., 2007; Arcidiacono et al., 2016) are precluded by the fact that admission decision are not directly observed.

[10] I include only facilities with available beds when computing these rejection rates.

[11] Examples include FCFS admissions (e.g., Connecticut General Statutes 19a-533), raising Medicaid reimbursement rates (e.g. California Assembly Bill No. 1629), limiting private-pay rates (e.g., Minnesota Statutes 256B.47 and North Dakota Century Code 50-24.4), and regulating facility capacities through Certificate of Need (CON) laws (e.g., Connecticut Statutes 19a-638 and Rhode Island General Laws 23-17-44) and bed-buybacks (e.g., Oregon Revised Statutes 410.070 and Louisiana Revised Statutes §40:2116). While CON laws and bed-buybacks reduce capacity, counterfactual simulations of increasing capacity may still be informative about the impacts of these policies.

[12] My counterfactual simulations hold facilities' characteristics fixed. Raising Medicaid reimbursement rates may also lead to additional welfare gains by incentivizing facilities to increase their quality (Hackmann, 2018).

Electronic copy available at: https://ssrn.com/abstract=3613950

are not limited to the nursing home industry. Providers may face similar incentives in other parts of the healthcare industry, especially those in which patient desirability is heterogeneous and providers face capacity constraints or diseconomies of scale. For example, previous work has expressed similar concerns about specialty hospitals (Cram et al., 2008) and dialysis clinics (Desai et al., 2009). The trend toward fully and partially capitated systems, such as Accountable Care Organizations, may also exacerbate financial incentives for providers to pick their patients (Watnick et al., 2012). Finally, an increasing reliance of patients, insurers, and regulators on outcome-based quality metrics may incentivize providers to pick their patients in order to boost these metrics (Dranove et al., 2003). Occupancy rates and other sources of variation in providers' policies may help to identify related models of providers picking their patients in these other healthcare markets. Moreover, the broader method of explicitly modeling suppliers' decisions to participate in demanders' choice sets, and of exploiting variation in suppliers' optimality conditions to identify suppliers' policies, may be extended to other contexts and industries with endogenous unobserved choice sets.[13]

The remainder of the paper is organized as follows. Section 2 provides background on the nursing home industry. Section 3 describes the data used in my analysis, and Section 4 provides preliminary evidence of selective admissions. Section 5 describes my model, and Section 6 gives my structural estimation procedure. Sections 7 and 8 respectively present model estimates and counterfactual simulations. Section 9 concludes.

2 Industry Background

This paper examines Medicare-certified skilled nursing facilities, which are certified by the Centers for Medicare and Medicaid Services (CMS) to provide a broad range of care, including skilled nursing care, specialized rehabilitative services, medically-related social services, and treatment for the mentally ill and mentally retarded (42 U.S.C. §1395i). Because SNFs are equipped to provide such a broad range of care, they often serve a census of residents with highly varied care requirements and lengths of stay.

Most SNF residents are initially admitted in order to receive rehabilitative and other therapy care following a discharge from an acute care facility. The majority of these residents are discharged to the community after receiving short-term rehabilitative therapy related to their preceding hospital stay. However, some continue to require long term care and continue to reside at the facility in order to receive daily nursing care and additional therapy care as needed.

The remainder of this section provides background on reimbursements in the industry, details facilities' incentives to pick their patients, and describes the history of regulations against selective admission practices.

[13] Many salient examples involve discrimination, including transportation (Ge et al., 2016), lending (Ladd, 1998; Blanchard et al., 2008; Hanson et al., 2016), employment (Heckman, 1998; Bertrand and Mullainathan, 2004), and real estate (Kain and Quigley, 1972; Page, 1995; Ahmed and Hammarstedt, 2008). In all cases, the suppliers' optimality condition must reflect the incentives and institutional details specific to the industry.

Electronic copy available at: https://ssrn.com/abstract=3613950

2.1 Reimbursement

There are three primary sources of reimbursement for nursing home care: Medicare, private, and Medicaid.

Medicare only reimburses SNF care for Medicare enrollees with a physician-certified need in relation to a recent acute care hospital stay lasting at least three inpatient days.[14] Medicare covers 100% of the first 20 days of qualifying care, requires coinsurance after 20 days ($119 per day in 2006), and is capped at 100 days. Medicare reimbursements are adjusted based on both patient care requirements and the cost of inputs in the facility's market. Because Medicare only covers post-acute care, residents covered by Medicare tend to require rehab and therapy care that is costly to provide and is therefore reimbursed at a high rate.

Residents who are ineligible or have exhausted their Medicare coverage and are not yet eligible for Medicaid—i.e. have not exhausted personal financial resources—are "private pay." Long term care insurance is uncommon (Brown and Finkelstein, 2007, 2009, 2011), so most private pay residents pay out of pocket. Private rates are per-diem and are usually lower than Medicare reimbursement rates, though the care required by private pay patients tends to be less intensive than the post-acute care covered by Medicare. Private rates are typically not adjusted based on a patient's care requirements, though they do vary within a facility based on whether a resident's room is private or shared.

Once a resident over 65 has exhausted her private financial resources, she qualifies for Medicaid if she continues to require a level of care that cannot reasonably be obtained outside of a skilled nursing facility. This usually means that the resident must demonstrate a need for around-the-clock availability of skilled nursing care that could not be provided by alternatives such as outpatient or home health care. The vast majority of facilities in my sample (94.34%) are Medicaid-certified and are therefore legally obligated to accept Medicaid reimbursements. Medicaid reimbursement rates in California are not adjusted according to individual residents' care requirements and are usually lower than private rates (Figure 3).

Table 1 shows that while only 26.01% of residents ever utilize Medicaid coverage, a large majority of SNF care (65.58% of days) is reimbursed by Medicaid. This is both because Medicaid-eligible residents tend to have longer stays and because long stays are more likely to exhaust private resources and result in Medicaid eligibility. Table 2 details the transitions that residents make between their admission and discharge payer sources. Nearly 58% percent of days are from residents who transition between payer sources during their stay, most commonly from Medicare to Medicaid.[15]

2.2 Incentives to Discriminate

Nursing homes face a number of incentives to pick their patients. First, as discussed above, reimbursement rates can vary substantially by payment source. In particular, Medicaid reimbursement rates tend to be

[14] For additional details, see https://www.medicare.gov/coverage/skilled-nursing-facility-snf-care.

[15] Note that 29.11% of residents in the sample are enrolled in Medicare Advantage. Insurers participating in Medicare Advantage are not required to submit claims data to CMS. Therefore, I impute the part of Medicare Advantage enrollees' stays that were covered by their Medicare Advantage plan. I impute these values using predictions based on resident assessment data. I train the predictive function using machine learning methods on data for Traditional Medicare enrollees since Medicare Advantage plans are required to cover SNF care when Traditional Medicare would have.

Electronic copy available at: https://ssrn.com/abstract=3613950

substantially lower than either the private rate or the Medicare reimbursement rate. Therefore, facilities may have strong financial incentives to screen for current and future Medicaid eligibility. In fact, some facilities require prospective residents to submit financial documentation that can be used to forecast when a resident is likely to become eligible for Medicaid based on an anticipated spend-down of assets on care. Facilities can even purchase commercial "admission analysis" software to assist in making these projections.[16]

In addition to variation in reimbursements, there may also be substantial uncompensated variation in the cost of providing care to different patients. For example, patients with behavioral problems or diagnoses such as dementia or obesity may require more staff time and facility resources than other residents. In California, only Medicare reimbursements are adjusted according to a patient's anticipated resource utilization. Facilities receive no additional compensation for high-needs patients on days not covered by Medicare, and even Medicare reimbursements may not perfectly insure the facility against heterogeneous care requirements. Legal prohibitions (42 CFR §483.10(a)(2)) and organizational challenges also prevent facilities from achieving higher margins by providing low-reimbursement patients lower quality care (Grabowski et al., 2008).

Facilities also face dynamic incentives to pick their patients. Most directly, each facility's capacity is constrained by its number of CMS-certified beds, so each admitted patient reduces the capacity available to admit more profitable patients in the future.[17] Figure 1 gives the capacities and occupancy rates of the SNFs in my sample. The average capacity is approximately 100 beds, and the median occupancy rate is 88%. The industry's high occupancy rates suggest that many facilities could quickly reach their capacity constraint if they were to admit additional residents. Facilities facing excess demand will therefore want to ration their capacity by turning away less desirable residents.

Furthermore, length of stay can vary substantially across residents. While most stays are brief, some residents stay at the facility for years. Figure 2 shows the distribution of stay lengths in my sample. While most stays are relatively brief—the 50th percentile resident stays just 25 days—the standard deviation of their lengths is large (333 days). I show in Appendix C that this variation is broadly predictable using only information that was plausibly observable at admission. Facilities practicing selective admissions may therefore be particularly wary of admitting low-margin residents predicted to stay for a very long time, especially since involuntarily discharging residents without cause is illegal (42 CFR §483.15(c)).

In addition to capacity constraints, facilities may also face diseconomies of scale. The primary input cost for nursing homes is staffing, and meeting demand above what long-term staff are equipped to handle may bear additional cost. For example, nursing cost report data from California indicate that facilities pay an average wage premium of 37% when hiring temporary registered nurses (RNs).[18] Temporary staff may also be less productive or require additional training in order to be effective. Such increasing marginal costs may lead facilities to ration admissions even when capacity constraints are unlikely to bind in the future.

[16] For example, American HealthTech's Admission Analysis module advertises being able "to project total cost of care per resident, as well as how much each will generate in revenue..." See https://www.healthtech.net/admissions-analysis.

[17] Capacity adjustments are rare because increasing capacity requires certification of new beds by CMS in addition to the space and staffing required to accommodate the additional beds.

[18] This premium is respectively 34% and 23% when weighting by a facility's reported full time and part time hours.

Electronic copy available at: https://ssrn.com/abstract=3613950

2.3 History and Regulation

State and Federal governments have passed a large number of regulations restricting selective admission practices on the basis of either disability or payer-status.

Section 504 of the Rehabilitation Act of 1973 prohibits nursing homes receiving either Medicare or Medicaid reimbursements from discriminating in admissions on the basis of disability.[19] Wagner v. Fair Acres Geriatric Center, 859 F. Supp. 776 (E.D. Pa. 1994), upheld these protections by finding that Fair Acres Geriatric Center violated the Rehabilitation Act when it denied Wagner admission on the basis of the behavioral difficulties resulting from Wagner's Alzheimer's.[20] The Americans with Disabilities Act of 1990, which defines disability to include "a physical or mental impairment that substantially limits one or more major life activities" (42 U.S. Code 12102 (1)(A)), extended protection against disability discrimination to places of "public accommodation," including all nursing homes (42 U.S. Code §12181 (7)(F)).[21] Furthermore, courts have held that nursing homes constitute "dwellings" under the Fair Housing Act (see Carlson (2012), Section IV), and therefore inquiries into a patient's disability when determining admission may be subject to additional scrutiny and regulation under the Fair Housing Act (24 CFR 100.202 (C)).[22]

There have also been multiple attempts to restrict and prohibit admissions discrimination against Medicaid-eligible patients. Section 1909(d)(1) of the 1977 Social Security Amendments made it a felony to solicit or receive payment in addition to Medicaid or Medicare reimbursements as a condition of admission or continued care. Despite this prohibition, discrimination against Medicaid patients continued. As Chairman of the Special Committee on Aging, Senator John Heinz observed the following in his opening remarks of Senate Hearing 98-1091 on "Discrimination Against the Poor and Disabled in Nursing Homes" (Senate, 1984):

> Findings of a recent committee investigation show that in some areas of this country, up to 80 percent of what are called federally certified nursing homes are reported to actively discriminate against medicaid beneficiaries in their admission practices. These acts of discrimination are a flagrant violation of U.S. law.

A common avenue for this discrimination was "duration of stay clauses," which required prospective residents to agree to forego enrollment in Medicaid for a period of time as a condition of admission. In response to these practices, the 1987 Nursing Home Reform Amendments explicitly prohibited facilities from requiring residents to waive rights to Medicare or Medicaid benefits (42 CFR 483.15 (a)). Furthermore, the Reform Amendments required that nursing homes provide a standardized admission agreement that more clearly

[19] The Act charges that individuals with disabilities not be "subjected to discrimination under any program or activity receiving Federal financial assistance or under any program or activity conducted by any Executive agency or by the United States Postal Service" (29 U.S.C. §794 (a)).

[20] However, refusing admission based on disability is legal if the patient's care requirements exceed the ability of the facility: Grubbs v. Medical Facilities of America, Inc., 879 F. Supp. 588 (W.D. Va. 1995) held that Medical Facilities of America was legally justified in denying readmission to Grubbs, whose worsening condition qualified her under Medicaid for sub-acute care, on the basis that her care requirements exceeded what Medical Facilities of America's nursing facilities were certified to provide.

[21] The Act lists "hospital, or other service establishment" as examples of places of public accommodation, and the 1994 Supplement to the Americans with Disabilities Act Title III Technical Assistance Manual states that "nursing homes are expressly covered in the title III regulation as social service center establishments."

[22] See Carlson (2012) for the basis and implications of applying the Fair Housing Act "'no inquiry" rule to SNFs.

Electronic copy available at: https://ssrn.com/abstract=3613950

notified prospective residents of their rights (Ambrogi, 1990). Many states, including California (SB 1061, 1997), passed laws standardizing admission agreements to this effect (see CA Health & Safety Code §1599.60-84).[23] As a result, all California admissions agreements contain the following clause:

> You should be aware that no facility that participates in the Medi-Cal program may require any resident to remain in private pay status for any period of time before converting to Medi-Cal coverage. Nor, as a condition of admission or continued stay in such a facility, may the facility require oral or written assurance from a resident that he or she is not eligible for, or will not apply for, Medicare or Medi-Cal benefits.

Selective admission practices have received less regulatory attention since the Reform Amendments, however evidence suggests that such practices may have continued in forms less discernable by policymakers. In response to complaints made to the Health Care Finance Administration and the Office of Civil Rights, the Health and Human Services Office of the Inspector General (HHS OIG) investigated the degree to which the use of financial screening led to defacto Medicaid discrimination in 1999. HHS OIG found that while 70% of hospital discharge planners surveyed reported that nursing homes denied access for financial reasons either somewhat or very often, less than 4% of Medicaid officials surveyed agreed (Brown, 2000).[24] In spite of this, the report concludes that "financial screening may cause access problems for some Medicaid beneficiaries, but these problems do not appear to be widespread." Financial screening continues today, and patients' rights groups continue to claim that these and other practices constitute illegal Medicaid discrimination.[25]

The conflicting responses in the HHS OIG report and the continued concern of patients' rights activists in spite of existing legal protections suggest that the prevalence of discriminatory admission practices after 1987 are not well understood. A primary contribution of this paper is to identify and quantify the form, severity, and impacts of continued selective practices.

3 Data

I combine a number of administrative datasets from the Centers for Medicare & Medicaid Services (CMS) to construct a panel of resident stays at California SNFs between 2004 and 2006. Resident assessments from the nursing home Minimum Data Set (MDS) form the base of this panel. Federal law (42 CFR §483.20) requires nursing homes to complete assessments of each resident at regular intervals, starting with admission and ending at discharge. These assessments collect a wide range of demographic and clinical information that nursing staff use to develop a care plan and that are reported to CMS for inclusion in the MDS. CMS uses these data to construct publicly available quality metrics and to determine Medicare reimbursements.

[23] In addition to regulating admission agreements, many states have passed laws directly regulating admission practices. Connecticut began requiring nursing homes to serve residents on a first come, first serve basis in 1980, and Ohio prohibited admission discrimination against Medicaid eligible patients until 80% of a facility's census is on Medicaid in 1983.

[24] Hospital discharge planners are hospital employees responsible for helping patients plan their discharge. One role of discharge planners is to help patients find a skilled nursing facility.

[25] See, for example, this California Advocates for Nursing Home Reform newsletter.

Electronic copy available at: https://ssrn.com/abstract=3613950

I augment the MDS with Medicare and Medicaid claims and enrollment data that identify payment sources throughout a resident's stay.[26] I identify the days of each stay that were reimbursed by Medicare using Medicare SNF claims from the Medicare Provider and Analysis Review (MedPAR) files.[27] Using acute care claims from MedPAR, I am also able to identify the likely hospital from which residents were discharged to a SNF for 98% of stays reimbursed by Traditional Medicare. I use three different data sources to identify Medicaid reimbursements: the Medicaid Analytic eXtract Long Term Care (MAX LT), Medicare-Medicaid Linked Enrollee Analytic Data Source (MMLEADS), and Beneficiary Summary File (BSF). The MAX LT consists of Medicaid long term care claims data, and the MMLEADS and BSF provide monthly Medicaid eligibility data.[28] In addition to information on Medicare and Medicaid enrollment, the BSF also provides 9-digit zip codes for all Medicare eligible individuals. I use these in conjunction with prior residence data from the MDS to geocode patients' prior residences.[29]

I also utilize a number of publicly available datasets on nursing facilities in my analysis. First, I compile facility characteristics from the Online Survey, Certification and Reporting (OSCAR) database and LTCFocus.org.[30] I augment these with Medicaid reimbursement rates and cost data from California's Medicaid Cost Reports.[31] Because private price data are not surveyed directly, I infer private prices using the revenue and quantity data from the cost reports (Huang and Hirth, 2016).

Table 3 enumerates the data sets used in my analysis, and Tables 4 and 5 give summary statistics for the resident and facility-level data, respectively.[32] Figures 5a and 5b map the distribution of residents and facilities at the state level and in the Los Angeles area. These maps reflect the geographic granularity of these data that plays a significant role in my analysis since most patients are admitted to SNFs that are close to their prior residence (Figure 4).

4 Preliminary Evidence of Selective Admission Practices

This section provides reduced form evidence of selective admission practices by examining how the composition of a facility's admitted patients covaries with its occupancy. If facilities tend to become more selective

[26] Combining multiple CMS datasets requires resolving inconsistencies between the datasets. I have largely based my construction of an aggregated panel on the Residential History File (Intrator et al., 2011), which resolves inconsistencies by preferencing claims data over assessment data. A full description of the data cleaning process can be obtained from the author on request.

[27] Since Medicare Advantage plans are not required to report their claims for inclusion in MedPAR, I use MDS data to impute Medicare Advantage coverage for Medicare Advantage enrollees' stays. Specifically, I use machine learning methods (Appendix E) to fit a function that predicts Traditional Medicare enrollees coverage using MDS, and use this function to impute coverage for Medicare Advantage enrollees. The key assumption underlying this imputation method is that the relationship between MDS variables and qualification for coverage under Medicare and Medicare Advantage is the same.

[28] I combine all three sources because Medicaid Managed Care plans do not always report their claims to CMS (Cheh, 2011). In such cases, Medicaid enrollees are still likely to appear as dual-eligibles in the MMLEADS and BSF. Additionally, I do not have Medicaid claims data for years after 2007.

[29] When prior residence is absent in both the BSF and MDS, I use the location of the hospital that discharged the resident to a SNF as an imputed location of prior residence.

[30] Data available on LTCFocus.org are provided by The Shaping Long Term Care in America Project at the Brown University Center for Gerontology and Healthcare Research, which is funded in part by the National Institute on Aging (1P01AG027296).

[31] The reimbursement rate and cost report data were collected from the California Department for Health Care Services and Office of Statewide Health Planning and Development websites, respectively.

[32] I exclude facilities from my analysis that do not file cost reports as SNFs in California since these facilities are likely to be specialized facilities, such as sub-acute care facilities or institutions specializing in mental diseases.

Electronic copy available at: https://ssrn.com/abstract=3613950

as they become more full, then we expect patient characteristics associated with admission primarily when facilities have low occupancy to be undesirable characteristics.[33] We similarly expect residents whose characteristics are associated with admission when facilities are relatively less full to be less desirable residents. Subsection 4.1 develops this intuition in a model with one facility and one possible discharge rate for patients. Subsection 4.2 then presents my reduced form estimates. I first show the relationship between admitted patient characteristics and facility occupancy. Then, I use machine learning methods to aggregate residents' many characteristics into a univariate desirability score for each resident.

4.1 Model: One Facility and One Discharge Rate

The following model gives intuition for why we expect a facility facing capacity constraints to be more selective as it becomes more full. Consider a lone nursing home with a capacity of b beds. Prospective residents arrive according to a Poisson process with rate parameter λ^A and have a profitability Π_i drawn from a known distribution F. Upon arrival, each patient instantaneously applies for admission at the facility, and the facility instantaneously determines whether to admit the patient. If the facility chooses to admit the patient, the facility receives an upfront payoff Π_i, and the patient resides at the facility until she is discharged according to an exponential process with discharge parameter λ^D. If a patient arrives when the facility is full, the patient is automatically rejected.

Fix a probability space and filtration $\mathcal{F}_t$ representing the arrival, admission, and discharge processes. The facility chooses an adapted admission plan $\{a_\tau\}$, where $a_\tau \subseteq \mathbb{R}$ is the set of profitabilities that would qualify a patient for admission at time τ.[34] In other words, a resident i arriving at τ is admitted if and only if the facility has an available bed and $\Pi_i \in a_\tau$. At each time t, the facility's admission plan maximizes the present discounted value of future admitted Π_i:

$$\mathbb{E}\left[\sum_{\{i:\tau_i^A \geq t, N_{\tau_i^A} < b, \Pi_i \in a_{\tau_i^A}\}} \exp\left(\rho(\tau_i^A - t)\right)\Pi_i \,\middle|\, \mathcal{F}_t\right], \tag{1}$$

where ρ is the discount rate, N_τ is the facility's level of occupancy at τ, and τ_i^A is the time that i arrived.

Since arrivals and discharges are memoryless and residents are indistinguishable after admission, the facility need only condition its policy on its current level of occupancy. Furthermore, because the facility should always prefer to admit more profitable residents to less profitable ones, optimal admission policies must be of the form $a_\tau = [\underline{\Pi}_\tau, \infty)$ for some threshold profitability $\underline{\Pi}_\tau$. Together, these imply that the facility's policy function is a threshold rule for each level of occupancy, where arriving residents are only admitted if their profitability exceeds the threshold rule for the facility's current level of occupancy. I denote

[33] The assumptions underlying this inference are discussed in Subsection 4.2.

[34] That the plan is adapted requires that it be measurable with respect to $\mathcal{F}_\tau$.

Electronic copy available at: https://ssrn.com/abstract=3613950

this rule by a function $\underline{\Pi} : \{0, 1, 2, \ldots, b-1\} \to \mathbb{R}$. Then the facility's value function is:

$$V(N_t) = \max_{\underline{\Pi}} \mathbb{E}\left[\sum_{\{i:\tau_i^A \geq t, N_{\tau_i^A} < b, \Pi_i \geq \underline{\Pi}(N_{\tau_i^A})\}} \exp\left(\rho(\tau_i^A - t)\right) \Pi_i \,\middle|\, N_t \right]. \tag{2}$$

The corresponding Bellman equation and optimal policies are:[35]

$$\rho V(N_t) = N_t \lambda^D \left(V(N_t - 1) - V(N_t)\right) + \lambda^A \max_{\underline{\Pi}} \int_{\underline{\Pi}}^{\infty} \left(\Pi + V(N_t + 1) - V(N_t)\right) dF(\Pi), \tag{3}$$

$$\underline{\Pi}(N_t) := V(N_t) - V(N_t + 1). \tag{4}$$

The Bellman equation (3) is intuitive: $N_t \lambda^D$ is the arrival rate of a discharge, and $V(N_t - 1) - V(N_t)$ is the change in the value function if a resident is discharged. Similarly, λ^A is the arrival rate of a new prospective resident, Π is the payoff received if the resident is admitted, and $V(N_t + 1) - V(N_t)$ is the opportunity cost of admitting the resident.

Theorem 1. *Threshold rule $\underline{\Pi}$ is increasing in N_t.*

Proof. See Appendix D.1. □

Theorem 1 indicates that the facility's threshold rule $\underline{\Pi}$ is increasing in occupancy. Intuitively, as the facility's occupancy increases, the likelihood that the facility will reach capacity and need to reject future profitable residents increases. Since the facility admits an increasingly censored distribution of residents as it becomes more full, we expect the average profitability of admitted residents to rise as the facility becomes more full. Correspondingly, the set of N_t such that $\Pi > \underline{\Pi}(N_t)$ is nested and increasing in Π. It follows that the average N_t at which residents with profitability Π are admitted is weakly increasing in Π. Therefore, residents whose characteristics are associated with admission when facilities are relatively less full can be inferred to be less desirable. This intuition underlies both the reduced form and structural estimation procedures in this paper.

4.2 Reduced Form Estimates

There are two important identifying restrictions required to infer resident desirability from the covariation between facility occupancy and admitted patient characteristics. The first is that the composition of residents seeking admission at the facility does not evolve over time in a way that is systematically correlated with the facility's occupancy.[36] I measure potential sources of such correlations in Appendix D.2 and find that they are small relative to my estimated results. Second, I assume that resident preferences for facilities are not affected by facilities' current occupancies. This assumption is not testable, however its violation is likely

[35] The Bellman equation and optimal policies are derived for a more general case in Appendix B.
[36] In the toy model above, this is satisfied by the assumption that $F(\Pi)$ is unchanging.

