Barriers to Choosing High-Quality Healthcare Providers: Evidence from the Nursing Home Market

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This paper studies demand- and supply-side explanations for why consumers often choose low-quality providers. Using rich administrative data, I estimate wide quality dispersion across nursing homes in California based on risk-adjusted mortality. Structural estimates show low responsiveness to quality by residents, with substantial heterogeneity, and systematic cream-skimming behavior by nursing homes in their admissions practices. After the star ratings were introduced, responsiveness rose heterogeneously, and nursing homes responded strategically, both in their quality investments and cream-skimming behavior. Counterfactual simulations show that increased responsiveness, quality-ranked shortlists from discharge planners, or stronger quality incentives may yield substantially larger benefits.

In many important markets where provider quality varies substantially, consumers are often matched with low-quality providers. Patients end up in lower-quality hospitals or nursing homes (Gaynor, Propper, and Seiler 2016; Hackmann 2019), families enroll in underperforming schools (Hastings and Weinstein 2008), and households rely on dishonest financial advisors (Egan, Matvos, and Seru 2019), leading to substantial welfare losses. These patterns raise a central question: why do consumers end up with such providers, even when the stakes are high?

Previous studies have established the importance of several explanations for these allocation patterns, including low consumer responsiveness to quality (Jin and Leslie 2003; Hastings and Weinstein 2008; Egan, Matvos, and Seru 2019), admissions constraints (Dranove, Kessler, McClellan, and Satterthwaite 2003; Epple, Romano, and Urquiola 2017; Gandhi 2023), and investments in quality (Cutler, Huckman, and Landrum 2004; Kolstad 2013; Hackmann 2019). However, what has been less emphasized are interactions between these channels, which if ignored, can lead to biased estimates and incomplete counterfactuals in certain settings. For instance, consumer responsiveness has a direct

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effect through its impact on consumer choice, and an indirect effect through its influence on providers' incentives to invest in quality. At the same time, capacity constraints and cream-skimming by providers may directly limit certain consumers' access to high-quality providers, and also bias consumer demand estimates that ignore these (potentially unobserved) choice set constraints.

In this paper, I study how these explanations interact to produce observed allocation patterns in the nursing home setting, using assessment-level administrative data on the universe of nursing home residents in California. In addition to the richness of the data, I study the nursing home setting for three reasons. First, this is a setting wherein quality significantly impacts consumer wellbeing. Indeed, understaffing, abuse, and negligence has been well documented, often resulting in severe health consequences, even death, for residents (Cenziper, Jacobs, Crites, and Englund 2020). Second, poor nursing home quality is an issue of great interest to policymakers, a prime example being former President Biden's proposal of a slew of reforms aimed at improving nursing home quality in his 2022 State of the Union speech. Third, nursing homes are an important part of the healthcare sector: 1.3 million Americans live in nursing homes (National Center for Health Statistics 2017), and more than half of those aged 57–61 today will spend some time in a nursing home (Hurd, Michaud, and Rohwedder 2017).

For my analysis, I proceed in four steps. First, in order to overcome concerns over publicly available measures of nursing home quality such as misreporting, I estimate nursing home quality based on risk-adjusted mortality, a commonly used health outcome in the economics literature (Doyle, Graves, Gruber, and Kleiner 2015; Deryugina and Molitor 2020; Finkelstein, Gentzkow, and Williams 2021; Abaluck, Bravo, Hull, and Starc 2021). I avoid overfitting with the large set of potential controls using a variable selection method motivated by double machine learning (Belloni, Chernozhukov, and Hansen 2014). In addition, to address concerns about selection on unobservables, I conduct a validation test for my quality estimates using an instrumental variables (IV) strategy based on distance between residents and nursing homes (Card 1993; Card, Fenizia, and Silver 2019).

In the second step, I use these quality estimates as inputs into a structural model to study residents' responsiveness to quality and cream-skimming by nursing homes. I focus on a particular type of cream-skimming behavior that has been documented in previous work — selective admissions (Gandhi 2023) — wherein nursing homes reject certain types of residents at higher rates when capacity is strained. Since failure to account for these (unobserved) choice set constraints may bias demand estimates, I jointly estimate consumer choice and provider admissions behavior. I use distance and temporary occupancy fluctuations as demand and supply instruments respectively in my structural demand model, and I estimate the model using Gibbs sampling with data augmentation to avoid the curse of dimensionality (Agarwal and Somaini 2022).

In the third step, I study the introduction of star ratings by the CMS in 2008, which was aimed at improving consumers' responsiveness to quality. Using the structural model developed in the previous step, I test whether the star ratings achieved its stated aim of increasing consumers' responsiveness to quality, and whether the ratings may have intensified cream-skimming incentives, which has the potential of lowering consumer welfare (Dranove, Kessler, McClellan, and Satterthwaite 2003). In addition, leveraging heterogeneity in nursing homes' exposure to changes in potential consumers' responsiveness, I implement an event study strategy to study nursing homes' quality response.

In the final step, I use counterfactual simulations to quantify the relative importance of different response margins to the star ratings on allocation and health, as well as to compare the effect of the star ratings with those of several counterfactual policies. Specifically, I consider counterfactual policies based on an increase in responsiveness to at least the 95th percentile of the estimated distribution, the provision of quality-ranked shortlists by discharge planners in acute-care hospitals to prospective nursing home residents, as well as financial incentives for nursing homes to increase staffing. For each policy, I assess whether the results vary qualitatively under different supply-side assumptions — namely, the estimated admissions policies, a ban on selective admissions, and the removal of capacity constraints. I also test if there are gains from prioritizing certain types of residents, by comparing a risk-stratified assignment rule with a uniform assignment rule. Finally, I calibrate an endogenous quality choice model with capacity constraints to simulate nursing homes' quality responses to the demand-side policies, solving for the Nash equilibrium under counterfactual responsiveness using fixed-point iteration.

I estimate substantial variation in nursing home quality across California — both overall and locally — and the distance-based IV strategy supports the validity of these quality estimates. These estimates imply that a resident who goes to a nursing home with one standard deviation higher quality is 2 percentage points less likely to die in the nursing home within 90 days of admission (all else equal), a 27 percent reduction relative to the baseline mortality rate. The correlations between my quality measure and publicly available nursing home characteristics have the expected signs, but my quality measure is a far stronger predictor of resident outcomes than these other variables.

Despite the high stakes for residents, I estimate that average responsiveness to quality is close to zero. At the same time, there is systematic heterogeneity in responsiveness to quality: residents who are less cognitively impaired, younger, more educated, and whose primary language is English are more responsive to quality. Allocation is also affected by selective admissions policies: nursing homes are more likely to reject residents who are covered by Medicaid or who have dementia, and less likely to reject residents from acute care hospitals. In addition, higher-quality nursing homes tend to be more selective in their admissions policies, a pattern that is consistent with these nursing homes expecting a higher future stream of applicants to select from.

I find mixed results on the effectiveness of the star ratings. The change in average consumer responsiveness to quality was small although there is again substantial heterogeneity, with larger improvements among consumers who were already relatively responsive before the star ratings. Event study estimates reveal that nursing homes are sensitive to these changes in responsiveness: quality increased the most among nursing homes that were low-quality to begin with and that were most exposed to increases in responsiveness among potential consumers. I also find evidence that report cards may affect cream-skimming behavior by providers: indeed, low-quality nursing homes became more selective after the introduction of star ratings, consistent with these nursing homes attempting to pool with higher-quality nursing homes when risk adjustment is imperfect.

My simulations show that star ratings increased the average quality of nursing homes residents are admitted to by 0.1 standard deviations (s.d.), and reduced mortality by 3 percent, driven primarily by nursing home's quality investments. On the other hand, counterfactual simulations show that other policies may yield much larger improvements in allocation and outcomes than star ratings. First, simulations show that an increase in responsiveness to at least the 95th percentile of the estimated distribution of responsiveness may improve allocation and survival outcomes by double the amount achieved by the star ratings. While this counterfactual is not directly tied to a specific real-world policy, back-of-the-envelope calculations using the steering elasticity with respect to profit from Cutler et al. (2020) suggest that reimbursing hospitals an additional $185 for each percentage point increase in the risk-adjusted survival for every patient they discharge to nursing homes may achieve results approximating this counterfactual. Second, the simulated improvements in allocation and health resulting from the provision of quality-ranked shortlists of nursing homes by discharge planners — relative to the common practice of providing patients with long, undifferentiated lists — is about 5–6 times that of star ratings. Third, simulations show that the effect of financial incentives for nursing homes to increase staffing — calibrated based on such a policy studied by Gandhi, Olenski, Ruffini, and Shen (2024) — is about 3–4 times greater than that of the star ratings. The relative effect sizes of these counterfactual policies remain similar under the different admissions rules considered. In addition, a comparison of the simulated effects of the risk-stratified and uniform assignment rules reveal that prioritizing the admission of patients with high baseline mortality risk at high-quality capacity-constrained nursing homes may yield further improvements in outcomes. Finally, simulations accounting for endogenous quality choice by nursing homes in the demand-side counterfactuals show that these quality responses may amplify these gains.

This paper contributes to several strands of literature. First, it adds to a literature on how consumers choose providers. In the context of healthcare, there is a large literature focusing on insurance choice (Abaluck and Gruber 2011, 2016, 2020; Abaluck, Bravo, Hull, and Starc 2021; Handel 2013; Handel and Kolstad 2015; Handel, Kolstad, Minten, and Spinnewijn 2021), which is quite different qualitatively from consumers' choice of nursing homes. Insurance choice is typically framed as a financial decision, and estimates of demand for said attributes are easier to interpret given that expected benefits and costs to the consumer are both measured in dollar terms. By contrast, nursing home choice is about quality of care — which is less obvious how to measure — and magnitude of demand estimates are more difficult to interpret. Challenges for demand estimation in the two settings also differ: consumers make repeated choices when choosing insurance and may be influenced by inertia, whereas nursing home choice is typically not a repeated choice environment but is complicated by capacity constraints and unobserved rejections by nursing homes. While it is difficult to compare demand-estimates across these settings for reasons mentioned above, I find that residents do not seem very sensitive to nursing home quality on average — even though this can have a meaningful effect on their short-run mortality risk — which echoes findings in the literature on insurance choice whereby consumers make seemingly puzzling choices (e.g., by choosing dominated insurance plans). More generally, this paper adds to a previous body of work on determinants of choice quality. In particular, my finding that disadvantaged residents tend to make worse nursing home choices echoes results in other settings, such as Handel, Kolstad, Minten, and Spinnewijn (2021) in the context of insurance choice in the Netherlands, and Walters (2012) in the context of school choice.

Second, this paper adds to a literature on provider responses to incentives. Cream-skimming by providers has been documented in both hospital and nursing home settings (Dranove, Kessler, McClellan, and Satterthwaite 2003; Gandhi 2023). The contribution of this paper is to show that these cream-skimming incentives vary by provider quality, are affected by report cards, and can bias consumer choice estimation and counterfactual simulations if unobserved choice set constraints arising from such cream-skimming behavior are not modeled. Another form of provider response to incentives is their choice of quality. While previous work has shown that nursing home quality may be affected by direct financial incentives to increase staffing (Gandhi, Olenski, Ruffini, and Shen 2024), reimbursement rates (Hackmann 2019), and ownership structure (Gupta, Howell, Yannelis, and Gupta 2021; Gandhi, Song, and Upadrashta 2022), this paper shows that nursing home quality also changes in response to policy-induced changes in consumer responsiveness to quality.

Third, this paper contributes to a body of work on the effect of report cards. Previous research has found that report cards may increase consumers' responsiveness to quality (Perraillon, Konetzka, He, and Werner 2019; Brown, Hansman, Keener, and Veiga 2023) and spur providers to improve quality (Cutler, Huckman, and Landrum 2004; Kolstad 2013), but may also exacerbate cream-skimming behavior (Dranove, Kessler, McClellan, and Satterthwaite 2003). This paper echoes many of these findings, albeit with some important differences. I find that the introduction of star ratings increased responsiveness to quality among some residents (although the overall effect is small), and that nursing homes were responsive to these changes. Increases in quality were concentrated among nursing homes that were initially of lower quality — similar to the finding in Cutler, Huckman, and Landrum (2006) — and nursing homes that were most exposed to increases in responsiveness among potential residents — patterns that are more consistent with profit incentives rather than intrinsic motivation (Kolstad 2013). In addition, this paper finds increased cream-skimming among lower-quality nursing homes after the star ratings were introduced, consistent with attempts to pool with higher-quality nursing homes under imperfect star ratings risk adjustment. However, while Dranove, Kessler, McClellan, and Satterthwaite (2003) finds that cardiac surgery report cards lowered consumer welfare due to this cream-skimming behavior, this paper finds that star ratings led to modest improvements in resident outcomes, in part due to the quality responses by nursing homes.

Fourth, methodologically, this paper contributes on two fronts — demand estimation under unobserved choice-set constraints, and value-added estimation. On the demand front, identification of models with unobserved choice set constraints typically assumes that these constraints arise from a specific source, such as consideration set formation (Abaluck and Adams-Prassl 2021), consumer search (Abaluck and Compiani 2020), or two-sided matching (Agarwal and Somaini 2022). Given that the unobserved choice set constraints in my paper are due to nursing homes' preferences over different types of residents, I use a structural demand model based on two-sided matching which incorporates recent advances in this area from Gandhi (2023) and Agarwal and Somaini (2022). Separately, my estimation of nursing home quality adds to a large literature on value-added estimation (Chetty, Friedman, and Rockoff 2014; Abaluck, Bravo, Hull, and Starc 2021; Angrist, Hull, Pathak, and Walters 2021) by providing one of the first applications of double machine learning in this area (Belloni, Chernozhukov, and Hansen 2014; Chernozhukov et al. 2018).

Finally, this paper contributes to a growing literature on the economics of nursing homes. Most prior work has focuses on provider behavior — including the effects of ownership structure (Gandhi, Song, and Upadrashta 2020; Gupta, Howell, Yannelis, and Gupta 2021), reimbursement rates and competition (Hackmann 2019), and financial incentives (Gandhi, Olenski, Ruffini, and Shen 2024) on nursing home quality, as well as strategic admission and discharge decisions by nursing homes (Gandhi 2023; Hackmann, Pohl, and Ziebarth 2020) — although there is also a smaller literature on consumer choice (Gandhi 2023) and quality estimation (Einav, Finkelstein, and Mahoney 2025; Hackmann, Rojas, and Ziebarth 2024). The present paper contains elements of all three, which allows me to study how consumer choice and provider incentives interact in the context of the star ratings system and to simulate effects of other potential policies, such as hospital steering (modeled as increased responsiveness), the provision of quality-ranked shortlists by discharge planners at acute-care hospitals, and financial incentives for higher quality.

This paper proceeds as follows. In Section 1, I provide background on the nursing home industry and its residents, and describe the data I use for my analysis. I then estimate nursing home quality and validate these estimates in Section 2, before using them to study residents' responsiveness to quality and cream-skimming behavior by providers in Section 3. In Section 4, I study the effect of star ratings on residents' responsiveness as well as cream-skimming and quality choice by nursing homes, before quantifying the effect of each margin on allocation and outcomes and comparing the star ratings to other counterfactual policies using simulations in Section 5. Section 6 concludes.

1 Background

1.1 Nursing Home Industry

There are roughly 15,000 skilled nursing facilities (SNFs) — which I colloquially refer to as nursing homes in this paper — in the US providing care for about 1.3 million Americans (National Center for Health Statistics 2017), and an estimated 56 percent of Americans currently aged 57–61 are expected to spend at least one night in a nursing home during their lifetimes (Hurd, Michaud, and Rohwedder 2017). Despite substantial health expenditures in nursing homes, which totaled approximately $170 billion in 2016 (or roughly 5 percent of all healthcare spending in the US), many residents still reside in low-quality nursing homes. In addition, the majority of nursing homes in the US are for-profit, which tend to be lower quality on average (Comondore et al. 2009; Einav, Finkelstein, and Mahoney 2025).[1]

Low quality is particularly problematic in the nursing home industry given the vulnerability of many residents. In particular, residents often suffer from physical and/or cognitive impairments, such that nursing home quality can have meaningful effects on mortality (Olenski 2023). Accordingly, nursing home quality is an issue of great concern to policymakers, who have passed a number of regulations over the years. One approach is policies targeted directly at nursing homes, such as minimum staffing mandates and financial incentives for higher staffing. Such policies often differ across states, and past studies on their effectiveness have found mixed results (Park and Stearns 2009; Chen and Grabowski 2015; Hackmann 2019; Gandhi, Olenski, Ruffini, and Shen 2024).

Demand-side policies instead try to influence which nursing homes consumer choose, e.g., by providing more information about nursing home quality. The most prominent example of this is the introduction of the five-star ratings system by the CMS in December 2008, the aim of which "is to help consumers make meaningful distinctions among high- and low-performing nursing homes".[2] To

[1] More recently, the rise of private equity ownership in the nursing home sector is also believed to have contributed to lower quality (Gandhi, Song, and Upadrashta 2020; Gupta, Howell, Yannelis, and Gupta 2021).

[2] Quote was retrieved from https://www.cms.gov/medicare/provider-enrollment-and-certification/certificationand-complianc/downloads/consumerfactsheet.pdf (accessed July 13 2024).

do so, the star ratings summarizes nursing home performance on a scale of one to five stars based on staffing, health inspections, and resident outcomes, and is published on the CMS Nursing Home Compare website. In theory, this may also incentivize nursing homes to provide higher quality. On the other hand, critics point out that report card systems such as the star ratings have the potential to increase cream-skimming by providers (Dranove, Kessler, McClellan, and Satterthwaite 2003). The concern of cream-skimming is particularly relevant in nursing homes, given that facilities face capacity constraints and residents differ dramatically in their profitability. To better understand cream-skimming incentives faced by nursing homes, I give a brief overview of the population of nursing home residents below.

Nursing home residents vary widely in their medical conditions and needs, but as a crude approximation, they fall into two broad categories: short-stay and long-stay. Short-stay residents typically require rehabilitative care following an acute care hospital stay — for example, to recover from knee or hip replacement surgery. These patients are expected to recover sufficiently during their nursing home stay to be discharged and are typically covered by Medicare for up to 100 days (which provides full coverage for the first 20 days of stay and requires coinsurance between days 21 and 100). Medicare reimbursement rates are relatively high, and are adjusted based on care requirements and local cost of inputs.

By contrast, long-stay residents often suffer from chronic conditions (e.g., cognitive decline), and are unlikely be discharged in the short term. Many of these residents are covered by Medicaid, either at admission, or after spending down their assets given that long-term care insurance is uncommon in the U.S. (Brown and Finkelstein 2007, 2008, 2011). Unlike Medicare, Medicaid reimbursement rates in California are not adjusted for residents' care requirements and are much lower on average — less than one-third Medicare rates in 2005 (California Healthcare Foundation 2007). This gives rise to severe cream-skimming incentives, particularly for nursing homes that are close to capacity.

1.2 Measuring Nursing Home Quality

In reality, nursing home quality is multidimensional, and reflecting this notion, a variety of quality measures have been used in the past, including skilled staffing levels, deficiency citations during inspections by regulators (which are typically conducted annually, but may also be triggered by complaints), resident outcomes, and the five-star rating system introduced towards the end of my sample. While it may be difficult to account for all dimensions of quality in my analysis, most of these quality measures are likely to be positively correlated (evidence of which is shown in Section 2.3.1). Hence, I use 90-day risk-adjusted survival rate as my primary quality measure, which is more reliable and easier to interpret for several reasons.

First, death tends to be recorded quite accurately, whereas there is greater scope for intentional or unintentional misreporting for other quality measures. Other resident outcomes may be gamed — as was suspected to be the case when schizophrenia diagnoses rose sharply after 2012 when the government began publicly releasing information about inappropriate antipsychotic use (Thomas, Gebeloff, and Silver-Greenberg 2021) — or mismeasured in a way that is systematically correlated with quality (e.g., if understaffed nursing homes fail to discover certain adverse outcomes such as pressure sores). Staffing levels were self-reported and often unaudited during this period, and were later found to be inflated when compared to payroll-based staffing data (Geng, Stevenson, and Grabowski 2019). Deficiency citations may not present an accurate picture of a nursing home's quality as well, since some nursing homes temporarily increase inputs during the period wherein annual inspections are expected to occur (Chen and Dillender 2025).

Second, interpretation of other outcome-based measures may be affected by competing risks or censoring. For instance, a nursing home with high risk-adjusted mortality rates may have lower rates of other adverse outcomes simply because residents die before experiencing them. Since I do not observe death after discharge for residents who do not have Medicare, I focus on deaths occurring within nursing homes, which in principle may also be subject to censoring. Nonetheless, even if we observed deaths after discharge for all residents, the extent to which nursing homes are "responsible" for these deaths becomes increasingly unclear the further after discharge we consider. Therefore, in my main analysis, I focus mortality prior to discharge within 90 days of admission, and show that the quality estimates remain stable even if we vary the time horizon over which we measure mortality.

Third, death shortly after admission is an undesirable outcome for most types of residents. This is important given that I am studying residents from all payer sources, and goals of care vary substantially across different types of residents. For instance, the quality measure based on discharge readiness developed by Einav, Finkelstein, and Mahoney (2025) is an excellent quality measure for the population they study — short-stay residents — but is a less appropriate quality measure for my sample, which also includes long-stay residents (who are by definition unlikely to be discharged in the short term). I drop the relatively small number of residents for whom short-term mortality may not be an appropriate quality measure, e.g., residents who were already comatose or on hospice at admission.

Finally, mortality is a commonly used health outcome in the prior economics literature (Doyle, Graves, Gruber, and Kleiner 2015; Deryugina and Molitor 2020; Finkelstein, Gentzkow, and Williams 2021; Abaluck, Bravo, Hull, and Starc 2021), which makes it easier to compare the magnitude of my consumer choice estimates with estimates from other healthcare settings (Chandra, Finkelstein, Sacarny, and Syverson 2016; Tay 2003). In contrast, while quality measures such as falls and different types of pressures sores are commonly used in the health services literature on nursing homes, the economic cost of such adverse outcomes are not well-established, making it hard to interpret the magnitude of consumer responsiveness to such quality measures.

1.3 Data

The primary data source for this paper is the Minimum Data Set 2.0 (MDS). All nursing homes that receive federal funding — which accounts for roughly 96 percent of all nursing homes (Grabowski, Gruber, and Angelelli 2008) — are required to fill out MDS assessment forms for all residents at regular intervals (42 CFR §483.20). Specifically, assessment forms must be completed upon admission, at discharge (or death), quarterly in between, and whenever there is a significant change in status.

MDS forms are typically filled out by a registered nurse (RN), or at least certified by one. Any willful misrepresentation in the MDS forms may result in penalties under the False Claims Act.[3] Several studies on the accuracy of MDS data have found it to be fairly reliable (Shin and Scherer

[3]This is not limited to upcoding and variables that affect reimbursements directly but also other variables related to resident well-being. This is because nursing homes "must provide services to attain or maintain the highest practicable physical, mental, and psychosocial well-being of each resident" (42 CFR §1395i–3) to be certified to receive federal funding. Hence, any misrepresentation pertaining to resident wellbeing may be interpreted as being related to misrepresentation connected to a requirement for federal funding, and thus falls under the False Claims Act.

2009).

I use the rich set of baseline demographic and health variables in the admission assessment form for risk adjustment in my quality estimation. This includes residents' zip code of prior address, demographics, cognitive status, communication and hearing patterns, vision patterns, mood and behavior patterns, psychosocial well-being, physical functioning and structural problems, continence issues, disease diagnoses (including ICD-9 codes), oral health, nutrition, dental status, skin conditions, activity pursuit patterns, medications, special treatments and procedures, and discharge potential (see Appendix Tables A.1 and A.2 for a finer breakdown of the different types of data collected on each resident).[4] In addition, I use the discharge assessment form to identify whether and when residents die, and also to keep track of daily nursing home occupancy (which is important for identifying cream-skimming by nursing homes, as described in Section 3).

Another important data set in my analysis is the Online Survey Certification and Reporting (OSCAR) survey, which contains annual information about nursing homes, including staffing levels, ownership status, and address.[5] By combining nursing home address from the OSCAR with residents' prior zip code from the MDS admission form, I am able to compute distances between residents and nursing homes, which is one of the most important determinants of consumer choice in this setting. Specifically, I convert nursing homes' street addresses (respectively, residents' zip code) to GPS coordinates using the Google Maps API (using the U.S. Department of Housing and Urban Development's ZIP Code Crosswalk Files for Quarter 1 of 2010), before computing distances between these coordinates using the "geodist" module in Stata.

While I use risk-adjusted survival rates as my main quality measure as discussed earlier, I consider several publicly available measures of nursing home quality as alternatives in Section 3 as robustness checks. In particular, I consider self-reported staffing levels from the OSCAR, as well as deficiency citations and five-star ratings (data on which are available from the CMS website).

I make several sample restrictions. First, I restrict to first stays of residents between 2000–2010, which is the period of overlap between the MDS 2.0 and OSCAR data. I also focus on first stays because residents with multiple stays often face a very different environment during subsequent stays. Second, I limit the sample to residents who were admitted to a nursing home with an identifier in the MDS that could be matched to a nursing home in the OSCAR data, since otherwise it would not be possible to compute distance to their chosen nursing homes. Third, I restrict the sample to a single state both for computational reasons and because nursing home regulations differ across states. Specifically, I choose California due to its large population, and because most of its population live relatively far away from state borders (so that nursing homes in other states are unlikely to be in their choice sets).

Fourth, I exclude nursing homes that do not file cost reports following Gandhi (2023), since these tend to be specialized facilities (e.g., specializing in subacute care or mental disease). Fifth, I only include nursing homes with more than 100 new first stays from 2000 to 2010 so that quality can be estimated relatively precisely. Finally, I exclude the relatively small number of residents who were

[4]The full MDS 2 assessment form is also available on the CMS website at: https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/NursingHomeQualityInits/downloads/MDS20MDSAllForms.pdf.

[5]The OSCAR data is available from 2000 onwards from LTCFocus.org, which is maintained by Brown University Center of Gerontology and Healthcare Research. LTCFocus is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health.

Table 1: Summary Statistics for Residents and Nursing Homes in California (2000–2010)

Panel A: Residents (N=653,946)		*Panel B: Nursing Homes (J=840)*	
Age	77.541	Number of Beds	105.065
	(12.991)		(48.194)
Race: White	0.735	Occupancy Rate	86.958
	(0.441)		(7.493)
Bachelor's/Graduate Degree	0.131	Chain	0.600
	(0.338)		(0.411)
Admitted from Acute Care Hospital	0.889	For-Profit	0.877
	(0.314)		(0.309)
Has Dementia	0.233	Deficiencies	6.259
	(0.423)		(3.541)
Death Within 90 days of Admission	0.075	RN hours per resident day	0.331
	(0.264)		(0.281)

Notes: This table contains summary statistics for residents and nursing homes in California between 2000 and 2010. The unit of observation for nursing homes' summary statistics is a nursing home-year.

already comatose or on hospice at admission, given that the survival-based quality measure may not be appropriate for them.

1.4 Summary Statistics

Panel A of Table 1 presents summary statistics for the residents (at admission) in my sample. We observe that the average resident age is 77 years old, the majority of residents are white, and only a minority have a Bachelor's or graduate degree. Most residents are admitted from an acute care hospital, and reflecting their poor state of health in general, almost a quarter of residents have dementia at admission, and 7.5 percent die within 90 days of admission.[6] As a point of reference, compared to the Medicare population in 2005, the rate of dementia rate among newly admitted nursing home residents is roughly three times higher, and the mortality rate is more than six times higher.

Panel B shows summary statistics for nursing homes.[7] We observe that nursing homes have 105 beds on average, occupancy rates tend to be quite high (87 percent on average)[8], and most are owned by chains or are for profit. In addition, nursing homes receive an average of more than six deficiency citations during annual inspections, and reflecting the prevailing wisdom that many nursing homes are understaffed, registered nurses (RNs) provide less than 20 minutes of care for each resident per day on average.

2 Quality Estimation

In this section, I estimate quality of nursing homes in California, and validate these estimates using

[6]The MDS also records the payer source for residents at admission; although, as I discuss in Appendix B, this is less accurate than claims data.

[7]These statistics are weighted by number of admissions, although the general patterns for statistics that are not weighted by number of admissions are qualitatively similar (see Appendix Table A.4).

[8]A histogram of nursing homes' occupancy rates is shown in Appendix Figure A.1.

a distance-based IV strategy. I then explore the relationship between my quality estimates and other potential quality measures, as well as the degree of geographical concentration in nursing home quality.

2.1 Framework for Quality Estimation and Validation

I follow a standard additive causal model from the value-added literature (described in greater detail in Appendix Section C). This model yields the following causal equation:

$$Y_i = \mu_1 + \sum_{j=1}^{J} \beta_j D_{ij} + X_i' \gamma + u_i, \; \mathbb{E}[X_i u_i] = 0, \tag{1}$$

where Y_i is a dummy for whether resident i survives at least 90 days after admission, β_j is the causal effect of nursing home j on survival, D_{ij} is a dummy for whether resident i chooses nursing home j, X_i is a vector of resident characteristics, and u_i is an unobserved health shock. We normalize the causal effects β_j to have mean zero, and denote the quality estimates by $\{\alpha_j\}$.

The literature on value-added estimation in education has often found that controlling for lagged values of the outcome variable is important (Chetty, Friedman, and Rockoff 2014). While controlling for lagged outcomes is impossible in the present setting with survival being the outcome variable, I control for residents' baseline mortality risk using more than 500 health and demographic variables (even without interaction terms) that are recorded for each resident upon admission.

An issue with using the full set of controls for quality estimation is the risk of overfitting, especially because some of the health controls correspond to relatively rare medical conditions, and the sample sizes for nursing homes are not huge. A common data-driven method to select from a high-dimensional set of controls is post-double-selection, as proposed in Belloni, Chernozhukov, and Hansen (2014). However, the method is designed for settings with only one (or at most a few) treatment variables, whereas in this setting the treatment variables are more than 800 nursing home indicators. Therefore, in my primary specification, I use a modification of post-double-selection based on a model reduction strategy that is motivated by a correlated effects approach to select an appropriate set of controls, as described in Appendix Section J.[9]

Having selected the controls, we have a choice of whether to estimate the causal effects β_j using fixed effects or empirical Bayes. Fixed effects estimates minimize the conditional mean-squared error (MSE) and are thus preferable if we are interested in the quality of a *specific* nursing home, whereas empirical Bayes quality estimates minimize the unconditional MSE (by accounting for statistical noise in the estimation procedure) and thus provide quality estimates that better approximate true quality on average. Given that the focus of this paper is on overall allocation patterns of residents to nursing homes, I use empirical Bayes quality estimates for my main results, and check that the fixed effects quality estimates are qualitatively similar.

Despite the rich set of controls, one may still be concerned about selection on unobservables, which could be due to resident sorting or selective admissions by nursing homes (based on unobserved health u_i). To check whether my quality estimates are likely to be affected by selection bias, I use a validation test from the value-added literature based on the following idea: if the quality estimates $\{\alpha_j\}$ are valid, then exogenous variation in the estimated quality of residents' nursing homes should predict outcomes

[9] It turns out that my quality estimates are not sensitive to the variable selection method. In particular, a regression of my main quality estimates (controlling only for the variables selected by the variable selection method mentioned above) on quality estimates with the full set of controls has an R-squared of 0.99.

one-for-one. So, to obtain plausibly exogenous variation in the quality of nursing homes that residents choose, I leverage residents' preferences for nursing homes that are closer to their address.

To elaborate, following Abaluck, Bravo, Hull, and Starc (2021), I derive the following structural equation from equation (1):

$$Y_i = \mu_1 + \lambda \alpha_i^{\sim t(i)} + X_i' \gamma + \tilde{u}_i, \tag{2}$$

where λ is known as the *forecast coefficient*, $\alpha_i^{\sim t(i)} \equiv \sum_{j=1}^{J} \alpha_j^{\sim t(i)} D_{ij}$ is the leave-year-out estimate of quality for the nursing home that resident i chooses, and $\tilde{u}_i \equiv u_i + \eta_i$ is a composite structural error term, with η_i being a "forecast residual" (see Appendix Section C for the derivation of the structural equation and the definition of the forecast residual η_i).

For this IV validation exercise, I use leave-year-out quality estimates $\alpha_i^{\sim t(i)}$ to avoid a mechanical relationship between resident outcomes and the quality estimate of residents' chosen nursing homes. Specifically, given that the outcome Y_i is used in the estimation of nursing home quality α_j, using the quality estimates $\alpha_i \equiv \sum_{j=1}^{J} \alpha_j D_{ij}$ as the endogenous variable will result in a mechanical relationship between Y_i and α_i. In addition, the leave-year-out definition also serves as a test of the stability of nursing home quality over time: if there is no persistent component to nursing home quality over time, $\alpha_i^{\sim t(i)}$ will not be predictive of resident outcomes Y_i.

I estimate equation (2) using IV, instrumenting $\alpha_i^{\sim t(i)}$ with the leave-year-out quality estimate of nursing homes close to resident i's prior address, Z_i. I then test whether λ is equal to one, which it should be in large samples if the quality estimates α_j are asymptotically unbiased on average.[10] For Z_i to be a valid instrument, several assumptions must be satisfied.

IV Assumption 1 (First Stage). *The instrument(s) must be relevant, i.e., we must have $\delta_Z \neq 0$ in the regression equation for the first stage:*

$$\alpha_i^{\sim t(i)} = \delta_0 + Z_i' \delta_Z + X_i' \delta_X + e_i, \; \mathbb{E}\left[(Z_i', X_i')' \, e_i \right] = 0. \tag{3}$$

IV Assumption 2 (Exclusion Restriction). *The instrument(s) must be uncorrelated with unobserved health shocks after accounting for resident characteristics, i.e.,*

$$Cov(\tilde{Z}_i, u_i) = 0, \tag{4}$$

where $\tilde{Z}_i$ denotes the instrument(s) Z_i residualized of resident characteristics X_i.

IV Assumption 3 (Fallback Condition). *The instrument(s) must be uncorrelated with the forecast residual after accounting for resident characteristics, i.e.,*

$$Cov(\tilde{Z}_i, \eta_i) = 0.$$

The first stage assumption can be easily tested by estimating equation (3) using OLS. As for the exclusion restriction, one way to interpret this condition is that the quality of nearby nursing homes can only affect a resident's outcome through the quality of the nursing home she ultimately chooses (after controlling for her characteristics). This may be violated, for instance, if residents choose where

[10] Strictly speaking, empirical Bayes estimates are not unbiased in finite samples, given that empirical Bayes minimizes the mean-squared error of the quality estimates according to the bias-variance tradeoff (which typically does not involve setting the bias to zero). So, I consider asymptotics wherein the number of residents in each nursing home over time tends to infinity, in which case the empirical Bayes and OLS estimates will eventually coincide.

they live based on nursing home quality and preferences varied by unobserved health status u_i, or if high-quality nursing homes choose to locate where unobservably healthier residents tend to live.

To account for potential sorting along these lines, I focus only on local variation in distance to nursing homes by including county fixed effects in all IV specifications. Precise sorting by residents at the local level is relatively unlikely in this setting, given that housing location decisions are often made decades before residents require nursing home care, and rates of migration among the elderly are low (US Census Bureau 2003). Finally, I also conduct a balance test to check whether the instrument is correlated with observable determinants of health.

I do not focus much on the fallback condition (Abaluck, Bravo, Hull, and Starc 2021), since it is difficult to interpret,[11] and the case wherein quality estimates are unbiased on average but the fallback condition fails is a knife-edge one (Chetty, Friedman, and Rockoff 2014). Moreover, because my instrument varies only at the geographical level, the inclusion of county fixed effects makes it less likely that the fallback condition is violated (similar to the exclusion restriction).

Finally, there is a positive correlation between the measurement error in the quality estimates and the instrument (which in my primary specification is an average of the quality estimates for nursing homes close to each resident), so the IV estimate may suffer from attenuation bias. In Appendix Section L, I show that the shrinkage underlying the empirical Bayes quality estimates cancels out the attenuation bias in the IV to a first order, and also derive a correction factor for the IV estimates when using the fixed effects quality estimates.

2.2 Quality Estimation Results

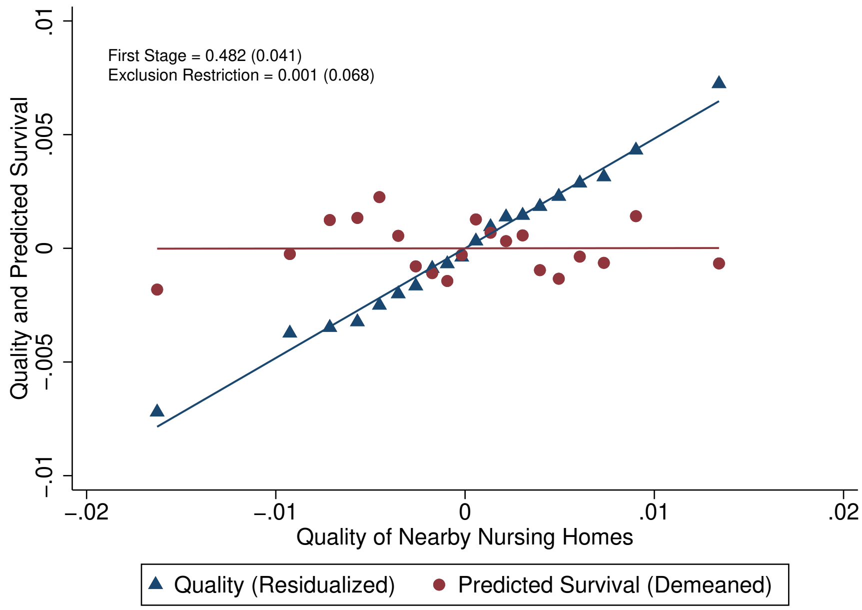
The standard deviation of my quality estimates is 0.02, which implies that a resident who goes to a nursing home with one standard deviation higher quality is 2 percentage points less likely to die within 90 days (all else equal). This is a 27 percent reduction in 90-day mortality compared to the baseline mortality rate of 7.5 percent, suggesting that nursing home choice can have a quantitatively meaningful impact on mortality even in the short run. Appendix Figure A.2 shows that the distribution of my quality estimates is roughly bell-shaped, with a notable left tail of low-quality nursing homes.

Next, I validate these quality estimates using the distance IV strategy. Figure 1 provides evidence supporting both the IV's first stage and exclusion restriction. There is a clear positive relationship between the instrument and the endogenous variable, which provides strong support for the first stage assumption: within a county, residents living in areas where the quality of the five nearest nursing homes is 1 s.d. higher on average tend to choose nursing homes with 0.482 (0.041) s.d. higher quality. By contrast, the lack of a clear relationship between the instrument and baseline health lends confidence to the exclusion restriction: we can rule out at the 95 percent confidence level that, within a county, residents living in areas where the quality among the five nearest nursing homes is 1 s.d. higher have baseline survival probabilities more than $(0.001 + 1.96 \cdot 0.068)(0.02)(100) \approx 0.271$ percentage points higher.[12]

[11] In particular, η_i is not a structural parameter but rather arises from a complicated statistical relationship between the causal parameters β_j and the quality estimates α_j.

[12] The balance test in Figure 1 checks whether the residualized instrument is correlated with survival probability. A stronger version of this test that checks whether the *unresidualized* instrument is correlated with survival probability is shown in Appendix Figure A.3. These results reveal that the instrument and survival probability are uncorrelated as long as county fixed effects are accounted for.

Figure 1: First Stage Assumption and Exclusion Restriction



Notes: The x-axis in this figure is the average quality of the five nearest nursing homes to each resident. All variables are residualized of baseline resident characteristics and county fixed effects, other than the probability of survival (which is demeaned so that it can plotted on the same scale).

Table 2 shows the first stage, reduced form, and 2SLS estimates of equation (2) in panels A, B, and C respectively, where the instrument is average (leave-year-out) quality of the K nearest nursing homes to each resident for different values of K. In all the specifications, the first stage F-statistics are over 100, and estimates of the forecast coefficient are not statistically different from one at the 5 percent significance level, supporting the validity of my quality estimates.

In addition, Appendix Table A.6 shows over-identified IV estimates of the forecast coefficient where I use quality of the 1–10 closest nursing home to each resident as separate instruments. In all cases, the estimated forecast coefficient is not statistically different from one at the five percent level and the F-statistic is greater than 10. Moreover, Appendix Figure A.9 shows that the first stage and reduced form estimates for the over-identified models display intuitive patterns, with the quality of nursing homes closer to a resident's prior address being more predictive of both the quality of her chosen nursing home and her survival.

As mentioned in Section 1.2, a disadvantage of including residents from all payer sources in my sample is that survival outcomes may be censored for residents who are not covered by Medicare (if they are discharged before 90 days).[13] To gauge whether censoring is likely to meaningfully affect my quality estimates, I estimate quality using survival for at least 19, 30, 60, and 180 days after admission as the outcome variables, and compare these estimates to my main quality estimates that are based on 90-day survival.[14] Appendix Figures A.5 and A.6 shows that quality estimates based on mortality over

[13]On the other hand, as noted in Section 1.2, even if I did observe deaths after discharge for all residents, it is unclear whether nursing homes are responsible for these deaths.

[14]I choose 19-day survival rate as one of the outcomes since Medicare switches from full to partial coverage on day 21

Table 2: IV Estimates of the Forecast Coefficient

Panel A: 1st Stage, Dep Var: Leave-Year-Out Quality E:	(1)	(2)	(3)	(4)
Instrument	0.173	0.384	0.482	0.594
	(0.016)	(0.032)	(0.041)	(0.059)
F-statistic	109.9	146.1	136.8	100.7
Panel B: Reduced form, Dep Var: 90-day Survival	(1)	(2)	(3)	(4)
Instrument	0.157	0.361	0.456	0.584
	(0.028)	(0.052)	(0.066)	(0.088)
Panel C: 2SLS, Dep Var: 90-day Survival	(1)	(2)	(3)	(4)
Leave-Year-Out Quality Estimates	0.908	0.939	0.946	0.984
	(0.120)	(0.089)	(0.089)	(0.089)
Instrument: Avg. Quality of K Nearest Nursing Homes	K=1	K=3	K=5	K=10
Demographic and Health Controls	X	X	X	X
County Fixed Effects	X	X	X	X
Number of Observations	632,162	632,207	632,207	632,207

Notes: This table presents the first stage, reduced form, and IV results for the estimates of the forecast coefficient. The outcome variable is 90-day mortality, the endogenous variable is the leave-year-out empirical Bayes quality estimates for nursing homes, and the instrument is average quality of the K nursing homes closest to each resident, with the value of K ranging across specifications. All regressions include the controls for residents' demographics and health, as well as county fixed effects. Standard errors clustered at the nursing home level are displayed in parentheses.

different time horizons are all highly correlated (with correlations ranging from about 0.73 to above 0.96), suggesting that truncation bias is unlikely to meaningfully affect my results.

Results for fixed effects quality estimates are similar. The standard deviation for the fixed effects quality estimates is 0.025 (slightly larger than the empirical Bayes quality estimates), and Appendix Table A.5 shows that the IV estimates of the forecast coefficient for fixed effects quality estimates are not statistically different from one at the 5 percent significance level after adjusting for the positive correlation in the measurement error between the endogenous variable and the instrument.