Electronic copy available at: https://ssrn.com/abstract=3613950

to attenuate rather than strengthen my results, since the residents I find to be most desirable—short-stay Medicare residents—are also the residents that most plausibly prefer lower occupancy rates. First, these patients disproportionately require rehab and therapy care, which may suffer in quality when resources are spread thin due to a high current occupancy rate. Second, occupancy at admission is more likely to be perceived as transitory by residents with longer anticipated stays.

The most straightforward test of selective admissions is to use facility occupancy as a covariate in predicting the characteristics of admitted residents:

$$y_{ijt} = \beta_j + \beta_{occ} occ_{jt}^{\%le} + \beta_h h_i + \epsilon_{ijt}, \tag{5}$$

where y_{ijt} is a given characteristic of interest of resident i admitted to facility j at time t, $occ_{jt}^{\%le}$ is facility j's percentile occupancy within its own distribution at time t, and h_i are other resident characteristics for which we wish to control.[37] Under the null-hypothesis that facilities are not picking their patients, we expect $\beta_{occ} = 0$ for all characteristics. Table 6 and Figure 6 show the results of such regressions for a number of characteristics that are anticipated to be undesirable, including residents' length of stay, use of Medicaid, and use of pharmaceuticals suggestive of challenging care requirements (e.g. antipsychotics). The magnitudes of these estimates suggest that selective admissions are correlated most strongly with reimbursement rates and length of stay, and to a lesser degree with care requirements.

While these regressions do provide evidence of selective admission practices, they do not coherently aggregate the many characteristics that may affect a resident's desirability. To accomplish this, I flip the regressions in (5) and instead predict facility occupancy at admission using individual characteristics. The intuition for this regression is that it approximates the answer to the question: "How full is facility j, on average, when it admits a resident with characteristics c_i?" If facilities admit an increasingly desirable distribution of residents as they become more full, then the answer to this question is monotonic in the desirability of residents with characteristics c_i.[38]

I use gradient boosted decision trees described in Appendix E to fit $\mathbb{E}\left[occ_{jt}^{\%le} | a_{ij}, c_i\right]$, where a_{ij} signifies that resident i was admitted at facility j and c_i are the characteristics of resident i.[39] This machine learning method allows me to approximate the conditional expectation as a flexible nonlinear function that minimizes the square of prediction error out of sample. I allow the model to condition flexibly on the admitting facility and hundreds of resident characteristics that were likely observable at time of admission. To reduce overfitting, I regularize the model's complexity to minimize its cross-validated out of sample fit. This procedure is analogous to cross-validating the penalty parameter in a LASSO or Ridge regression and allows me to use

[37] In other words, values of 0 and 1 for $occ_{jt}^{\%le}$ respectively correspond to facility j's lowest and highest occupancy days.

[38] The assumptions in Subsection 4.1 guarantee an increasing relationship between profitability and occupancy rate. When allowing for multiple discharge rates or interactions between resident profitability, however, this increasing relationship is plausible but not guaranteed since multiple census compositions can have the same level of occupancy. Therefore, in interpreting the results in this section, I implicitly assume that the realized distribution of censuses and interactions between resident profitabilities are sufficiently well-behaved that this intuitive relationship between occupancy and selectivity holds on average.

[39] The results are qualitatively similar if using a linear regression: Medicaid utilization, lengthy anticipated stays, and high care requirements are associated with lower expected occupancy at admission.

Electronic copy available at: https://ssrn.com/abstract=3613950

a high dimensional input without over-fitting.

To construct a "desirability score" z_i for each resident i that is comparable across residents, I take the average of i's predicted occupancy percentile at admission for each facility in California:

$$z_i := \frac{1}{|J_{CA}|} \sum_{j \in J_{CA}} \hat{\mathbb{E}} \left[occ_{jt}^{\%le} | a_{ij}, c_i \right] \tag{6}$$

where $\hat{\mathbb{E}} \left[occ_{jt}^{\%le} | a_{ij}, c_i \right]$ is the predicted occupancy percentile for i admitted at j, and J_{CA} includes all California facilities. Residents with higher z_i scores are those who facilities tend to agree are more desirable, and those with lower z_i scores are those who facilities tend to agree are less desirable.

Figure 7 shows how the distribution desirability scores z_i vary with different characteristics. Subfigures (a) and (b) respectively show that Medicaid eligible residents and residents with longer anticipated stays tend to have much lower desirability scores than their non-Medicaid and short-stay counterparts.[40] Subfigure (c) shows that both low- and high-staffing facilities admit high-desirability residents but that low-desirability residents are admitted primarily at low staffing facilities. Subfigure (d) shows that the machine learning model has predictive power: low-desirability patients are much more likely to be admitted in low occupancy states than high occupancy ones.[41] I project these desirability scores onto a linear model of resident characteristics in Appendix D.3 in order to provide additional intuition and interpretation of the patterns discerned by the machine learning algorithm.

5 Theoretical Model

In this section I present a model of selective admissions in the nursing home industry that informs my estimation procedure in Section 6. I first provide an overview of the matching process. I then expand on the resident choice problem and the facility admission control problem. Finally, I define an equilibrium concept for beliefs and strategies.

5.1 Overview of the Matching Process

I model the industry through the following decentralized matching process. Patients requiring skilled nursing care arrive to the market according to a Poisson process with rate parameter λ^A. The characteristics of these residents (c_i) are distributed according to a known distribution F_c and include:

1. loc_i: location of the patient's prior residence.

[40] Note that a score of $z_i = 50$ is the theoretical upper bound for a desirability score, since such a score would suggest that a resident is always admitted regardless of occupancy level.

[41] The out of sample R^2 for the predictive function is .25.

Electronic copy available at: https://ssrn.com/abstract=3613950

2. J_i: The set of all facilities that are within 20 kilometers of loc_i, i.e. $J_i := \{j : d(loc_i, loc_j) \leq 20km\}$.[42]

3. $\{u_{ij}\}_{j \in J_i}$: The resident's utility from admission at each facility.

4. $\{\Pi_{ij}\}_{j \in J_i}$: The resident-specific payoff that each facility j expects to receive from admitting i.[43]

5. ϕ_i: The resident's stayer-type governing the resident's exponential discharge rate, which we denote $\lambda^D_{j\phi_i}$ for each facility j.[44] In my empirical exercise, I allow ϕ_i to be one of $\Phi = \{\text{short, long, very long}\}$, and I assign ϕ_i using information that was likely observable at admission. (See Appendix C.)

Upon i's arrival to the market, all facilities in J_i instantaneously observe c_i and independently decide whether or not to offer admission to i. In offering admission to resident i, facility j is choosing to be in i's choice set, which I denote $\mathcal{O}_i$.[45] Resident i considers all $j' \in \mathcal{O}_i$ and is admitted to her preferred facility $j \in \mathcal{O}_i$:[46]

$$j = \arg\max_{j' \in \mathcal{O}_i} u_{ij'}. \tag{7}$$

It is important to note that "admitted" in this context means that a resident actually receives care at a facility. While this terminology is common in the healthcare literature, it differs from uses in other contexts, such as college admissions, where "admitted" signifies an offer to attend.

This model aims to reflect the process by which many residents are actually matched with a SNF. The process by which an acute care patient is discharged to a SNF often involves a hospital discharge planner assessing which facilities are likely to accept the patient. Historically, these determinations were made by a combination of the discharge planner's knowledge of local facilities and facilities' responses to referrals. Electronic systems have increasingly allowed discharge planners to quickly solicit expressions of interest in admitting a patient from a large number of local SNFs. Healthcare information technology company Allscripts describes one such system in a February 2008 press release (accessed October 2018):

> "Allscripts enables a detailed electronic referral to be sent to selected locations across its proprietary network of 90,000 providers, and interested facilities reply, often within minutes. The patient and family then receive a discharge packet that details their facility choices, making their decision more transparent and informed."

This set of facilities that express interest in the resident are represented by $\mathcal{O}_i$ in the model.

[42] In my empirical estimation, I limit potential admissions to facilities within 20 kilometers for computational reasons. The vast majority of residents in the sample (87.4%) have an identified location of prior residence within 20 kilometers of their chosen facility. I treat the arrival and admission of residents who either do not have an identified location of prior residence or who have a location of prior residence that is outside of the 20km radius as an exogenous Poisson process for each facility.

[43] I assume that $\{\Pi_{ij}\}_{j \in J_i}$ are distributed with finite expectation and unbounded support.

[44] An exponential discharge process implicitly assumes that facilities do not learn gain additional information about a resident's likely length of stay after admission, including advance notice of discharge, and that facilities cannot affect a resident's rate of discharge. While there are strong legal protections against early discharge, recent work has shown some evidence that providers may speed up discharge rates when more full (Hackmann and Pohl, 2018). If facilities have some control over discharge rates, it would likely reduce facilities' incentives to pick their patients.

[45] Since $\mathcal{O}_i$ is a subset of the full set of local facilities, J_i, it is analogous to a consideration set in the marketing and inattention literatures (Sovinsky Goeree, 2008).

[46] If $\mathcal{O}_i = \emptyset$, then i is not admitted to any facility.

Electronic copy available at: https://ssrn.com/abstract=3613950

Another natural way to model the matching process in the nursing home industry is for each arriving resident to instantaneously and iteratively submit applications to facilities in decreasing order of her preference until she finds a facility willing to admit her. If facilities' willingness to admit a resident are unaffected by knowing whether other facilities wished to admit her, then the matches yielded by this algorithm will be identical to matches yielded by the matching algorithm described in this section.[47] Assumption 1 in the next section satisfies this requirement for equivalence. This suggests that an alternative way to think about a prospective resident i willing to accept an offer of admission from j is as an "applicant" at j under this alternative matching algorithm.

5.2 Facility Admission Control Problem

In this section, I present the facility's admission control problem and optimal admission policy. I model facilities as profit maximizers that observe the characteristics c_i of each arriving local resident requiring care and determine whether to make the resident an offer of admission based on her characteristics, the facility's own current census of residents, and the facility's beliefs about potential residents it may admit in the future.

5.2.1 Assumptions

I make two key assumptions that greatly simplify the optimal control problem:

Assumption 1. *Facility j conditions its belief about the probability that resident i will accept an offer of admission only on characteristics c_i.*[48] *I denote this belief by $\mu_j(c_i) := P(u_{ij} \geq u_{ij'}\ \forall j' \in \mathcal{O}_i | c_i)$ and give its equilibrium condition in Subsection 5.3.*

Assumption 2. *Facility j receives a lump-sum payoff Π_{ij} when admitting resident i and continuous flow payoff $\Psi_j(N_{jt})$ based on its current census counts $N_{jt} := (N_{jt\phi})_\phi$, where $N_{jt\phi}$ denotes the number of residents of stayer-type ϕ residing at j at time t.*

Assumption 1 is not entirely innocuous. While I have already assumed that the stochastic arrival process of residents requiring care is unchanging, the likelihood of any given resident i accepting an offer of admission at j is also a function of the offers made by other facilities in J_i. Assumption 1 prohibits facility j from using the past and present censuses of facilities in J_i to inform its beliefs about the likelihood that residents who arrive to the market in the future will accept an offer of admission from j. This assumption is satisfied if facilities lack either the information or sophistication to forecast competitors' future admission policies.

There are reasons to believe that Assumption 1 approximates reality. First, it is implausible that facilities know the exact current census of all other local facilities since facilities are not required to disclose this information publicly. In my interviews with nursing staff and facility managers, none have suggested

[47] Non-equivalence could stem from facilities updating their beliefs about other facilities' future admission policies based on other facilities' admission decisions for the currently arrived resident.

[48] In fact, this restriction need only apply to j's beliefs about i that may arrive in the future. This is because once i has arrived, the probability that this specific i will accept admission is not relevant to whether facility j would like to admit her.

Electronic copy available at: https://ssrn.com/abstract=3613950

that they track the censuses of other facilities in an attempt to anticipate competitors' future admission policies. Furthermore, most J_i are large: approximately 50 facilities on average. Therefore, weak or negative correlation in the selectivity of other facilities in J_i may attenuate discernible variation in the probability that offers made by j will be accepted.[49]

Assumption 2 imposes that facility profits can be decomposed into resident-specific components, Π_{ij}, and a census component, $\Psi_j(N_{jt})$. The resident-specific components encompass the variation in residents' profitabilities based on their health and payment characteristics and does not vary with facilities' current census. I parameterize Π_{ij} in Section 6. That Π_{ij} is a lump-sum is without significant loss of generality. I show in Appendix B.3 that if facilities were to receive resident-specific flow payoffs instead of lump-sums, then facilities' admission policies are identical to those in a translated game with lump-sums. Specifically, if facilities were to receive flow payoff $\pi_{ij}(t - \tau_i^A)$ at time t for resident i who arrived at τ_i^A, the facility's optimal policies are identical to the case in which it instead received upfront payoffs Π_{ij} equal to the i's expected admission-discounted π_{ij}:

$$\Pi_{ij} := \mathbb{E}_{\tau_i^D - \tau_i^A}\left[\int_0^{\tau_i^D - \tau_i^A} \exp\left(-\rho\tau\right)\pi_{ij}(\tau)d\tau\right], \tag{8}$$

where τ_i^D is i's time of discharge, and ρ is the discount rate. Intuitively, this follows from facilities' risk neutrality and the assumption that the π_{ij} flow payoff neither affects nor is affected by any other current or future residents. Together, these imply that a facility's incentive to admit a resident is the same whether it expects to receive a flow payoff or an equivalent value lump-sum payoff.

Assumption 2 restricts that all non-separable payoffs occur only through N_{jt}, the census count of the different stayer-types. This prohibits, for example, that particularly sick patients increase the marginal costs of other patients. On the other hand, $\Psi_j(N_{jt})$ may encompass or approximate a number of plausible interactions such as diseconomies of scale.[50] I parameterize $\Psi_j(N_{jt})$ in Section 6.

5.2.2 Admission Control Problem

Facility j chooses an adapted admission plan $\{a_{j\tau}\}$, where j offers admission to resident i arriving at τ if and only if j has a bed available and $c_i \in a_{j\tau}$. At each time t, the facility's admission plan maximizes the present discounted value of future admitted Π_{ij}:

$$\mathbb{E}\left[\sum_{\{i:\tau_i^A \geq t, \|N_{j\tau_i^A}\|_1 < b_j, c_i \in a_{j\tau_i^A}, u_{ij} \geq u_{ij'}\ \forall j' \in \mathcal{O}_i\}} \exp\left(\rho(\tau_i^A - t)\right)\Pi_{ij} + \int_t^\infty \exp(-\rho\tau)\Psi_j(N_{j\tau})d\tau \mid \mathcal{F}_t^j\right], \tag{9}$$

[49] Appendix D.2 estimates the relationship between local facilities' censuses to be relatively weak. However, Assumption 1 might still be concerning in concentrated markets in which stochastic variation in the policy of one facility may have non-trivial impacts on the likelihood that offers from competing facilities are accepted.

[50] For example, if short-stay residents are likely to disproportionately consume resources required for rehab care and long-stay and very-long-stay residents are more likely to consume resources required for long-term care, then $\Psi_j(N_{jt})$ could represent increasing marginal costs in these respective resources through linearly separable increasing marginal costs in the number of short-stayers and the number of long- and very-long-stayers.

Electronic copy available at: https://ssrn.com/abstract=3613950

where τ_i^A denotes the time that i arrives to the market, b_j is the capacity of facility j, $\mathcal{F}_t^j$ is a filtration representing j's information, and the expectation is taken given j's beliefs.[51] I show in Appendix B.1 that Assumptions 1 and 2 imply that the optimal admission policy can be characterized by threshold profitabilities for each stayer-type, $\{\underline{\Pi}_{j\phi}\}_\phi$, that vary only with the facility's current census counts N_{jt}. In other words, facility j offers admission to i arriving at time t if and only if $\Pi_{ij} \geq \underline{\Pi}_{j\phi_i}(N_{jt})$.[52] Theorem 2 gives these threshold policies explicitly.

Theorem 2. *Facility j offers admission to resident i if and only if:*

$$\Pi_{ij} \geq \underline{\Pi}_{j\phi_i}(N_{jt}) := V_j(N_{jt}) - V_j(N_{jt} + 1^{\phi_i}), \tag{10}$$

where V_j is the facility's value function and 1^ϕ denotes a unit-vector increment of element ϕ. The facility's corresponding Bellman equation is:

$$\begin{aligned} \rho V_j(N_{jt}) = \Psi_j(N_{jt}) &+ \sum_\phi \lambda_{j\phi}^D N_{jt\phi} \left(V_j(N_{jt} - 1^\phi) - V_j(N_{jt})\right) \\ &+ \sum_\phi \lambda_{j\phi}^A \int \max\left\{0, \Pi + V_j(N_{jt} + 1^\phi) - V_j(N_{jt})\right\} dF_{j\phi}^\Pi(\Pi), \end{aligned} \tag{11}$$

where $\lambda_{j\phi}^A := \lambda^A P(j \in J_i, \phi_i = \phi)$ and $F_{j\phi}^\Pi(\Pi) := \int_{\{c_i : \Pi_{ij} \leq \Pi\}} \mu_j(c_i) dF_c(c_i | j \in J_i, \phi_i = \phi)$.

Proof. See Appendix B.2. □

Theorem 2 is central to my estimation procedure. In particular, the optimal admission policy (10) does not vary with other facilities' censuses, the facility's own history, or anything about the facility's current census other than counts N_{jt}. I have emphasized Assumptions 1 and 2 in this section as they underlie this result. Without Assumption 1, optimal policies would need to incorporate anticipated dynamic variation in other facilities' policies, and without Assumption 2, optimal policies might need to incorporate additional characteristics and even arrival times of current residents. I discuss the implications of relaxing these assumptions further in Appendix B.4 and find that relaxing either assumption even slightly leads to an explosion in the size of facilities' policy-relevant state spaces.

5.3 Equilibrium Concept and Beliefs

I define an equilibrium to be a set of strategies $\{\underline{\Pi}_{j\phi}\}$ and beliefs $\{\mu_j\}$ such that for each facility j, $\{\underline{\Pi}_{j\phi}\}_\phi$ satisfies optimality under Theorem 2 given μ_j, and μ_j satisfies the following condition:

$$\mu_j(c_i) = \int \mathbf{1}\left\{u_{ij} \geq u_{ij'} \ \forall j' \in \mathcal{O}_{i-j}\right\} dP\left(\mathcal{O}_{i-j}\right), \tag{12}$$

[51] In particular, the measure with respect to which the expectation is taken must satisfy Assumption 1.
[52] In terms of (9): $a_{j\tau} = \{c_i : \Pi_{ij} \geq \underline{\Pi}_{j\phi}(N_{jt})\}$.

Electronic copy available at: https://ssrn.com/abstract=3613950

$$\mathcal{O}_{i-j} := \mathcal{O}_i \setminus \{j\} \tag{13}$$

where $P(\mathcal{O}_{i-j})$ is the long-run joint distribution of offers made by other facilities implied by $\{\underline{\Pi}_{j\phi}\}$.[53] Intuitively, (12) imposes a consistency requirement on the beliefs in Assumption 1. Assumption 1 implies that facilities behave as if playing a single-agent game in which the arrival process of residents willing to accept an offer of admission is constant, and (12) requires that these beliefs be consistent with the unconditional distribution of other facilities' offers.

6 Structural Estimation

In this section, I present my procedure to estimate a structural model of admissions in the nursing home industry. The key challenge to estimation is that only realized admissions are observed. This entails estimating demand with unobserved choice set restrictions. In particular, I cannot infer that a patient's admitting facility was her most preferred local facility since she may have preferred a different facility to which she was denied admission.[54] Analogously, this data restriction also entails estimating admission policies and the structural parameters in facilities' admission control problems without directly observing facilities' actions.

I address this challenge by explicitly modeling patients' choice sets as being determined by facilities' admission policies. In a first stage, I parameterize facilities' threshold rules as functions of facilities' characteristics and current census counts so that a facility is in a patient's choice set if the patient's expected profitability exceeds the facility's threshold at its current census. Given a patient's choice set, I let the patient's choice probabilities be distributed according to a logit demand model in which the patient's preferences for each facility are functions of the facility's characteristics, its distance from the patient's home, and the amount the resident expects to pay out of pocket at the facility. Preferences over characteristics are allowed to differ for Medicaid-eligible patients so that disparate admission patterns for dual-eligibles may potentially be attributed to heterogeneous preferences.

I estimate this first stage via maximum likelihood, where the likelihood of an observed admission is computed by integrating the patient's logit choice probabilities over the distribution of choice sets that may have been available to her given her characteristics and the current censuses of her local facilities.[55] As in Section 4, the key restriction allowing patient preferences and selective admissions to be separately identified is that current facility censuses are excluded from residents' preferences. Because admission policies vary with current census counts but patient preferences do not, the relationship between facilities' censuses and

[53] The $P(\mathcal{O}_{i-j})$ corresponding to $\{\underline{\Pi}_{j\phi}\}$ is unique. This follows from the fact that unbounded support for Π_{ij} and nonzero discharge rates imply that the Markov process characterizing the joint evolution of all facilities' states given $\{\underline{\Pi}_{j\phi}\}$ has a unique recurrent class.

[54] Availability variation has been addressed in the marketing and economics literatures (see Hickman and Mortimer (2016)), and my model of unobserved choice set variation mirrors these approaches. Two unusual features of this setting are that choice sets are never observed and that they are are plausibly correlated with the preferences of individual demanders. Therefore, common methods to estimate the product availability process in a first stage are not feasible.

[55] Note that even given the parameterizations of facilities' threshold rules and residents' profitabilities, I allow for uncertainty in residents' choice sets by allowing a component of each resident's profitability to be unobserved by the econometrician. The probability of each choice set is then computed using the parametric distribution of this unobserved component of profitability.

Electronic copy available at: https://ssrn.com/abstract=3613950

realized admission patterns identifies facilities' admission policies.

While this first stage identifies both residents' preference parameters and facilities' admission policies, the estimates cannot be used to simulate how facilities would change their threshold rules in response to counterfactual policies. Only the first of my three counterfactuals—the strict enforcement of first come, first served admission policies—can be simulated using these first-stage estimates.[56] I therefore estimate the structural profitability parameters underlying facilities' admission policies in a second stage. In my chosen parameterization, these parameters characterize the baseline profitabilities of different stayer-types. I estimate the second stage by matching admission patterns implied by optimal policies computed from Theorem 2 to moments in the data.[57] These structural parameters allow me to simulate how facilities would adjust their admission policies in response to counterfactual government policies by recomputing admission policies and beliefs that satisfy the equilibrium optimality and belief conditions given in Section 5.3.

The remainder of this section details the first and second stage estimation procedures.

6.1 First Stage

In the first stage, I jointly estimate resident preferences and facility admission policies via maximum likelihood. I denote by $\boldsymbol{X}_i$ the set of observed data related to resident i and the facilities in J_i. These observed data include the resident's health and demographic characteristics (h_i), stayer-type (ϕ_i), and desirability score (z_i), as well as the characteristics and states of all of the resident's local facilities ($\{(X_j, N_{jt})\}_{j \in J_i}$).[58]

I parameterize resident i's indirect utility for each facility $j \in J_i$ by:

$$u_{ij} = X_j \beta_i^X + f(D_{ij}, \beta^D) - \alpha \mathbb{E}[OoP_{ij}] + \xi_j + \epsilon_{ij}^u, \tag{14}$$

$$\beta_i^X = \beta^X + h_i \beta^{Xh}, \tag{15}$$

where X_j are the characteristics of facility j, $D_{ij} := d(loc_i, loc_j)$ is the distance from i's prior residence to facility j, $\mathbb{E}[OoP_{ij}]$ is the admission-discounted average daily out-of-pocket payment that i expects to make at j, ξ_j is facility quality unobserved to the econometrician, and ϵ_{ij}^u is Type-I Extreme Value distributed. Rather than placing a parametric distribution on ξ_j, I include facility fixed effects:

$$Q_j = X_j \beta^X + \xi_j. \tag{16}$$

These fixed effects encompass both the observed and unobserved components of facility quality. While fixed effects greatly increase the computational burden of estimation, they allow me to capture unobserved quality and help the model to match aggregate shares for each facility.

[56] Optimal admission policies need not be computed in this counterfactual since they are exogenously mandated to be FCFS.

[57] In order to reduce the computational burden of the second stage, I hold fixed first-stage estimates of residents' preferences, the relative profitabilities of residents within each stayer-type, and facilities' beliefs about the arrival process of patients willing to accept an offer of admission.

[58] The construction of the desirability score is detailed in Section 4.

Electronic copy available at: https://ssrn.com/abstract=3613950

While this preference model does not include random coefficients, it does allow preferences over facilities' characteristics to vary with patients' health and demographic characteristics at admission. In particular, I allow Medicaid-eligible residents to have different preferences over facilities' staffing ratios of registered nurses and licensed practical nurses. This allows the model to incorporate some preference heterogeneity between low- and high-margin patients. Importantly, (14) does not allow preferences over a facility's census at time of admission. This is the key exclusion restriction that allows me to use within-facility covariation between facility census and admitted patient characteristics to identify selective admission practices.