Given the evidence presented in this subsection on the validity of the quality estimates, for notational simplicity in subsequent text I will not distinguish between quality β_j and the quality estimates α_j (except when making a distinction is absolutely necessary, e.g., when discussing issues such as measurement error), and use q_j to denote quality.

2.3 Discussion of Nursing Home Quality Estimates

2.3.1 Commonality of Quality Measures

Table 3 shows that the correlations between my quality estimates and observable nursing home characteristics have the expected signs: skilled staffing levels and CMS star ratings are positively correlated with my quality measure, whereas for-profit status and number of cited deficiencies are negatively correlated with quality (Grabowski et al. 2016; You et al. 2016).[15]Appendix Table A.7 shows that the same patterns hold for the fixed effects quality estimates.

after admission, so nursing homes may have a financial incentive to discharge some residents around this cutoff if there are concerns over potential non-payment by the resident. Hence, there may be fewer sample selection issues when using 19-day survival rate, compared to survival rates over longer time horizons.

[15]The CMS introduced a five-star rating system for nursing homes in late 2008 in an effort to provide consumers with a simple metric with which to gauge nursing home quality. The introduction of star ratings comes towards the end of my sample period, but to the extent that relative nursing home quality remains roughly stable over time, the association between my quality measures and the star ratings remains informative of how predictive star ratings are of nursing home quality.

Table 3: Relationship Between Quality Estimates and Nursing Home Characteristics

	Quality Estimates (s.d.)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2009 Star Ratings (s.d.)	0.0783							0.0483
	(0.0310)							(0.0315)
RN hours per resident day (s.d.)		0.0942						0.218
		(0.0352)						(0.0490)
LPN hours per resident day (s.d.)			0.100					0.116
			(0.0209)					(0.0324)
CNA hours per resident day (s.d.)				0.0908				-0.0398
				(0.0158)				(0.0259)
Deficiencies (s.d.)					-0.0467			-0.0206
					(0.0157)			(0.0132)
For-Profit (s.d.)						-0.0881		-0.0693
						(0.0297)		(0.0261)
Chain (s.d.)							-0.0346	-0.0158
							(0.0279)	(0.0263)
N	9,988	9,994	9,995	9,989	9,997	9,997	9,997	9,975
R-squared	0.009	0.013	0.015	0.012	0.003	0.011	0.002	0.043

Notes: This table shows correlations between the nursing home quality estimates and various nursing home characteristics. The unit of observation is a nursing home-year. Observations are weighted such that the total weight each nursing home receives is equal to the number of residents it has over the sample period. Standard errors are clustered by nursing home.

On the other hand, the R-squared of 0.04 in column 8 shows that only a small fraction of the variation in my quality measure can be explained by these publicly available quality measures. In Appendix Table A.8, I show that my quality measure is a stronger (out-of-sample) predictor of resident outcomes than these quality indicators. Specifically, in a regression of 90-day survival on the leave-year-out quality estimates and other quality measures (all standardized to facilitate comparisons), the coefficient on the leave-year-out quality estimate in these regressions is highly statistically significant and an order of magnitude larger than coefficients on other quality indicators (which are mostly statistically insignificant at the 5 percent significance level). This suggests that the quality estimates in this section contain information about nursing home quality beyond that which can be gleaned through publicly available metrics.

I also explore the relationship between my quality measure and quality estimates based on resident outcomes other than death, such as development of pressure sores, use of physical restraints, and antipsychotic use. Issues of misreporting competing risks, and censoring for these other outcomes aside, Appendix Figures A.7 and A.8 show that the correlations between quality estimates based on these other outcomes and my survival-based quality estimates have the expected signs.

In addition, I explore whether quality is a "common good" within nursing homes, in the sense that a nursing home providing high-quality care to one group of residents also does so for others (Grabowski, Gruber, and Angelelli 2008). This may be violated for instance if certain nursing homes specialize in caring for specific types of residents, but are ill-equipped to care for other types of residents. This matters for the interpretation of the structural estimates later in the paper: if quality is not a common good, then a lack of responsiveness to my quality measure by some residents may be due to the quality measure not being relevant for them. To test this, I estimate quality based on different subsamples — splitting by post-acute care, age, dementia, and education — and test whether quality estimates based on different subsamples are correlated. Appendix Figure A.4 shows that there is a strong positive association between quality estimates based on different subsamples, supporting the interpretation of quality as a common good.

2.3.2 Geographical Variation in Nursing Home Quality

Finally, while the quality estimates indicate substantial variation in nursing home quality across California, the degree of local variation is also important for consumer choice; in particular, if quality is highly geographically concentrated, then residents living in certain areas may not have access to high-quality nursing homes. To shed light on whether this is the case, Figure 2 plots empirical cumulative distribution functions (ECDFs) showing the overall variation in the empirical Bayes nursing home quality estimates as well as the within- and between-county variations in quality.

The figure shows that there is almost as much variation in nursing home quality within counties as there is overall, and that within-county variation in quality accounts for far more of the overall variation than between-county variation in quality. In particular, while the Kolmogorov-Smirnov test for equality of distributions clearly rejects the null that the overall and across-county distributions of quality are equal, it does not reject the null that the overall and within-county distributions of quality at the 5 percent significance level. Appendix Figure A.10 shows that the same pattern holds for fixed effects quality estimates. This shows that there tends to be both high-quality and low-quality nursing homes close to each resident. Whether residents are able to take advantage of this variation is the main topic of the next section.

3 Consumer Choice and Provider Cream-Skimming

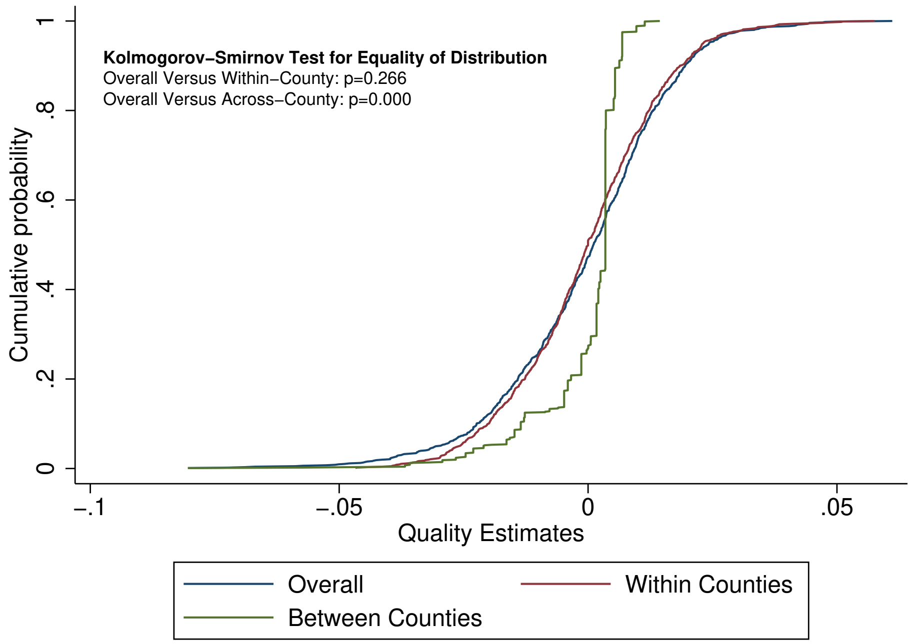
In this section, I use my survival-based quality estimates as inputs into a structural model to study consumer choice and cream-skimming behavior by nursing homes. I start in Section 3.1 by introducing selective admissions as a type of cream-skimming behavior by nursing homes (Gandhi 2023). I present evidence that nursing homes engage in such admissions practices and show that failing to account for the resulting unobserved choice set constraints may bias consumer choice estimates. In Section 3.2, I present and estimate a structural model of consumer choice and provider cream-skimming using recent advancements in the empirical matching literature (Agarwal and Somaini 2022). Finally, I present the structural estimates in Section 3.3, and conduct robustness checks in Section 3.4.

3.1 Selective Admissions by Nursing Homes

Residents vary widely in their profitability to nursing homes, which gives nursing homes a financial incentive to reject certain residents. Naïve demand estimates that ignore unobserved choice set constraints arising from such rejections are likely to be misleading in two ways. First, demand estimates may be biased downwards if higher-quality nursing homes tend to face greater capacity strain, since unobserved rejections by these nursing homes are interpreted as residents not being responsive to quality. Second, naïve estimates would interpret nursing homes' tendency to reject certain types of residents as demand heterogeneity.

To illustrate the relevance of these problems in the present setting, I show how naïve conditional logit estimates of residents' responsiveness to nursing home quality which ignore choice set constraints vary predictably with capacity strain faced by nursing homes close to them. The idea of this exercise is that if higher-quality nursing homes close to a resident face relatively greater capacity strain when

Figure 2: ECDF of Empirical Bayes Quality Estimates (Overall, Within Counties, and Between Counties)



Notes: This figure plots the empirical CDFs showing the overall variation in nursing home quality, as well as the within-county and across-county variations in quality in blue, red, and green respectively. Within-county variation is plotted using the residuals from a regression of the quality estimates on county fixed effects, and across-county variation is plotted using the averages of the quality estimates within each county. The p-values from two-sample Kolmogorov-Smirnov tests for equality of distributions comparing the overall distribution of quality to the within-county and between-county distributions of quality are also shown in the figure.

she was choosing her nursing home, she may be "forced" to choose a lower-quality nursing home than she would like. Hence, naïve demand estimates for these types of residents would be lower, and vice versa for residents where higher-quality nursing homes nearby face relatively lower capacity strain.

To operationalize this, for nursing homes close to each resident i, I regress a measure of capacity strain faced by these nursing homes on their quality, and denote the estimated coefficient by $\hat{\Delta}_i$.[16] I then estimate conditional logit models where I allow responsiveness to quality to vary as a quartic function of the occupancy-quality gradient $\hat{\Delta}_i$:

$$\tilde{v}_{ij} = \sum_{p=0}^{4} \tilde{\kappa}^{q}_{(p)} \hat{\Delta}^{p}_{i} q_j + \tilde{\kappa}^{dist} dist_{ij} + \tilde{\epsilon}_{ij}.$$

Figure 3 shows that conditional logit estimates of responsiveness to quality are indeed decreasing in the occupancy-quality gradient across a range of different quality measures: the causal mortality-based (empirical Bayes or fixed effects) quality estimates from the previous section, RN staffing, LPN staffing, (fewer) deficiency citations, and star ratings. This implies that failing to account for capacity

[16]Specifically, I use the lagged seven-day average of log occupancy, residualized of nursing-home-by-month fixed effects as the measure of capacity strain, as discussed in greater detail later in this subsection.

constraints and unobserved rejections by nursing homes may bias estimates of average responsiveness to quality. Moreover, the patterns of heterogeneity seen in these figures would normally be interpreted as heterogeneous responsiveness to quality for different types of residents, yet based on contextual knowledge residents' responsiveness seems unlikely to be related to fluctuations in occupancy of nearby nursing homes.[17] More generally, if nursing homes give priority to certain types of residents in their admissions policies, a structural demand model that ignores the potential for such behavior (even if it accounts for capacity constraints) may misattribute such provider behavior as demand-side heterogeneity.

Having shown that selective admissions are likely relevant for demand estimation, I outline a model of selective admissions based on Gandhi (2023) to help provide some intuition for the structural estimation. The full model — which also incorporates nursing homes' initial quality choice to derive some additional comparative statistics — is described in Appendix Section D.

Suppose that arrivals and discharges occur stochastically over time. Residents vary in their profitability to nursing homes, which also face capacity constraints. When a resident applies to a nursing home, the facility may choose whether to accept the resident if it still has spare capacity, but must reject the resident if it is already at capacity.

Even when an applicant has positive direct margin — i.e., expected payments exceed expected care costs — a profit-maximizing nursing home with spare capacity may still choose to reject the resident due to the option value of spare beds. In particular, admitting a resident now increases the probability that the nursing home will be full if/when more profitable residents apply in the future. The optimal admissions rule takes a simple threshold form: a nursing home admits an applicant if and only if the profitability of the applicant exceeds a cutoff, and this cutoff is increasing in how close the facility is to being full. This model yields two testable predictions.

Prediction 1. *When occupancy within a nursing home is higher than usual, the nursing home is less likely to admit new residents.*

Prediction 2. *Residents with characteristics associated with higher profitability are more often admitted when occupancy is higher than usual, relative to when occupancy is lower than usual.*

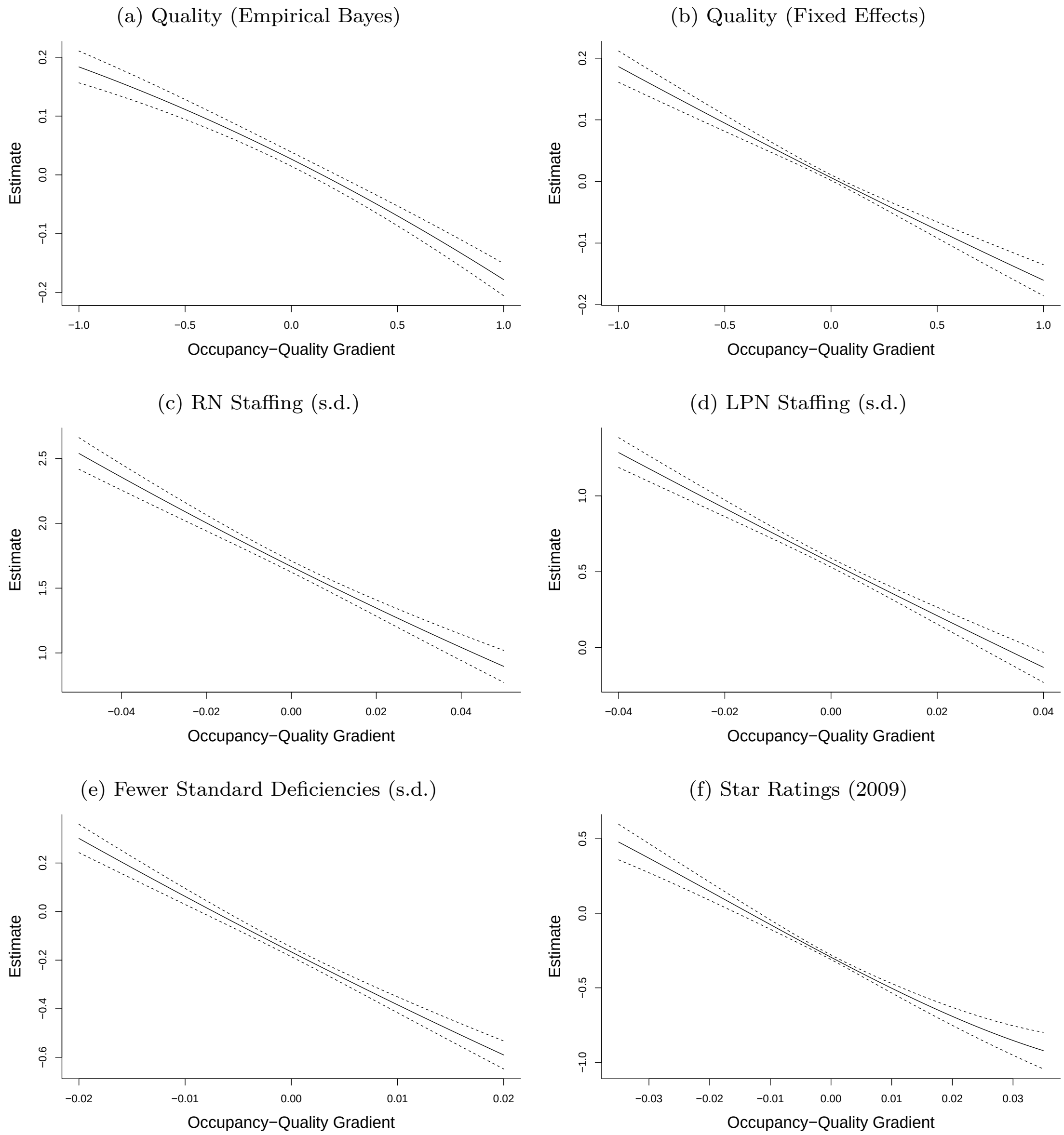
This model also makes clear why we may not necessarily expect a positive correlation between quality and occupancy percentage in equilibrium. In particular, if residents are responsive to quality, higher-quality nursing homes expect a greater future stream of applicants, which increases the option value of spare beds. In other words, higher-quality nursing homes can "afford" to be more selective given future expected demand, and may even choose to leave more beds unfilled.

To measure capacity strain faced by nursing homes at each point in time, I use temporary occupancy fluctuations, defined as within-nursing-home-by-month variation in the lagged seven-day average of an occupancy measure — either log occupancy, occupancy in levels, or occupancy percentile.[18] I prefer these measures over occupancy percentage and number of spare beds for several reasons. First, the total number of beds in a nursing home is only reported annually, and thus subject to substantial

[17]It is possible that some residents can delay their choice until capacity strains at their preferred nursing homes ease. However, this is unlikely to explain the results seen here, given that the majority of residents in my sample are post-acute care, and face time pressure to choose a nursing home before they are discharged from their hospital. I will revisit this point later when discussing the structural demand estimates.

[18]I use the seven-day average because post-acute care residents typically choose their nursing homes prior to discharge and not on the day of their discharge, and seven days is a reasonable approximation of the time window during which they are making these choices.

Figure 3: Conditional Logit Estimates of Residents' Responsiveness to Quality as a Function of $\hat{\Delta}_i$



Notes: In each subfigure, I plot conditional logit estimates of residents' responsiveness to quality as a quartic function of $\hat{\Delta}_i$ ($\sum_{p=0}^{4} \tilde{\kappa}^{q}_{(p)} \hat{\Delta}_i^{p} / (-\tilde{\kappa}^{dist})$), where $\hat{\Delta}_i$ is the coefficient estimate from a regression of capacity strain on the quality measure in question for nursing homes in resident i's choice set. Dashed lines indicate 95 percent pointwise confidence intervals. The subfigure headings indicate the quality measure being considered in the regression.

measurement error. Second, the measurement error in beds implies that using occupancy rate as the occupancy measure may conflate capacity strain with nursing home expansions or contractions. Third, functional capacity (e.g., due to staffing constraints) is often more relevant than spare beds, and this varies across nursing homes. Hence, deviations from average occupancy patterns at each nursing home is a more appropriate measure.

Table 4 shows results supporting prediction 1 based on regressions at the nursing home-day level:

Table 4: Effect of Occupancy on Admissions

	Number of New Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.857		
	(0.0466)		
Lagged 7-Day Avg. Occupancy		-0.0197	
		(0.000437)	
Lagged 7-Day Avg. Occ. Percentile			-0.00574
			(0.000131)
Nursing Home x Month Fixed Effects	X	X	X
Number of Observations	3,426,363	3,426,363	3,426,363

Notes: This table shows regression results at the nursing home-day level wherein the dependent variable is number of new patients, and the independent variables are various measures of nursing home occupancy. Standard errors are clustered at the nursing home level.

conditional on nursing home-month fixed effects, nursing homes admit fewer new residents on days when occupancy is higher than usual, and this finding is not sensitive to the functional form used for occupancy. Appendix Table A.9 shows that these results are also robust to alternative measures of new admissions, such as an indicator for any new admissions, and net admissions (i.e., admissions minus discharges).

Figure 4 tests prediction 2 by showing bin scatters of indicators for whether an admitted resident is on Medicaid, is admitted from an acute-care hospital, or has Alzheimer's/dementia against the lagged seven-day average of log occupancy at the admitting nursing home, controlling for nursing home-year fixed effects (and other demographic characteristics in some specifications).[19] We observe that nursing homes facing greater capacity strain are less likely to admit residents on Medicaid and residents suffering from Alzheimer's or dementia, and more likely to admit residents from acute-care hospitals. This is consistent with lower Medicaid reimbursement rates, the fact that post-acute care residents are often covered by Medicare and tend to have short stays (and are thus less likely to end up on Medicaid), as well as nursing homes' complaints that they are not reimbursed adequately for residents with dementia (Kosar, Mor, Werner, and Rahman 2023).[20] Appendix Figures A.11 and A.12 shows that these results remain qualitatively similar if we use occupancy in levels or occupancy percentile instead of log occupancy, while Appendix Table A.10 shows that these results are also robust to using nursing home-month fixed effects instead of nursing home-year fixed effects.

3.2 Structural Model

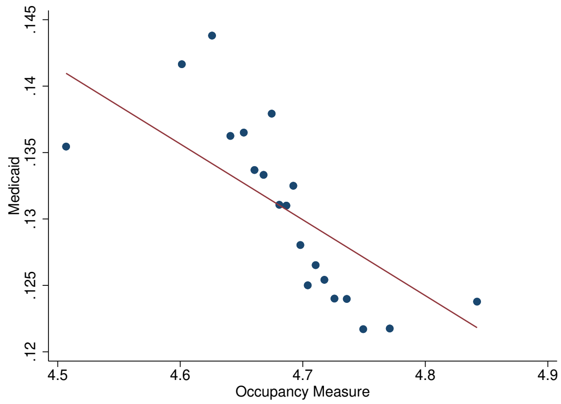
Having documented cream-skimming behavior by nursing homes, in this subsection I describe a structural model and estimation procedure that accounts for unobserved choice set constraints arising from selective admissions.

[19]While I used nursing home-month fixed effects for the nursing home-day level regressions in Table 4, in these bin scatters I use nursing home-year fixed effects because the unit of observation is a resident and including nursing home-month fixed effects absorbs most of the useful variation at smaller nursing homes. Nonetheless, Appendix Table A.10 shows that the results are still robust to the inclusion of nursing home-month fixed effects.

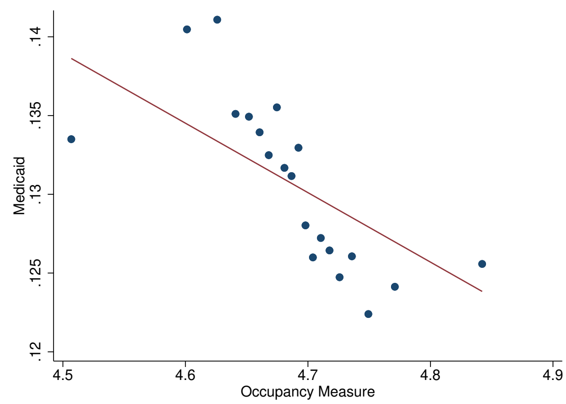
[20]Residents with dementia have higher care requirements, which places an additional burden on understaffed nursing homes, to the point that nursing homes sometimes use antipsychotic medication to sedate dementia residents.

Figure 4: Reduced Form Evidence of Selective Admissions

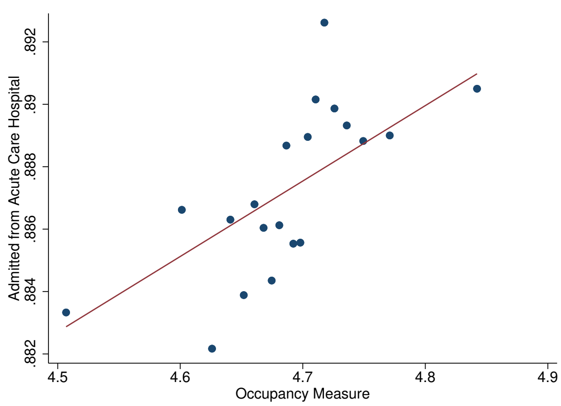
(a) Medicaid (without controls)



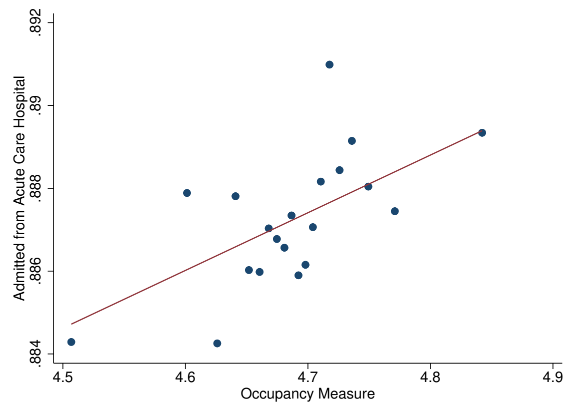
(b) Medicaid (with controls)



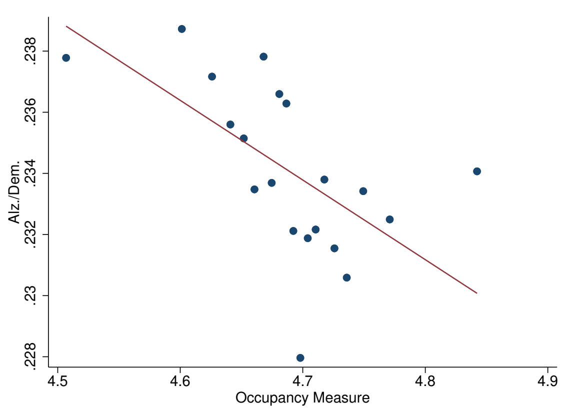
(c) Post-Acute Care (without controls)



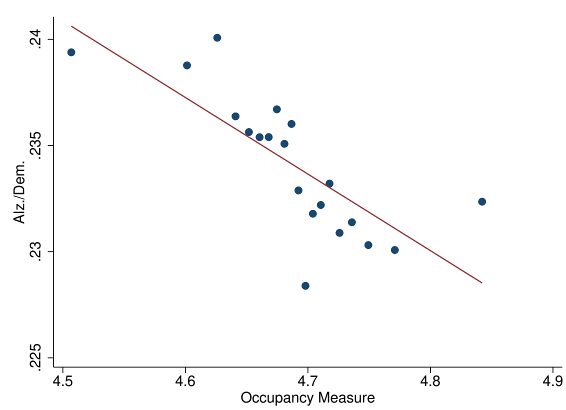
(d) Post-Acute Care (with controls)



(e) Alzheimer's/Dementia (without controls)



(f) Alzheimer's/Dementia (with controls)



Notes: These bin scatters show indicators for Medicaid status and Alzheimer's/dementia of admitted residents as a function of lagged seven-day average log occupancy for the nursing home as of the date of admission for the resident. The bin scatters include nursing home-year fixed effects, and in some specifications, controls for Medicaid status, post-acute care, Alzheimer's/dementia, age, education, primary language, and race, omitting the control that matches the outcome (e.g., Medicaid is not included as a control when Medicaid is the outcome in the bin scatter). The unit of observation is a resident.

3.2.1 Identification of Two-Sided Matching Model

Given that nursing homes have rankings over residents and vice versa, the setting is well-approximated by a many-to-one two-sided matching market: each resident $i \in \mathcal{I}$ is matched to exactly one nursing home, whereas a nursing home $j \in \mathcal{J}$ can be matched with more than one resident. I model this using a random utility model, where residents' (decision) utilities v_{ij} and nursing homes' profits π_{ij} are given by:

$$\begin{aligned} v_{ij} &= v_j^1(x_i, \zeta_i) - v_j^2(x_i, dist_{ij}), \\ \pi_{ij} &= \pi_j(x_i, \zeta_i, occ_{ij}). \end{aligned} \tag{5}$$

Denote resident characteristics by x_i, and let ζ_i represent resident-specific heterogeneity. In addition, denote distance between resident i and nursing home j by $dist_{ij}$, and let occ_{ij} be a measure of short-term fluctuations in nursing home j's occupancy as resident i is choosing her nursing home.

Agarwal and Somaini (2022) establish a sharp set of conditions under which these preferences are non-parametrically identified. The key substantive requirement for identification is the existence of demand and supply instruments,[21] which in my case are $dist_{ij}$ and occ_{ij} respectively. The intuition for why we need the supply-side instrument is explained in the previous subsection: without fluctuations in nursing home occupancy, we cannot tell whether certain types of residents tend to choose higher-quality nursing homes because they are more responsive to quality or because nursing homes are more willing to admit them.

On the other hand, if distance is omitted from the utility equation, we do not know whether our estimates of residents' responsiveness to quality is due to residents living further from (or closer to) higher-quality nursing homes. Moreover, estimates of heterogeneity in responsiveness to quality could either be due to certain types of residents being truly more responsive, or simply living closer to higher-quality nursing homes. Finally, we also need distance as a scaling variable in order to interpret the magnitude of residents' responsiveness to quality.[22]

Similar to standard IV, the validity of these instruments relies on relevance (i.e., first stage) conditions and exclusion restrictions, which I state below.

Assumption D1 (Relevance). *The demand and supply instruments must be relevant (i.e., $\partial v_{ij}/\partial dist_{ij} \neq 0$, and $\partial \pi_{ij}/\partial occ_{ij} \neq 0$).*

Assumption D2 (Exclusion Restrictions). *The supply instrument must be excluded from the demand side ($\partial v_{ij}/\partial occ_{ij} = 0$), and the demand instrument must be excluded from the supply side ($\partial \pi_{ij}/\partial dist_{ij} = 0$).*

Relevance of the demand instrument $dist_{ij}$ is demonstrated in the first stage of the distance IV, and similarly, relevance of the supply instrument occ_{ij} was shown when we tested prediction 1 in Table 4. The exclusion restriction for distance as the demand instrument is also quite intuitive: there is little reason for nursing homes to care where their residents lived prior to admission.

[21] See Appendix E for the full list of the technical assumptions required for identification, as well as a discussion on how they relate to my setting.

[22] While price is often used as a scaling variable in structural demand estimation, most residents are covered by insurance in this context. The true expected marginal/shadow price (as opposed to the spot price) faced by residents depends on a number of factors, including the length of their stay which can be difficult to predict at the time of nursing home choice, and Brot-Goldberg et al. (2017) show that even relatively healthy consumers choosing between health insurance plans do not necessarily react to the price that is relevant to them. Indeed, Gandhi (2023) computes the expected shadow price for nursing home residents, and find that low responsiveness by residents to this price.

The assumption that merits most discussion is the exclusion restriction for temporary occupancy fluctuations as the supply instrument. Let us first consider why simply using occupancy (rather than fluctuations in it) as the supply instrument is likely to violate the exclusion restriction, and how this will affect our demand estimate. Suppose that high-quality nursing homes tend to have higher occupancy rates on average but that all else equal, residents prefer nursing homes with lower occupancy rates (which violates the exclusion restriction). This will bias our demand estimate downwards because it conflates residents' preferences for quality and lower occupancy rates.

To avoid such a bias, I use only within-nursing home-month variation for my occupancy measure. This is important for several reasons. First, it is more plausible that demand is not responsive to short-term fluctuations in occupancy rates. Second, this definition of the supply instrument ensures that it does not vary systematically with nursing home quality — indeed, Appendix Figure A.13 shows that the distributions of occ_{ij} at above-median and below-median quality nursing homes are essentially identical. Third, focusing on within-nursing home-month variation as opposed to simply within-nursing home variation also controls for changes in nursing home capacity over time (e.g., if nursing homes expand or contract).

These exclusion restrictions give rise to two sources of quasi-experiments that identify the demand and supply sides. On the supply side, nursing homes' preferences are identified by comparing characteristics of residents when occ_{ij} is higher or lower (similar to Figure 4), given that occ_{ij} is excluded from residents' preferences. On the demand side, relative distance to nearby nursing homes shifts residents' rankings of nursing homes without affecting facilities' willingness to admit them. More concretely, consider a pair of nursing homes j and k that have different quality ($q_j \neq q_k$), and a set of otherwise similar residents who face different relative distances to these nursing homes — $\Delta dist_{ijk} \equiv dist_{ij} - dist_{ik}$ — and who are applying at a time when both occ_{ij} and occ_{ik} are low. As we shift the relative distance $\Delta dist_{ijk}$, the rate of change in choice probabilities for these two nursing homes among this resident type reveals how these residents trade off distance against quality, given that distance is excluded from nursing homes' admissions policies.

3.2.2 Estimation Framework

Although preferences of residents and nursing homes are non-parametrically identified, non-parametric estimation is likely to have slow rates of convergence. Hence, I consider the following parametrization of residents' and nursing homes' preferences:

$$
\begin{aligned}
v_{ij} &= w_j'\kappa^1 + w_j'\kappa^2 x_i + dist_{ij}'\kappa^{dist} + \epsilon_{ij}, \\
\pi_{ij} &= x_i'\psi^1 + w_j'\psi^2 x_i + occ_{ij}'\psi^{occ} + \omega_{ij},
\end{aligned} \tag{6}
$$

where x_i contains resident i's characteristics, w_j denotes nursing home j's characteristics (including quality β_j), and ϵ_{ij} and ω_{ij} follow independent Gaussian distributions. I impose the location normalization for residents' utility by setting the utility of a nursing home and the intercept to zero,[23] and the location normalization for nursing homes' admission rules by assuming that nursing home j is willing to accept resident i if and only if $\pi_{ij} \geq 0$. To set the scale normalizations, I set the variances of ϵ_{ij} and ω_{ij} to one.

[23]Note that all residents in the sample choose a nursing home by construction, so we cannot estimate the value of the outside option of no nursing home.

I define each resident i's choice set as the set of all nursing homes within 15 miles of her prior address, $\mathcal{J}_i$.[24] Some of the nursing homes in $\mathcal{J}_i$ may be unwilling to admit resident i but their identities are unobserved by the econometrician. This gives rise to a curse of dimensionality, as the number of possibilities for the set of nursing homes that the resident can actually choose from is $2^{|\mathcal{J}_i|}-1$.[25] This makes methods such as maximum likelihood that involve directly integrating over each possibility computationally infeasible, unless one is willing to make further assumptions to rule out some possibilities, or to restrict the number of nursing homes in each resident's choice set. For example, Gandhi (2023) assumes that there are no idiosyncratic differences between nursing homes' admission rules for a given resident (i.e., he assumes that $\omega_{ij}=\omega_i$ for all j in the notation of our model), which reduces possibilities for the set of nursing homes that are willing to admit the resident from $2^{|\mathcal{J}_i|}$ to $|\mathcal{J}_i|$. However, this might be violated in several ways, such as if nursing homes vary in their staffing expertise or specialization which make them more/less suited to care for a particular resident, or if nursing homes' current room composition affects the suitability of specific residents (e.g., if only shared rooms with an existing female resident are available, the nursing home is unwilling to admit a male resident). Similarly, choosing a smaller radius than 15 miles will reduce the computational burden but at the expense of excluding residents who choose nursing homes further away, which may result in a less representative sample.[26]

To address the curse of dimensionality, I estimate the model using a Gibbs sampler with data augmentation on the latent variables v_{ij} and π_{ij}, a method that provides a convenient dimension reduction without requiring further substantive assumptions (Agarwal and Somaini 2022). At a high level, the Gibbs sampling method follows a Bayesian approach, so the parameters $\theta \equiv (\kappa', \psi')'$ are treated as random, with some prior distribution, and a posterior distribution that is updated in each iteration. In each iteration, I draw the structural error terms (ϵ', ω') and the parameters θ in a way that respects the matching outcomes. For example, in each iteration, denoting the nursing home that resident i is admitted to by $\mu(i)$, I draw these parameters and error terms while ensuring that $\pi_{i,\mu(i)} \geq 0$, and that the resident prefers $\mu(i)$ over all other nursing homes that she is eligible for (i.e., $v_{i,\mu(i)} \geq v_{ij}$ for all j such that $\pi_{ij} \geq 0$). For other nursing homes $j \neq \mu(i)$, I draw these terms while ensuring that either j is less desirable than her chosen nursing home ($v_{ij} \leq v_{i,\mu(i)}$) or that j would reject i ($\pi_{ij} < 0$). Appendix F describes the full algorithm for the Gibbs sampler in detail.

Under standard conditions — specifically, that the transition kernel for the Gibbs sampler is irreducible and aperiodic (Robert and Smith 1994) — the draws of θ will eventually converge to the stationary distribution. To check for convergence, I visually inspect the Markov chain, check whether the potential scale reduction factor is close to one (Brooks and Gelman 1998), and consider the effective sample size (Vats, Flegal, and Jones 2019). I then take the mean and standard deviation of the draws of θ after an initial burn-in period as my parameter estimates and standard errors respectively. Note

[24] I prefer this definition of residents' choice sets to the county, given that counties vary significantly in size and using them as residents' choice sets does not exploit the substantial within-county variation in residents' and nursing homes' locations. I used county fixed effects for the distance IV in the previous section rather than 15-mile radii around each resident because these radii overlap.

[25] The average value of $|\mathcal{J}_i|$ is 50, and in this case there are $2^{50}-1 > 10^{15}$ possibilities for the set of nursing homes that the resident is actually able to choose from. Moreover, $|\mathcal{J}_i|$ can be larger than 200, in which case there are $2^{200}-1 > 10^{60}$ possibilities.

[26] Indeed, the ECDF of residents' distances to their chosen nursing homes in Appendix Figure A.14 shows that while more than 80 percent of residents choose a nursing home within 15 miles, only less than 60 percent of residents choose a nursing home within 5 miles.

that although the Gibbs sampler is derived following a Bayesian approach, this method of inference is justified even under a frequentist point of view, since the Bernstein-von Mises theorem implies that the distribution of θ will converge to the distribution of the maximum likelihood estimator.

3.3 Structural Estimation Results

Table 5 presents estimates of the structural model. I present results for the full sample (columns 1 and 3), as well as for the subsample of post-acute care residents (columns 2 and 4) who face greater time constraints when choosing nursing homes, given the potential concern that some residents may be able to wait until capacity at their preferred nursing home is less strained.

First, we observe that across all specifications, the coefficients on the demand- and supply-side instruments (distance to nursing home and occupancy fluctuations) are highly statistically significant. Hence, the model is unlikely to suffer from weak identification.

Next, focusing on the demand-side estimates, we observe in columns 1 and 2 that estimates of residents' average responsiveness to quality are positive (statistically insignificant in the full sample but significant for residents admitted from acute care hospitals). At the same time, columns 3 and 4 show that there is systematic heterogeneity: residents who are older and have Alzheimer's or dementia tend to be less responsive to quality, whereas residents who are more educated and have English as their first language are more responsive. These patterns are consistent with previous work by Handel, Kolstad, Minten, and Spinnewijn (2021) showing that "choice quality" varies with consumer characteristics.

In terms of magnitude, residents' responsiveness to quality is small. Consider residents with characteristics associated with higher responsiveness: i.e., residents who do not have Alzheimer's or dementia, are 65 years old (relative to the median age of roughly 80 in the sample), and have a Bachelor's degree and English as their primary language. Even among these relatively responsive residents, the implied marginal rate of substitution (MRS) between quality (in percentage points of risk-adjusted 90-day survival) and distance (in miles) is 0.54–0.59 based on the estimates in columns 3 and 4,[27] which is smaller than estimates in hospital settings that range from 1.8 at the low end (Chandra, Finkelstein, Sacarny, and Syverson 2016) to 8 at the high end (Tay 2003). Alternatively, assuming full information on the part of these residents, this MRS estimate implies that in exchange for a one-mile reduction in travel distance, they are willing to tolerate a $1/0.59 \approx 1.69$ to $1/0.54 \approx 1.85$ percentage point higher probability of dying within 90 days.

Turning to the supply side, we observe that nursing homes' admissions policies vary by resident characteristics. In particular, when capacity is strained, nursing homes are less likely to admit residents who are covered by Medicaid or who have Alzheimer's or dementia, and more likely to admit post-acute care residents, consistent with the evidence presented in Figure 4. Moreover, the negative coefficient estimate on quality implies that higher-quality nursing homes tend to more selective, consistent with a model of profit-maximizing nursing homes: if higher-quality nursing homes expect a greater future

[27] Specifically, let $Q = 100q$ denote quality based on risk-adjusted 90-day survival in percentage points, and assume that race is White for concreteness even though estimates of responsiveness do not vary significantly by race. The MRS for this group of residents based on the estimates in column 3 is:

$$MRS = -\frac{\partial v/\partial Q}{\partial v/\partial dist} = -\frac{(0.01)(18.261 - 0.218 \cdot 65 + 2.884 + 2.200)}{-0.171} \approx 0.54.$$

Table 5: Structural Model Estimates

	Full Sample	Post-Acute Care	Full Sample	Post-Acute Care
Resident Preferences	(1)	(2)	(3)	(4)
Distance to Nursing Homes (in Miles)	-0.171	-0.172	-0.171	-0.172
	(0.001)	(0.001)	(0.001)	(0.001)
Quality	0.222	0.850	18.261	18.727
	(0.325)	(0.339)	(1.055)	(1.215)
Quality x Alzheimer's/Dementia			-0.967	-1.101
			(0.289)	(0.299)
Quality x Age			-0.218	-0.215
			(0.013)	(0.015)
Quality x At Least Bachelor's Degree			2.884	3.101
			(0.356)	(0.375)
Quality x English as Primary Language			2.200	2.180
			(0.321)	(0.347)
Quality x Black			0.088	0.001
			(0.546)	(0.439)
Quality x Hispanic			-0.096	-0.339
			(0.372)	(0.394)
Nursing Homes' Admissions Policies				
Capacity Strain	-10.729	-10.547	-10.159	-9.567
	(0.260)	(0.253)	(0.238)	(0.211)
Quality	-0.968	-4.055	-15.121	-18.446
	(1.361)	(1.244)	(0.689)	(1.172)
Medicaid	-0.070	-0.201	-0.166	-0.108
	(0.022)	(0.016)	(0.031)	(0.033)
Post-Acute Care	0.243		0.014	
	(0.044)		(0.036)	
Alzheimer's/Dementia	-0.145	-0.180	-0.137	-0.068
	(0.017)	(0.020)	(0.019)	(0.020)
Age	0.032	0.030	0.032	0.034
	(0.001)	(0.001)	(0.001)	(0.001)
At Least Bachelor's Degree	-0.008	-0.024	-0.075	-0.096
	(0.028)	(0.014)	(0.039)	(0.023)
English as Primary Language	0.054	0.036	-0.047	-0.059
	(0.041)	(0.019)	(0.025)	(0.038)
Black	-0.537	-0.490	-0.424	-0.395
	(0.033)	(0.014)	(0.042)	(0.012)
Hispanic	-0.012	-0.017	-0.085	-0.092
	(0.040)	(0.043)	(0.022)	(0.037)
Year Fixed Effects in Supply Equation	X	X	X	X
Number of Observations	5,492,614	5,124,314	5,492,614	5,124,314

Notes: This table shows estimates from the structural estimation using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used.

stream of applicants, they can afford to be more selective about which applicants to admit.

To better understand the magnitude of the effects of admissions policies, Appendix Table A.11 shows how rejection rates vary across resident characteristics and nursing home quality across the full sample of resident-nursing home pairs used for the structural estimation. First, from the dependent variable means, we observe that the overall rejection rate is 21.7 percentage points, and that it is considerably higher (26.2 percentage points) at above-median quality nursing homes, and lower at below-median quality nursing homes (17.3 percentage points). In addition, the variation in rejection rates by resident characteristics is also substantial: Medicaid residents are 6.3 percentage points more likely to be rejected than non-Medicaid residents across all nursing homes (29 percent of the overall rejection rate), post-acute care residents are 2.3 percentage points less likely to be rejected (10.5 percent of the mean), and residents with Alzheimer's/dementia are 3.9 percentage points more likely to be rejected (18 percent of the mean).