Given a choice set $\mathcal{O}_i$, I denote the admission probability of resident i at facility $j \in J_i$ by $s_{ij}^{\mathcal{O}_i}$:

$$s_{ij}^{\mathcal{O}_i} = \begin{cases} \frac{\exp\left(X_j \beta_i^X + f(D_{ij}, \beta^D) - \alpha \mathbb{E}[OoP_{ij}] + \xi_j\right)}{\sum_{j' \in \mathcal{O}_i} \exp\left(X_{j'} \beta_i^X + f(D_{ij'}, \beta^D) - \alpha \mathbb{E}[OoP_{ij'}] + \xi_{j'}\right)} & \text{if } j \in \mathcal{O}_i \\ 0 & \text{if } j \notin \mathcal{O}_i. \end{cases} \tag{17}$$

If $\mathcal{O}_i$ were observed, the likelihood of observing resident i admitted at facility j would be $s_{ij}^{\mathcal{O}_i}$. However, since $\mathcal{O}_i$ is not observed, the econometrician must integrate over the likelihood of all possible $\mathcal{O}_i$. Denote i's admission at j by a_{ij}. Then the econometrician's likelihood of observing resident i admitted at facility j is:

$$P\left(a_{ij} | \theta_1, \boldsymbol{X}_i\right) = \sum_{\mathcal{O} \in 2^{J_i} \setminus \emptyset} P\left(\mathcal{O}_i = \mathcal{O} | \theta_1, \boldsymbol{X}_i\right) s_{ij}^{\mathcal{O}}, \tag{18}$$

where 2^{J_i} denotes the set of all subsets of J_i, θ_1 are the parameters to be estimated governing residents' preferences and facilities' admission policies, and $P\left(\mathcal{O}_i = \mathcal{O} | \theta_1, \boldsymbol{X}_i\right)$ is the probability that the resident's choice set is $\mathcal{O}_i$.

Since residents' choice sets are determined by facilities' admission policies, $P\left(\mathcal{O}_i = \mathcal{O} | \theta_1, \boldsymbol{X}_i\right)$ can be expressed in terms of the admission policies of the facilities in J_i. In doing this, it is helpful to first scale Π_{ij} so that it is more easily interpreted and compared across stayer-types.

Definition 6.1. *Define $\tilde{\pi}_{ij}$ to be the average admission-discounted resident-specific flow profit from i at j:*

$$\tilde{\pi}_{ij} := \left(\rho + \lambda_{j\phi_i}^D\right) \Pi_{ij}. \tag{19}$$

In other words, $\tilde{\pi}_{ij}$ is the unique constant flow payoff that, if received throughout resident i's stay, is expected to yield an admission discounted payoff of Π_{ij}. Because $\tilde{\pi}_{ij}$ is scaled in terms of flows, it is more easily comparable across stayer-types than Π_{ij}. If the unit of time is days, then $\tilde{\pi}_{ij}$ is an average discounted daily resident-specific profitability. By Theorem 2, facility j offers admission to resident i arriving at time t if and only if:

$$\tilde{\pi}_{ij} \geq \underline{\tilde{\pi}}_{j\phi_i}(N_{jt}) := \left(\rho + \lambda_{j\phi_i}^D\right) \underline{\Pi}_{j\phi_i}(N_{jt}). \tag{20}$$

Electronic copy available at: https://ssrn.com/abstract=3613950

Since neither $\tilde{\pi}_{ij}$ nor $\underline{\tilde{\pi}}_{j\phi_i}(N_{jt})$ are observed directly, I parameterize them:[59]

$$\tilde{\pi}_{ij} = \tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \epsilon_i^\pi, \tag{21}$$

$$\underline{\tilde{\pi}}_{j\phi}(N_{jt}) = \underline{\tilde{\pi}}(N_{jt}, X_j, \phi; \gamma_{\underline{\pi}}), \tag{22}$$

where ϵ_i^π follows a standard normal distribution. The specific parameterization I use for $\tilde{\pi}$ is a polynomial in z_i and $z_i^{\%le}$ with intercepts in ϕ_i. Similarly, I parameterize $\underline{\tilde{\pi}}$ to include intercepts in ϕ and a polynomial in $\mathbb{E}[z_i|a_{ij}, N_{jt}]$ and the difference between the average z_i of j's residents and the average z_i of j's local community. I provide additional details on these parameterizations in Appendix F. Note that a consequence of parameterization (21) is that $\tilde{\pi}_{ij}$ does not vary across facilities since z_i, ϕ_i, and ϵ_i^π do not vary across facilities.[60] Therefore, variation in i's admission offers at different facilities derives entirely from variation across facilities in current threshold rules $\underline{\tilde{\pi}}_{j\phi_i}(N_{jt})$.

Another implication of each resident's ϵ_i^π being shared by all facilities is that the set of possible choice sets is much smaller than $2^{|J_i|}$. To see this, order facilities in J_i by decreasing willingness to admit residents of type ϕ_i:

$$\underline{\tilde{\pi}}(N_{1t}, X_1, \phi_i; \gamma_{\underline{\pi}}) \leq \underline{\tilde{\pi}}(N_{2t}, X_2, \phi_i; \gamma_{\underline{\pi}}) \leq .... \leq \underline{\tilde{\pi}}(N_{|J_i|t}, X_{|J_i|}, \phi_i; \gamma_{\underline{\pi}}) \tag{23}$$

Then all possible choice sets are of the form $[k] := \{1, 2, ..., k\}$.[61] By Theorem 2:[62]

$$\begin{aligned} P(\mathcal{O}_i = [k]|\theta_1, \boldsymbol{X}_i) &= P\left(\tilde{\pi}_{ij} \geq \underline{\tilde{\pi}}_{j\phi_i}(N_{jt})\ \forall\, j \in [k], \tilde{\pi}_{ij} < \underline{\tilde{\pi}}_{j\phi_i}(N_{jt})\ \forall\, j \notin [k]|\theta_1, \boldsymbol{X}_i\right) \\ &= P\left(\tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \underline{\tilde{\pi}}(N_{kt}, X_k, \phi_i; \gamma_{\underline{\pi}}) \geq \epsilon_i^\pi \geq \tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \underline{\tilde{\pi}}(N_{k+1t}, X_{k+1}, \phi_i; \gamma_{\underline{\pi}})\right) \\ &= F_{\epsilon^\pi}\left(\tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \underline{\tilde{\pi}}(N_{kt}, X_k, \phi_i; \gamma_{\underline{\pi}})\right) - F_{\epsilon^\pi}\left(\tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \underline{\tilde{\pi}}(N_{k+1t}, X_{k+1}, \phi_i; \gamma_{\underline{\pi}})\right). \end{aligned} \tag{26}$$

Therefore the log-likelihood of observing resident i admitted at j is:[63]

$$\log\left(P\left(a_{ij}|\theta_1, \boldsymbol{X}_i\right)\right) = \log\left(\sum_{k=j}^{|J_i|} s_{ij}^{[k]} P\left(\mathcal{O}_i = [k]|\gamma_\pi, \gamma_{\underline{\pi}}, \boldsymbol{X}_i\right)\right), \tag{28}$$

where $\theta_1 = \{\gamma_\pi, \gamma_{\underline{\pi}}, \beta^D, \beta^{Xh}, \alpha, \{Q_j\}_j\}$, F_{ϵ^π} is the CDF of the standard normal distribution, and the relevant terms are substituted from (24), (25), and (26).[64] The parameters $\{\beta^D, \beta^{Xh}, \alpha, \{Q_j\}_j\}$ characterize

[59] While it would be ideal to parameterize $\tilde{\pi}_{ij}$ and $\underline{\tilde{\pi}}_{j\phi_i}(N_{jt})$ with facility-specific functions, this is both computationally infeasible and requires a large sample for each facility.

[60] While this is a consequence of my chosen parameterizations, it is not a requirement of my estimation procedure.

[61] It is straightforward to verify that if (20) holds for k—i.e. if k offers admission to i—then (20) holds for $k' < k$. This relies primarily on the assumption that ϵ_i^π is not facility-specific.

[62] For completeness:

$$P(\mathcal{O}_i = \emptyset|\theta_1, \boldsymbol{X}_i) = 1 - F_\epsilon\left(\tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \underline{\tilde{\pi}}(N_{1t}, X_1, \phi_i)\right), \tag{24}$$

$$P(\mathcal{O}_i = [|J_i|]|\theta_1, \boldsymbol{X}_i) = F_\epsilon\left(\tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \underline{\tilde{\pi}}(N_{|J_i|t}, X_{|J_i|}, \phi_i)\right). \tag{25}$$

[63] In estimation, the econometrician must additionally condition on i being observed in the data (i.e., on $\mathcal{O}_i \neq \emptyset$):

$$\log\left(P\left(a_{ij}|\theta_1, \boldsymbol{X}_i, \mathcal{O}_i \neq \emptyset\right)\right) = \log\left(P\left(a_{ij}|\gamma_\pi, \gamma_{\underline{\pi}}, \boldsymbol{X}_i\right)\right) - \log\left(P\left(\mathcal{O}_i = \emptyset|\gamma_\pi, \gamma_{\underline{\pi}}, \boldsymbol{X}_i\right)\right). \tag{27}$$

[64] The ϕ-specific intercept terms in $\tilde{\pi}(z_i, \phi_i; \gamma_\pi)$ and $\underline{\tilde{\pi}}(N_{jt}, X_j, \phi; \gamma_{\underline{\pi}})$ are not identified since only their difference, $\tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \underline{\tilde{\pi}}(N_{jt}, X_j, \phi_i; \gamma_{\underline{\pi}})$, appears in the likelihood.

Electronic copy available at: https://ssrn.com/abstract=3613950

residents' preferences, γ_π characterizes the relative profitabilities of residents within each stayer-type, and $\gamma_{\underline{\pi}}$ characterizes facilities' admission thresholds.[65]

6.2 Second Stage

While the first-stage estimates do characterize facilities' admission policies, they are not sufficient to simulate how facilities would adjust their threshold rules in response to counterfactual government policies. Doing so requires computing threshold rules as the solution to facilities' admission control problems. I therefore estimate the remaining primitives underlying facilities' admission control problems in a second stage by matching admission patterns implied by optimal admission policies to moments in the data.

The structural parameters I estimate in the second stage are ψ parameterizing $\Psi_j(N_{jt})$:

$$\Psi_j(N_{jt}) = N'_{jt}\psi. \tag{29}$$

The vector ψ gives a baseline profitability for each stayer-type. Intuitively, where the γ_π in the first stage identified the relative profitabilities of residents within each stayer-type, ψ identifies the levels of profitability relative to not admitting the patient.[66] Note that this specification includes neither heterogeneity in Ψ across facilities nor diseconomies of scale. Therefore, selective admission practices under this specification primarily reflect the opportunity costs to admissions that are due to facilities' capacity constraints. Optimal threshold rules may vary across facilities by capacity constraints and the arrival process of residents willing to accept an offer of admission. They may also vary within facility over time with census counts.

I compute facilities' optimal admission policies via policy function iteration. Computing optimal threshold rules given V_j is direct from (20). On the other hand, computing V_j given admission policies $\{\tilde{\underline{\pi}}_{j\phi}\}_\phi$ requires integrating over the facility's beliefs about the profitability distribution of arriving residents willing to accept an offer of admission, $F^{\Pi}_{j\phi}$. In order to reduce the computational burden of the estimation procedure, I simulate beliefs $\hat{F}^{\Pi}_{j\phi}$ using first-stage estimates of residents' preferences and other facilities' admission policies.[67] Additional details are provided in Appendix G. After substituting $\hat{F}^{\Pi}_{j\phi}$ into (11), V_j can be solved in terms of $\{\tilde{\underline{\pi}}_{j\phi}\}_\phi$ as the solution to a system of equations.[68]

Denote the optimal admission thresholds solving facility j's admission control problem by $\tilde{\underline{\pi}}_j(N_{jt};\psi,\hat{\theta}_1)$. The admission probabilities implied by the model are:

$$P\left(a_{ij}|\psi,\hat{\theta}_1,\boldsymbol{X}_i\right) = \sum_{k=j}^{|J_i|} s_{ij}^{[k]} P\left(\mathcal{O}_i = [k]|\psi,\hat{\theta}_1,\boldsymbol{X}_i\right), \tag{30}$$

[65] Heuristically, the preference parameters are identified off of admission patterns for patients with similar predicted choice sets, while the admission policies are identified off the relationship between admission patterns and facilities' censuses.

[66] In particular, ψ identifies the intercept terms that were not identified in the first stage. See footnote 64.

[67] Note that because beliefs $\hat{F}^{\Pi}_{j\phi}$ are fixed throughout the second stage estimation procedure, there is no guarantee that $\hat{F}^{\Pi}_{j\phi}$ implied by our first stage policy estimates is the same as that implied by our second stage policy estimates. This is often the case for two-step estimators, and ensuring internal consistency would require recomputing the beliefs and optimal policies as a fixed point during the estimation procedure, which is computationally prohibitive.

[68] Solving (11) for V_j also requires $\{\lambda^A_{j\phi}\}$ and $\{\lambda^D_{j\phi}\}$, which I estimate via maximum likelihood prior to the second stage.

Electronic copy available at: https://ssrn.com/abstract=3613950

$$P\left(\mathcal{O}_i = [k]|\psi, \hat{\theta}_1, \boldsymbol{X}_i\right) = F_{\epsilon^\pi}\left(\tilde{\pi}(z_i, \phi_i; \hat{\gamma}_\pi) - \underline{\tilde{\pi}}_k(N_{jt}; \psi, \hat{\theta}_1)\right) - F_{\epsilon^\pi}\left(\tilde{\pi}(z_i, \phi_i; \hat{\gamma}_\pi) - \underline{\tilde{\pi}}_k(N_{jt}; \psi, \hat{\theta}_1)\right). \quad (31)$$

I estimate ψ by matching the following moments in the data:[69]

$$\mathbb{E}\left[\mathbf{1}\left\{a \leq occ_{jt}^{\%le} \leq b, \phi_i = \phi\right\}\right], \quad (32)$$

$$\mathbb{E}\left[\tilde{\pi}(z_i, \phi_i; \hat{\gamma}_\pi)\mathbf{1}\left\{a \leq occ_{jt}^{\%le} \leq b, \phi_i = \phi\right\}\right], \quad (33)$$

for each $\phi \in \Phi$ and $(a, b) \in \{(0, \frac{1}{3}), (\frac{1}{3}, \frac{2}{3}), (\frac{2}{3}, 1)\}$, where $occ_{jt}^{\%le}$ is facility j's percentile occupancy within its own occupancy distribution.[70] In other words, I match the degree to which residents of different stayer-types and levels of profitability are admitted to facilities in low, middle, or high occupancy states.

7 Estimates

In this section, I present and discuss the demand and supply estimates from my model.

7.1 Demand Estimates

Table 9 presents the preference parameter estimates. Column 1 gives the estimates from the main specification. These estimates indicate that residents are highly sensitive to the distance of a facility from their previous residence: the average elasticity of demand with respect to distance is 4.15%. This high degree of sensitivity is consistent with the prior literature estimating demand models for both nursing homes (Rahman et al., 2014a; Hackmann, 2018) and hospitals (Tay, 2003; Ho, 2006; Ho and Pakes, 2014; Gowrisankaran et al., 2015; Shepard, 2015). Residents may prefer closer facilities because of their likely proximity to the resident's family, friends, and community. It is also plausible that residents are less aware of distant facilities.[71]

The estimates also suggest that while all residents prefer facilities with higher nursing staff ratios, these preferences are weaker for Medicaid-eligible residents. The average own-staffing elasticity of demand for Registered Nurses (RNs) and Licensed Practical Nurses (LPNs) are respectively .91% and 1.21% for non-Medicaid residents and .59% and .65% for Medicaid residents. This estimated preference disparity can be interpreted in a number of ways. First, Medicaid-eligible residents may truly care less about staffing ratios because their longer stays and differing disease diagnoses may benefit less from high staffing ratios than residents who primarily utilize short-term rehab and therapy care. Alternatively, it may be that Medicaid-eligible residents have similar preferences to non-Medicaid residents but are less able to identify and apply to high-staffing facilities. For example, admission assessments from the MDS data indicate that Medicaid-eligible residents are less likely to have present and responsible family members, which suggests that these residents may have less assistance in selecting a facility. Lastly, if the model does not fully capture the

[69] As with the first stage, the econometrician must also condition i being observed in the data (i.e., on $\mathcal{O}_i \neq \emptyset$).

[70] There are 18 moments in total, six for each of the three stayer-types.

[71] For example, the default for CMS' Nursing Home Compare tool is to sort by distance. Because awareness is unobserved, my model cannot distinguish true preference over distance from a lack of awareness and attributes both to preferences.

Electronic copy available at: https://ssrn.com/abstract=3613950

extent of admissions discrimination against Medicaid-eligible residents, then estimates of Medicaid residents' preference for staffing are likely to be biased downward. This is clearest when contrasting the demand estimates from the main specification (Column 1) to those from a demand model without selective admission practices (Column 3). The estimated average staffing elasticities of demand are substantially lower when failing to account for selective admissions, especially for Medicaid-eligible residents: the average own-staffing elasticity of demand for RNs and LPNs are respectively .74% and .81% for non-Medicaid residents and just .3% and .06% for Medicaid-eligible residents.

I estimate price sensitivities to be very small: the average elasticity of demand with respect to out-of-pocket expenditure is just .015%. Because I include facility fixed effects in the estimation, price sensitivity is identified from variation in residents' expected out-of-pocket payments at the same facility. Therefore, while these low estimates may indicate a truly minuscule price sensitivity, they may also indicate that my model of out-of-pocket expenditure does not align with the resident's anticipated out-of-pocket expenditure. I discuss the computation of expected out-of-pocket costs and potential concerns with identifying price sensitivity in Appendix H.

7.2 Supply Estimates

Figure 8 depicts the relationship between resident-specific profitability $\tilde{\pi}_{ij}$ and desirability score z_i. As anticipated, profitability is generally increasing in desirability score. Figures 9 and 10 describe the estimated first-stage policy functions, $\tilde{\underline{\pi}}(\cdot;\hat{\gamma}_{\underline{\pi}})$. Figure 9 shows how facilities' admission thresholds and corresponding probabilities of making admission offers vary with facility occupancy. Specifically, Subfigure 9a depicts how cutoffs increase with occupancy, and Subfigure 9b shows the corresponding decrease in offer probabilities with occupancy. They also show that offer probabilities tend to decrease in anticipated length of stay. Subfigures 9c and 9d show further that facilities that tend to admit patients with higher z_i scores than their local community (see Appendix F) are estimated to have higher cutoff rules and lower offer probabilities. Figure 10 compares the model's predicted relationship between occupancy and admission probabilities to the data. Both the model and data agree that admission probabilities decrease with occupancy and that the magnitude of this relationship increases with anticipated length of stay and Medicaid-eligibility.

Figure 12 gives the estimated distribution of residents' preference ranks for their admitting facility. A large majority of patients (81%) are admitted to their first choice facility, suggesting that selective admissions do not affect the choice sets for most residents. The 19% of residents who are not admitted to their most-preferred facilities are disproportionately Medicaid-enrollees with very long anticipated stays. In fact, just 51% of Medicaid very-long-stay residents are admitted to their first choice facility. Moreover, because these residents tend to have lengthy stays, the impacts of selective admissions are much larger when measured by days rather than residents: 40% of resident days are spent at facilities other than the resident's first choice.

Due to the computational requirements of computing facilities' optimal policies, I estimate the second

Electronic copy available at: https://ssrn.com/abstract=3613950

stage only on the San Diego area.[72] This region has 67 facilities and approximately 50 thousand arriving residents in my sample. Figure 11 compares occupancy's relationship to admission probabilities and admitted patient profitabilities in the estimated model to the data. The estimated model matches the trends in the data, but it does so less precisely than the first stage.[73]

8 Counterfactuals

In this section, I present the simulated impact of three counterfactual policies intended to prevent or mitigate selective admission practices. The first is to prevent selective admissions by strictly enforcing that all facilities adhere to "first come, first serve" (FCFS) admission policies. Because admission policies are fixed by the regulator in this counterfactual, I am able to simulate the policy impacts for all of California using only preference parameter estimates. The second counterfactual I examine is to reduce incentives to discriminate against Medicaid eligible residents by raising the Medicaid reimbursement rate. The third counterfactual is to increase capacity at facilities in a way that is targeted to benefit Medicaid eligible residents. Because the latter two counterfactuals require computing counterfactual admission policies, I only simulate their impacts for the San Diego area.

All counterfactual simulations presented in this section hold facility characteristics fixed, including price, staffing, and unobserved measures of quality. While I do not allow facilities to adjust their characteristics, I present some evidence that suggests how facilities might adjust their staffing and other quality metrics if able in response counterfactual policies.

8.1 Counterfactual 1: First Come, First Serve

Since my model does not incorporate waitlisting, I model FCFS as a requirement that facilities with a vacancy must offer admission to all arriving residents.[74] Under this rule, residents are admitted to their first choice facility with an available bed. I use the preference estimates from the first stage to simulate the distribution of admissions that would occur under this rule.[75]

Figure 13 gives the preference rankings of residents' admitting facilities under FCFS. The distributions of preference ranks does not vary substantially by payment source or stayer-type because all arriving residents receive equal treatment under FCFS. Comparing Figure 13 to Figure 12 indicates that FCFS increases the likelihood that Medicaid eligible and very-long-stay residents are matched to preferred facilities, while the opposite is true for non-Medicaid and short-stay residents. Figures 14 and 15 show similar distributional

[72] San Diego area was chosen as the subsample for its size and geographic separation from other markets (see Figure 5a).

[73] This is likely because admission policies in the second stage have fewer degrees of freedom and are constrained by facilities' optimality conditions, as well as because the sample used in estimating the second stage is smaller.

[74] This is equivalent to a prohibition on selective admissions.

[75] Specifically, I simulate the arrival of 100 years of residents and allow these residents to be admitted at their most preferred facility with available occupancy at their time of arrival. I draw observable resident characteristics from the data and simulate each resident's idiosyncratic preferences, length of stay, and unobserved profitability parametrically. I initialize facilities to their mean census counts in the data and burn the first three years of simulation.

Electronic copy available at: https://ssrn.com/abstract=3613950

impacts of FCFS on residents' utilities and the staffing ratios at residents' admitting facilities. As a best-case benchmark, these figures also include the impact of FCFS without capacity constraints, under which all residents are admitted to their most-preferred facility.

The findings of these simulations are intuitive: residents who experience substantial admissions discrimination under selective admissions are likely to benefit from more equitable access under FCFS, while residents who received preferential treatment under selective admissions fare worse under FCFS because they are more likely to be crowded out of their preferred facilities. Overall, consumer welfare increases under FCFS because capacity at high-quality facilities is more heavily utilized. On average, consumers value enforcing FCFS equivalently to an additional 0.20 hours (1.1 standard deviations) of registered nurse care per day.[76] The cost to hire this additional care at the average California RN wage and benefits ($38.81) would be $7.68 per resident-day. Intuitively, this net increase in consumer welfare under FCFS results largely from greater utilization of beds at high-quality facilities.[77]

Lastly, Figure 16 shows that average admitted patient profitability is less strongly increasing in facility quality and staffing levels under FCFS. This suggests that if facilities are able to adjust their characteristics, high-quality facilities are likely to reduce their expenditure on staffing and quality under FCFS.

8.2 Simulating Counterfactual Beliefs

Simulating the remaining counterfactuals requires computing facilities' equilibrium optimal admission policies under the counterfactual. To accomplish this, I simulate 100 years of resident arrivals to San Diego and compute counterfactual policies and beliefs jointly as a fixed point in the simulation. I initialize facility policies to be FCFS and compute facilities' beliefs about the distribution of residents willing to accept an offer of admission based on these policies.[78] I then iteratively update facilities' optimal policies based on beliefs and beliefs based on policies until I reach a fixed point.[79] The simulated admissions given these fixed point beliefs and policies represent the admissions that occur under the counterfactual.

8.3 Counterfactual 2: Raising the Medicaid Reimbursement Rate

Section 6 parameterizes average admission-discounted resident profitability, $\tilde{\pi}_{ij}$, in terms of desirability score z_i. While z_i, and therefore $\tilde{\pi}_{ij}$, incorporates information about the share of a resident's stay anticipated to be reimbursed by each payer source, it does not identify the structural relationship between daily reimbursement

[76] Medicaid and non-Medicaid residents respectively value enforcing FCFS at 0.26 and 0.05 hours of RN care per day. Since the demand model allows different preferences for RN staffing for Medicaid and non-Medicaid residents, I apply the corresponding sensitivity in translating the welfare impacts to RN hours for each group.

[77] Note that this net effect is positive in spite of the fact that the majority of residents are short stay non-Medicaid residents, a group that does worse under FCFS. This is because FCFS disproportionately benefits very-long-stay residents, who constitute a majority of care days.

[78] I initialize each facility in the simulation at its empirical mean census and burn the first three years of simulated arrivals in computing its beliefs.

[79] I consider the algorithm to have converged when facilities' updated policies disagree with the previous policies on fewer than 5 in 10,000 applicants (i.e., individuals willing to accept an offer of admission). Note that there is no theoretical guarantee that this equilibrium is unique.