To better understand the interaction between admissions policies and quality provision, as well as the types of residents that are most likely to be affected by these admissions policies, Appendix Tables A.12 and A.13 show the association between nursing homes' average rejection rates and the characteristics of nursing homes and residents living within 5 miles respectively. We observe in Appendix Table A.12 that rejection rates tend to be increasing in the quality of the nursing home, consistent with the structural model's estimates; this association is particularly strong for the value-added quality measure, but also present for other quality measures such as staffing and fewer deficiencies. Appendix Table A.13 shows a mixed pattern when it comes to the types of residents who live disproportionately close (specifically, within five miles of) nursing homes with higher rejection rates: while nursing homes with higher rejection rates tend to be located closer to residents who are on Medicaid, minority residents, and residents whose primary language is not English — characteristics often used as proxies for disadvantaged residents — these nursing homes also tend to be located closer to post-acute care residents, residents free from dementia, and younger residents – who are often thought of as less disadvantaged residents.

Finally, Appendix Table A.14 shows naïve demand-side estimates that do not account for admissions policies for comparison. We observe that estimates of responsiveness to quality in the first two columns are even smaller than those seen in Table 5. Moreover, columns 3 and 4 show that estimates of heterogeneity in responsiveness may also be biased by failure to account for admissions policies: for instance, these estimates suggest that Black residents are less responsive to quality even though in the full structural estimates their responsiveness to quality was not statistically distinguishable from White residents. This can be explained by nursing homes rejecting Black residents at higher rates (as seen in the supply-side estimates in Table 5), which is misinterpreted as lower responsiveness by Black residents in the model without admissions policies.

3.4 Robustness Checks for Structural Estimates

One explanation for why estimated responsiveness to quality is low is that there are other dimensions of quality that residents care more about, some of which may be negatively correlated with my quality measure. For example, perhaps high-quality nursing homes according to my survival-based measure provide an overly medicalized regime at the expense of residents' comfort. To test the plausibility of this explanation, I show estimates of residents' responsiveness to various nursing home characteristics, including staffing levels and deficiency citations in columns 2 and 4 of Appendix Table A.15. These results show that while residents value RN and LPN staffing, the estimate on deficiency citations has the "wrong" sign (suggesting that residents prefer nursing homes with more deficiency citations).

A second related concern with these estimates of low responsiveness to quality is omitted variables bias in the demand equation. However, this seems unlikely since in order for this to bias the demand estimate downwards it has to be valued by residents but negatively correlated with quality, and Table 3 showed that my quality measure is positively correlated with nursing home characteristics in intuitive ways. Indeed, when we include these other nursing home characteristics alongside my quality measure in the demand equation, we observe in columns 1 and 3 of Appendix Table A.15 that estimated responsiveness to quality becomes smaller than the main estimates in columns 1 and 2 of Table 5.

In addition, I perform a sensitivity analysis in the spirit of Altonji, Elder, and Taber (2005) and Oster (2019), to gauge how severe the omitted variables problem must be in order to completely explain the result of low responsiveness to quality. In particular, using methods from Cheng (2023) on selection on unobservables for discrete choice models, Appendix Figure A.15 shows that in order for omitted variables bias to completely explain the discrepancy between my demand estimate and previous estimates from the hospital setting, residents need to value the omitted variable more than 100 times they do observable quality measures, based on a similar assumption on the proportional selection relationship adopted by Oster (2019).

As another test of whether selection on unobservables may explain the low responsiveness estimates, I use average quality of other nursing homes nearby as an instrument, similar to Berry, Levinsohn, and Pakes (1995). I implement this using the control function approach described in Petrin and Train (2009): specifically, I first regress quality on the instruments, and then include the residual from this regression in the indirect utility equation. Comparing the estimated responsiveness to quality with and without the control function approach in the even and odd columns of Appendix Table A.16 respectively, we observe that the control function approach leads to a larger estimate in the full sample, but a smaller estimate in the post-acute care sample. Moreover, the estimated responsiveness with and without using the control function approach are not statistically distinguishable at conventional significance levels. Hence, I view this as further evidence supporting the interpretation that the low estimates of responsiveness to quality is not due to omitted variables bias.

A third possible explanation for the low demand estimate is that residents may not directly observe nursing home quality β_j. A natural way to model this is to assume residents only receive a noisy signal of quality, which they combine with publicly available information about nursing homes to make an optimal forecast about β_j.[28] I illustrate with a simple model in Appendix Section M that if this is the case, residents should value nursing home characteristics that are positively correlated with β_j. Yet, this is at odds with the negative demand coefficient on fewer deficiencies in Appendix Table A.15.

Finally, a fourth explanation for the low demand estimate is that it may be due to functional form misspecification, or attenuation bias since quality was estimated. To test this possibility, I replace quality with nursing home fixed effects in residents' utility equation, and plot these mean utilities against nursing home quality in Appendix Figure A.16. This scatterplot shows that there is hardly any relationship between residents' preferences and nursing home quality (linear or otherwise), suggesting that functional form misspecification is unlikely to be driving my results. Moreover, Abaluck et al. (2021) shows that even if there is estimation noise in quality, the slope of the best fit line in this figure provides an upper bound for demand, yet we observe that the implied upper bound for the MRS remains substantially smaller than MRS estimates from the literature.

[28] For example, we can imagine the noisy quality signal as word-of-mouth recommendations, or the resident's (or her family's) impression of the nursing home after visiting it.

Turning to the estimates of heterogeneity in responsiveness to quality, one concern with the estimates in Table 5 is that it may be confounded by heterogeneity in nursing homes' admissions policies. For example, if high-quality nursing homes penalize residents with dementia more than low-quality nursing homes do, then this may contribute to our estimate of lower responsiveness among residents with dementia. To test whether such confounding explains the previous patterns of heterogeneity in responsiveness to quality, I include interactions between nursing home quality and resident characteristics on the supply side. The resulting estimates in Appendix Table A.17 of demand-side response heterogeneity are qualitatively similar: residents with Alzheimer's and older residents are less responsive to quality, while residents with a Bachelor's degree and whose primary language is English are more responsive.

As a further test of these patterns, Appendix Table A.18 shows heterogeneity in responsiveness to other quality measures (QMs), namely RN and LPN staffing. Results are mostly qualitatively similar: while the results on age are mixed, residents without dementia, who have a Bachelor's degree, and whose primary language is English are more responsive to staffing.

There are several possible interpretations for these patterns of low average responsiveness to quality and heterogeneity in responsiveness. One interpretation is that residents face information frictions about nursing home quality, with the extent of these frictions varying across residents. The patterns of response heterogeneity shown above are consistent with this explanation: information frictions are likely positively correlated with dementia and age, and negatively correlated with higher education and having English as a primary language. Another interpretation is that this heterogeneity can explained by residents making different yet rational tradeoffs between quality and distance: for example, the remaining life expectancy of older individuals is shorter on average, so they may place less weight on the survival-based quality measure. While it is difficult to pin down which of these explanations is responsible for the estimated demand patterns, in the next section I study the effects of an intervention by the CMS which targets the first explanation: its introduction of the star ratings system at the end of 2008.

4 Demand and Supply-Side Effects of the Star Ratings

The CMS Five-Star Quality Ratings, introduced in December 2008, provides a useful policy intervention for evaluating how information disclosure affects consumer and provider behavior. Using the model developed in the previous section, I first examine how the star ratings affected the two mechanisms in the model: consumers' responsiveness to quality and cream-skimming by nursing homes. I then complement the model-based analysis with event study estimates to test whether nursing home quality responds to changes in residents' responsiveness to quality.

4.1 Effects on Responsiveness to Quality and Cream-Skimming

Given that the stated aim of the star ratings is to provide consumers with information about nursing home quality, it is natural to study effects on consumers' responsiveness to quality. At the same time, the star ratings may also affect cream-skimming incentives by nursing homes for at least three reasons (Dranove, Kessler, McClellan, and Satterthwaite 2003):

1. If the effect of nursing home quality on outcomes is greater for sicker residents, low-quality nursing homes may be incentivized to avoid sick residents in order to pool with high-quality

nursing homes under the star ratings.

2. If the star ratings' risk adjustment is imperfect and nursing homes have private information about residents' health, then nursing homes have incentives to select residents with characteristics that are not included in the risk adjustment but which predict good health.
3. If nursing homes are risk-averse and the variance in outcomes for sicker residents not explained by risk adjustment is higher, this may also lead to nursing homes avoiding sicker residents.

To test whether these mechanisms are at play, I estimate a more flexible version of the structural model described in the previous section. On the demand side, I allow responsiveness to quality to vary as a function of a richer set of resident characteristics than the previous section,[29] whether the resident made her choice after the star ratings was introduced, as well as allowing for the change in responsiveness post-star ratings to vary by resident characteristics. On the supply side, I allow for nursing homes' admissions policies to depend on nursing home quality, resident characteristics, an indicator for post-star ratings, as well as two-way and three-way interactions between these sets of variables.

I summarize the results from this structural model in Figure 5. Panel (a) shows the estimated distributions of responsiveness to quality pre- and post-star ratings (in blue and red respectively). We observe that there is substantial heterogeneity in responsiveness both before and after the star ratings, and although average responsiveness may have increased slightly after the introduction of star ratings, this increase is small relative to the overall heterogeneity. Qualitative interviews conducted by Konetzka and Perraillon (2016) suggest that consumers' lack of awareness and/or mistrust of the star ratings may have contributed to this limited response. Panel (b) shows the distributions of openness in nursing homes's admissions policies pre- and post-star ratings, where openness is defined as the average π_{ij} from the model for each nursing home net of the idiosyncratic error term and the capacity strain term. Similar to the results for responsiveness, we see substantial heterogeneity in openness across nursing homes, with a small decrease in mean openness post-star ratings.

While the change in responsiveness after the star ratings is relatively small, panels (c) and (d) show that there is substantial heterogeneity. While the estimates are somewhat noisy (especially for the top few ventiles), panel (c) shows that increases in responsiveness to quality are positively correlated with responsiveness pre-star ratings, suggesting that this aspect of the star ratings may have been regressive. In addition, panel (d) shows that responsiveness typically increased by more among residents who were favored by nursing homes in their admissions policies.

Panels (e) and (f) tests whether star ratings affected nursing homes' cream-skimming behavior, focusing on the three hypotheses outlined above. Panel (e) shows that low-quality nursing homes tightened their admissions policies, consistent with the first hypothesis: low-quality nursing homes may become more selective in order to pool with higher-quality nursing homes under the star ratings, if the effect of quality on outcomes is greater for sicker residents. This interpretation is further supported by Appendix Figure A.17, which shows that the survival-quality gradient is much higher for residents with below-median baseline health compared to residents with above-median baseline health. On the other hand, panel (f) shows that the star ratings did not lead to a fall in the admissions priority of

[29] These characteristics include whether the resident has Alzheimer's or dementia, five-year age bins, gender, marital status, race indicators, education, primary language, and pre-admissions living arrangements.

residents with poorer health at baseline,[30] so we do not find evidence supporting the second and third hypotheses.

4.2 Quality Responses by Nursing Homes

While average responsiveness to quality did not increase substantially following the star ratings, we saw in panel (d) of Figure 5 that it increased by a greater amount among residents favored by nursing homes. This suggests that the star ratings may have provided incentives for nursing homes to increase quality. To test this theory, in this subsection I estimate event study specifications which compare changes in quality between nursing homes that were more or less exposed to this change in responsiveness.

To implement this research design, I first estimate time-varying quality q_{jt} using the methodology in Section 2 but at the annual level, using this as the outcome for the event studies. I then partition nursing homes into four quartiles based on average change in responsiveness of residents living within 15 miles to form my treatment groups, denoting indicators for each of these quartiles by $D_j^{\Delta\kappa\in Q1}$, $D_j^{\Delta\kappa\in Q2}$, $D_j^{\Delta\kappa\in Q3}$, and $D_j^{\Delta\kappa\in Q4}$. Finally, even though the star ratings were introduced to consumers at the end of 2008, the CMS started developing the star ratings as early as April and announced its plans to make these ratings public in June 2008. Since increasing quality by hiring and training additional staff takes time, I include 2008 as a treatment year. The event study specification can thus be written as:

$$q_{jt} = \sum_{m=-5}^{2} \left[\left(\beta_{Q2}^{(m)} \times \Delta D_j^{\Delta\kappa\in Q2} + \beta_{Q3}^{(m)} \times D_j^{\Delta\kappa\in Q3} + \beta_{Q4}^{(m)} \times D_j^{\Delta\kappa\in Q4}\right) \cdot \mathbb{I}[t-2008=m]\right] + \delta_t^{es} + \gamma_j^{es} + \epsilon_{jt}^{es}, \tag{7}$$

where I use the lowest quartile of change in responsiveness as the reference group. In addition, since we may expect convex costs to increasing quality, I estimate separate event studies for nursing homes with below-median and above-median quality separately.

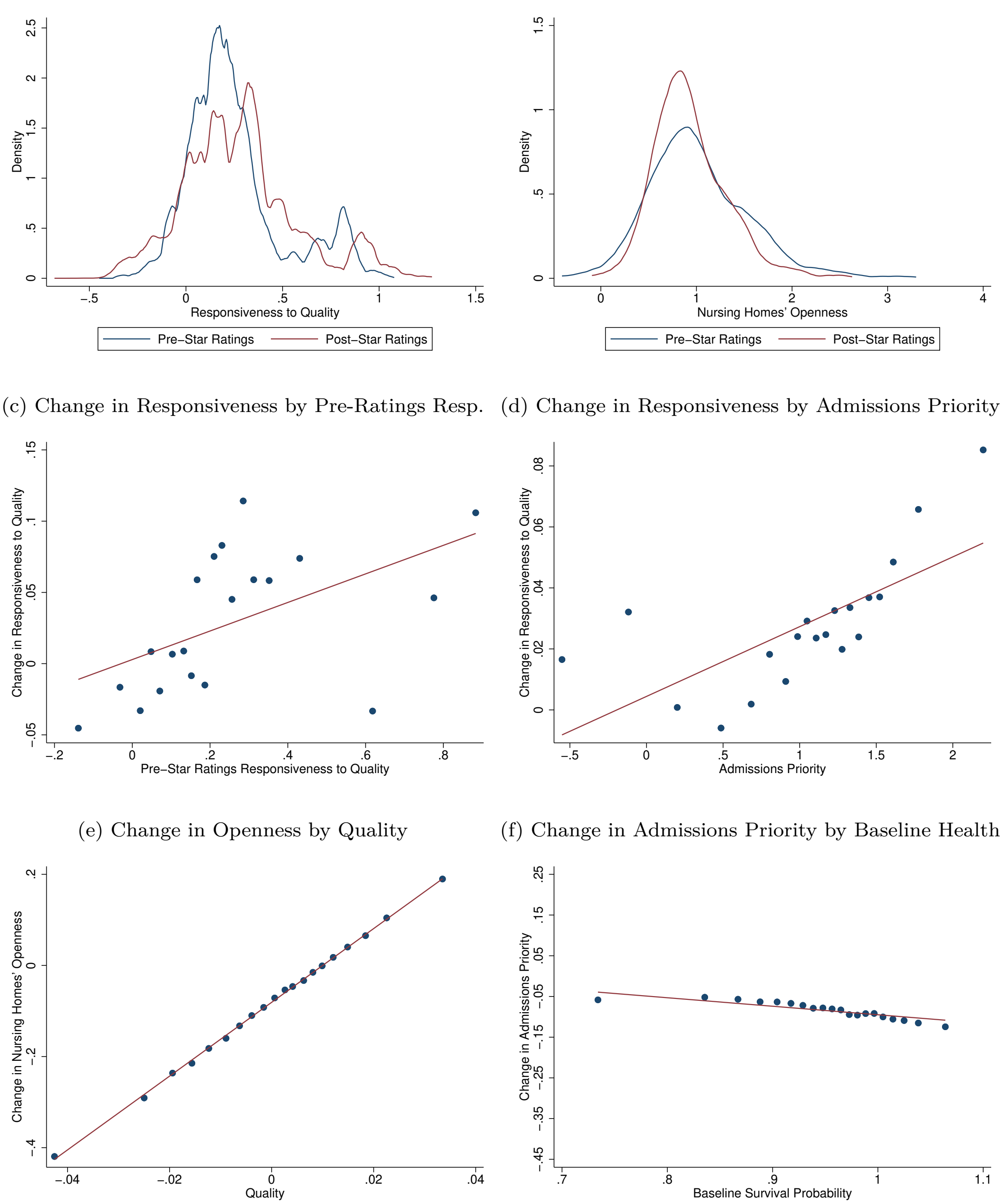
Figure 6 plots event study estimates of equation (7) with 95 percent confidence intervals, for nursing homes with below-median and above-median pre-star ratings quality in panels (a) and (b) respectively. The top-right of each panel also shows the pooled two-way fixed effects estimates. We observe that the pre-trend coefficients in either panel are mostly statistically insignificant, supporting the parallel trends assumption. In panel (a), we see that for nursing homes with below-median pre-star ratings quality, the effect of the star ratings on quality investment is increasing in their exposure to consumers whose responsiveness increased post-ratings. In particular, the pooled estimate for nursing homes in the highest quartile of exposure is an increase of 0.005 (i.e., a 0.25 s.d. increase in quality) and is statistically significant at the 5 percent level. By contrast, in panel (b), we observe that the star ratings had a much smaller effect on nursing homes with above-median pre-star ratings quality, consistent with convex costs to increasing quality.

4.3 Summary of Consumer and Provider Responses to the Star Ratings

The evidence in this section showed that consumers and nursing homes responded to the star ratings, but in very heterogeneous ways. While the increase in average responsiveness to quality was small, it was larger for residents who were already relatively responsive prior to the star ratings, and for residents who were favored by nursing homes in their admissions policies. These changes in responsiveness

[30] If anything, the negative slope implies the opposite, although the effect is small in magnitude.

Figure 5: Responsiveness to Quality and Admissions Policies Pre- and Post-Star Ratings



(a) Distribution of Responsiveness to Quality

(b) Distribution of Nursing Home Openness

(c) Change in Responsiveness by Pre-Ratings Resp.

(d) Change in Responsiveness by Admissions Priority

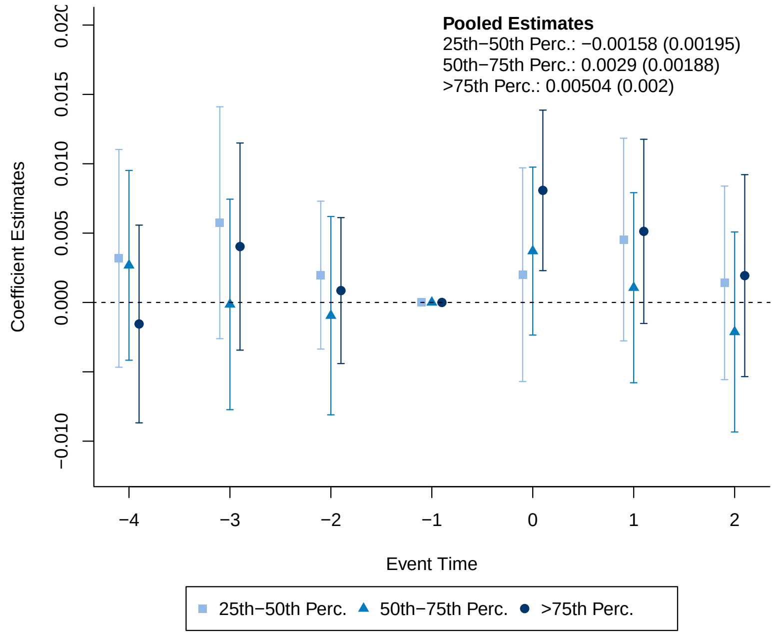
(e) Change in Openness by Quality

(f) Change in Admissions Priority by Baseline Health

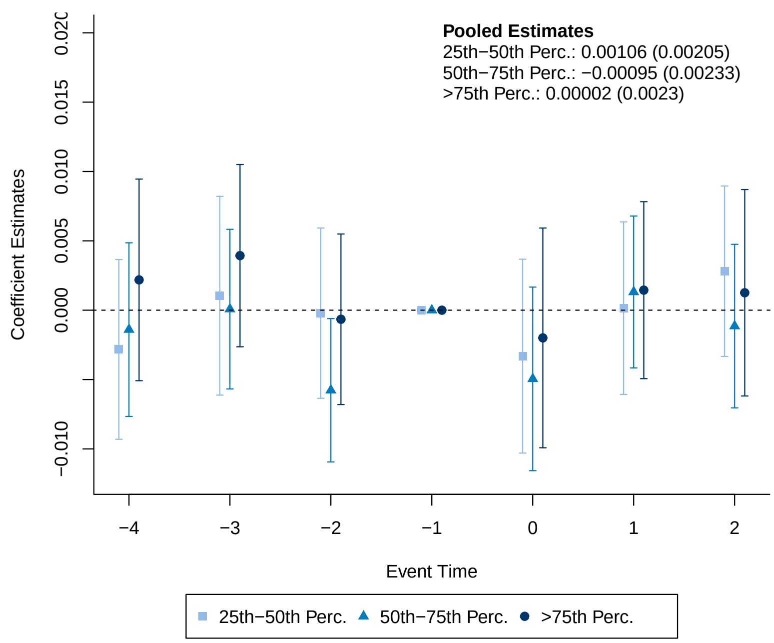
Notes: Panels (a) shows a kernel density plot of the estimated pre- and post-star ratings distributions of responsiveness to quality, where the unit of observation is a resident. Panel (b) shows a kernel density plot of the estimated pre- and post-star ratings distributions of nursing home openness, where the unit of observation is a nursing home, and openness is defined as the average for a nursing home of π_{ij} net of the idiosyncratic error term and capacity strain. Panels (c) and (d) show binscatters of the change in responsiveness to quality as a function of pre-ratings responsiveness and admissions priority (defined as the average for each resident of π_{ij} net of the idiosyncratic error term and capacity strain), where the unit of observation is a resident. Panel (e) shows a binscatter of the change in nursing home openness as a function of quality, where the unit of observation is a nursing home. Panel (f) shows the change in admissions priority by baseline health (defined as the predicted probability of 90-day survival net of nursing home effects, as was used in Figure 1), where the unit of observation is a resident. To account for potential changes in resident characteristics over time, resident characteristics used to compute pre- and post-star ratings responsiveness to quality and admissions thresholds are based on characteristics of residents admitted to nursing homes in 2009.