Electronic copy available at: https://ssrn.com/abstract=3613950

rates and $\tilde{\pi}_{ij}$. Additional assumptions are therefore required to model raising the Medicaid reimbursement rate by raising $\tilde{\pi}_{ij}$ for residents on Medicaid. Appendix I estimates the relationship between reimbursement rates and $\tilde{\pi}_{ij}$ by attributing to reimbursement rates the variation in $\tilde{\pi}_{ij}$ that is correlated with a resident's anticipated payer source after controlling for the resident's health characteristics and stayer-type.[80] My estimates suggest approximating raising the Medicaid reimbursement rate to match the private rate by raising $\tilde{\pi}_{ij}$ by $.765 w_{ij}^{mcaid}$, where w_{ij}^{mcaid} is the admission-discounted share of a resident i's stay at facility j that is expected to be reimbursed by Medicaid.

Figure 17 shows the impacts of raising the Medicaid reimbursement rate halfway to the private rate, to the private rate, and halfway again above the private rate. Raising Medicaid reimbursement rates at this magnitude only slightly improves access and utility for Medicaid residents, and these gains occur largely at the expense of crowding out non-Medicaid residents. Raising the Medicaid reimbursement rate to match the private rate would cost approximately \$37.26 per resident-day, and Medicaid residents value the corresponding increased access equivalently to just .02 hours of RN care per day.

It is important to reiterate that these counterfactual simulations hold facility characteristics fixed. It is also possible that facilities would respond to an increase in the Medicaid reimbursement rate by increasing quality in order to attract Medicaid residents (Hackmann, 2018). As such, these results are best interpreted as showing that raising the Medicaid reimbursement rates is a very expensive way to improve Medicaid residents' access to existing higher quality facilities. Multiple factors contribute to this inefficacy. First, the majority of Medicaid eligible residents are already admitted to their preferred facility. Second, capacity constraints severely limit the degree to which access can be increased. Even when Medicaid residents are treated equitably under FCFS, capacity constraints prevent 36% of residents utilizing Medicaid from being admitted at their preferred facility. Third, my estimates suggest that facilities find residents on Medicare most attractive, and raising the Medicaid rate to match the private rate may not increase Medicaid residents' desirability sufficiently to capture a significant share of beds at high-quality facilities from Medicare.

8.4 Counterfactual 3: Increasing Capacity

The last counterfactuals I simulate are to expand capacities at nursing homes with high marginal utility excess demand from Medicaid residents.[81] Figure 18 gives the simulated impacts of adding 200, 400, 600, and 800 beds to the San Diego area's existing stock of 7,283 beds. In contrast to raising the Medicaid reimbursement rate, both Medicaid and non-Medicaid residents benefit from increased capacity: the welfare gain from expanding capacity by 800 beds is valued equivalently to .13 RN hours per day by Medicaid eligible

[80] The relationship between health characteristics and profitability may be different when residents are on Medicare than when they are on private pay or Medicaid. This is both because Medicare reimbursement rates are intensity adjusted and because the rehab and therapy care typically received on Medicare is different than the long term care typically received by Medicaid and private pay patients. In order to address this, I allow the impact of health characteristics on $\tilde{\pi}_{ij}$ to differ depending on the share of a resident's stay that is is reimbursed by Medicare.

[81] I enumerate the algorithm I use for allocating beds in Appendix J.

Electronic copy available at: https://ssrn.com/abstract=3613950

residents and .06 RN hours per day by non-Medicaid residents.[82] Providing this equivalent RN care at the average hourly wage plus benefits in San Diego ($36.20) would cost $27,384 per day: $4.78 and $2.16 per resident-day for Medicaid and non-Medicaid residents, respectively.

Cost reports suggest an approximate cost of expanding a facility by one bed of $14.43/day.[83] By this metric, adding 800 beds to San Diego facilities would cost $11,544 per day, which is approximately $2.60 per day of Medicaid-covered SNF care in San Diego. This is both less costly than raising the Medicaid reimbursement rate and results in larger welfare gains for both Medicaid and non-Medicaid residents. Moreover, the cost of expanding capacity is lower than the cost of utility-equivalent hours of RN care.

The welfare gains of increasing capacity do not derive primarily from additional RN care. In fact, hours of RN care received by residents on Medicaid increases by just 4.9% when adding 800 beds. Instead, the simulations suggest that gains derive largely from residents being admitted at facilities with higher unobserved quality and for which the resident has greater idiosyncratic preference. Since higher RN staffing has been shown to improve health outcomes (Schnelle et al., 2004; Friedrich and Hackmann, 2017), policymakers may be particularly interested in adjusting capacity to increase the amount of RN care received by residents. Figure 19 shows the impact of targeting capacity expansions based on RN staffing. In spite of this targeting, the improvements are still small, which suggests that residents' strong preferences for characteristics other than quality may pose a significant obstacle to using increased capacity to improve the amount of RN care received by residents.

9 Conclusion

Whether healthcare providers pick their patients has important implications for academics and policymakers concerned with healthcare inequality. In spite of existing anti-discrimination laws, this paper finds evidence of selective admission practices in the nursing home industry along a number of dimensions, including Medicaid eligibility, anticipated length of stay, and care requirements. I estimate that 19% of residents in California are unable to gain admission at their first choice facility. These residents are disproportionately very-long-stay residents on Medicaid, and their care constitutes 40% of all resident days in the state. Counterfactual simulations indicate that prohibiting selective admission practices benefits these disadvantaged residents by increasing their access to quality facilities, though the gains are partially offset by the crowding out of other residents. Simulations also suggest that raising the Medicaid reimbursement rate is a costly way to increase access for Medicaid-eligible residents at existing high-quality facilities. Moreover, the small benefits are largely at the expense of non-Medicaid residents. Targeted capacity increases, on the other hand, are more

[82] While the capacity expansions are targeted at facilities with excess demand from Medicaid-eligible residents, many of the added beds are still allocated by facilities to non-Medicaid residents. Furthermore, vacancy chains allow more than just the individual occupying the new vacancy to benefit. If the additional beds were reserved for Medicaid eligible residents, the impacts are expected to favor Medicaid eligible residents more heavily.

[83] I compute this approximation using facilities' per-bed lease expenditures and gross property, plant, and equipment (PP&E) as a metric for the cost of adding an additional bed. I use an interest rate of 5% to amortize the PP&E over a 30 year depreciation period.

Electronic copy available at: https://ssrn.com/abstract=3613950

cost-effective and benefit both Medicaid and non-Medicaid residents.

There are a number of potential avenues for future related work. For example, my counterfactual simulations hold fixed facility characteristics such as staffing ratios. Endogenizing facilities' choice of characteristics in context of their dynamic optimal control problems could provide further insights into the impacts of the policies I study. Additionally, there is evidence that hospitals may steer patients toward particular SNFs preferred by the hospital (Rahman et al., 2013). This suggests both that hospitals may affect residents' preferences and that hospitals may be able to leverage relationships with SNFs to better place low-margin patients.[84] Future work may incorporate these factors into the resident-SNF matching process.

While this paper directly examines nursing homes, concerns about providers picking their patients extend to many parts of the healthcare industry. The methods I use to model and identify selective admissions may be extended to these contexts and even to non-healthcare markets with discrimination or unobserved endogenous choice sets.

References

Agarwal, Nikhil, "An Empirical Model of the Medical Match," *American Economic Review*, 2015, *105* (7), 1939–1978.

Ahmed, Ali M. and Mats Hammarstedt, "Discrimination in the Rental Housing Market: A Field Experiment on the Internet," *Journal of Urban Economics*, 2008, *64* (2), 362–372.

Ambrogi, Donna Myers, "Legal Issues in Nursing Home Admissions," *Law, Medicine & Health Care*, 1990, *18* (3), 254–262.

Anupindi, Ravi, Maqbool Dada, and Sachin Gupta, "Estimation of Consumer Demand with Stock-Out Based Substitution: An Application to Vending Machine Products," *Marketing Science*, 1998, *17* (4), 406–423.

Arcidiacono, Peter, Patrick Bayer, Jason R. Blevins, and Paul B. Ellickson, "Estimation of Dynamic Discrete Choice Models in Continuous Time with an Application to Retail Competition," *Review of Economic Studies*, 2016, *83* (3), 889–931.

Backhaus, Ramona, Hilde Verbeek, Erik van Rossum, Elizabeth Capezuti, and Jan P H Hamers, "Nurse Staffing Impact on Quality of Care in Nursing Homes: A Systematic Review of Longitudinal Studies," *Journal of the American Medical Directors Association*, 2014, *15* (6), 383–393.

Bajari, Patrick, Lanier Benkard, and Jonathan Levin, "Estimating Dynamic Models of Imperfect Competition," *Econometrica*, 2007, *75* (5), 1331–1370.

[84]For example, hospitals may use the threat of steering future high-margin patients away to coerce SNFs into admitting low-margin patients as well.

Electronic copy available at: https://ssrn.com/abstract=3613950

Bertrand, Marianne and Sendhil Mullainathan, "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination," *American Economic Review*, 2004, *94* (4), 991–1013.

Blanchard, Lloyd, Bo Zhao, and John Yinger, "Do Lenders Discriminate Against Minority and Woman Entrepreneurs?," *Journal of Urban Economics*, 2008, *63* (2), 467–497.

Brown, Jeffrey R. and Amy Finkelstein, "Why is the Market for Long-Term Care Insurance so Small?," *Journal of Public Economics*, 2007, *91* (10), 1967–1991.

_ **and** _ , "The Private Market for Long-Term Care Insurance in the United States: A Review of the Evidence," *Journal of Risk and Insurance*, 2009, *76* (1), 5–29.

_ **and** _ , "Insuring Long-Term Care in the United States," *Journal of Economic Perspectives*, 2011, *25* (4), 119–141.

Brown, June Gibbs, "The Effect of Financial Screening and Distinct Part Rules on Access to Nursing Facilities," Technical Report June, Department of Health and Human Services Office of Inspector General 2000.

Bruno, Hernn A. and Naufel J. Vilcassim, "Structural Demand Estimation with Varying Product Availability," *Marketing Science*, 2008, *27* (6), 1126–1131.

Carlson, Eric M., "20 Common Nursing Home Problems—and How To Resolve Them," Technical Report 2005.

_ , "Discrimination in Long-Term Care: Using the Fair Housing Act to Prevent Illegal Screening in Admissions to Nursing Homes and Assisted Living Facilities," *Notre Dame Journal of Law, Ethics & Public Policy*, 2012, *21* (2), 363–404.

Castle, Nicholas G. and Jamie C. Ferguson, "What is Nursing Home Quality and How is it Measured?," *Gerontologist*, 2010, *50* (4), 426–442.

Cheh, Valerie, "Which States Have Limited Medicaid Managed Care Enrollment for Long-Term Care Users," *Medicaid Policy Brief*, 2011, *3*, 1–8.

Ching, Andrew T., Fumiko Hayashi, and Hui Wang, "Quantifying the Impacts of Limited Supply: The Case of Nursing Homes," *International Economic Review*, 2015, *56* (4), 1291–1322.

Conlon, Christopher T. and Julie Holland Mortimer, "Demand Estimation under Limited Product Availability," *American Economic Journal: Microeconomics*, 2013, *5* (4), 1–30.

Cram, Peter, Hoangmai H Pham, Vaughan-S, and Mary S Arrazin, "Insurance Status of Patients Admitted to Specialty Cardiac and Competing General Hospitals," *Medical Care*, 2008, *46* (5), 467–475.

Electronic copy available at: https://ssrn.com/abstract=3613950

Crawford, Gregory S., Rachel Griffith, and Alessandro Iaria, "Demand Estimation with Unobserved Choice Set Heterogeneity," *CEPR Discussion Papers*, 2017.

Desai, Amar A., Roger Bolus, Allen Nissenson, Glenn M. Chertow, Sally Bolus, Matthew D. Solomon, Osman S. Khawar, Jennifer Talley, and Brennan M.R. Spiegel, "Is there 'Cherry Picking' in the ESRD Program? Perceptions from a Dialysis Provider Survey," *Clinical Journal of the American Society of Nephrology*, 2009, *4* (4), 772–777.

Draganska, Michaela and Daniel Klapper, "Choice Set Heterogeneity and The Role of Advertising: An Analysis with Micro and Macro Data," *Journal of Marketing Research*, 2011, *48* (4), 653–669.

Dranove, David, Daniel Kessler, Mark McClellan, and Mark Satterthwaite, "Is More Information Better? The Effects of 'Report Cards' on Health Care Providers," *Journal of Political Economy*, 2003, *111* (3), 555–588.

Dubois, Pierre and Morten Saethre, "On the Effect of Parallel Trade on Manufacturers' and Retailers' Profits in the Pharmaceutical Sector," *TSE Working Papers*, 2018, *18* (883), 1–63.

Ettner, Susan L., "Do Elderly Medicaid Patients Experience Reduced Access to Nursing Home Care?," *Journal of Health Economics*, 1993, *11*, 259–280.

Fershtman, Chaim and Ariel Pakes, "Dynamic Games with Asymmetric Information: A Empirical Framework," *Quarterly Journal of Economics*, 2012, pp. 1611–1661.

Foster, Andrew D. and Yong Suk Lee, "Staffing Subsidies and the Quality of Care in Nursing Homes," *Journal of Health Economics*, 2015, *41*, 133–147.

Friedman, Jerome H., "Greedy Function Approximation: A Gradient Boosting Machine," *The Annals of Statistics*, 2001, *29* (5), 1189–1232.

_ , "Stochastic Gradient Boosting," *Computational Statistics & Data Analysis*, 2002, *38*, 367–378.

Friedrich, Benjamin U and Martin B Hackmann, "The Returns to Nursing: Evidence from a Parental Leave Program," *NBER Working Paper Series*, 2017.

Ge, Yanbo, Christopher R. Knittel, Don MacKenzie, and Zoepf Stephen, "Racial and Gender Discrimination in Transportation Network Companies," *NBER Working Paper Series*, 2016, (22776), 1–38.

Gertler, Paul J., "Medicaid and the Cost of Improving Access to Nursing Home Care," *The Review of Economics and Statistics*, 1992, *74* (2), 338–345.

Goeree, Michelle Sovinsky, "Limited Information and Advertising in the U.S. Personal Computer Industry," *Econometrica*, 2008, *76* (5), 1017–1074.

Electronic copy available at: https://ssrn.com/abstract=3613950

Gowrisankaran, Gautam, Aviv Nevo, and Robert Town, "Mergers When Prices Are Negotiated: Evidence from the Hospital Industry," *American Economic Review*, 2015, *105* (1), 172–203.

Grabowski, David C., Jonathan Gruber, and Joseph J. Angelelli, "Nursing Home Quality as a Common Good," *Review of Economics and Statistics*, 2008, *90* (4), 754–764.

Greenlees, John S., John M. Marshall, and Donald E. Yett, "Nursing Home Admissions Policies under Reimbursement," *The Bell Journal of Economics*, 1982, *13* (1), 93–106.

Gruenberg, Leonard W. and Thomas R. Willemain, "Hospital Discharge Queues in Massachusetts," *Medical Care*, 1982, *20* (2), 188–201.

Hackmann, Martin B., "Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home," *Working Paper*, 2018, pp. 1–108.

_ **and R. Vincent Pohl**, "Patient vs. Provider Incentives in Long Term Care," *Working Paper*, 2018.

Hanson, Andrew, Zackary Hawley, Hal Martin, and Bo Liu, "Discrimination in Mortgage Lending: Evidence from a Correspondence Experiment," *Journal of Urban Economics*, 2016, *92*, 48–65.

Heckman, James T., "Detecting Discrimination," *Journal of Economic Perspectives*, 1998, *12* (2), 101–116.

Hickman, William and Julie Holland Mortimer, "Demand Estimation with Availability Variation," in "Handbook on the Economics of Retailing and Distribution" 2016, p. 512.

Ho, Kate and Ariel Pakes, "Hospital Choices, Hospital Prices and Financial Incentives to Physicians," *American Economic Review*, 2014, *104* (February), 3841–3884.

_ **and Robin S Lee**, "Equilibrium Provider Networks: Bargaining and Exclusion in Health Care Markets," *NBER Working Paper Series*, 2018, *No. 23742*.

Ho, Katherine, "The Welfare Effects of Restricted Hospital Choice in the US Medical Care Market," *Journal of Applied Econometrics*, 2006, *21*, 1039–1079.

_ , "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, 2009, *99* (1), 393–430.

Hotz, V. Joseph and Robert A. Miller, "Conditional Choice Probabilities and the Estimation of Dynamic Models," *The Review of Economic Studies*, 1993, *60* (3), 497–529.

_ **,** _ **, Seth Sanders, and Jeffrey Smith**, "A Simulation Estimator for Dynamic Models of Discrete Choice," *The Review of Economic Studies*, 1994, *61* (2), 265–289.

Electronic copy available at: https://ssrn.com/abstract=3613950

Huang, Sean Shenghsiu and Richard A. Hirth, "Quality Rating and Private-Prices: Evidence from the Nursing Home Industry," *Journal of Health Economics*, 2016, *50* (202), 59–70.

Intrator, Orna, Jeffrey Hiris, Katherine Berg, Susan C. Miller, and Vince Mor, "The Residential History File: Studying Nursing Home Residents' Long-Term Care Histories," *Health Services Research*, 2011, *46* (1), 120–137.

Kain, John F. and John M. Quigley, "Housing Market Discrimination, Homeownership, and Savings Behavior," *American Economic Review*, 1972, *62* (3), 263–277.

Kalouptsidi, Myrto, "Time to Build and Fluctuations in Bulk Shipping," *American Economic Review*, 2014, *104* (2), 564–608.

_ , "Detection and Impact of Industrial Subsidies: The Case of Chinese Shipbuilding," *Review of Economic Studies*, 2018, *85* (2), 1111–1158.

Ke, Guolin, Qi Meng, Taifeng Wang, Wei Chen, Weidong Ma, and Tie-Yan Liu, "A Highly Efficient Gradient Boosting Decision Tree," *Advances in Neural Information Processing Systems 30*, 2017, pp. 3148–3156.

Ladd, Helen F., "Evidence on Discrimination in Mortgage Lending," *Journal of Economic Perspectives*, 1998, *12* (2), 41–62.

Lin, Haizhen, "Revisiting the Relationship Between Nurse Staffing and Quality of Care in Nursing Homes: An Instrumental Variables Approach," *Journal of Health Economics*, 2014, *37* (1), 13–24.

Musalem, Andres, "When Demand Projections are Too Optimistic: A Structural Model of Product Line and Pricing Decisions," *Working Paper*, 2015, pp. 1–41.

_ , Marcelo Olivares, Eric T. Bradlow, Christian Terwiesch, and Daniel Corsten, "Structural Estimation of the Effect of Out-of-Stocks," *Management Science*, 2010, *56* (7), 1180–1197.

National Center for Health Statistics, *Health, United States, 2016: With Chartbook on Long-term Trends in Health* 2017.

Nyman, John A., "Prospective and 'Cost-Plus' Medicaid Reimbursement, Excess Medicaid Demand, and the Quality of Nursing Home Care," *Journal of Health Economics*, 1985, *4* (3), 237–259.

Page, Marianne, "Racial and Ethnic Discrimination in Urban Housing Markets: Evidence from a Recent Audit Study," 1995.

Pakes, Ariel, Michael Ostrovsky, and Steven Berry, "Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples)," *RAND Journal of Economics*, 2007, *38* (2), 373–399.

Electronic copy available at: https://ssrn.com/abstract=3613950

Rahman, Momotazur, Andrew D. Foster, David C. Grabowski, Jacqueline S. Zinn, and Vincent Mor, "Effect of Hospital-SNF Referral Linkages on Rehospitalization," *Health Services Research*, 2013, *48*, 1898–1919.

_ **, David C. Grabowski, Pedro L. Gozalo, Kali S. Thomas, and Vincent Mor**, "Are Dual Eligibles Admitted to Poorer Quality Skilled Nursing Facilities?," *Health Services Research*, 2014, *49* (3), 798–817.

_ **, Pedro Gozalo, Denise Tyler Tyler, David C. Grabowski, Amal Trivedi, and Vincent Mor**, "Dual Eligibility, Selection of Skilled Nursing Facility, and Length of Medicare Paid Postacute Stay," *Medical Care Research and Review*, 2014, *71*, 384–401.

Rust, John, "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 1987, *55* (5), 999–1033.

Ryan, Stephen P, "The Costs of Environmental Regulation in a Concentrated Industry," *Econometrica*, 2012, *80* (3), 1019–1061.

Schnelle, John F., Sandra F. Simmons, Charlene Harrington, Mary Cadogan, Emily Garcia, and Barbara M. Bates-Jensen, "Nursing Home Staffing and Quality of Care," *Health Services Research*, 2004, *39* (2), 225–255.

Senate, United States Congress, "Discrimination Against the Poor and Disabled in Nursing Homes," 1984.

Shah, Denish, V. Kumar, and Yi Zhao, "Diagnosing Brand Performance: Accounting for the Dynamic Impact of Product Availability with Aggregate Data," *Journal of Marketing Research*, 2015, *52* (2), 147–165.

Shepard, Mark, "Hospital Network Competition and Adverse Selection : Evidence from the Massachusetts Health Insurance Exchange," *Working Paper*, 2015.

Sullivan, Christopher J., "The Ice Cream Split: Empirically Distinguishing Price and Product Space Collusion," *Working Paper*, 2017, pp. 1–54.

Tay, Abigail, "Assessing Competition in Hospital Care Markets: The Importance of Accounting for Quality Differentiation.," *RAND Journal of Economics*, 2003, *34* (4), 786–814.

Tenn, Steven and John M. Yun, "Biases in Demand Analysis Due to Variation in Retail Distribution," *International Journal of Industrial Organization*, 2008, *26* (4), 984–997.

Uili, Robin M., "Resident Selection in a Connecticut Nursing Home: A View from Within," *Journal of Aging and Health*, 1995, *7* (1), 139–159.

Electronic copy available at: https://ssrn.com/abstract=3613950

Watnick, Suzanne, Daniel E. Weiner, Rachel Shaffer, Jula Inrig, Sharon Moe, and Rajnish Mehrotra, "Comparing Mandated Health Care Reforms: The Affordable Care Act, Accountable Care Organizations, and the Medicare ESRD Program," *Clinical Journal of the American Society of Nephrology*, 2012, *7* (9), 1535–1543.

Wollmann, Thomas, "Trucks Without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles," *American Economic Review*, 2018, *108* (6), 1364–1406.

Wright, Jennifer L., "Medicaid Discrimination in Long Term Care," *Oregon State Bar: Elder Law Newsletter*, 2002, *5* (3), 1–16.

Electronic copy available at: https://ssrn.com/abstract=3613950

A Tables and Figures

Table 1: Reimbursement Shares

	Days	**Revenue**	**Residents**
% Medicare	17.28%	39.38%	73.80%
% Private	17.13%	16.05%	46.26%
% Medicaid	65.58%	44.56%	26.01%
Sum	100.00%	100.00%	146.07%

The residents column does not sum to 100% because some residents used more than one payer source during their stay.

Table 2: Payer Source Transitions

(a) Share of Residents

		Admission			
		MC	PR	MA	Sum
Disch.	MC	31%			31%
	PR	29%	14%		43%
	MA	14%	1%	10%	26%
	Sum	74%	16%	10%	100%

(b) Share of Days

		Admission			
		MC	PR	MA	Sum
Disch.	MC	6%			6%
	PR	13%	6%		19%
	MA	48%	4%	22%	75%
	Sum	67%	11 %	22%	100%

This table gives the share of residents that were admitted and discharged with each respective payer source. MC, PR, and MA respectively denote Medicare, private, and Medicaid. The table assumes that residents may only move from Medicare to private and from private to Medicaid. Medicare eligibility and days of Medicare coverage are imputed using resident assessment data for residents enrolled in Medicare Advantage (29.11%).