Figure 6: Event Study Estimates of the Effect of Star Ratings on Nursing Homes Quality

(a) Below-Median Quality Pre-Star Ratings



(b) Above-Median Quality Pre-Star Ratings



Notes: Panels (a) and (b) show event study estimates of equation (7) for nursing homes with below-median quality pre-star ratings and above-median quality pre-star ratings respectively. Nursing homes are grouped into quartiles based on the average change in responsiveness to quality for residents within 15 miles of the nursing home, and the bottom quartile is the reference category. The top-right of each panel shows the pooled two-way fixed effects estimates. The unit of observation is a nursing home-year, and observations are weighted by the number of admissions in the nursing home-year. Standard errors are clustered at the nursing home level, and bars indicate 95 percent confidence intervals.

seemed to influence nursing homes' quality choice: quality increased the most among nursing homes that were most exposed to increases in responsiveness to quality among potential consumers and that had low quality pre-star ratings. On the other hand, the introduction of star ratings also had an effect on nursing homes' cream-skimming incentives, with lower-quality nursing homes tightening their admissions policies, consistent with these homes attempting to pool with higher-quality providers if the outcome-quality gradient is steeper for sicker residents.

While the analysis above documents behavioral responses to the star ratings by consumers and providers, it is unclear from the evidence presented so far how important these channels are for allocation and health outcomes. Hence, in the next section I combine the structural and event study estimates to conduct counterfactual simulations which quantify the effect of each of these channels on allocation and health. In addition, I compare these effects to those of alternative policy interventions to assess the relative effectiveness of different levers for improving resident outcomes.

5 Counterfactual Simulations

In this section, I conduct counterfactual simulations to study the effect of the star ratings and several counterfactual policies on allocation and health outcomes. I start in Section 5.1 by describing how I combine estimates from the previous sections with a competing risks model of death and discharges in the counterfactual simulations. Section 5.1 presents simulation results on the effect of key behavioral responses to the star ratings, as well as the projected impacts of further increases in residents' responsiveness to quality, the provision of quality-ranked shortlists by hospital discharge planners on allocation and health, and financial incentives for nursing homes to increase staffing. Finally, in Section 5.3, I calibrate a simple endogenous quality model to assess how nursing homes may adjust quality in response to these counterfactual policies.

5.1 Simulation Procedure

5.1.1 Competing Risks Model of Deaths and Discharges

For a given level of occupancy across nursing homes, estimates from the structural model in Section 3 allow us to simulate nursing home choice by residents under various demand-side and supply-side environments. However, occupancy across nursing homes changes dynamically, and will generally differ in the counterfactuals from occupancy patterns observed in the data. Moreover, occupancy is a state variable that depends not only on admissions but also on exits from the nursing home, the hazard rate of which varies across nursing homes.

An additional layer of complication arises from the fact that while estimating nursing home-specific exit hazard for residents is sufficient for simulating the evolution of occupancy, exits from nursing homes consist of deaths and discharges, and the former is an outcome of interest. Given that deaths and discharges are competing risks,[31] standard hazard methods that do not account for this codependency will typically produce misleading estimates.[32] Therefore, in order to realistically simulate the evolution

[31] For a resident who dies in her nursing home, we do not observe when she would have been discharged had she stayed alive. Similarly, for a resident who is discharged from her nursing home, it is unknown whether she would have died if she had stayed in her nursing home.

[32] For example, if one simply used the Kaplan-Meier estimates of the survival functions for deaths and discharges separately, the sum of these two estimates would exceed the Kaplan-Meier estimate of the survival function for the composite event (i.e., any type of exit), regardless of whether the two types of events were independent.

of occupancy and mortality outcomes in different counterfactuals, I combine the the structural estimates with a competing risks model of deaths and discharges. Specifically, I estimate a cause-specific hazards model semiparametrically, where the cause-specific hazards depend on resident and nursing home characteristics. Appendix Section G describes the competing risks model and its estimation in greater detail.

5.1.2 Outline of Simulation Algorithm

For each day of the simulation, I draw $\bar{n}$ residents from the data. First, I simulate admissions using the structural model in Section 3: residents are admitted to the nursing home they value the most (based on their counterfactual preferences) among the set of nursing homes willing to admit them (based on counterfactual occupancies). Then, I simulate exit times and causes based on the competing risks model, using exit times to update future nursing home occupancy when my simulation reaches that stage. Finally, before moving onto the next day in the simulation, I update nursing home occupancies for the start of the next day based on admissions and exits that occur on the current day of the simulation. I repeat the entire simulation procedure for each counterfactuals 20 times, and take the average over these replications. For the full simulation algorithm and assumptions underlying the counterfactual simulations, see Appendix Sections G.5 and G.1 respectively.

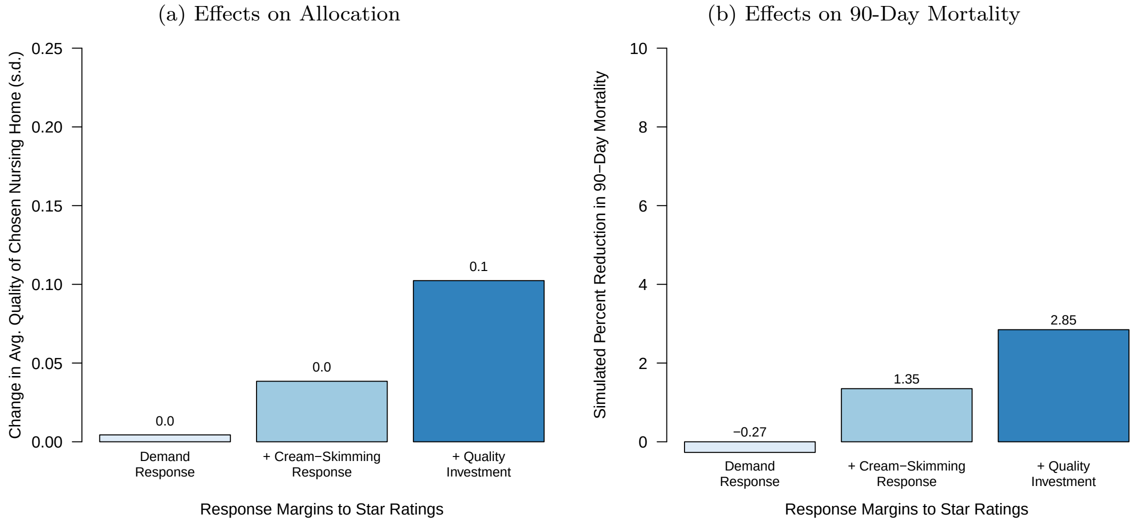
5.2 Simulation Results

5.2.1 Effects of Different Response Margins to the Star Ratings

Figure 7 shows the simulated effect of different response margins to the star ratings on allocation and mortality. We observe in the first bar of panel (a) that the effect of changes in responsiveness on the average quality of nursing homes chosen by residents (before accounting for changes in nursing home quality) is extremely small. This is consistent with the patterns observed in Figure 5, whereby average changes in responsiveness is small, and increases tend to be among the types of residents who were already relatively sensitive pre-star ratings (and thus more likely to choose higher-quality nursing homes anyway). The second bar shows that accounting for cream-skimming by nursing homes increases average quality of chosen nursing homes by 0.04 s.d. This can be explained by lower-quality nursing homes tightening their admissions policies, which pushes residents towards higher-quality nursing homes. The third bar shows that factoring in nursing homes' endogenous quality investments increases average quality of chosen nursing homes by an additional 0.06 s.d.

Panel (b) of Figure 7 shows symmetric effects on the percent reduction in simulated 90-day mortality: change in responsiveness by itself hardly affects mortality (and even increases it slightly), whereas adding nursing homes' cream-skimming responses and quality adjustments reduces mortality by 3 percent of the pre-star ratings baseline. The very slight increase in mortality when accounting only for change in responsiveness is slightly surprising given that there is a very small increase in the average quality of chosen nursing homes in the corresponding simulation in panel (a). This result arises from the fact that responsiveness increased more among healthy residents, whereas the survival-quality gradient is much steeper among sick residents, as shown in Appendix Figure A.17. As an additional check on the plausibility of the model's predictions, I test if the simulated effect on mortality is consistent with the reduced form estimate from an interrupted time series. Specifically, I regress 90-day mortality on a rich set of resident characteristics, a linear time trend, and an indicator for post-star ratings at

Figure 7: Simulated Effect of Response Margins to the Star Ratings on Allocation and Mortality



Notes: This figure shows the simulated effects of different margins of response to the star ratings. Panel (a) plots the simulated average change in quality of nursing homes chosen by residents (in standard deviations), and panel (b) plots the percent reduction in simulated 90-day mortality relative to pre-star ratings. The bars sequentially add different margins of response: (i) changes in residents' responsiveness to quality, (ii) changes in nursing homes' cream-skimming behavior, and (iii) endogenous quality investments by nursing homes.

the resident level. Reassuringly, the estimated discontinuity of 0.00287 (0.00100) — shown graphically in Appendix Figure A.18 — corresponds to a 3.75 (1.31) percent reduction in mortality relative to the pre-star ratings baseline, similar to the simulated reduction in mortality.

5.2.2 Other Counterfactuals

Figure 7 shows that most of the star ratings' effects on allocation and mortality did not operate directly through its intended effect of increasing residents' responsiveness to quality. This raises the question of exactly how important responsiveness to quality is, and whether interventions that are more directly targeted at consumer choice can be effective. To explore this, I consider two demand-side counterfactuals: first, an increase in responsiveness to quality among less responsive residents, and second, the provision of quality-ranked shortlists through hospital discharge planners. In this subsection, I start by conducting partial equilibrium simulations of these counterfactuals, leaving endogenous quality adjustments to these demand-side changes to the next section. Since providers may increase quality in response to stronger consumer preferences, these partial equilibrium simulations likely represent lower bounds on the potential effects of these counterfactual policies. In addition, given evidence on the importance of quality investments shown in Figure 7, I consider a third counterfactual where nursing homes are offered financial incentives to increase staffing. Finally, motivated by the descriptive evidence in Appendix Figure A.17 that quality matters more for the outcome of sicker residents, I test whether a simple capacity-aware assignment heuristic that prioritizes the admission of sicker residents at capacity-strained high-quality nursing homes can improve outcomes relative to a uniform assignment rule.

In the first counterfactual, I increase residents' responsiveness to the 95th percentile of the estimated distribution if their original responsiveness fell below this level, while leaving higher responsiveness unchanged. For brevity, I will refer to this throughout as "increasing responsiveness to the 95th percentile". However, given that the star ratings failed to increase average responsiveness substantially, it is fair to ask whether such a counterfactual is realistic, i.e., whether it can be anchored to a plausible real-world policy. One potential policy that could "mimic" such an increase in responsiveness is to offer hospitals financial incentives to discharge residents to higher-quality nursing homes, motivated by prior evidence that hospitals are highly sensitive to financial incentives in directing nursing home referrals. In particular, Cutler at al. (2020) find that a 1 percent increase in expected profit raises probability of self-referral by 2.5 percent when the hospital is vertically integrated with the nursing home. Using this elasticity, along with my model's simulated responsiveness-quality share gradient and average Medicaid reimbursement amounts, I estimate that a linear incentive scheme reimbursing hospitals $185 per percentage point increase in risk-adjusted survival for each patient it discharges to a nursing home would approximate the effects of this counterfactual. Appendix Section H describes this back-of-the-envelope calculation in detail.

The second counterfactual is tied directly to the discharge process for patients from hospitals to nursing homes, and related to a large literature on default effects (Choi et al. 2003; Brot-Goldberg et al. 2023) and consideration sets (Abaluck and Adams-Prassl 2021). Nursing home placement decisions for post-acute care residents are heavily influenced by the discharge process, yet discharge planners often provide them with a (potentially very long) undifferentiated list of nursing homes without much additional guidance (Tyler et al. 2017). Part of this reluctance to provide patients with nursing home recommendations is due to patient choice statutes (originally intended as a protection for patients), which suggests that policymakers can improve resident outcomes by clarifying or amending these statutes. Hence, in this counterfactual, I simulate an alternative discharge planning process where planners provide residents with a shortlist of the five highest-quality nursing homes in the surrounding area that are willing to admit them.

The third counterfactual directly targets nursing home quality by offering them financial incentives to increase staffing. I calibrate this counterfactual using Gandhi, Olenski, Ruffini, and Shen's (2024) estimates of the effects of such a regulation targeted at nursing homes with high Medicaid shares when it was introduced in Illinois. Combining their estimates of effects on staffing with the correlations between staffing and quality shown in Table 3, I simulate changes in nursing home quality that may result from such a policy.

In addition to the basic versions of the three counterfactuals described above, I also conduct versions of these simulations where there is a ban on cream-skimming by nursing homes, or where there are no capacity constraints. The ban on cream-skimming is likely to have distributional consequences, but may also have a net effect on allocation and mortality depending on the correlation between responsiveness and admissions priorities, and the heterogeneity in the mortality-quality gradient (as illustrated in Appendix Figure A.17). The counterfactuals which remove capacity constraints can be interpreted in two ways. On the one hand, they can be viewed as the long-run effect of these policies if nursing homes adjust their capacity in response to changes in demand. Alternatively, we can also interpret the difference between simulations without capacity constraints and with the status quo admissions policies as the bias that would arise from naïvely ignoring capacity constraints in counterfactual simulations.

Figure 8 shows the simulated effects of the star ratings and three alternative counterfactuals on allocation in panel (a) and 90-day mortality in panel (b). The light-blue bars show simulation results based on the estimated admissions policies, while the medium-blue and dark-blue bars reflect simulations under a ban on selective admissions and no capacity constraints respectively. Focusing on the light-blue bars to start, we observe that all three counterfactuals — raising responsiveness to quality, provision of quality-ranked shortlists by discharge planners, and financial incentives for nursing homes to increase staffing — result in larger gains than the star ratings. Specifically, compared to the cumulative effects of star ratings, the increase in average quality of chosen nursing homes is approximately six times larger under the discharge planner counterfactual, four times larger under financial incentives to increase staffing, and twice as large under an increase in responsiveness to quality. These improvements in allocation translate to similar proportional reductions in mortality.

Finally, I test whether average quality of chosen nursing homes is a sufficient statistic for health outcomes by comparing two simple assignment rules: a “uniform” assignment rule that assigns all residents to the highest-quality nursing home below a fixed threshold of capacity strain, and a “risk-stratified” assignment rule that allows this threshold to vary by residents’ baseline mortality risk. The results in Appendix Figure A.20 shows that while the average quality of residents’ assigned nursing homes is similar under the two rules (in fact, the increase in average quality is about 5 percent higher under the uniform assignment rule), the reduction in mortality is about 9 percent higher under the risk-stratified assignment rule. This shows that in addition to increasing responsiveness to nursing home quality and incentivizing nursing homes to increase quality, risk-stratified rationing may also improve resident outcomes.

5.3 Endogenous Quality Choice

The demand-side counterfactual simulations above treat quality as fixed. However, in practice, nursing homes may endogenously adjust quality in response to changes in residents’ behavior, as we saw in Section 4 for the star ratings. In this subsection, I develop a stylized model of endogenous quality choice, which I calibrate and use to predict quality choices by nursing homes under the demand-side counterfactuals in the previous subsection. I provide a summary of the model here, and provide a more detailed description as well as implementation via fixed point iteration in Appendix Section I.

I assume that nursing homes maximize expected profits subject to their capacity constraints. In particular, nursing home j solves the following maximization problem:

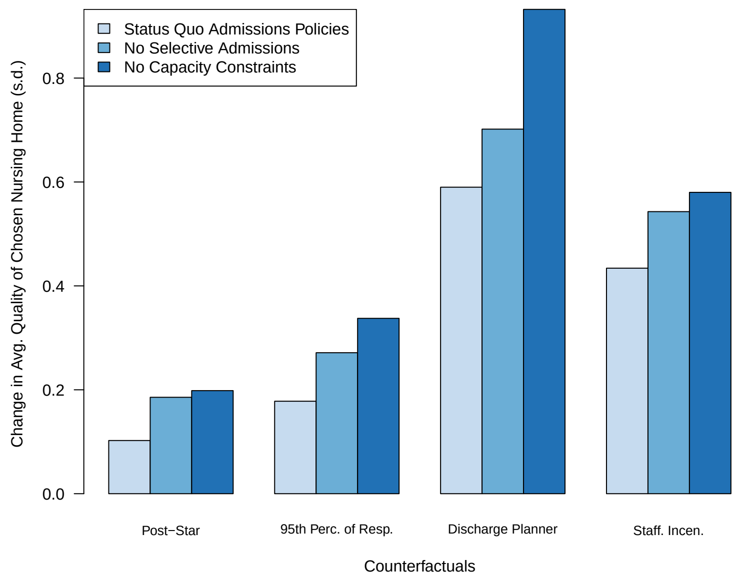
$$\max_{q_j} \left[R - C_j(q_j)\right] D_j(q_j, q_{\sim j}) \text{ s.t. } D_j(q_j, q_{\sim j}) \leq \bar{N}_j,$$

where R and $C_j(q_j)$ are per-resident revenue and costs respectively, $D_j(q_j, q_{\sim j})$ is demand for nursing home j (which depends on both j’s quality choice as well as the quality choice of all other nursing homes), and $\bar{N}_j$ is j’s capacity constraint. To simplify notation, I normalize $R = 1$, as well as demand to be the fraction of the nursing home market j is located in: $D_j(q_j, q_{\sim j}) = p_j(q_j, q_{\sim j}) \in [0, 1]$. For tractability, I abstract away from heterogeneity in profitability across residents.

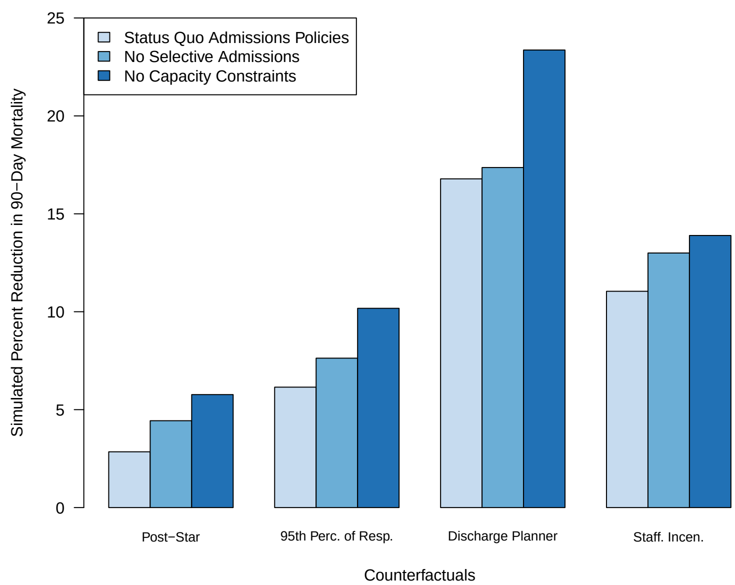
To operationalize the model, I impose a logit demand structure and assume a convex cost function. Specifically, on the demand side, in the absence of capacity constraints I assume that nursing home

Figure 8: Simulated Effect of Different Counterfactuals on Allocation and Mortality

(a) Effects on Allocation



(b) Effects on 90-Day Mortality



Notes: This figure shows the simulated effects of the star ratings, as well as three counterfactuals. Panel (a) plots the simulated average change in quality of nursing homes chosen by residents (in standard deviations), and panel (b) plots the percent reduction in simulated 90-day mortality relative to pre-star ratings. The three counterfactuals (other than the star ratings) are: (1) an increase in responsiveness to quality to the 95th percentile of the distribution of responsiveness (for residents with responsiveness below the 95th percentile), (2) the provision of a shortlist of the five highest-quality available nursing homes by discharge planners to post-acute care residents, and (3) financial incentives for nursing homes to increase staffing. The light-blue bars uses the estimated nursing home admissions policies, the medium-blue bars assume that nursing homes treat all residents the same in their admissions policies, and the dark-blue bars assume that nursing homes do not have capacity constraints and admit all residents that apply.

j's share of its market $m(j)$ is:

$$p_j(q_j, q_{\sim j}) = \frac{e^{\bar{\kappa}_j^q q_j + \kappa^{dist} \bar{dist}_j}}{\sum_{j':m(j')=m(j)} e^{\bar{\kappa}_{j'}^q q_{j'} + \kappa^{dist} \bar{dist}_{j'}}},$$

where $\bar{\kappa}_j^q$ is the average responsiveness to quality of potential residents living close to j, and $\bar{dist}_j$ is the average distance between residents in j's market and j.[33] On the supply side, I assume the following convex cost function:

$$C_j(q_j) = -c_j \cdot log\left(\frac{q_{max} - q_j}{q_{max} - q_{min}}\right),$$

where q_{min} and q_{max} are the largest and smallest values of quality estimated in the data, in order to avoid unreasonable extrapolations of nursing homes' choice of quality.