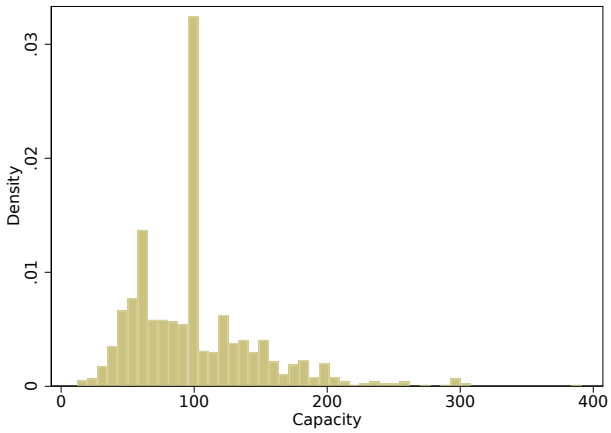
Table 3: Data Sources

Data Source	**Years**	**Relevant Data**
MDS	1999-2010	Demographics, health status, entry and discharge dates
MedPAR	2004-2010	Medicare claims, hospital source, entry and discharge dates
MAX LT	2004-2007	Medicaid claims, entry and discharge dates
MMLEADS	2008-2009	Medicaid eligibility
BSF	2004-2010	Dual eligibility, zip code
OSCAR	2004-2007	Facility characteristics
LTCFocus	2004-2007	Facility characteristics
Medi-Cal Data	2004-2007	Facility cost data, private rates

Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 1: Capacities and Occupancy Rates

(a) Capacities



(b) Occupancy Rates

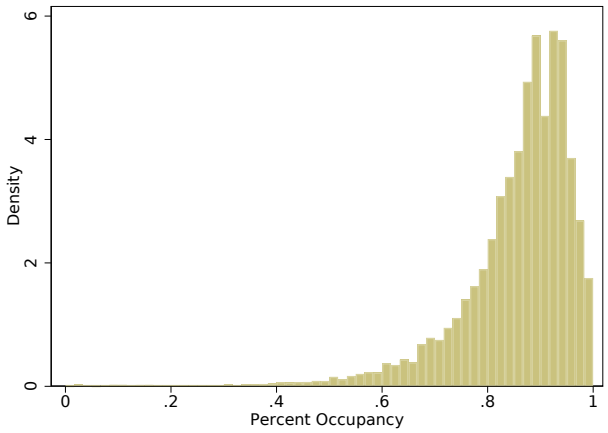


Table 4: Resident Summary Statistics

	Mean	SD	N
# Local Facilities	46.70	44.49	554,852
Length of Stay	143.47	332.77	554,852
Medicare	18.78	35.70	554,852
Private	24.20	122.83	554,852
Medicaid	94.48	298.39	554,852
Dual-Eligible (Start)	0.31	0.46	554,852
ADL Score	2.29	0.76	454,077
Dementia	0.25	0.43	391,390
Weight	149.75	38.97	445,842

Table 5: Facility Summary Statistics

	Mean	SD	N
Beds	100.69	47.66	970
% Occupancy	87.05	7.95	970
% Medicaid	63.79	22.82	970
% Medicare	13.70	10.63	970
RNs Per Bed-Day	0.31	0.18	970
LPNs Per Bed-Day	0.77	0.22	970
CNAs Per Bed-Day	2.46	0.53	970
Case Mix Index	1.06	0.09	969

Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 2: Length of Stay Distribution

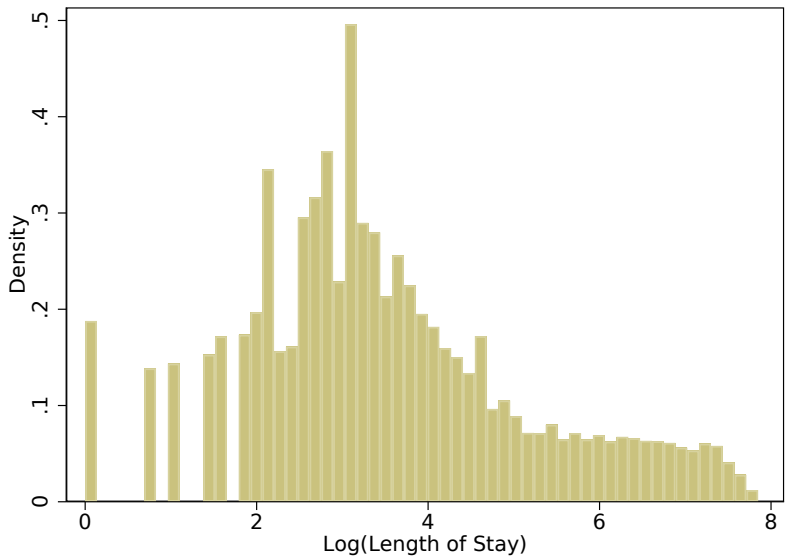
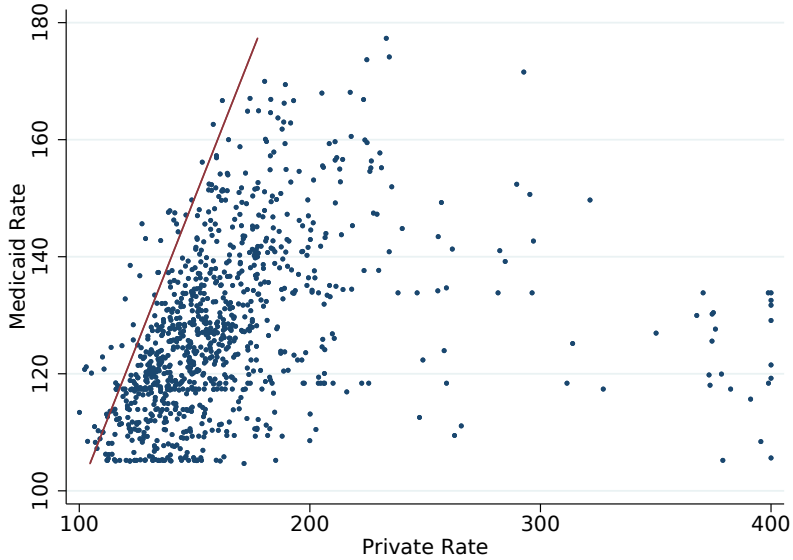


Figure 3: Private and Medicaid Rates



Red line is the 45-degree line. Private rates are calculated as the total revenue from private sources divided by the total number of private-pay days, windsorized at $100 and $400.

Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 4: Distance to Admitting Facility

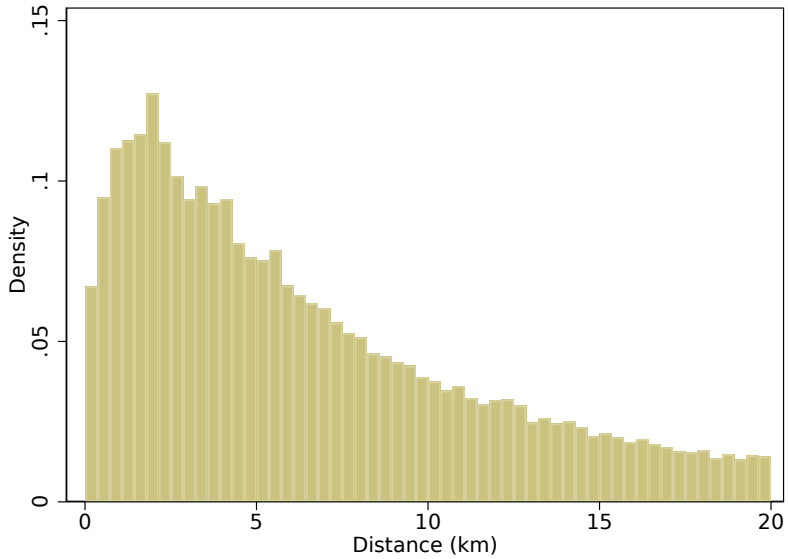
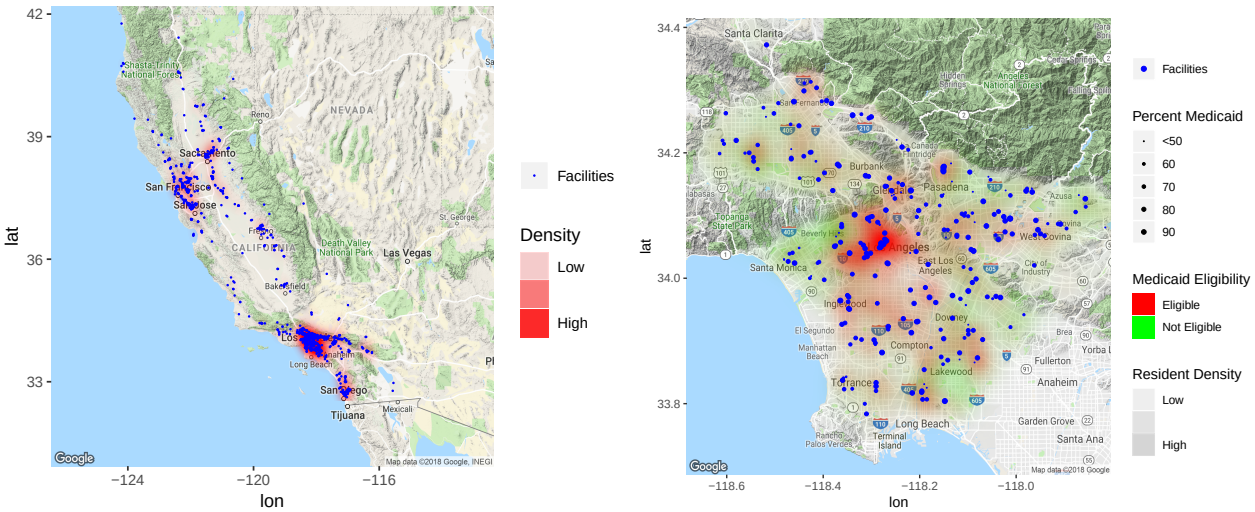


Figure 5: Maps of Facilities and Residents

(a) California

(b) Los Angeles



Electronic copy available at: https://ssrn.com/abstract=3613950

Table 6: Relationship Between Occupancy and Admitted Patient Characteristics

	(1) Length of Stay	(2) Medicaid Eligible	(3) Medicaid Days	(4) Dementia	(5) Antipsychotics Days/Week	(6) Antianxiety Days/Week	(7) Antidepressants Days/Week	(8) Inappropriate Behavior	(9) Conflict Staff	(10) Conflict Residents
Occupancy	-42.38	-0.0433	-38.34	-0.00883	-0.106	-0.0491	-0.139	-0.00685	-0.00149	-0.000561
Percentile	(1.539)	(0.00195)	(1.380)	(0.00243)	(0.0118)	(0.00959)	(0.0155)	(0.00189)	(0.000577)	(0.000264)
Mean	143.5	0.308	94.09	0.246	1.004	0.654	1.797	0.0760	0.0107	0.00227
Facility FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	555,170	555,170	555,170	391,602	454,304	454,295	454,308	452,637	390,539	390,539
R^2	0.0869	0.247	0.0871	0.0518	0.128	0.0226	0.0201	0.0631	0.0573	0.0617

Notes: Standard errors in parenthesis. Occupancy percentiles are scaled between 0 and 1.

Table 7: Relationship Between Occupancy and Arriving Patient Characteristics

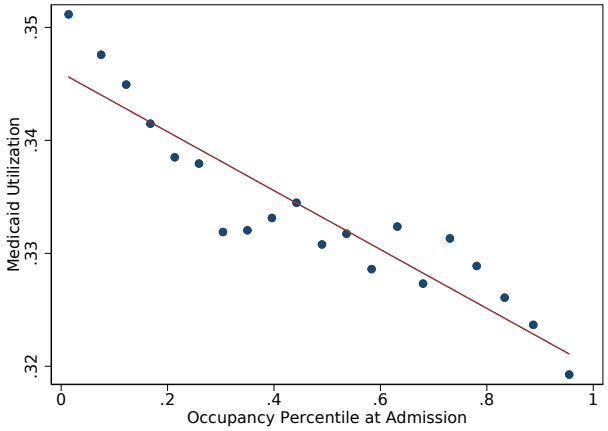
	(1) Length of Stay	(2) Medicaid Eligible	(3) Medicaid Days	(4) Dementia	(5) Antipsychotics Days/Week	(6) Antianxiety Days/Week	(7) Antidepressants Days/Week	(8) Inappropriate Behavior	(9) Conflict Staff	(10) Conflict Residents
Occupancy	-3.494	-0.00376	-3.028	-0.00144	-0.0111	-0.00404	-0.00567	-0.000968	-0.0000492	-0.0000678
Percentile	(0.231)	(0.000323)	(0.207)	(0.000357)	(0.00192)	(0.00135)	(0.00219)	(0.000303)	(0.0000707)	(0.0000390)
Mean	152.0	0.371	101.4	0.257	1.190	0.613	1.693	0.0903	0.00748	0.00227
Facility FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	25,881,609	25,881,609	25,881,609	18,145,527	20,918,487	20,918,336	20,918,487	20,827,388	18,078,972	18,078,972
R^2	0.00878	0.0516	0.00859	0.00296	0.00847	0.00258	0.00332	0.00173	0.00253	0.000484

Notes: Standard errors in parenthesis. Occupancy percentiles are scaled between 0 and 1.

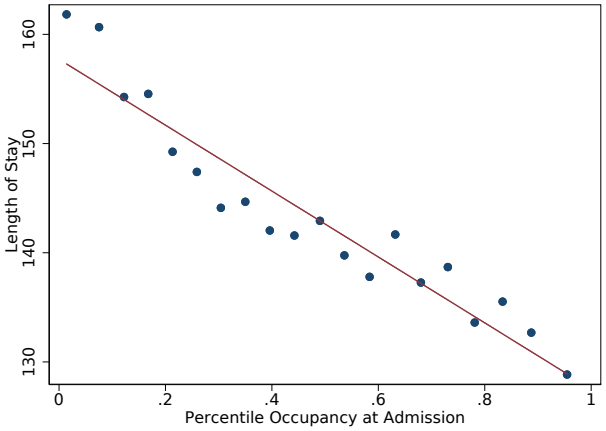
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 6: Binscatters: Resident Characteristics on Percentile Occupancy

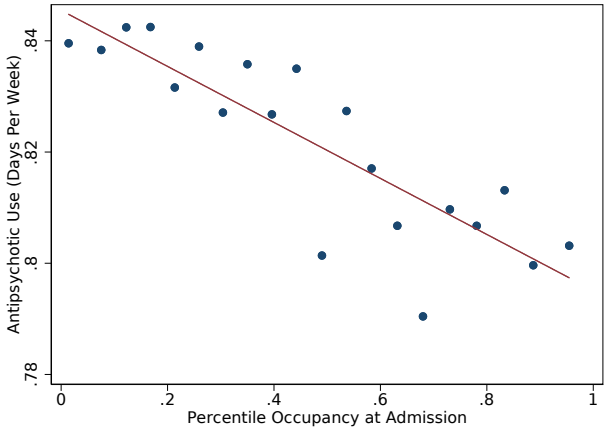
(a) Medicaid Utilization



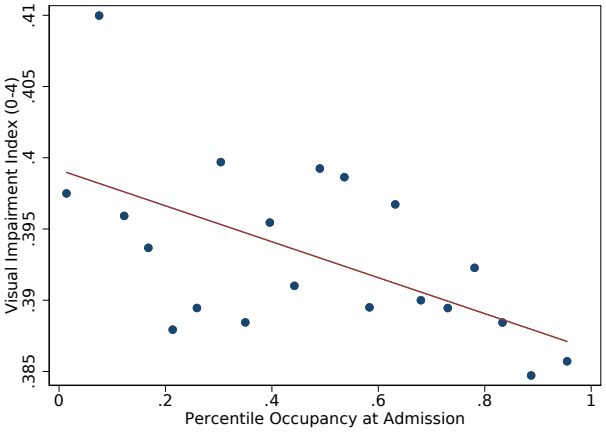
(b) Length of Stay



(c) Antipsychotic Days/Week



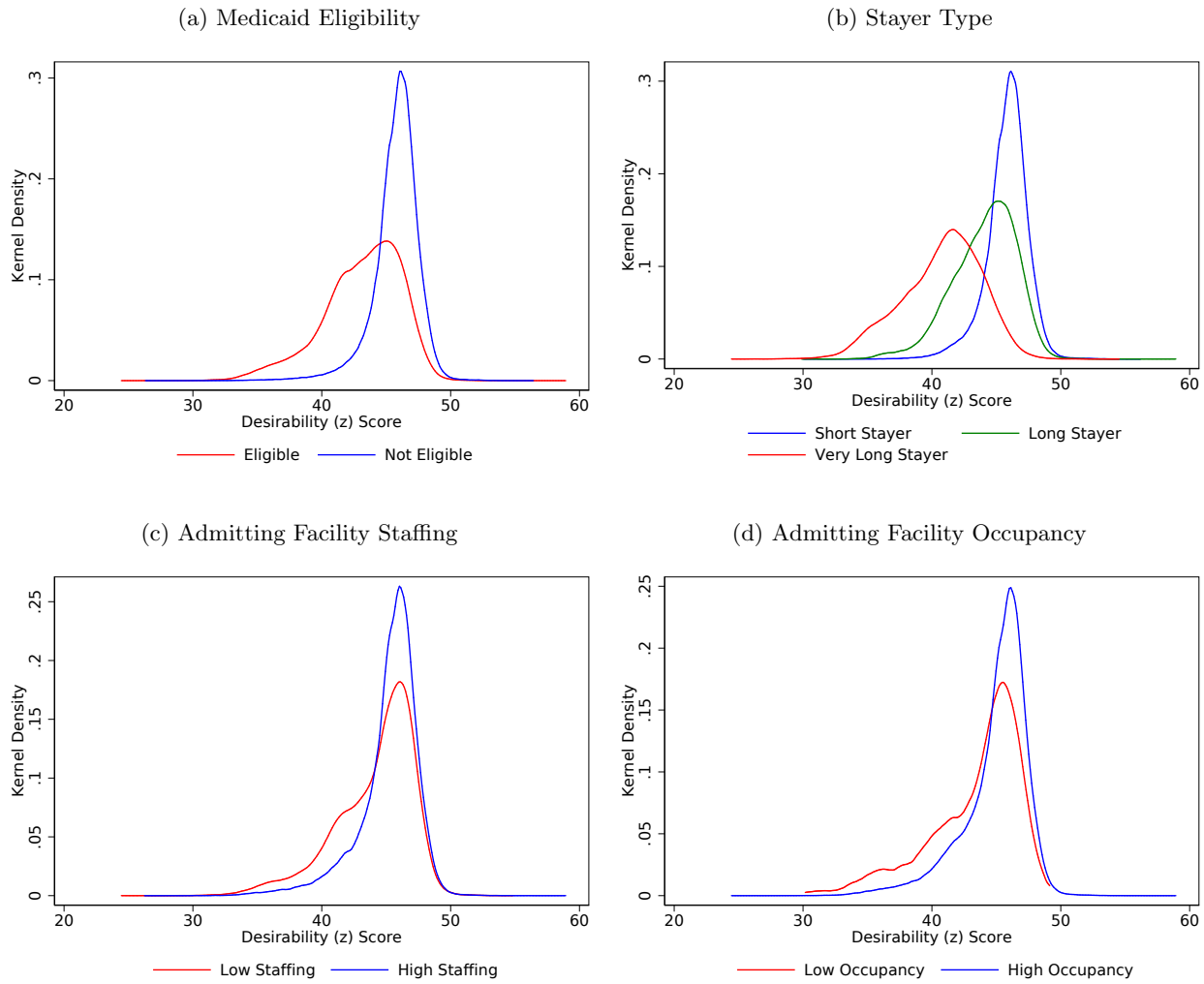
(d) Visual Impairment



All binscatters include facility fixed effects and controls for independent variables in other panels. Short, long, and very-long stayers respectively constitute the 1-70, 70-90, and 90-100 percentiles of predicted length of stay.

Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 7: Distribution of Desirability Scores by Subgroup



Short, long, and very-long stayers respectively constitute the 1-70, 70-90, and 90-100 percentiles of predicted length of stay.

Table 8: Relationship Between Local Facility Occupancies

		(1)	(2)	(3)	(4)	(5)	(6)
$occ^{\%le}_{j't}$		0.0286	0.0187	0.0223			
of closest j'		(0.00149)	(0.00113)	(0.00149)			
	X # fac. in 5km	-0.000777	-0.000241	-0.000816			
		(0.000179)	(0.0000891)	(0.000179)			
Mean $occ^{\%le}_{j't}$					0.152	0.0767	0.128
of closest 5 j'					(0.00316)	(0.00219)	(0.00317)
	X # fac. in 5km				-0.00829	-0.000562	-0.00896
					(0.000392)	(0.0000995)	(0.000392)
	Facility FEs	Y	N	Y	Y	N	Y
	Date FEs	N	Y	Y	N	Y	Y
	N	1,045,151	1,045,151	1,045,151	1,054,363	1,054,363	1,054,363
	R-squared	0.00153	0.00689	0.00785	0.00267	0.00775	0.00821

Notes: Standard errors in parenthesis. The standard deviation of the mean occupancy percentile of a facility's closest 5 competitors is .134.

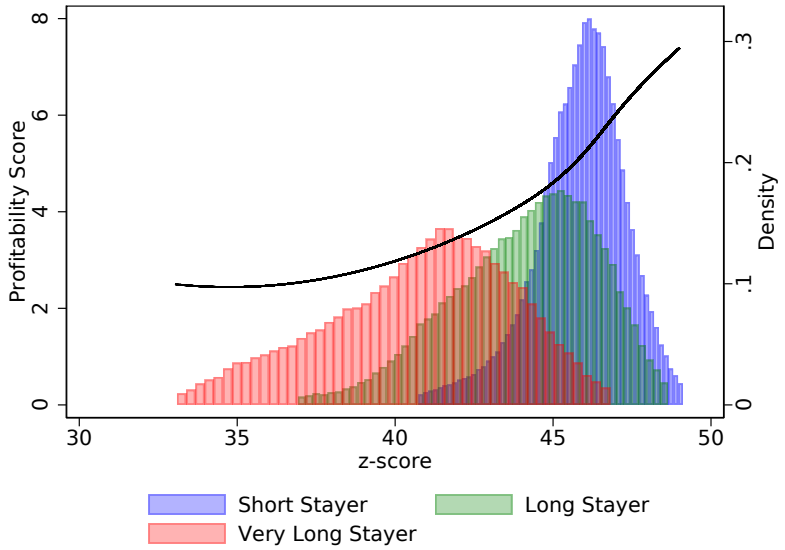
Electronic copy available at: https://ssrn.com/abstract=3613950

Table 9: Preference Parameter Estimates

	Main (1)	No Preference Heterogeneity (2)	No Selective Admission (3)
Distance (km)	-0.36	-0.36	-0.34
	(0.0014)	(0.0014)	(0.0013)
Distance-squared	0.0069	0.0069	0.0064
	(0.00007)	(0.00007)	(0.00007)
Out of Pocket ($100)	-0.05	-0.0086	-0.13
	(0.01)	(0.01)	(0.01)
RN Hours	3.45	3.30	2.98
	(0.34)	(0.33)	(0.27)
RN Hours X Medicaid Eligible	-1.05		-1.83
	(0.026)		(0.025)
LPN Hours	1.71	1.48	1.18
	(0.25)	(0.24)	(0.19)
LPN Hours X Medicaid Eligible	-0.76		-1.10
	(0.02)		(0.02)
For Profit	0.22	0.20	0.34
	(0.17)	(0.16)	(0.13)
Facility Fixed Effects	X	X	X
N	485,065	485,065	485,065

Notes: Mean preference terms (RN Hours, LPN Hours, and For Profit) are by regressing facility characteristics on estimated facility fixed effects. Standard errors are in parenthesis.

Figure 8: Profitability ($\tilde{\pi}$) and Desirability (z) Scores, by Stayer-Type

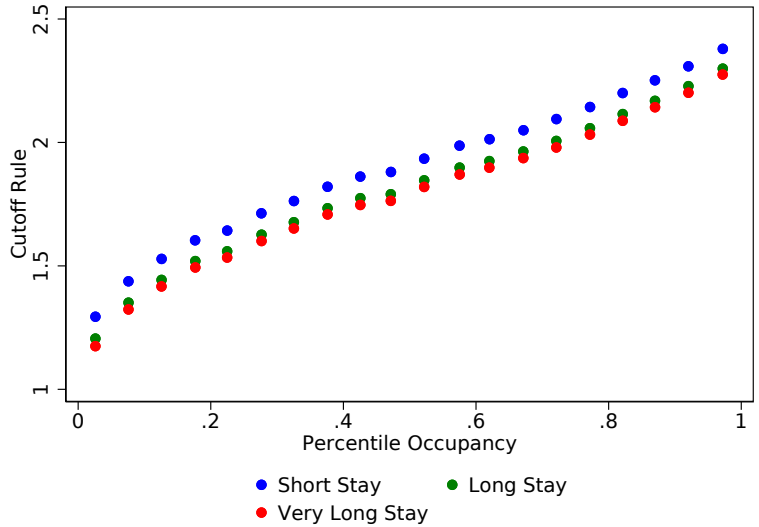


Notes: Short, long, and very-long stayers respectively constitute the 1-70, 70-90, and 90-100 percentiles of predicted length of stay. The intercepts of $\tilde{\pi}$ are not identified.