Under these assumptions, if the capacity constraint is slack, the first-order condition (FOC) for optimal choice of quality q_j^* is:

$$\begin{aligned}\bar{\kappa}_j^q \cdot p_j(q_j^*, q_{\sim j}) \left(1 - p_j(q_j^*, q_{\sim j})\right) = &\left(\frac{c_j}{q_{max} - q_j}\right) p_j(q_j^*, q_{\sim j}) \\ &- c_j \cdot log\left(\frac{q_{max} - q_j}{q_{max} - q_{min}}\right) \cdot \bar{\kappa}_j^q p_j(q_j^*, q_{\sim j}) \left(1 - p_j(q_j^*, q_{\sim j})\right), \quad (8)\end{aligned}$$

where the left-hand-side represents marginal revenue from an incremental increase in quality, and the right-hand-side captures marginal cost. If instead the capacity constraint binds, nursing homes choose quality such that demand equals capacity. To obtain the nursing home-specific cost parameters c_j, I estimate quality pre- and post-star ratings, and use the first-order condition or capacity constraint to back out the cost parameter. Note that the cost parameter is only partially identified in the case where nursing homes are constrained in both periods, and in these cases I assume that the cost parameter is equal to the upper bound. Appendix Figure A.16 shows a strong negative correlation between nursing home quality and the calibrated cost parameters.

I parametrize the demand-side counterfactuals by varying the level of κ^q. In the counterfactual which increases responsiveness, I set κ^q to the average of the counterfactual distribution of responsiveness. By contrast, the counterfactual for the provision of quality-ranked shortlists does not map directly to a specific value of κ^q. To address this, I approximate this demand-side change by choosing a value of κ^q that generates the same average increase in quality of chosen nursing homes (based on the logit shares with capacity constraints) as the average increase for this corresponding counterfactual observed in panel (a) of Figure 8.

Note that each nursing home's optimal quality choice depends on the quality of all other nursing homes in its market. Therefore, to compute nursing homes' quality adjustments under the demand-side counterfactuals, I substitute a counterfactual value of κ_q and solve for the Nash equilibrium numerically via fixed point iteration, repeatedly updating nursing homes' best-response quality until convergence.

Appendix Figure A.21 shows the simulated effects on allocation and mortality for the two demand-side counterfactuals once nursing homes' quality adjustments are accounted for. We observe that accounting for quality adjustments leads to substantially greater improvements in allocation and sur-

[33] There is no universally agreed upon definition of what constitutes a nursing home market, so I approximate a market using Health Service Areas (HSA). HSAs have been used as proxies for hospital markets, and given that most of my sample consists of residents discharged from acute care hospitals to nearby nursing homes, this suggests that HSAs may also serve as a reasonable market definition for nursing homes in this context.

vival. While the magnitude of the quality adjustments should be interpreted with caution given the model's simplifying assumptions, these results suggest that quality adjustments by providers may substantially amplify the effects of the demand-side counterfactuals considered.

6 Conclusion

In this paper, I study why consumers often choose low-quality providers in the Californian nursing home market. I demonstrate that despite substantial variation in nursing home quality and the consequential impact quality can have on resident health, average responsiveness to quality is low, with substantial variation across residents. Cream-skimming by nursing homes serves as an additional barrier to access for certain types of residents.

The introduction of the star ratings — the primary goal of which was to increase responsiveness to quality — had a net (albeit modest) positive effect on allocation and survival outcomes, but not necessarily through the channels that policymakers envisioned. Average increase in responsiveness was small and concentrated among the types of residents who were already relatively responsive prior to the star ratings. Nonetheless, nursing homes that were most exposed to these demand changes that were low-quality to start with responded by increasing their quality. In addition, lower-quality nursing homes tightened their admissions policies as a result of the star ratings (consistent with an attempt to pool with higher-quality providers), which also improved allocation and outcomes.

On the other hand, counterfactual simulations show that several other policy interventions may lead to even greater improvements in allocation and health outcomes. Increasing responsiveness to quality to the 95th percentile (which could potentially be achieved via financial incentives for hospital steering) and the provision of quality-ranked shortlists by hospital discharge planners may produce gains that are about twice or six times as large respectively holding quality fixed, with simulations from a stylized model suggesting even larger improvements if endogenous quality responses by nursing homes are accounted for. Financial incentives for increasing nursing home staffing calibrated using estimates from a policy in Illinois (Gandhi, Olenski, Ruffini, and Shen 2024) also lead to improvements that are four times greater than the star ratings in the simulations.

Therefore, while this paper demonstrates that both demand- and supply-side frictions contribute meaningfully to the mismatch between residents and high-quality nursing homes, it also highlights several promising levers that policymakers can use to improve allocation and resident outcomes.

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Appendix

A Additional Background on Nursing Homes

A.1 Brief History of the Nursing Home Industry

The growth and development of the nursing home industry in its early days was driven in large part by the creation of the Medicare and Medicaid programs in the 1960s. Since then, reimbursements from federal and state governments have been a major source of revenue for the industry, and as such, federal and state oversight bodies have a significant influence on nursing home quality. The large role played by Medicare and Medicaid has also meant that most residents face limited variation in out-of-pocket price when choosing nursing homes.

Despite the entry of nursing homes during this early era, demand often outstripped supply, with many nursing homes operating at maximum capacity, and essentially having to ration care. This "excess demand" limited competition between nursing homes, and dampened financial incentives to compete by providing better quality. The establishment of the Health Care Financing Administration (HCFA) in 1977 was in part a response to the persistently low quality of care at many nursing homes. Process quality indicators were introduced as part of the attempt to increase nursing home accountability, but lobbying efforts by the nursing home industry as well as the increasing complexity of residents' medical needs limited quality improvements.

These persistent issues led to the Nursing Home Reform Act in 1987 (which refers to parts of the Omnibus Budget Reconciliation Act of 1987 [OBRA-1987] that were specific to nursing homes), which brought about significant and wide-ranging changes in the nursing home industry. These changes included a revision of quality standards and penalties, and the introduction of the Resident Assessment instrument, which includes the MDS. Over the years, elements and regulations introduced by the Nursing Home Reform Act were revised and updated — for instance, the MDS 2.0 superseded the original MDS in 1995, and was in turn replaced by the MDS 3.0 in 2010. In addition, changes were made to the way that data on nursing home quality was presented to the public — a major component of these changes was the introduction of the CMS five-star ratings in 2008, which attempted to simplify information on nursing home quality for residents by summarizing a number of different quality indicators in a composite measure. Occupancy rates at nursing homes have also fallen substantially over the years, but remain relatively high.

There is general agreement that nursing home quality has improved over the past few decades, even among resident advocates. For example, one industry insider remarked that whereas chemical restraints were used openly by nursing homes 20 years ago, there is at least now a recognition that this is not an acceptable practice (although some nursing homes may still use it to some extent behind closed doors). However, a plethora of lawsuits as well as reports from investigative journalism have revealed that quality in some nursing homes remains poor. In addition, these cases have shown that various indicators of nursing home quality (e.g., the five-star ratings) are not always reliable, as nursing homes have found ways to game these quality measures.

Recently, the COVID-19 pandemic has shaken up the nursing home industry. First, the significant number of COVID-related nursing home deaths has increased public scrutiny over nursing home quality.[34] Second, the pandemic led to a precipitous fall in short-stay residents at nursing homes, as individuals have shied away from medical procedures (e.g., knee surgeries) that may require them to stay in a nursing home. Given that nursing home care for these individuals is typically covered by Medicare, which has substantially higher reimbursement rates than Medicaid, this trend threatens the financial viability of nursing homes that were already operating on thin profit margins before the pandemic.

A.2 More Details on Various Nursing Home Quality Measures

Donabedian (1985) provides a useful classification of the numerous quality measures that have been used for nursing homes. Specifically, Donabedian argued that these quality measures are either based on structures (S), processes (P), or outcomes (O). Structural measures refer to nursing home characteristics that are associated with the provision of care for residents (e.g., staffing levels). Process measures refer to the care received by residents, negative examples of which include the use of physical restraints and inappropriate antipsychotic use. Finally, outcomes measures include mortality (the primary measure used in this paper) and other adverse outcomes such as pressure sores and avoidable falls.

Some quality indicators span several of these categories. For example, regulators conduct inspections of nursing homes annually (or as a result of a complaint), and deficiency citations refer to areas wherein inspectors determine that the nursing home has failed to meet CMS requirements. More than 200 aspects covering 19 categories are examined during inspections, and in addition, deficiency citations are rated based on severity (level of jeopardy to resident health) and scope (e.g., whether this is an isolated incident or a systemic problem). Some types of deficiency citations (e.g., inadequately trained staff) fall under the structures (S) category of Donabedian's classification, whereas other types fall under the process (P) category (e.g., abuse or neglect of residents), and the severity of these deficiency citations are often based on resident outcomes (O).

One of the most well-known measures is the five-star rating system, which the CMS introduced at the end of 2008. The goal of the five-star rating system is to allow consumers to assess nursing home quality more easily — even though consumers were previously already able to access data on quality measures such as staffing levels, ownership status, and deficiency citations through the Nursing Home Compare website, the concern was that the multitude of indicators made it difficult for consumers to compare nursing homes. Hence, the five-star rating provides a summary index of many of the quality measures discussed here.

Specifically, the star ratings are calculated based on scores on three domains: the health inspection domain, the staffing domain, and the quality measure domain. The health inspection score is determined by results of the inspections of nursing homes by regulators, the staffing score is calculated using case-mix adjusted staffing hours (for different types of staff) per resident day, and the quality measure domain combines performance on 15 types of resident outcomes (10 of which are derived from MDS assessments and five from Medicare claims).

[34]The Kaiser Family Foundation found that long-term care facility residents and staff account for at least 23 percent of all COVID-19 deaths in the U.S, as of the end of January 2022.

A persistent issue with many of these quality measures is gaming by nursing homes. Staffing levels during the period of my sample were self-reported, rarely audited, and likely to be inflated (Geng, Stevenson, and Grabowski 2019). Outcome-based measures also show signs of manipulation; for example, after the government began publicly releasing information about inappropriate antipsychotic use in 2012, schizophrenia diagnoses rose sharply, the implication being that some were made not on a clinical basis but simply so that nursing homes could continue administering antipsychotics to residents as a form of chemical restraint without having it counted as inappropriate antipsychotic use (Thomas, Gebeloff, and Silver-Greenberg 2021). Deficiency citations may not always provide an accurate picture of nursing home quality either, given that nursing homes may behave differently around the time of inspections. For instance, Geng, Stevenson, and Grabowski (2019) find that staffing levels at nursing homes spike during the week of inspections, and there are anecdotal accounts of other strategic behaviors by nursing homes.[35]

B Data Appendix

B.1 Sample Construction

The provider number recorded in MDS assessments cannot always be matched to a nursing home in the OSCAR dataset. I examine each of these unmatched provider numbers and find that most of these are due to errors in the provider number recorded in MDS assessments. I correct obvious typos (e.g. where the digit "0" is replaced with the alphabet "O") and drop observations when it cannot be determined which nursing home the provider number corresponds to. In addition, I drop the relatively small number of residents with errors in birth or death dates (e.g., with different birth or death dates recorded across different assessments), or with missing values of the resident characteristics that I control for in the quality estimation. These controls include all baseline resident characteristics recorded in the MDS, other than a few variables that are missing for a large proportion of residents (e.g., HIV status).

For the structural demand estimation sample, I consider only resident-nursing home pairs within 15 miles of each other. I also drop nursing homes that admit fewer than 30 residents over the period of my structural estimation sample (2008–2010) to ensure sufficient power. For computational reasons and for easier interpretation of the coefficients, I include a smaller set of variables in the structural estimation (and the hazard estimation) compared to the quality estimation.

I do not include expected out-of-pocket price in residents' utility equation because there is relatively little variation in out-of-pocket costs for residents covered by insurance, and Gandhi (2023) finds very little price sensitivity on the part of residents. Moreover, a large portion of the variation in expected prices comes from differences in the distribution of lengths of stay and when residents will switch to a different payer source (e.g., because Medicare coverage expires in the case of short-stay residents or because residents spend down their assets sufficiently to become eligible for Medicaid in the case of long-stay residents), and these are often uncertain to residents at the time of their nursing home choice. It is therefore unclear the extent to which residents react to the spot price or highly uncertain future prices — previous studies have rejected the hypotheses of both fully myopic and fully forward-looking individuals (Aron-Dine, Einav, Finkelstein, and Cullen 2015; Guo and Zhang 2019), and given

[35] As an example, management at a nursing home under private equity ownership had a designated code to covertly alert staff of the presence of inspectors, e.g., "Marilyn Woods, line twelve" (Rafiei 2022).

the heterogeneity in cognitive limitations of many nursing home residents (e.g., with dementia rates at admission that are three times that of the Medicare population in 2005), we may also expect corresponding variation in their degree of foresight.

B.2 Payer Source Data

The data on payer source at admission recorded in the MDS is less reliable than claims data. This is in part because nursing homes are sometimes unsure at the time of admission (which is when they complete the initial MDS assessment form) how they are ultimately going to be reimbursed for the resident. In fact, claims submitted by nursing homes may be rejected months after. For example, as the CEO of a firm providing billing assistance to nursing homes put it:

Most patients that need Medicaid for long term care don't actually have Medicaid for long term care in place when they are coming into the facility... There's been so many scenarios where a patient comes into the facility, the responsible party or power attorney says, sure Mom and Dad are eligible... but when you get your hands on those accounts, you see that there was $50,000 transferred out of that account 3 months before the patient comes into the nursing home, which is a potential disqualifier.

Nonetheless, I use payer source at admission in the MDS for my analysis for two reasons. First, using the MDS data instead of claims data allows me to study residents from all payer sources.[36] Second, given that I use payer source primarily to study/control for selective admissions by nursing homes, it is unclear whether the actual payer source from claims data is preferable. This is because nursing homes' admission decisions depend on what they expect the payer source to be (which is presumably the payer source recorded in the initial MDS assessment form) rather than what the ultimate payer source ends up being (which is recorded in the claims data).

A separate issue with the payer source recorded in the MDS is that it is often not updated in assessments subsequent to the initial admission assessment (Grabowski, Gruber, and Angelelli 2008). This shortcoming of the MDS data is largely irrelevant to my analysis because I use the initial assessment form for most of my analysis, only using subsequent assessment forms to determine future outcomes of residents.

B.3 Variable Definitions

Many of the answers to MDS questions are categorical (e.g., questions requiring the assessor to check all boxes that apply). In these cases, I include a dummy variable for each category (other than an omitted category, if it exists). There are also a number of numerical variables, such as weight, height, and age. For residents' weights, I create dummies for weights in 10-pound intervals starting from 60–69 pounds up to 390–399 pounds (as well as a dummy for less than 60 pounds), and for heights I create dummies for heights in 5-inch intervals from 40–44 inches to 70–74 inches (and a dummy for less than 40 inches). Similarly, I create the following dummies for residents' ages: less than 40, 40–49, 50–59, 60–64, 70–74, 75–79, and 80–84. I use these dummies as controls in the quality estimation rather than assume a linear relationship. Finally, the assessor filling in the MDS can include up to five ICD-9 codes for each resident. I create a dummy for each unique first 3 digits of the ICD-9 codes, which equals

[36] If one insisted on using claims data for verification of payer source we would need claims data from numerous programs (e.g., Medicare, Medicaid, and the Veterans Health Administration) and will likely still not be able to verify payer sources for residents on private insurance or who are private pay.

one for each resident if any of the five ICD-9 codes entered for the resident has the corresponding first three digits, and zero otherwise.

C Model for Quality Estimation

Equation (1) in the main text can be derived from a simple additive causal model such as the one in Abaluck, Bravo, Hull, and Starc (2021). Suppose that:

$$Y_{ij} = \mu_j + a_i, \tag{9}$$

where Y_{ij} is the potential outcome for resident i in nursing home j, μ_j is a measure of nursing home j's quality (in terms of the nursing home's causal effect on the outcome Y), and a_i is a residual for resident i.

I can relate potential outcomes to realized outcomes by summing across nursing homes in equation (9) to obtain:

$$\begin{aligned} Y_i &= Y_{i1} + \sum_{j=2}^{J} (Y_{ij} - Y_{i1}) D_{ij} \\ &= \mu_1 + \sum_{j=2}^{J} \beta_j D_{ij} + a_i, \end{aligned} \tag{10}$$

where D_{ij} is a dummy variable for whether resident i chooses nursing home j, and β_j is the quality of nursing home j relative to the omitted nursing home, indexed by $j = 1$. Finally, I decompose the resident-specific residual, a_i, into a component explained by resident characteristics X_i and an idiosyncratic component u_i by projecting a_i onto X_i:

$$a_i = X_i'\gamma + u_i, \ \mathbb{E}[X_i u_i] = 0, \tag{11}$$

and substitute this into equation (10) to obtain equation (1) in the main text.

To derive equation (2), which forms the basis of the IV estimation of the forecast coefficient, I consider the infeasible regression of causal effects β_j on the quality estimates α_j, normalizing η_j to have mean zero:

$$\beta_j = \lambda\alpha_j + \eta_j, \ \mathbb{E}[\alpha_j \eta_j] = 0. \tag{12}$$

Substituting equation (12) into equation (1), I obtain equation (2) as desired.

D Model of Selective Admissions

The model in this section closely follows Gandhi (2023), other than the fact that it incorporates quality choice by nursing homes at time $t = 0$.

Nursing homes differ in their quality q_j (which they choose at time $t = 0$), and their total number of beds b_j (which we take as given). There is a nursing home-specific flow cost of quality given by $c_j(q_j)$. Residents arrive at some Poisson rate λ^A, and nursing homes are able to observe a number of characteristics associated with the resident, denoted c_i, which include:

1. The resident's indirect utility from admission to each facility $v_{ij}(q_j)$, which is a function of quality.

2. The instantaneous payoff received by the nursing home if it admits the resident, Π_{ij}.
3. The stayer-type of the resident ϕ_i, which we assume takes a finite number of values. Following admission into a nursing home j, a resident with stayer-type ϕ is discharged at Poisson rate $\lambda^D_{j\phi}$.

We assume that residents only ever choose nursing homes within a certain distance (15 miles in the empirical implementation), and denote this set by J_i. When a resident i arrives, all nursing homes in J_i simultaneously observe her characteristics c_i, and a subset $\mathcal{O}_i \subseteq J_i$ offer her admission. The resident then chooses the nursing home $\mu(i)$ that yields the highest indirect utility $v_{ij}(q_j)$ within her constrained choice set:

$$\mu(i) = \{j : v_{ij} \geq v_{ij'} \; \forall j' \in \mathcal{O}_i\}.$$

Following Gandhi (2023), I make two simplifying assumptions.

Assumption 1. Nursing home j forms its belief about the probability that it will be the resident's most preferred nursing home among the set of nursing homes willing to admit the resident should it offer the resident admission, $\hat{p}_j(c_i) \equiv Pr\left(v_{ij} \geq v_{ij'} \forall j' \in \mathcal{O}_i\right)$ based only on the resident's characteristics c_i.

Assumption 2. When a resident i is admitted to a nursing home j, the nursing home receives a lumpsum payoff Π_{ij} (which depends on c_i), and a continuous payoff $\Psi_j(N_{jt})$ which depends on the number and type of residents at the nursing home N_{jt}.

Assumption 1 rules out the possibility that nursing homes decide whether or not to admit a resident based on the censuses of other nursing homes close to the resident, which Gandhi (2023) argues is a reasonable approximation of reality. Gandhi also shows that Assumption 2 is not very restrictive, in that nursing homes' admissions policies will still be identical if they instead received (translated) resident-specific flow payoffs.

Nursing homes' optimal control problem is to choose an admission policy $\{a_{j\tau}\}$ such that it admits a resident who applies at time τ (and it has an available bed) if and only if $c_i \in a_{j\tau}$. Nursing homes' quality and admission policy are chosen to maximize the expected PDV of profits $\Pi_j(a_j, q_j, t; q_{\sim j})$, given by:

$$\mathbb{E}\Big[\sum_{\{i:\tau_i^A \geq t, ||N_{j\tau_i^A}||_1 < b_j, c_i \in a_{j\tau_i^A}, v_{ij}(q) \geq v_{ij'}(q_{j'}) \; \forall j' \in \mathcal{O}_i\}} exp(\rho(\tau_i - t))\Pi_{ij} \\ + \int_0^\infty exp(\rho(t-\tau))\left(\Psi_j(N_{jt}) - c_j(q_j)\right) d\tau | \mathcal{F}_t^j]]\Big],$$

where $t = 0$ when the nursing home is choosing quality.