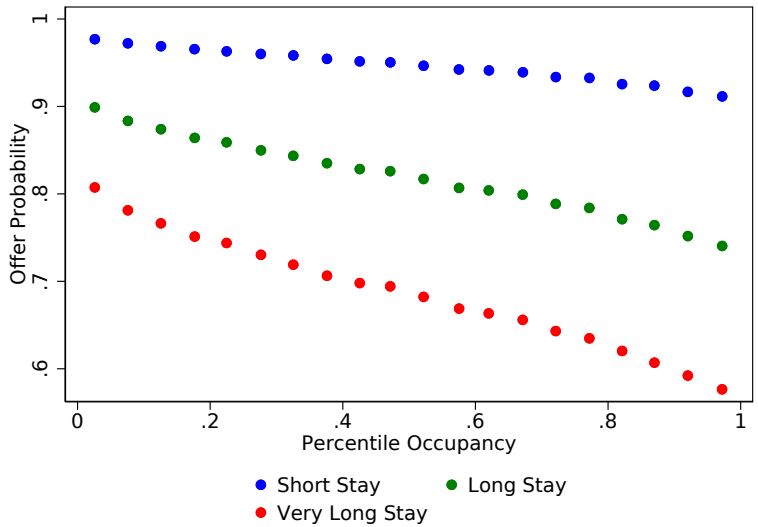
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 9: First Stage Cutoff Rules and Offer Probabilities

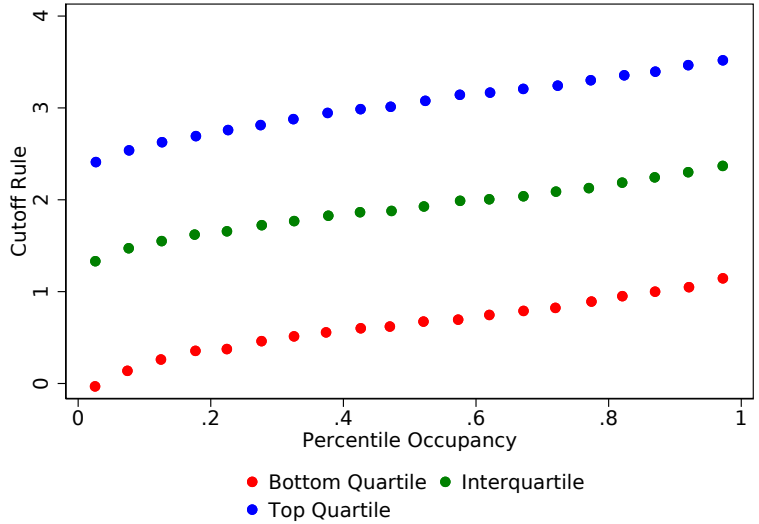
(a) Cutoff Rules, by Stayer-Type



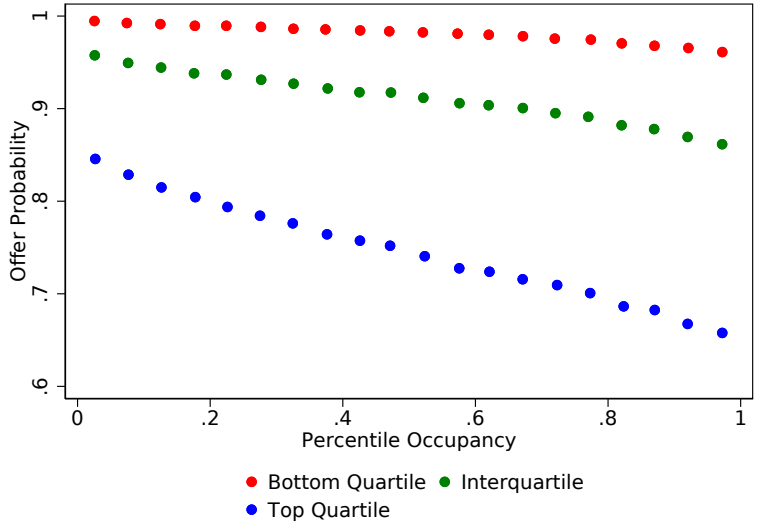
(b) Offer Probabilities, by Stayer-Type



(c) Cutoff Rules, by Community Deviation



(d) Offer Probabilities, by Community Deviation

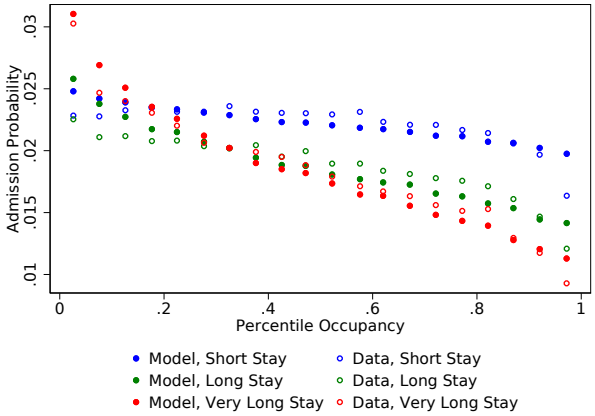


Notes: The intercepts of the cutoff rules are not identified.

Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 10: First Stage Model and Data Comparison

(a) By Stayer-Type



(b) By Medicaid Eligibility

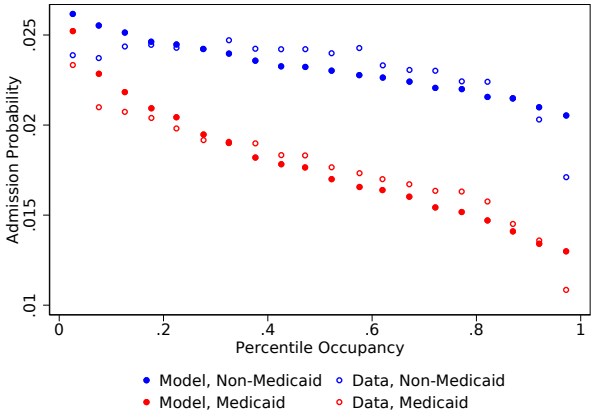
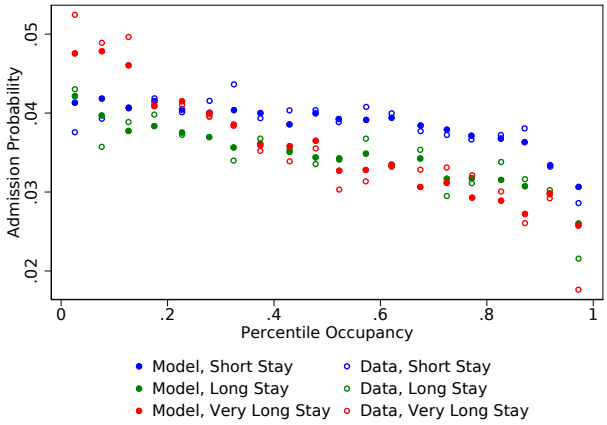
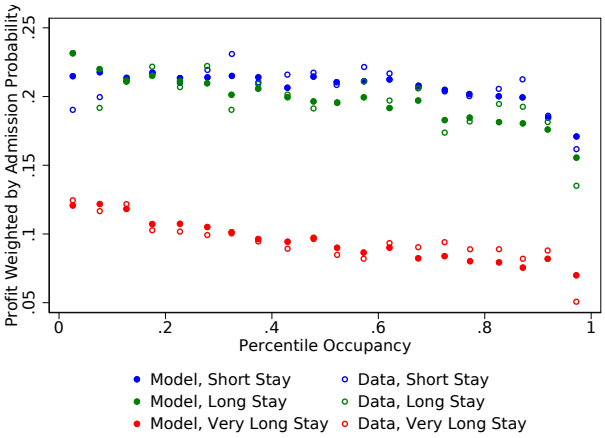


Figure 11: Second Stage Model and Data Comparison

(a) Admission Probability by Stayer-Type



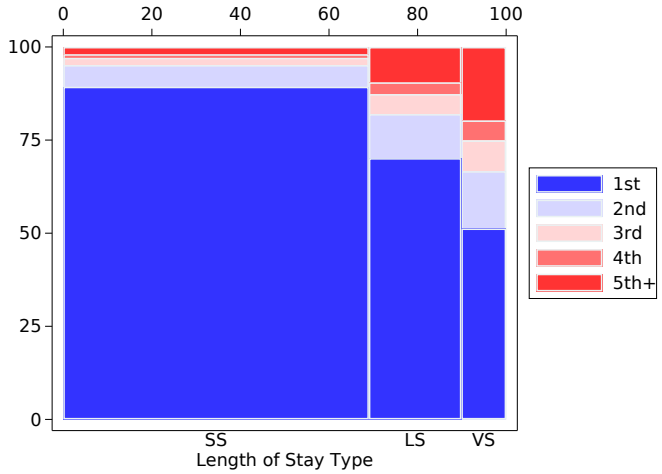
(b) Admission Profit by Stayer-Type



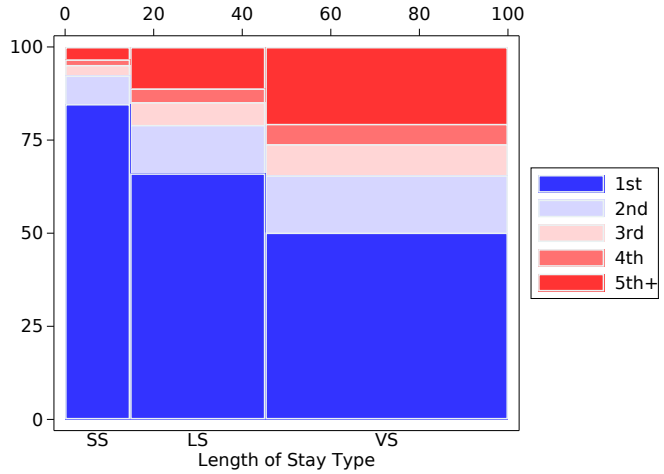
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 12: Preference Rank of Admitting Facility

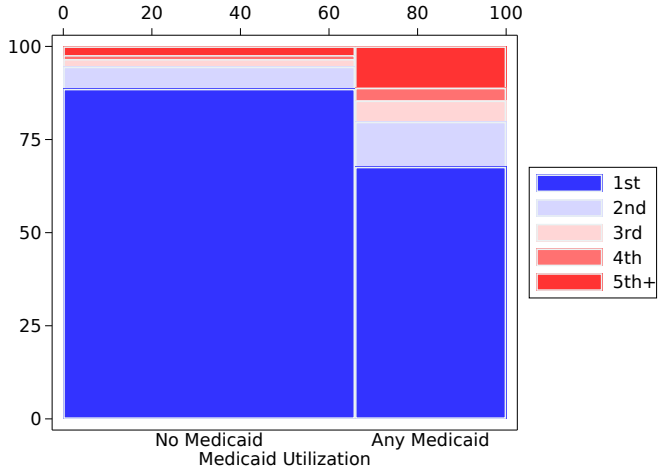
(a) Percent of Residents, by LOS-Type



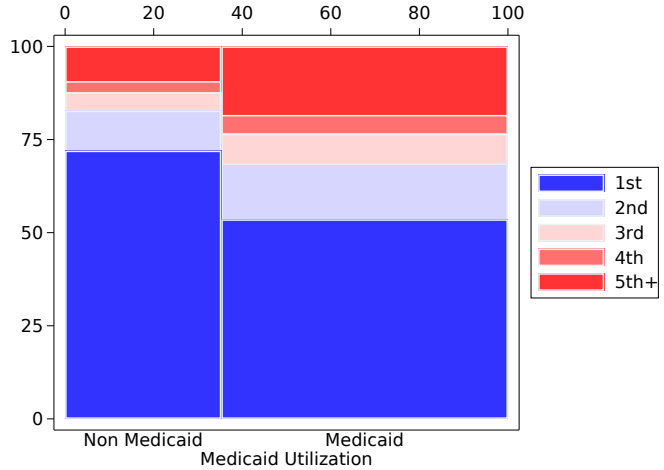
(b) Percent of Days, by LOS-Type



(c) Percent of Residents, by Medicaid Enrollment



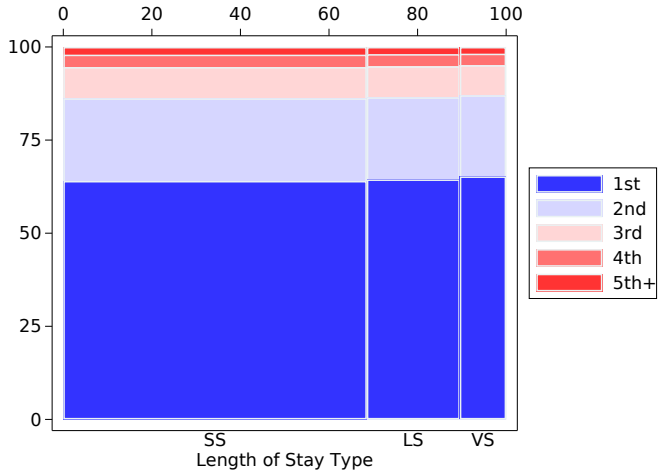
(d) Percent of Days, by Medicaid Enrollment



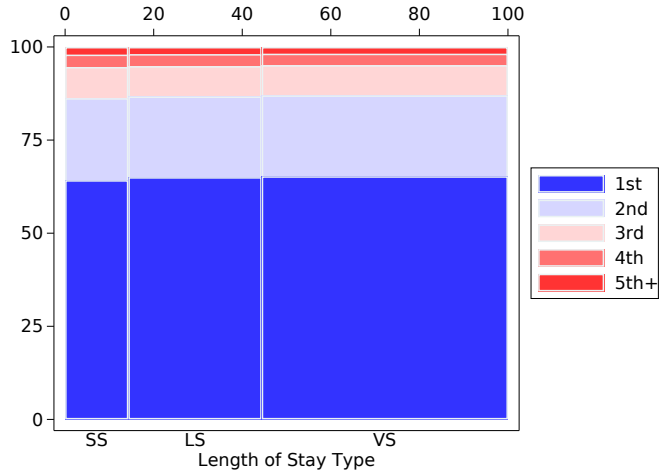
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 13: Preference Rank of Admitting Facility under FCFS

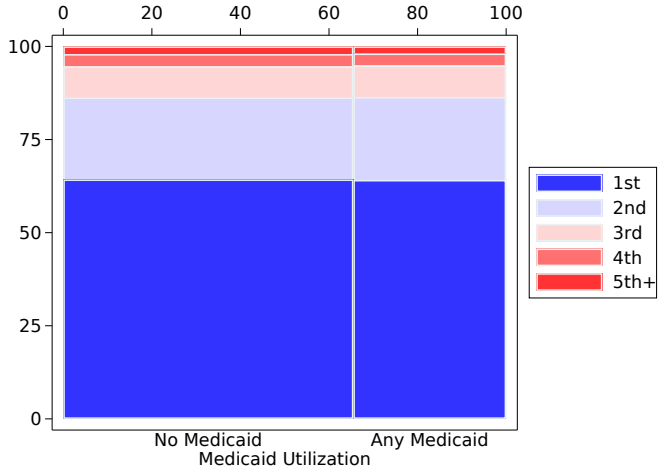
(a) Percent of Residents, by LOS-Type



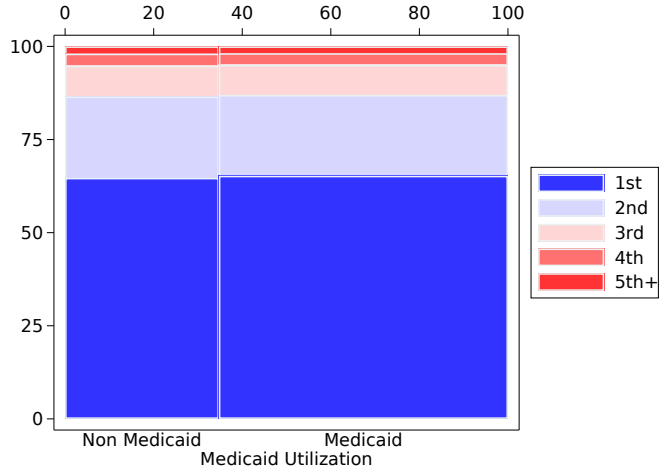
(b) Percent of Days, by LOS-Type



(c) Percent of Residents, by Medicaid Eligibility



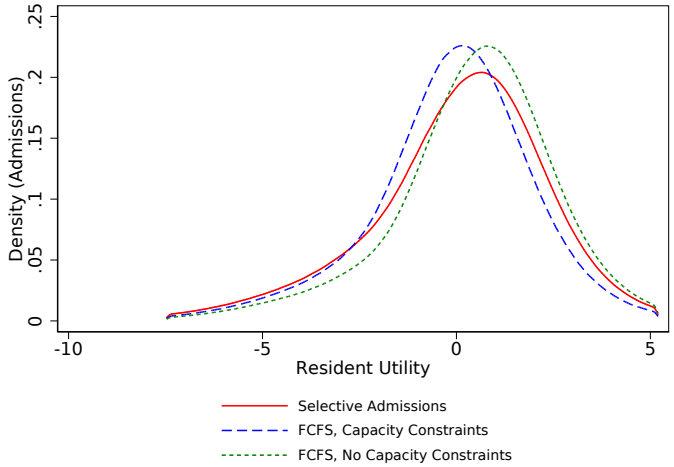
(d) Percent of Days, by Medicaid Eligibility



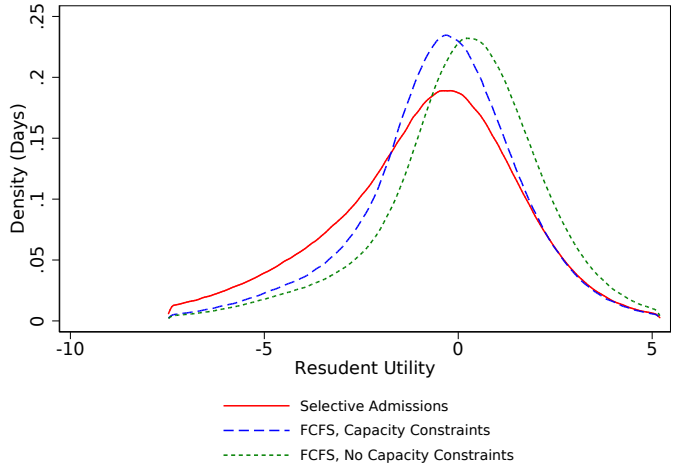
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 14: Counterfactual Utility under FCFS

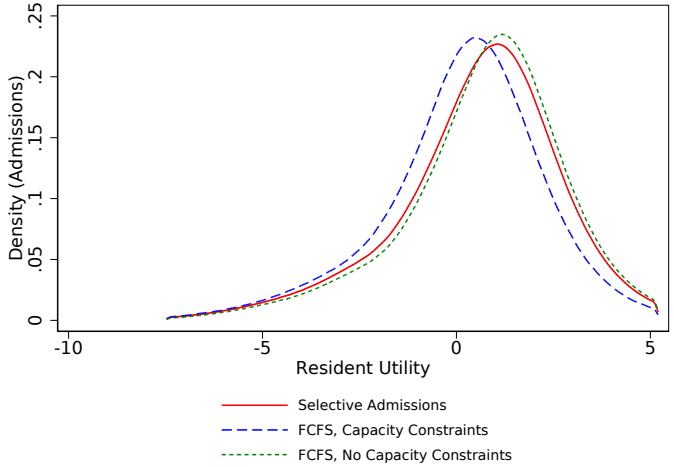
(a) All Residents



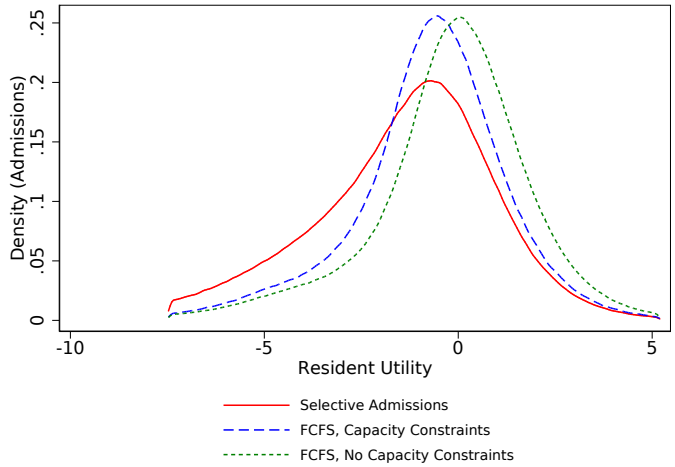
(b) All Residents, weighted by LOS



(c) Non-Medicaid Short Stay Residents



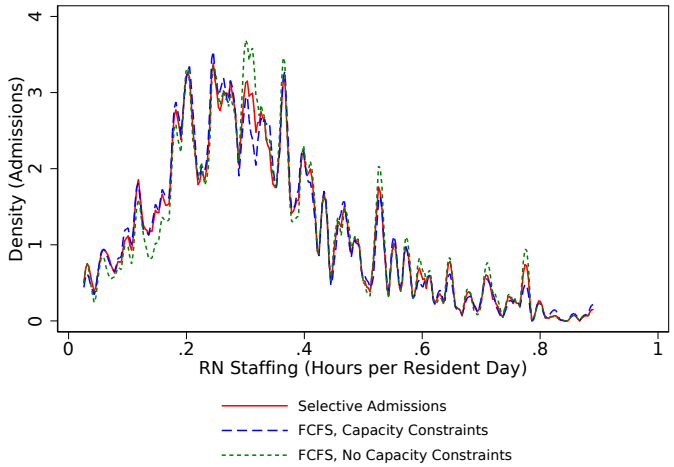
(d) Medicaid Very Long Stay Residents



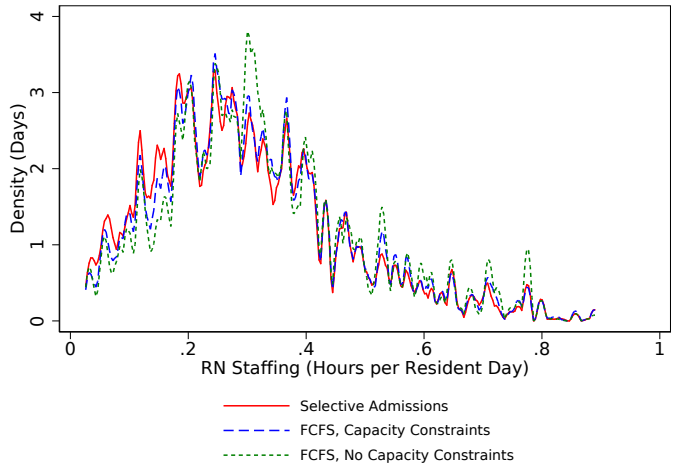
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 15: Factual and Counterfactual Admitting Facility Staffing Ratios under FCFS

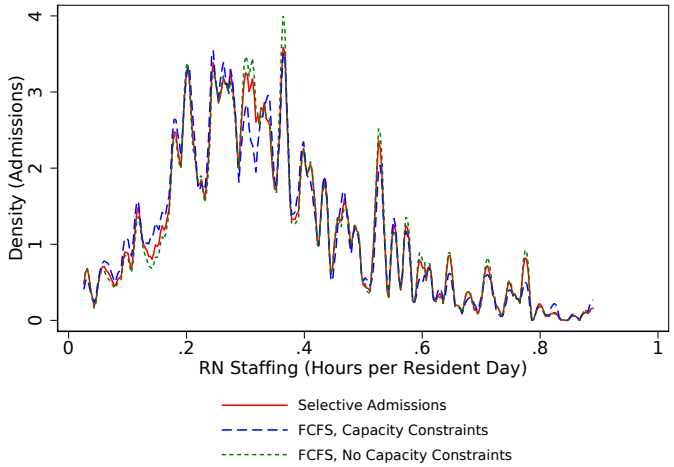
(a) All Residents



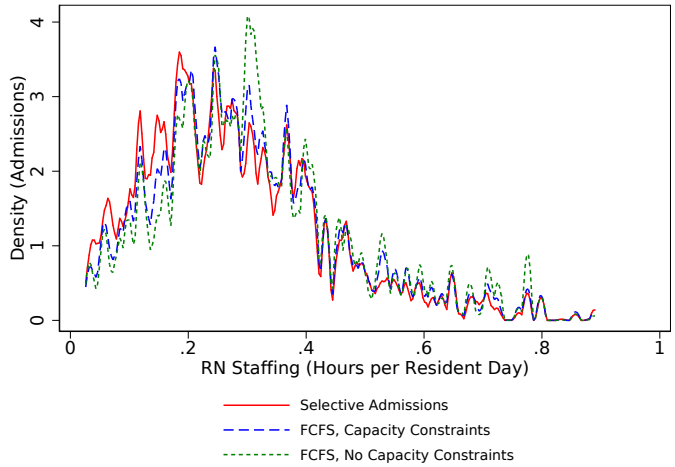
(b) All Residents, weighted by LOS



(c) Non-Medicaid Short Stay Residents



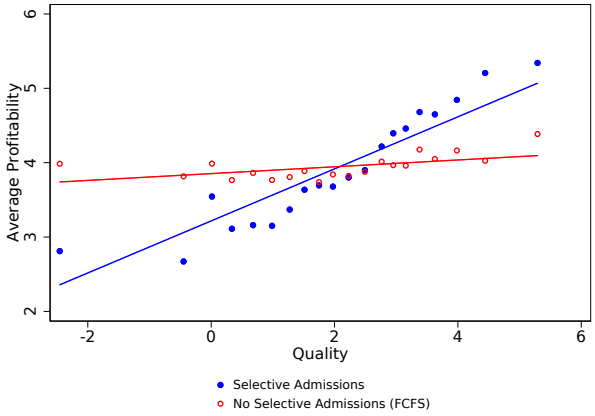
(d) Medicaid Very Long Stay Residents



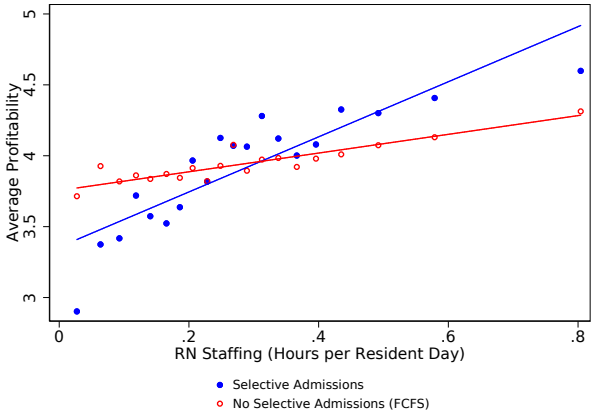
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 16: Average Resident Profitability Under Selective Admissions and FCFS

(a) Quality



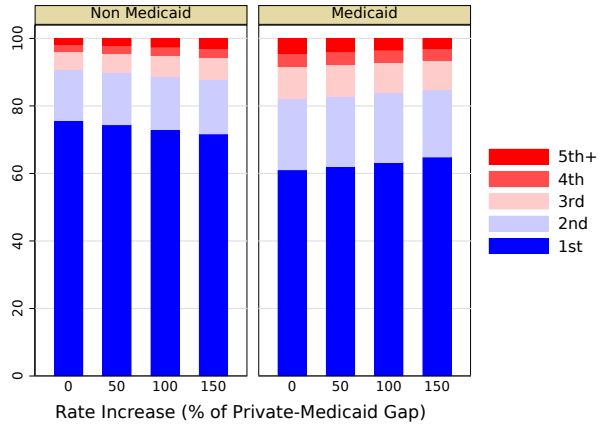
(b) Registered Nurse Hours



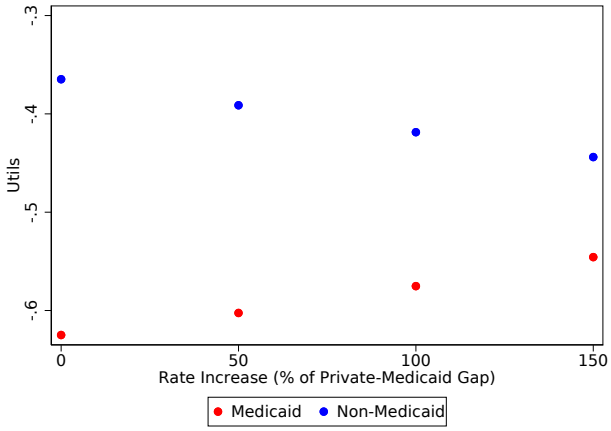
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 17: Counterfactual: Raising Medicaid Reimbursements

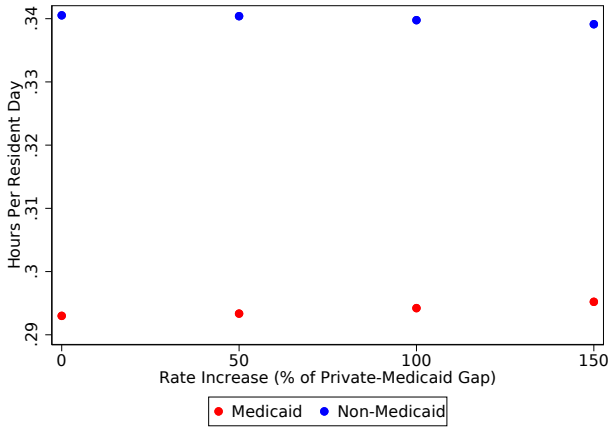
(a) Preference Rank of Admitting Facility



(b) Mean Utility Relative to First Choice



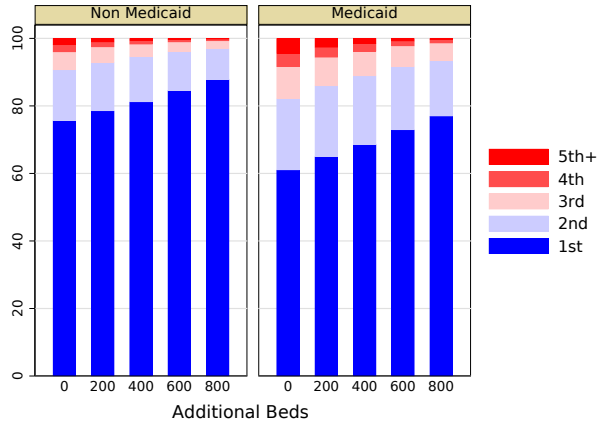
(c) Registered Nurse Staffing



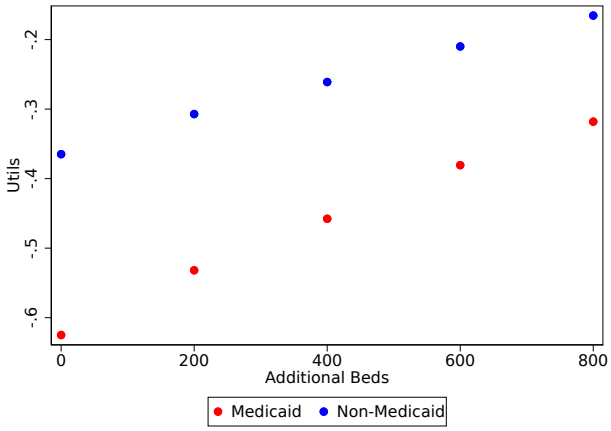
Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 18: Counterfactual: Expanding Capacity

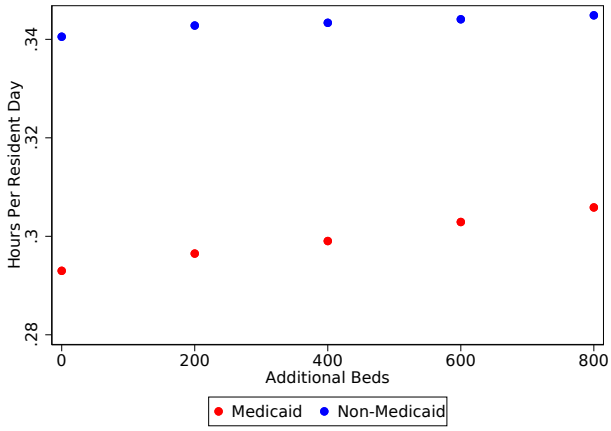
(a) Preference Rank of Admitting Facility



(b) Mean Utility Relative to First Choice

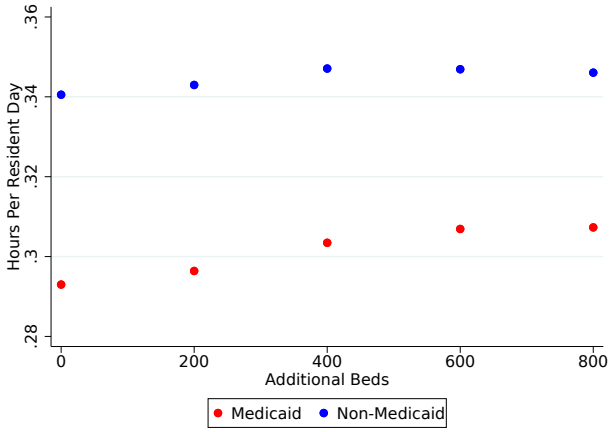


(c) Mean Registered Nurse Staffing



Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 19: Targeting Capacity Expansion to Raise Medicaid Resident Nurse Staffing



Electronic copy available at: https://ssrn.com/abstract=3613950

B Model Appendix

B.1 The Optimal Control Problem

At each time t, the facility chooses an adapted admission plan $\{a_\tau\}_{\tau \geq t}$ to maximize:

$$\mathbb{E}\left[\sum_{\{i:\tau_i^A \geq t, c_i \in a_{\tau_i^A}, \|N_{j\tau_i^A}\|_1 < b_j, u_{ij} \geq u_{ij'}\ \forall j' \in \mathcal{O}_i\}} \exp\left(\rho(\tau_i^A - t)\right)\Pi_{ij} + \int_t^\infty \exp(-\rho\tau)\Psi_j(N_{j\tau})d\tau \mid \mathcal{F}_t^j\right], \quad (34)$$

where $\mathcal{F}_t^j$ is a filtration representing j's information, b_j is the total number of beds at the facility, and the expectation is taken with respect to j's beliefs.[85]

Assumptions 1 and 2 imply that facilities condition their admission policies only on N_{jt}. Assumption 1 implies that facilities' perceive the arrival of future prospective residents to be independent of the facility's history, and Assumption 2 and memoryless discharge processes imply that all current residents of a given stayer-type ϕ are indistinguishable in their effect on j's future payoffs. Therefore, the facility perceives no benefit to conditioning its strategy on anything other than N_{jt}.

The same arguments imply that the facility only considers ϕ and Π_{ij} when admitting a resident. Furthermore, because the facility always prefers higher Π_{ij} given ϕ_i, admission policies are thresholds $\underline{\Pi}_\tau \in \mathbb{R}^{|\Phi|}$, where i is offered admission only if $\Pi_{ij} \geq \underline{\Pi}_{\tau\phi_i}$.

Together, these imply that the facility's admission policy is a vector of threshold rules that vary by census counts N_{jt}. I denote this policy by functions $\{\underline{\Pi}_{j\phi}\}_\phi$, where $\underline{\Pi}_{j\phi} : \{N : N \in \mathbb{Z}_{\geq 0}^{|\Phi|}, \|N\|_1 < b_j\} \to \mathbb{R}$. Thus, the facility chooses $\{\underline{\Pi}_{j\phi}\}_\phi$ to maximize:

$$\mathbb{E}\left[\sum_{\{i:\tau_i^A \geq t, \Pi_{ij} \geq \underline{\Pi}_{j\phi_i}(N_{j\tau_i^A}), \|N_{j\tau_i^A}\|_1 < b_j, u_{ij} \geq u_{ij'}\ \forall j' \in \mathcal{O}_i\}} \exp\left(\rho(\tau_i^A - t)\right)\Pi_{ij} + \int_t^\infty \exp(-\rho\tau)\Psi_j(N_{j\tau})d\tau \mid \mathcal{F}_t^j\right]. \quad (35)$$

B.2 Proof of Theorem 2

Without loss of generality, I exclude the facility index j. I derive the continuous time Bellman equation and optimal policies as the limit of the analogous discrete time problem with vanishingly small discrete time

[85] Note that the measure with respect to which the expectation is taken must satisfy Assumption 1.

Electronic copy available at: https://ssrn.com/abstract=3613950

intervals Δt. For small Δt, $\exp(-\rho\Delta t) \approx 1 - \rho\Delta t$. Then, since the problem is stationary:[86]

$$\begin{aligned} V(N_t) &= \max_{a_t} \left\{ \Delta t \Psi(N_t) + (1-\rho\Delta t)\mathbb{E}\left[\sum_{\{i: i\in A_t, c_i \in a_t\}} \Pi_{ij} + V(N_{t+\Delta t}) | \mathcal{F}_t^j \right] \right\} \\ \implies \rho V(N_t)\Delta t &= \max_{a_t} \left\{ \Delta t \Psi(N_t) + (1-\rho\Delta t)\mathbb{E}\left[\sum_{\{i: i\in A_t, c_i \in a_t\}} \Pi_{ij} + V(N_{t+\Delta t}) - V(N_t) | \mathcal{F}_t^j \right] \right\}, \end{aligned} \tag{36}$$

where A_t is the set of residents that arrive to the market at t and are willing and able to accept an offer of admission from the facility. Applying the Poisson arrival processes and the exponential discharge rates:[87]

$$\begin{aligned} \mathbb{E}\left[V(N_{t+\Delta t}) - V(N_t) | \mathcal{F}_t^j \right] = &\sum_\phi \left(\lambda_\phi^A \Delta t + o(\Delta t) \right) \int \mathbf{1}\{\Pi_{ij} \in a_t\} \mu(c_i) \left(\Pi_{ij} + V(N_t + 1^\phi) - V(N_t) \right) dF(c_i | \phi_i = \phi) \\ &+ \sum_\phi N_{t\phi} \left(\lambda_\phi^D \Delta t + o(\Delta t) \right) \left(V(N_t - 1^\phi) - V_j(N_t) \right) + o(\Delta t), \end{aligned} \tag{37}$$

where $o(\Delta t)$ are terms such that $\lim_{\Delta t \to 0} \frac{o(\Delta t)}{\Delta t} = 0$. Substituting (37) into (36), dividing both sides by Δt, and taking $\Delta t \to 0$ yields the result:

$$\begin{aligned} \rho V(N_t) &= \Psi(N_t) + \sum_\phi \lambda_\phi^D N_{t\phi} \left(V(N_t - 1^\phi) - V(N_t) \right) \\ &\quad + \sum_\phi \lambda_\phi^A \max_{a_t} \int \mathbf{1}\{\Pi_{ij} \in a_t\} \left(\Pi_{ij} + V(N_t + 1^\phi) - V(N_t) \right) \mu(c_i) dF_c \left(c_i | j \in J_i, \phi_i = \phi \right) \\ &= \Psi(N_{jt}) + \sum_\phi \lambda_\phi^D N_{t\phi} \left(V(N_t - 1^\phi) - V(N_t) \right) \\ &\quad + \sum_\phi \lambda_\phi^A \int \max\left\{ 0, \Pi_{ij} + V(N_t + 1^\phi) - V(N_t) \right\} \mu(c_i) dF_c \left(c_i | j \in J_i, \phi_i = \phi \right), \\ &= \Psi(N_{jt}) + \sum_\phi \lambda_\phi^D N_{t\phi} \left(V(N_t - 1^\phi) - V(N_t) \right) \\ &\quad + \sum_\phi \lambda_\phi^A \int \max\left\{ 0, \Pi + V(N_t + 1^\phi) - V(N_t) \right\} dF_{j\phi}^\Pi(\Pi), \end{aligned} \tag{38}$$

$$F_{j\phi}^\Pi(\Pi) := \int_{\{c_i : \Pi_{ij} \le \Pi\}} \mu_j(c_i) dF_c \left(c_i | j \in J_i, \phi_i = \phi \right). \tag{39}$$

It is clear from the maximand in (38) that $a_t = \{c_i : \Pi_{ij} \ge V(N_t) - V(N_t + 1^\phi)\}$ up to a measure-zero set.

[86] When $N_t = b$, the capacity constraint can be enforced by imposing that either of A_t or a_t is empty.

[87] When $N_{t\phi} = 0$, define $N_{t\phi} \left(\lambda_\phi^D \Delta t + o(\Delta t) \right) \left(V(N_t - 1^\phi) - V_j(N_t) \right)$ to be 0 since $V(N_t - 1^\phi)$ is not defined.

Electronic copy available at: https://ssrn.com/abstract=3613950

B.3 Relationship Between Continuous and Upfront Payoffs

Theorem 3. *The admission policies given continuous flow payoffs $\pi_{ij}(t - \tau_i^A)$ and upfront payoffs Π_{ij} satisfying (8) are identical.*

Proof of Theorem 3. Without loss of generality, we drop the facility index j. First, consider the case with flow payoffs. I index residents by their stayer-type ϕ, flow profit function function $\pi_i(\cdot)$ and arrival time τ_i^A. Therefore, it is helpful to articulate the facility state I_t as $(I_t^{\phi,\pi,\tau})_{\phi,\pi,\tau}$, where $I_t^{\phi,\pi,\tau}$ an indicator for if a resident of stayer-type ϕ with profitability function π was admitted at τ and is still resident at time t.[88] At each time t, the facility chooses an adapted admission plan $\{a_\tau\}_{\tau \geq t}$. The facility believes that the state I_t evolves according to the Poisson arrival and exponential discharge processes described in the main text, where residents of type (ϕ, π, τ) are made offers of admission if and only if the facility has an available bed and $(\phi, \pi, \tau) \in a_\tau^{\phi,\pi}$.[89] The sequence control problem for the facility is:[90]

$$
\begin{aligned}
V(I_t) &= \sup_a \mathbb{E}\left[\int_t^\infty e^{-\rho(\tau-t)} \left(\sum_{\left\{(\phi,\pi,\tau'): I_\tau^{\phi,\pi,\tau'} > 0\right\}} \pi(\tau - \tau') + \Psi(N_\tau) \right) d\tau | \mathcal{F}_t^j \right] \\
&= \sum_{\left\{(\phi,\pi,\tau'): I_t^{\phi,\pi,\tau'} > 0, \tau' < t\right\}} \mathbb{E}\left[\int_t^\infty e^{-\rho(\tau-t)} I_\tau^{\phi,\pi,\tau'} \pi(\tau - \tau') d\tau\right] \\
&\quad + \sup_a \left\{ \mathbb{E}\left[\sum_{\left\{(\phi,\pi,\tau'): \tau' \geq t, I_{\tau'}^{\phi,\pi,\tau'} > 0\right\}} \int_{\tau'}^\infty e^{-\rho(\tau-t)} I_\tau^{\phi,\pi,\tau'} \pi(\tau - \tau') d\tau | \mathcal{F}_t^j \right] + \mathbb{E}\left[\int_t^\infty \Psi(N_\tau) d\tau | \mathcal{F}_t^j\right] \right\} \\
&= \sum_{\left\{(\phi,\pi,\tau'): I_t^{\phi,\pi,\tau'} > 0, \tau' < t\right\}} \Pi(\phi, \pi, \tau', t) \\
&\quad + \sup_a \left\{ \mathbb{E}\left[\sum_{\left\{(\phi,\pi,\tau'): \tau' \geq t, I_{\tau'}^{\phi,\pi,\tau'} > 0\right\}} e^{-\rho(\tau'-t)} \Pi(\phi, \pi) | \mathcal{F}_t^j \right] + \mathbb{E}\left[\int_t^\infty \Psi(N_\tau) d\tau | \mathcal{F}_t^j\right] \right\},
\end{aligned}
\tag{40}
$$

$$
\Pi(\phi, \pi, \tau', t) := \mathbb{E}\left[\int_t^\infty I_\tau^{\phi,\pi,\tau'} e^{-\rho(\tau-t)} \pi(\tau - \tau') d\tau | \mathcal{F}_t^j\right], \tag{41}
$$

$$
\Pi(\phi, \pi) := \Pi(\phi, \pi, \tau', \tau') \text{ where } I_{\tau'}^{\phi,\pi,\tau'} > 0. \tag{42}
$$

Since $\Pi(\phi_i, \pi_i) = \Pi_{ij}$ from (8), the maximand above is identical to that in (9), the sequence problem when the facility receives upfront Π_{ij}. Since the maximands are identical in both problems, the optimal admission policies in both problems are the same.

□

[88] I do not account for simultaneous arrivals because the probability of such an event ever occurring is measure zero.

[89] I require that j's beliefs satisfy Assumption 1.

[90] Note that $N_t = (N_{t\phi})_\phi$ is as in the main text, so $N_{t\phi}$ is the number of elements in $\{(\pi, \tau') : I_t^{\phi,\pi,\tau'} > 0, \tau' \leq t\}$.

Electronic copy available at: https://ssrn.com/abstract=3613950

Intuitively, Theorem 3 derives from the fact that once a resident is admitted, their π_{ij} flow payoff is not affected by and does not affect the flow payoffs received from other current or future residents. Therefore, the continued π_{ij} flow payoffs from current residents do not factor into admissions decisions, and hence disregarding these continued payments in the translated game with lump-sum payoffs does not affect the optimal admission policies.[91] An important implication of Theorem 3 is that even if the facility receives flow payoffs $\pi_{ij}(\cdot)$ that vary throughout a resident's stay, one need only characterize Π_{ij} in (8) to characterize optimal admission policies.

B.4 Relaxing Model Assumptions

Corollary 3.1. *The size of the policy-relevant state space, i.e.* $N_j := \{N : \|N\|_1 \leq b_j\}$, *is* $\binom{b_j+|\Phi|}{|\Phi|}$.

It is worth considering the impact that relaxing either Assumption 1 or 2 even slightly would have on the size of facilities' state space. Under Assumptions 1 and 2, a facility with 150 beds (i.e. $b_j = 150$) has 585,276 policy-relevant states. Slightly relaxing Assumption 2 by allowing Ψ to also be a function of just a count of the number of "high needs" patients at the facility increases the number of payoff-relevant states to 18,161,699,556. Similarly, if the facility were to condition its beliefs about the probability that future residents will accept offers of admission on just the current $N_{j't}$ of its closest competitor j' (with $b_{j'} = 150$), then the size of the facility's state space would be 342,547,996,176.[92]

C Categorizing Stayer-Types

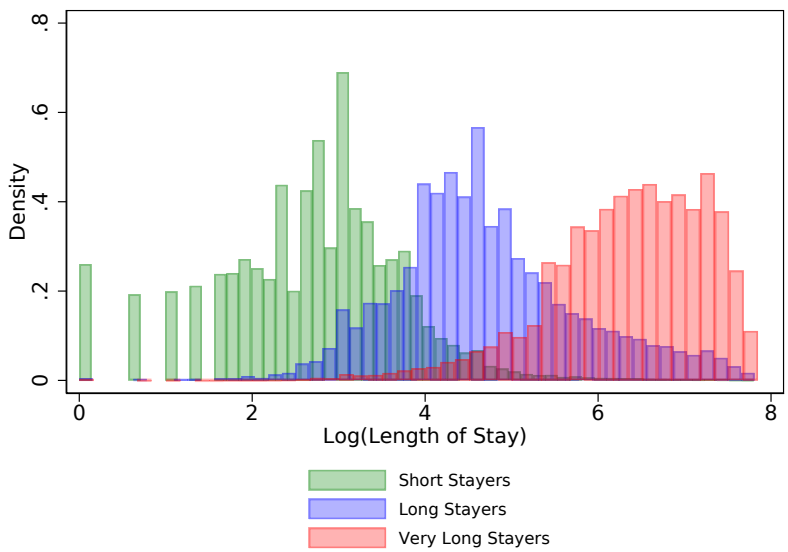
While residents' lengths of stay are highly varied (see Figure 2), I find them to be broadly predictable using information that was likely available at admission. I use regularized and cross-validated machine learning methods outlined in Appendix E to predict the natural logarithm of residents' length of stay using residents' first available assessment and claims data. I then bin residents into three categories based on their predicted length of stay: short stay (70%), long stay (20%), and very long stay (10%). Figure 20 shows the realized length of stay distribution for residents in each category.

[91] Note that while the optimal policies are shared between these games, it is not true that the value functions are shared. In particular, they differ by the expected remaining flow payoffs from the current census of residents.

[92] A possible alternative would be to allow facilities to condition on coarse information about competitors' censuses in an experience based equilibrium (Fershtman and Pakes, 2012).

Electronic copy available at: https://ssrn.com/abstract=3613950

Figure 20: Length of Stay Distribution by Predicted Stayer-Type



Short, long, and very-long stayers respectively constitute the 1-70, 70-90, and 90-100 percentiles of predicted length of stay.

D Preliminary Evidence Appendix

D.1 Proofs

Proof of Theorem 1. Towards induction, assume that $V(N-1) - V(N) \leq V(N) - V(N+1)$. Compare (3) evaluated at N and $N+1$. Note that $\rho V(N) \geq \rho V(N+1)$, and by the inductive hypothesis:[93]

$$N\lambda^D \left(V(N-1) - V(N)\right) \leq (N+1)\lambda^D \left(V(N) - V(N+1)\right). \tag{43}$$

Therefore, it must be that:

$$\lambda^A \int_{V(N)-V(N+1)}^{\infty} \left(\Pi + V(N+1) - V(N)\right) dF(\Pi) \geq \lambda^A \int_{V(N+1)-V(N+2)}^{\infty} \left(\Pi + V(N+2) - V(N+1)\right) dF(\Pi), \tag{44}$$

which holds only if $V(N+1) - V(N+2) \geq V(N) - V(N+1)$, proving the inductive step. The base case holds by the same argument where $V(0) - V(1) > 0$ is used in lieu of the inductive hypothesis. □

D.2 Robustness

Table 7 gives analogous regressions to Table 6 but also includes resident-facility pairs where the resident arrived locally to the facility but was admitted to a different facility. While these estimates do indicate that a facility's occupancy is correlated with characteristics of arriving residents, the estimated coefficients

[93] That V is decreasing follows from the fact that any admission plan by a facility in $N+1$ can be mimicked by a facility in N to yield at least the same value.

Electronic copy available at: https://ssrn.com/abstract=3613950

are very small, especially when compared to the coefficient estimates in Table 6. This suggests that the covariance between facility occupancy and admitted patient characteristics that we identify in Table 6 is not driven by variation in the distribution of arriving patient characteristics.

Table 8 gives estimates from regressing a facility's occupancy percentile on the occupancy percentiles of its local competitors. I estimate only a small positive relationship that is strongest in highly concentrated markets. For example, the occupancy percentile of a facility with the average number of competitors within 5km is only expected to increase by 1.72 between its geographically closest competitor's least full day and most full day in the sample. Similarly, a one standard deviation increase in the average occupancy percentile of a facility's closest 5 competitors corresponds to a .97 percentile increase in the facility's occupancy percentile. Insofar as variation in competitors' occupancies reflects variation in competitors' admission policies, the small magnitudes of the coefficients in Table 8 suggest that the covariance between facility occupancy and admitted patient characteristics is unlikely to driven by simultaneous variation in competitors' policies.

D.3 Projecting Desirability Scores Onto a Linear Model

Table 10 gives the estimates of a regression of resident characteristics on desirability scores. These coefficient estimates must be interpreted cautiously because they are not causal and because they are a linear approximation to a highly nonlinear function. Still, Table 10 provides valuable insight into the correlations being exploited by the machine learning algorithm. The estimates agree with Figure 7 that Medicaid residents and residents with longer anticipated stays are less desirable, and they further suggest that Medicare coverage is more desirable than private pay. The positive coefficient on Case Mix Index (CMI) are explained by the fact that Medicare reimbursements are determined using CMI. I estimate a negative coefficient on DRG weights likely because the additional care requirements associated with higher DRG weights are not compensated by Medicare except through correlation with CMI. Additionally, consistent with Table 6, I find small negative coefficients on health characteristics associated with uncompensated care requirements. Finally, I find that even controlling for the aforementioned, black and Hispanic residents have lower expected desirability scores.

Electronic copy available at: https://ssrn.com/abstract=3613950

Table 10: Regression on Desirability (z) Scores

Share of Stay:	Medicare	43.71
		(0.0488)
	Private Pay	43.03
		(0.0488)
	Medicaid	41.36
		(0.0498)
Stayer Type:	Long Stayer	-0.455
		(0.00772)
	Short Stayer	-3.034
		(0.0147)
	Native American	2.331
		(0.0573)
Race:	Asian	2.415
		(0.0486)
	Black	1.892
		(0.0485)
	Hispanic	2.167
		(0.0482)
	White	2.426
		(0.0477)
Resource Utilization:	Case Mix Index	0.0124
		(0.000480)
	DRG Weight	-0.531
		(0.0135)
Health:	Visual Impairment (0-4)	-0.118
		(0.00313)
	Diabetes	-0.0560
		(0.00611)
	Chewing Problems	-0.0307
		(0.00692)
	Varied Mental Function	-0.0993
		(0.00765)
	Antipsychotics (days/week)	-0.0730
		(0.00139)
	Antienxiety (days/week)	-0.0853
		(0.00160)
	Antidepressants (days/week)	-0.0456
		(0.000985)
	Socially Inappropriate Behavior (0-3)	-0.164
		(0.00899)
	Conflict with Staff	-0.176
		(0.0310)
	Conflict with Residents	-0.508
		(0.0827)
	Body Mass Index	-0.00841
		(0.000492)
	Underweight	-0.0777
		(0.00935)
	N	555,170
	R^2	0.567

Notes: Standard errors in parenthesis. Regression includes addition controls for whether each characteristic is observed for each resident. Shares of stay are the expected present-discounted share of a resident's stay reimbursed by a given source. See Appendix I.

Electronic copy available at: https://ssrn.com/abstract=3613950

E Machine Learning

The primary machine learning tool I use in this paper is Microsoft's open source gradient boosted decision tree (GBDT) implementation, LightGBM (Ke et al., 2017). Gradient boosting is a procedure to train a predictive function that is an ensemble of weak learners (Friedman, 2001, 2002). As its name suggests, these weak learners are decision trees in the case of GBDT.

By composing many simple functions (decision trees), the predictive function can approximate highly non-linear patterns in the data. However, without restriction on either the trees' or ensemble's complexity, this flexibility will result in over-fitting. To prevent this, I regularize the number of leaves in each tree, the number of trees in the ensemble, and the relative weight that the predictive function places on successive trees (i.e., the "learning rate"). Tuning these parameters is analogous to tuning the penalty parameter in a LASSO or Ridge regression. Parameter values are selected to minimize the model's k-fold cross-validated out of sample loss. When the number of features are too large for parameter tuning to be computationally feasible with the full feature set, the features input to the tuning process are selected by excluding those with very low influence on a model trained with fixed parameter values.

F Preferred Parameterizations

I parameterize $\tilde{\pi}_{ij}$ to be only a function of univariate desirability score z_i, stayer-type ϕ_i, and profitability shock ϵ_i^{π} that is observed by facilities but unobserved to the econometrician:

$$\tilde{\pi}_{ij} = \tilde{\pi}(z_i, \phi_i; \gamma_\pi) - \epsilon_i^{\pi}, \tag{45}$$

where $\tilde{\pi}(z_i, \phi_i; \gamma_\pi)$ is a second degree polynomial in z_i and $z_i^{\%le}$ with intercepts in ϕ_i.

I parameterize cutoff rules as functions of facility characteristics and current census counts:

$$\underline{\tilde{\pi}}_{j\phi}(N_{jt}) = \underline{\tilde{\pi}}(N_{jt}, X_j, \phi; \gamma_{\underline{\pi}}), \tag{46}$$

Specifically, I parameterize $\underline{\tilde{\pi}}(N_{jt}, X_j, \phi; \gamma_{\underline{\pi}})$ to include intercepts in ϕ and a polynomial in:

- $\mathbb{E}[z_i|N_{jt}, a_{ij}]$: the expected z_i of residents admitted to facility j given census counts N_{jt}. I use gradient boosted decision trees (GBDT) described in Appendix E to fit $\mathbb{E}[z_i|N_{jt}, a_{ij}]$.[94] The use of GBDT allows me to fit $\mathbb{E}[z_i|N_{jt}, a_{ij}]$ with a highly flexible non-linear function that varies both across facilities as well as over N_{jt} within the same facility.

- $x_j^{\Delta z}$: the difference between the average z_i of j's residents and the average z_i of j's local community.[95] I define the average z_i of j's local community using a weighted average of the z_i of all patients in the data

[94] I additionally impose monotonicity in N_{jt} since I expect facilities to become more selective in z_i as they become more full.
[95] I weight these averages by residents' lengths of stay.

Electronic copy available at: https://ssrn.com/abstract=3613950

with prior residences near j, including patients admitted to a facility other than j. Because patients are more likely to be admitted at facilities near their prior residence, I use a weight that decreases in a patient's distance of prior residence from the facility. Specifically, I weight local residents' z_i by their predicted admission probability at the facility from a logit regression of admission on a second degree polynomial in the distance between prior residence and the facility. Intuitively this weights residents according to their likelihood of admission at the facility when only conditioning on distance.

I expect both across-facility and within-facility variation in $\mathbb{E}\left[z_i|N_{jt}, a_{ij}\right]$ to be informative about facilities' admission policies. Across-facility variation is likely to be informative because high average z_i scores may indicate that a facility is highly selective.[96] Within-facility variation is likely to be informative since increasing thresholds suggest an increasingly censored distribution of z_i admitted at the facility. Similarly, large values of $x_j^{\Delta z}$ may also correspond to facilities censoring the distribution of z_i that they admit.

It is important to emphasize that $\underline{\tilde{\pi}}(N_{jt}, X_j, \phi; \gamma_{\underline{\pi}})$ is not structural. The objective in parameterizing $\underline{\tilde{\pi}}(N_{jt}, X_j, \phi; \gamma_{\underline{\pi}})$ is to capture the variation in facilities' policies in a parsimonious way.[97] While this allows use of predictive but non-structural terms such as $x_j^{\Delta z}$ and $\mathbb{E}\left[z_i|N_{jt}, a_{ij}\right]$ when parameterizing the policy functions, it also places a severe restriction on the counterfactuals that can be simulated using those policy functions. In particular, $\gamma_{\underline{\pi}}$ cannot be used to simulate how facilities adjust their admission policies in counterfactuals.

G Simulating the Applicant Distribution

Observe that:

$$\begin{aligned}
F_{j\phi}^{\Pi}(\Pi) &= \int_{\{c_i:\Pi_{ij}<\Pi\}} \mu_j(c_i) dF\left(c_i|j \in J_i, \phi_i = \phi\right) \\
&= \int_{\{\boldsymbol{X}_i, \epsilon_i^{\pi}, \epsilon_i^{u}: \tilde{\pi}(z_i,\phi_i) - \epsilon_i^{\pi} < (\rho + \lambda_{j\phi_i})\Pi\}} \mathbf{1}\left\{u_{ij} \geq u_{ij'} \forall j' \in \mathcal{O}_i\right\} dP\left(\boldsymbol{X}_i, \epsilon_i^{\pi}, \epsilon_i^{u}|j \in J_i, \phi_i = \phi\right) \\
&= \int_{\{\boldsymbol{X}_i, \epsilon_i^{\pi}: \tilde{\pi}(z_i,\phi_i) - \epsilon_i^{\pi} < (\rho + \lambda_{j\phi_i})\Pi\}} s_{ij}^{\mathcal{O}_i \cup \{j\}} dP\left(\boldsymbol{X}_i, \epsilon_i^{\pi}|j \in J_i, \phi_i = \phi\right) \\
&= \int \int_{\{\epsilon_i^{\pi}: \tilde{\pi}(z_i,\phi_i) - \epsilon_i^{\pi} < (\rho + \lambda_{j\phi_i})\Pi\}} s_{ij}^{\mathcal{O}_i \cup \{j\}} dF_{\epsilon^{\pi}}(\epsilon_i^{\pi}) dP\left(\boldsymbol{X}_i|j \in J_i, \phi_i = \phi\right) \\
&= \int \sum_k s_{ij}^{[k] \cup \{j\}} P\left(\tilde{\pi}(z_i,\phi_i) - \epsilon_i^{\pi} < (\rho + \lambda_{j\phi_i})\Pi|\boldsymbol{X}_i, \mathcal{O}_i = [k]\right) P\left(\mathcal{O}_i = [k]|\boldsymbol{X}_i\right) dP\left(\boldsymbol{X}_i|j \in J_i, \phi_i = \phi\right),
\end{aligned} \tag{47}$$

[96] It may also indicate that the facility's local community of residents has generally high z_i scores. This is also likely to correspond to a high degree of selectivity since the facility likely anticipates an abundance of high-margin patients willing to accept an offer of admission.

[97] Since facility policies are not observed, a more precise statement is that we would like to parameterize $\underline{\tilde{\pi}}$ so that $\tilde{\pi} - \underline{\tilde{\pi}}$ is highly informative about the covariation between facility occupancy and admitted resident composition.

Electronic copy available at: https://ssrn.com/abstract=3613950

where facilities are are numbered in increasing order of $\underline{\tilde{\pi}}_k(N_{kt})$, as in (23). This suggests a number of simulators for $F^{\Pi}_{j\phi}$, the most direct of which is:

$$\hat{F}^{\Pi}_{j\phi}(\Pi) = \frac{\sum_{\{i:j\in J_i,\phi_i=\phi\}}\sum_k \hat{s}^{[k]\cup\{j\}}_{ij} P\left(\tilde{\pi}(z_i,\phi_i;\hat{\gamma}_\pi)-\epsilon^\pi_i < (\rho+\lambda_{j\phi_i})\Pi|\hat{\theta}_1,\boldsymbol{X}_i,\mathcal{O}_i=[k]\right) P\left(\mathcal{O}_i=[k]|\hat{\theta}_1,\boldsymbol{X}_i\right)}{|\{i:j\in J_i,\phi_i=\phi\}|}, \tag{48}$$

where $P(\mathcal{O}_i=[k]|\hat{\theta}_1,\boldsymbol{X}_i)$ is from equation (26), and $\hat{s}^{[k]\cup\{j\}}_{ij}$ is computed according to (17).[98] The remaining term, $P\left(\tilde{\pi}(z_i,\phi_i;\hat{\gamma}_\pi)-\epsilon^\pi_i < (\rho+\lambda_{j\phi_i})\Pi|\hat{\theta}_1,\boldsymbol{X}_i,\mathcal{O}_i=[k]\right)$, can be computed analytically using F_{ϵ^π}.

H Computing Expected Out-of-Pocket Expenditure

In this section I describe my model of resident beliefs about their expected admission-discounted daily out-of-pocket expenditure, $\mathbb{E}[OoP_{ij}]$. I model residents as transitioning from Medicare to private pay to Medicaid based on the resident's Medicare eligibility and wealth. First, I assume a cap of 100 days on Medicare coverage ($\bar{L}^{mcare}_i = 100$) if i's stay qualifies for Medicare coverage and 0 days ($\bar{L}^{mcare}_i = 0$) if i's stay does not. Second, I infer i's wealth from the number of days i was private pay at her admitting facility until she transitioned to Medicaid—i.e. $W_i = P^{priv}_j L^{priv}_{ij}$, where j was i's admitting facility. In cases where i was never observed to transition to Medicaid, I assume that i did not expect to ever transition to Medicaid at any facility ($W_i = \infty$). Inferred wealth is then used to forecast the number of days that i could have afforded as a private payer at other $j' \in J_i$ (i.e., $\bar{L}^{priv}_{ij'} = \frac{W_i}{P^{priv}_{j'}}$).

Since Medicare out-of-pocket rates do not vary with facilities, I only model the out-of-pocket expenditures during private pay.[99] Then the resident's expected out-of-pocket contribution can be computed analytically:

$$\begin{aligned}\mathbb{E}\left[OoP_{ij}\right] &= P^{priv}_j\left(\rho+\lambda^D_{j\phi_i}\right)\left(\int_{\overline{L}^{mcare}_i}^{\overline{L}^{mcare}_i+\overline{L}^{priv}_{ij}}\int_{\overline{L}^{mcare}_i}^{L_{ij}}\exp(-\rho l)dldF(L_{ij})\right.\\ &\left.+\int_{\overline{L}^{mcare}_i+\overline{L}^{priv}_{ij}}^{\infty}\int_{\overline{L}^{mcare}_i}^{\overline{L}^{mcare}_i+\overline{L}^{priv}_{ij}}\exp(-\rho l)dldF(L_{ij})\right)\\ &= \left(\exp\left(-(\lambda^D_{j\phi_i}+\rho)\overline{L}^{mcare}_i\right)-\exp\left(-(\lambda^D_{j\phi_i}+\rho)(\overline{L}^{mcare}_i+\overline{L}^{priv}_i)\right)\right)P^{priv}_j,\end{aligned} \tag{49}$$

where L_{ij} signifies resident i's length of stay at j, and the coefficient on P^{priv}_j is the admission-discounted share of a resident's stay that is anticipated to be private pay.

An important feature of this procedure to compute $\mathbb{E}[OoP_{ij}]$ is that it takes into account the fact that many residents who end up on Medicaid would likely have exhausted their private resources at any facility

[98] I use first stage ($\hat{\theta}_1$) preference estimates in computing $\hat{s}^{[k]\cup\{j\}}_{ij}$.

[99] Note that this is assumption excludes the possibility that residents adjust their beliefs about out-of-pocket expenditures made while on Medicare based on across-facility variation in discharge rates. This assumption primarily affects short-stay residents likely to discharge between the start of Medicare coinsurance (20 days) and the end of Medicare coverage (100 days).

Electronic copy available at: https://ssrn.com/abstract=3613950

and should therefore have been largely indifferent to variation in facility prices.[100]

I Changing Reimbursement Rates

Because $\tilde{\pi}_{ij}$ is a discounted average anticipated flow profit over a resident's stay, it does not distinguish the precise flow profit generated on different days under different reimbursements. In order to translate raising the Medicaid reimbursement rate into a change in $\tilde{\pi}_{ij}$, I assume the following functional form for resident-specific flow profitability:

$$\pi_{ij}(t-\tau_i^A) = \begin{cases} \pi_{ij}^{mcare} & \text{if } t-\tau_i^A \leq \overline{L}_i^{mcare} \\ \pi_{ij}^{priv} & \text{if } \overline{L}_i^{mcare} < t-\tau_i^A \leq \overline{L}_i^{mcare} + \overline{L}_{ij}^{priv} \\ \pi_{ij}^{mcaid} & \text{if } t-\tau_i^A > \overline{L}_i^{mcare} + \overline{L}_{ij}^{priv}. \end{cases} \tag{50}$$

Under this assumption, the average present discounted value of resident-specific profit that j expects to receive from admitting i can be computed as:

$$\tilde{\pi}_{ij} = w_{ij}^{mcare}\pi_{ij}^{mcare} + w_{ij}^{priv}\pi_{ij}^{priv} + w_{ij}^{mcaid}\pi_{ij}^{mcaid}, \tag{51}$$

$$w_{ij}^{mcare} = 1 - \exp\left(-(\lambda_{j\phi_i}^D + \rho)\overline{L}_i^{mcare}\right), \tag{52}$$

$$w_{ij}^{priv} = \exp\left(-(\lambda_{j\phi_i}^D + \rho)\overline{L}_i^{mcare}\right) - \exp\left(-(\lambda_{j\phi_i}^D + \rho)(\overline{L}_i^{mcare} + \overline{L}_i^{priv})\right), \tag{53}$$

$$w_{ij}^{mcaid} = \exp\left(-(\lambda_{j\phi_i}^D + \rho)(\overline{L}_i^{mcare} + \overline{L}_i^{priv})\right). \tag{54}$$

The coefficients $\{w_{ij}^{mcare}, w_{ij}^{priv}, w_{ij}^{mcaid}\}$ sum to 1 and represent the present discounted share of time that the resident is expected to spend as each payer type. The derivation of these coefficients is shown in Appendix I.1. I additionally place the following functional form restrictions on the flow profitabilities:

$$\pi_{ij}^{mcare} := \pi^{mcare}(h_i) + \epsilon_{ij} \tag{55}$$

$$\pi_{ij}^{priv} := \bar{P}^{priv} - mc(h_i) + \epsilon_{ij}, \tag{56}$$

$$\pi_{ij}^{mcaid} := \bar{P}^{mcaid} - mc(h_i) + \epsilon_{ij}. \tag{57}$$

This functional form allows that Medicare mark-ups may vary flexibly with the health characteristics of i. It also allows that the residents' marginal costs may vary with health characteristics when on private pay or Medicaid. These marginal costs may differ from the marginal costs while the resident is on Medicare since the type of care that qualifies for Medicare coverage is likely to differ from the typical care required

[100] While such residents are largely indifferent to private rates, they are not entirely so. For example, there is nonzero probability that a resident could be discharged after a time that would have resulted in exhaustion of private wealth at an expensive facility but not at a less expensive facility.

Electronic copy available at: https://ssrn.com/abstract=3613950

when on private pay or Medicaid.[101] The parameterization of $\tilde{\pi}_{ij}$ in my estimation procedure implies that $\tilde{\pi}_{ij}$ is common to all facilities $j \in J_i$ under current reimbursements. In the same vein, I impose the average state-wide private rate and Medicaid reimbursement rates on all facilities in the parameterizations of π_{ij}^{priv} and π_{ij}^{mcaid}.[102]

This parameterization suggests regressing estimated individual specific profitabilities $\tilde{\pi}(z_i, \phi_i; \hat{\gamma}_\pi)$ on $\{w_{ij}^{mcare}, w_{ij}^{priv}, w_{ij}^{mcaid}\}$, health controls, and health controls interacted with w_{ij}^{mcare}.[103] Since marginal cost is assumed to be the same whether a patient is on Medicaid or private pay, the difference in the coefficients on w_{ij}^{priv} and w_{ij}^{mcaid} identifies the relationship between $\tilde{\pi}_{ij}$ and $\bar{P}^{priv} - \bar{P}^{mcaid}$. Table 11 gives the results of such regressions. Column (3) is the preferred specification that allows marginal costs to differentially vary with health characteristics depending on whether the patient is currently receiving care reimbursed by Medicare. The estimates suggest that after controlling for health characteristics, the difference in desirability between patients on private pay and Medicaid corresponds to a .765 difference in $\tilde{\pi}_{ij}$. Attributing this disparity entirely to the difference in reimbursement rates suggests modeling raising the Medicaid reimbursement rate to match the private rate by increasing $\tilde{\pi}_{ij}$ by $.765 w_{ij}^{mcaid}$.

Table 11: Payer Source Regression

	(1) Model 1	(2) Model 2	(3) Model 3
Medicare Weight	5.506	4.992	4.989
	(0.00170)	(0.0209)	(0.0388)
Private Weight	4.780	4.340	4.220
	(0.00275)	(0.0210)	(0.0245)
Medicaid Weight	3.923	3.532	3.455
	(0.00415)	(0.0210)	(0.0244)
Stayer-Type Controls	Y	Y	Y
Health Controls	N	Y	Y
Health Controls X Rehab Weight	N	N	Y
R^2	0.525	0.544	0.549
N	555,170	555,170	555,170

Notes: Standard errors in parenthesis.

[101] The marginal cost when the resident is on Medicare is in $\pi^{mcare}(h_i)$.

[102] Note that I must allow the error term ϵ_{ij} to vary across j in order to match the modeling assumption in my estimation procedure that $\tilde{\pi}_{ij}$ is common across all $j \in J_i$.

[103] I include only realized admissions in these regressions.

Electronic copy available at: https://ssrn.com/abstract=3613950

I.1 Derivation of Payer Source Coefficients

Observe that:

$$
\begin{aligned}
\Pi_{ij} &= \int_0^\infty \int_0^{L_i} \exp(-\rho l)\, \pi_{ij}(t) dl dF(L_i) \\
&= \int_0^{\overline{L}_i^{mcare}} \pi_{ij}^{mcare} \int_0^{L_i} \exp(-\rho l)\, dl dF(L_i) \\
&+ \int_{\overline{L}_i^{mcare}}^{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}} \left(\pi_{ij}^{mcare} \int_0^{\overline{L}_i^{mcare}} \exp(-\rho l)\, dl + \pi_{ij}^{priv} \int_{\overline{L}_i^{mcare}}^{L_i} \exp(-\rho l)\, dl \right) dF(L_i) \\
&+ \int_{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}}^{\infty} \left(\pi_{ij}^{mcare} \int_0^{\overline{L}_i^{mcare}} \exp(-\rho l)\, dl + \pi_{ij}^{priv} \int_{\overline{L}_i^{mcare}}^{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}} \exp(-\rho l) + \pi_{ij}^{mcaid} \int_{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}}^{L_i} \exp(-\rho l)\, d\tau \right) dF(L_i) \\
&= \pi_{ij}^{mcare} \underbrace{\left(\int_0^{\overline{L}_i^{mcare}} \int_0^{L_i} \exp(-\rho l)\, dl dF(L_i) + \int_{\overline{L}_i^{mcare}}^{\infty} \int_0^{\overline{L}_i^{mcare}} \exp(-\rho l)\, d\tau dF(L_i) \right)}_{\frac{w_{ij}^{mcare}}{\rho+\lambda_{j\phi_i}^D}} \\
&+ \pi_{ij}^{priv} \underbrace{\left(\int_{\overline{L}_i^{mcare}}^{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}} \int_{\overline{L}_i^{mcare}}^{L_i} \exp(-\rho l)\, dl dF(L_i) + \int_{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}}^{\infty} \int_{\overline{L}_i^{mcare}}^{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}} \exp(-\rho l)\, d\tau dF(L_i) \right)}_{\frac{w_{ij}^{priv}}{\rho+\lambda_{j\phi_i}^D}} \\
&+ \pi_{ij}^{mcaid} \underbrace{\int_{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}}^{\infty} \int_{\overline{L}_i^{mcare}+\overline{L}_{ij}^{priv}}^{L_i} \exp(-\rho l)\, d\tau dF(L_i)}_{\frac{w_{ij}^{mcaid}}{\rho+\lambda_{j\phi_i}^D}}.
\end{aligned}
\tag{58}
$$

The result follows from integrating where F is an exponential distribution with rate parameter $\lambda_{j\phi_i}^D$.

J Algorithm for Allocating Additional Beds

Determining the true optimal allocation of additional beds to benefit Medicaid residents is a complex problem that requires forecasting dynamic equilibrium changes in facility policies and realized resident admissions. Therefore, I implement a simple algorithm that a policymaker might plausibly use to target capacity expansions. Before enumerating the algorithm, it is helpful to define R_j to be the set of simulated residents for whom j was their first choice but did not receive an offer of admission from j. The algorithm aims to allocate additional beds to facilities where R_j includes a large share of Medicaid-enrollees that would gain substantial additional utility from being admitted at j.

The specific algorithm I implement to allocate a fixed number of additional beds is:

1. For each facility, compute:

$$
\frac{\sum_{i \in R_j} (u_{ij} - u_{ij'}) w_{ij}^{mcaid} L_{ij}}{\sum_{i \in R_j} L_{ij}}, \tag{59}
$$

   where j' is the facility that i was admitted to. This metric is intended to approximate the Medicaid-

Electronic copy available at: https://ssrn.com/abstract=3613950

enrollee welfare increase that would occur if an extra bed were allocated to an arbitrary rejected resident for whom j was their first choice.

2. Iterate cyclically over facilities in decreasing order of (59) and allocate up to half of the beds required to satisfy the Medicaid-weighted bed-days in R_j:[104]

$$\frac{1}{2T} \sum_{i \in R_j} w_{ij}^{mcaid} L_{ij}, \tag{60}$$

where T is the length of the simulation. Repeat until all additional beds are allocated.

In my counterfactuals, I allocate 200, 400, 600, and 800 additional beds by iteratively applying the algorithm above in batches of 200 beds. In addition to the algorithm above, I have also implemented other allocation algorithms, such as allocating in proportion to the probability that facilities are full under FCFS, and the counterfactual results are qualitatively similar.

[104] I also prohibit expanding facilities above twice their original capacity.

Electronic copy available at: https://ssrn.com/abstract=3613950