At time $t = 0$, the first order condition for the quality choice of each nursing home is:

$$\frac{d \max_{a_j} \Pi_j(a_j, q_j, 0; q_{\sim j})}{dq_j} = 0.$$

After choosing quality, at any time $t \geq 0$, nursing homes' optimal admissions policy take a threshold form. Specifically, nursing home j is willing to admit a resident i if and only if:

$$\underline{\Pi} \geq \underline{\Pi}_{j\phi}(N_{jt}) = V_j(N_{jt}) - V_j(N_{jt} + 1^{\phi_i}),$$

where $V_j(N_{jt})$ is the nursing homes' value function when its current mix of residents is N_{jt}, and 1^{ϕ} denotes a vector that is one in the ϕth position, and zero elsewhere. In addition, the optimal admissions policy must satisfy the Bellman equation:

$$\rho V_j(N_{jt}) = \Psi_j(N_{jt}) + \sum_{\phi} \lambda^D_{j\phi} N_{jt} \left(V_j(N_{jt} - 1^{\phi}) - V_j(N_{jt}) \right)$$
$$\sum_{\phi} \lambda^A_{j\phi} \int \max \left\{ 0, \Pi + V_j(N_{jt} + 1^{\phi}) - V_j(N_{jt}) \right\} dF^{\Pi}_{j\phi}(\Pi),$$

where $\lambda^A_{j\phi} \equiv Pr(j \in J_i, \phi_i = \phi)$, and $F^{\Pi}_{j\phi}(\Pi) = \int_{\{c:\Pi_{ij} \leq \Pi\}} \hat{p}(c_i) dF_c(c|j \in J_i, \phi_i = \phi)$. In equilibrium, nursing homes' beliefs $\hat{p}_j(c_i)$ must also be consistent with the long-run distribution of other nursing homes' policies:

$$\hat{p}_j(c_i) = \int \mathbb{I}\left[v_{ij} \geq v_{ij'} \ \forall j \in \mathcal{O}_i \backslash \{j\} \right] dP\left(\mathcal{O}_i \backslash \{j\} \right).$$

Nursing homes' optimal admissions policy is affected by its quality choice q_j through $\hat{p}_j(c_i)$. In particular, holding other nursing homes' quality constant, the higher q_j is the greater the probability that future residents will choose it if offered a spot, and the higher $\hat{p}(c_i)$ will be (assuming residents are responsive to quality). This also suggests that $\underline{\Pi}_{j\phi}(N_{jt})$ may be higher for high-quality nursing homes since the option value of spare beds is more valuable. Hence, it is not necessarily the case that higher-quality nursing homes will have higher occupancy rates in equilibrium. Motivated by this observation, in my structural estimation I allow nursing homes' selective admissions policies to depend on quality.

E Identification of the Matching Model

This section discusses how the model of demand and selective admissions maps into the framework in Agarwal and Somaini (2022), and the formal assumptions required for identification. I also briefly comment on how these assumptions relate to the setting in this paper.[37]

Recall that residents' and nursing homes' preferences are given by:

$$v_{ij} = v^1_j(x_i, \zeta_i) - v^2_j(x_i, dist_{ij}),$$
$$\pi_{ij} = \pi(x_i, \zeta_i, occ_{ij}),$$

where I denote resident-specific preference heterogeneity by ζ_i. We can set $|v^2_j(x_i, dist_{ij})| = 1$ for the scale normalization for resident preferences, and set the utility for an arbitrary nursing home to be zero for the location normalization, e.g., $v_{i1} = 0$ (and do not include an intercept term).

I set the location normalization for the supply side equation so that nursing homes' acceptance decision can be written as:

$$\sigma_{ij} = \sigma_j(x_i, \zeta_i, occ_{ij})$$
$$= \mathbb{I}[\pi(x_i, \zeta_i, occ_{ij}) \geq 0].$$

Assumption I1*.* *Unobserved consumer-specific heterogeneity* ζ_i *is conditionally independent of* $(dist'_i, occ'_i)$ *given* x_i*.*

This is the formal statement for the exclusion restriction for the demand and supply instruments, which I provide evidence in support of in the main text.

[37]The few differences in the description below from my setup in Section 3.2 (e.g., scale normalizations) make no difference to the identification argument and avoids the need to introduce additional notation.

Assumption I2. *The acceptance decision function* $\sigma_j(x_i, \zeta_i, occ_{ij})$ *is weakly decreasing in* occ_{ij}*. In addition, for all nursing homes* j *and resident characteristics* x_i*, and unobserved preference heterogeneity* ζ_i*, we have* $\lim_{occ\to-\infty}\sigma_j(x_i, \zeta_j, occ) = 1$*, and* $\lim_{occ\to\infty}\sigma_j(x_i, \zeta_j, occ) = 0$.

Recall that my occupancy measure represents temporary fluctuations (so negative values of occ make sense). The assumption that the acceptance decision function is weakly decreasing in the occupancy measure is the relevance condition for the supply instrument, which I provided evidence for when testing prediction 1 in the main text. The fact that nursing homes have finite capacities is consistent with the requirement that $\lim_{occ\to\infty}\sigma_j(x_i, \zeta_j, occ) = 0$. Finally, for $\lim_{occ\to-\infty}\sigma_j(x_i, \zeta_j, occ) = 1$ to be true, the direct costs of caring for each resident (i.e., not accounting for the option value of using up a spare bed) must be less than the marginal revenue the resident brings in. Gandhi (2023) provides evidence that this is true for most residents: even Medicaid reimbursement rates (which are much lower than Medicare rates) are typically sufficient to cover direct costs of care.

For a more succinct statement of the next assumption, I introduce some terminology. We will say that nursing homes j and k are strict substitutes in $dist_{ij}$ at $(x_i, dist_i, occ_i)$ if $\partial s_j(x_i, dist_i, occ_i)/\partial dist_{ik}$ and $\partial s_k(x_i, dist_i, occ_i)/\partial dist_{ij}$ both exist and are strictly positive, where $s_j(x_{i,} dist_i, occ_i)$ is the share of residents with $(x_{i,} dist_i, occ_i)$ who are matched with nursing home j. Define $\Sigma(x_i, dist_i, occ_i)$ to be the matrix with (j, k)th entry equal to one if j and k are strict substitutes in $dist$ at $(x_i, dist_i, occ_i)$ and zero otherwise. In addition, let $\Sigma(x_i, dist_i) \equiv \vee_{occ\in supp(occ)}\Sigma(x_i, dist_i, occ)$ so that the (j, k)th entry is one if j and k are strict substitutes at some occupancy.

Assumption I3. *For every* x_i *and all but a finite set of* $dist_{ij}$ *in its support, the graph of* $\Sigma(x_i, dist_i)$ *has a path connecting any two nursing homes.*

Roughly speaking, this assumption requires a path between any two pairs of nursing homes. An example where this assumption may potentially be violated is if I tried to estimate demand for nursing homes in California and Massachusetts (which are on different coasts of the US) in the same model. If no resident ever substitutes from a nursing home in California to one in Massachusetts and vice versa, we cannot identify how residents rank nursing homes in the two states relative to each other. In my setting where I study only nursing homes in California, given that residents and nursing homes are spread out over California, Assumption I3 seems plausible.

Assumption I4. *(i) The support of the random vector* $dist_i$ *is rectangular with non-empty interior. (ii) For each* x_i *and* j*, the function* $v_j^2(x_i, dist_j)$ *is continuously differentiable in* $dist_j$ *with* $v_j^{2\prime}(x_i, dist_j) \neq 0$ *for all* $dist_j$.

The second part of Assumption I4 is satisfied if residents' utility for each nursing home is sufficiently smooth and strictly decreasing in her distance to it for all possible distances, and the first part is a weak requirement on the support of the demand instrument.

Under the assumptions above, residents' preferences and nursing homes' admission rules are nonparametrically identified.

Theorem 1 *(Agarwal and Somaini 2022). If Assumptions I1–I4 hold and* $|\mathcal{J}| > 1$*, then for every* w*, (i) the function* $v_j^2(x, \cdot)$ *is identified for every* $j \in \mathcal{J}$ *and* $dist_j \in supp(dist_j)$*, and (ii) the joint distribution of* (u_i, π_i^{cutoff}) *is identified for every value* (u, π) *in the interior of* $v^2(x, supp(dist)) \times supp(occ) = \Pi_{j=1}^J v_j^2(x, supp(dist_j)) \times supp(occ)$*, where* $\pi_i^{cutoff}(x_i, \zeta_i) \equiv sup\{occ : \pi(x_i, \zeta_i, occ) \geq 0\}$.

F Algorithm for the Gibbs Sampler

To ease the computational burden of this estimation, I only consider nursing homes within 15 miles of each resident, dropping residents who choose a nursing home further away. Denote the potential set of nursing homes in resident i's choice set by $\mathcal{J}_i \equiv \{j \in J | dist_{ij} \leq 15 \text{ miles}\}$. Even after restricting to nursing homes within 15 miles, the size of residents' choice sets (before any supply side constraints) $J_i \equiv |\mathcal{J}_i|$ tends to be quite large: it has a median of roughly 30, a mean of 50, and can take values greater than 200.

In the following description for the Gibbs sampler, when drawing structural error terms in sequence for $j \in \mathcal{J}_i$, I assume an increasing order (although obviously any other order works as well). In addition, to simplify notation, I denote variables in residents' utility and nursing homes' admissions equations by $\mathbf{X}_{ij}$ and W_{ij} respectively,[38] and refer to the nursing home that resident i ends up in by $\mu(i)$.

Denoting iterations of the Gibbs sampler by k and indicating the values of various parameters in the kth iteration of the Gibbs sampler using a superscript k, the steps for implementing the Gibbs sampler are as follows.

1. Initialization ($k = 0$): I assume that $(\epsilon_{ij}, \omega_{ij}) \sim^{i.i.d.} N(0, I_2)$ and set the following conjugate priors for the parameters: $(\kappa', \psi')' \sim N(0, 100I)$.
   (a) Set the initial values of the parameters $\theta^0 = \left(\kappa^{0\prime}, \psi^{0\prime}\right)$ at their prior mean.
   (b) Initial data augmentation: For each resident i, draw the vector ϵ_i^0 such that $v_{i,\mu(i)}^0 \geq v_{ij}^0$ for all $j \in \mathcal{J}_i$.
      i. Draw $\omega_{i,\mu(i)}^0$ such that $\omega_{i,\mu(i)}^0 \geq -W_{ij}'\psi^0$ and for $j \neq \mu(i)$ draw ω_{ij}^0 from the unconditional distribution.
      ii. Set $\epsilon_{i,\mu(i)}^0$ equal to three times the standard deviation of the prior. For $j \neq \mu(i)$, draw ϵ_{ij}^0 such that $\epsilon_{ij}^0 \leq \left(\mathbf{X}_{i,\mu(i)} - \mathbf{X}_{ij}\right)' \kappa^0 + \epsilon_{i,\mu(i)}^0$ if $\pi_{ij}^0 \geq 0$ or draw ϵ_{ij}^0 unconditionally otherwise.
2. For $k + 1 = 1, ..., K$:
   (a) Draw the profit shocks $\omega_i^{k+1} | v_i^k; \psi^k$ in sequence for $j \in \mathcal{J}_i$.
      i. If $v_{ij}^k < v_{i,\mu(i)}^k$, draw ω_{ij}^{k+1} unconditional on assignment (given that even if i is eligible for j, i would not choose j).
      ii. If $v_{ij}^k > v_{i,\mu(i)}^k$, draw ω_{ij}^{k+1} from a truncated normal with mean and variance given by the conditional distribution and truncation point $\omega_{ij}^{k+1} < -W_{ij}\psi^k$ (given that otherwise i would choose j over $\mu(i)$).
      iii. Finally, if $j = \mu(i)$, draw from the conditional distribution with truncation point given by $\omega_{ij}^{k+1} \geq -W_{ij}'\psi^k$ (given that i must always be eligible for the facility she was ultimately assigned to).
   (b) Update π_i^{k+1} according to $\pi_{ij}^{k+1} = W_{ij}'\psi^k + \omega_{ij}^{k+1}$.
   (c) Draw the utility shocks $\epsilon_i^{k+1} | \pi_i^{k+1}; \kappa^k$ in sequence, for $j \in \mathcal{J}_i$.
      i. If $\pi_{ij}^{k+1} < 0$, draw ϵ_{ij}^{k+1} unconditionally (given that i would not choose such a facility

[38] These include resident characteristics x_i, nursing home characteristics w_j, distance between residents and nursing homes $dist_{ij}$, occupancy fluctuations at nursing homes occ_{ij}, and interactions between these variables.

even if she were eligible for it).

ii. If $\pi_{ij}^{k+1} \geq 0$ and $j \neq \mu(i)$, draw ϵ_{ij}^{k+1} from the conditional distribution with truncation point given by $v_{ij}^{k+1} < \mathbf{X}'_{ij}\kappa^k$.

iii. For $j = \mu(i)$, draw $\epsilon_{i,\mu(i)}^{k+1}$ such that $v_{i,\mu(i)}^{k+1}$ is larger than the current values of $v_{i,j'}$ for $j' \neq j$ and $\pi_{ij'} \geq 0$.

(d) Update v_i^{k+1} according to $v_{ij}^{k+1} = \mathbf{X}'_{ij}\kappa^k + \epsilon_{ij}^{k+1}$.

(e) Update the parameters θ based on the new indirect utilities v^{k+1} and profits π^{k+1}.

i. First, we update κ. Denote the design matrix in the equation for indirect utilities by $\mathbb{X}$. In matrix notation, we have:

$$v = \mathbb{X}\kappa + \epsilon, \ \epsilon \sim N(0, I).$$

We have a normal conjugate prior for κ, with mean μ_κ^0 and covariance matrix Σ_κ^0. The posterior distribution of κ conditional on v and W is:

$$\kappa|(v, \mathbb{X}) \sim N(\tilde{\mu}_\kappa, \tilde{\Sigma}_\kappa),$$

where the posterior mean and covariance matrix are given by:

$$\begin{aligned}\tilde{\mu}_\kappa &= \left(\frac{\mathbb{X}'\mathbb{X}}{\sigma_\epsilon^2} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\kappa^0\right)^{-1}\mu_\kappa^0 + \frac{\mathbb{X}'\kappa}{\sigma_\epsilon^2}\right) \\ &= \left(\mathbb{X}'\mathbb{X} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\kappa^0\right)^{-1}\mu_\kappa^0 + \mathbb{X}'\kappa\right),\end{aligned}$$

$$\begin{aligned}\tilde{\Sigma}_{\theta_v} &= \left(\frac{\mathbb{X}'\mathbb{X}}{\sigma_\epsilon^2} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1} \\ &= \left(\mathbb{X}'\mathbb{X} + \left(\Sigma_\kappa^0\right)^{-1}\right)^{-1}.\end{aligned}$$

We then set κ^{k+1} by drawing from this posterior distribution.

A. Next, we will update ψ. Denote the design matrix in the equation for the admissions rule by W. In matrix notation, we have:

$$\pi = W\psi + \omega, \ \omega \sim N(0, I).$$

We have a normal prior for ψ, with mean μ_ψ^0 and covariance matrix Σ_ψ^0, so the posterior distribution of θ_π conditional on π and W is:

$$\psi|(\pi, W) \sim N(\tilde{\mu}_\psi, \tilde{\Sigma}_\psi),$$

with posterior mean and covariance matrices given by:

$$\begin{aligned}\tilde{\mu}_\psi &= \left(\frac{W'W}{\sigma_\omega^2} + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\psi^0\right)^{-1}\mu_\psi^0 + \frac{W'\psi}{\sigma_\omega^2}\right) \\ &= \left(W'W + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1}\left(\left(\Sigma_\psi^0\right)^{-1}\mu_\psi^0 + W'\psi\right),\end{aligned}$$

$$\tilde{\Sigma}_\psi = \left(\frac{W'W}{\sigma_\omega^2} + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1}$$
$$= \left(W'W + \left(\Sigma_\psi^0\right)^{-1}\right)^{-1}.$$

We then set ψ^{k+1} by drawing from this posterior distribution.

G Simulation Details

G.1 Assumptions for Counterfactual Simulations

To simulate what happens under various counterfactuals, we need to make several assumptions, which I discuss below.

Assumption C1. *Decisions made by nursing homes to increase or reduce capacity do not change in the counterfactuals.*

Assumption C2. *Entry and exit decisions by nursing homes do not change in the counterfactuals.*

Assumption C3. *Nursing homes' quality of care does not change with temporary fluctuations in occupancy.*

Assumption C4. *Residents' most preferred nursing home among those willing to accept them in the counterfactual is preferable to the outside option of not going to a nursing home.*

Assumption C5. *Nursing homes' discharge behavior does not change in the counterfactual.*

Assumptions C1, C2, and C3 are necessary because modeling nursing homes' capacity choices, entry and exit decisions, and the way in which quality varies with occupancy fluctuations is out of the scope of this paper. Assumptions C1 and C2 will be violated, for instance, if high-quality nursing homes add beds in response to greater demand, or if low-quality nursing homes exit the market due to insufficient demand (over the counterfactual period). To increase the plausibility of Assumptions C1 and C2, I restrict my counterfactual simulations to the single year of 2009, given that the myriad regulations make it more difficult to make large adjustments to capacity, and exits in any given year are relatively rare events. Indeed, only 0.8 and 0.4 percent of nursing homes entered and exited the market respectively in 2009, and the average percent change in number of beds reported by nursing homes from 2008–2009 is only 1.1 percent.

The main threat to Assumption C3 is that nursing homes that are experiencing a temporary spike in occupancy may provide poorer care during this period (e.g., because they are short-staffed). To test this hypothesis, in Appendix Figure A.25 I show a bin scatter of resident outcomes against my occupancy measure, controlling for resident characteristics and nursing home fixed effects. If care provided by nursing homes deteriorates when occupancies are temporarily elevated, we would expect a negative relationship between resident outcomes and occupancy. Instead, Appendix Figure A.25 shows the lack of a clear relationship between outcomes and occupancy, which provides support for Assumption C3.

Assumption C4 is required to ensure that residents do not choose the outside option (of not going to any nursing home) if no nursing home at least as desirable as her chosen nursing home is available to her in the counterfactual. This assumption cannot be tested directly because we only have data on admitted residents (and thus cannot estimate the relative value of the outside option). Nonetheless, several qualitative facts support the assumption that these residents will still prefer going to a nursing home in these counterfactuals. First, nursing home residents discharged from an acute care hospital (which comprise the majority of my sample) typically require some rehabilitative support before they are discharged to the community, and nursing homes provide most of such rehabilitative care.[39] Second, long-stay residents are often admitted to nursing homes when most other options are exhausted, considering that living in a nursing home is typically considered an unattractive option.[40] Third, most residents end up in a higher-quality nursing home in the counterfactuals that I consider, so the possibility that they would prefer the outside option is relatively unlikely.

Finally, Assumption C5 is required because modeling nursing homes' discharge decisions is outside the scope of this paper. This condition may be violated, for instance, if nursing homes expedite discharges of their existing residents when they are close to capacity and a more desirable resident applies. Nonetheless, discharging residents on short order is presumably more difficult than it is for a nursing home to reject (or dissuade) an applicant,[41] and nursing homes face legal liabilities if they try to forcefully evict residents who are not ready to be discharged (§483.10, §483.21).[42] Hence, there is reason to believe that selective admissions are more important than selective discharges as a means for nursing homes to manage their occupancy level.

G.2 Background on the Cause-Specific Hazard Model

In my modeling of nursing home exits, there are two competing risks: death and discharge. In particular, if a resident dies in the nursing home, we do not know when she would have been discharged if she had remained alive; and similarly, if a resident is discharged, we do not know when she would have died if she had stayed in the nursing home instead.

The presence of competing risks means that standard tools for analyzing survival data may not suffice. For example, the Kaplan–Meier estimator is commonly used to estimate the survival function $S(t)$ nonparametrically, and is defined by:

$$\hat{S}(t) = \prod_{i:t_i \leq t} \left(1 - \frac{d_i}{n_i}\right),$$

where t_i is the event time for individual i, d_i is the number of individuals experiencing the event at time t_i, and n_i is the number of individuals that have not experienced the event until at least time t. Initially, it may seem natural to simply use the Kaplan–Meier estimator separately for each event type, i.e.,

$$\hat{S}_{death}(t) = \prod_{i:t_i^{death} \leq t} \left(1 - \frac{d_i^{death}}{n_i^{death}}\right), \ \hat{S}_{discharge}(t) = \prod_{i:t_i^{discharge} \leq t} \left(1 - \frac{d_i^{discharge}}{n_i^{discharge}}\right).$$

However, this has the undesirable property that the sum of these separate survivor function estimates

[39] Long-term care hospitals also admit patients from acute care hospitals, but these are typically more clinically intensive cases.

[40] According to a Nationwide Retirement Institute survey conducted by the Harris Poll, more than half of the almost 1,300 surveyed US adults aged 24 or above responded that they would rather die than live in a nursing home (Novotney 2020).

[41] There is a lengthy list of steps that nursing homes must follow in the discharge planning process (§483.21).

[42] Valid reasons for eviction are if the needs of the resident are greater than the nursing home can provide, refusal to pay for nursing home care in spite of "reasonable and appropriate notice" (pending Medicaid applications do not justify eviction), nursing home care no longer being necessary for the resident, the resident's presence jeopardizing the health or safety of other residents, and nursing home closure.

will generally exceed the survivor function estimate for the composite outcome:

$$\hat{S}_{death}(t) + \hat{S}_{discharge}(t) \geq \hat{S}_{death\ or\ discharge}(t),$$

which is the case even if the competing risks are independent.[43]

Competing risks models avoid this problem. In particular, a key concept in competing risks models is the cause-specific cumulative incidence function (CIF), defined as $CIF_c(t) \equiv Pr(T \leq t, C = c)$, where T is the time of the first event, and C is the cause (i.e., the type of event). In words, the cause-specific CIF tells us the probability that an event occurs before time t *and* that the cause is c. An attractive feature of CIFs is that they have the property that:

$$CIF_{death}(t) + CIF_{discharge}(t) = CIF_{death\ or\ discharge}(t),$$

in contrast to the Kaplan–Meier estimates in the presence of competing risks. If we introduce covariates $\mathbf{X}$ into the model, we can define the CIF analogously as being conditional on $\mathbf{X}$, i.e., $CIF(t|\mathbf{X})$.

For my analysis, I use the cause-specific hazard model, which is commonly used model of competing risks. This involves estimating cause-specific hazard functions, which are defined as:

$$h_c(t|\mathbf{X}) \equiv \lim_{\Delta t \to 0} \frac{Pr(t \leq T < t + \Delta t, C = c|T \geq t, \mathbf{X})}{\Delta t}, \tag{13}$$

for each cause c. I model these functions semi-parametrically:

$$h_c(t|\mathbf{X}) = h_{c,0}(t) exp(\mathbf{X}'\beta_{c,haz}), \tag{14}$$

letting the cause-specific baseline hazard $h_{c,0}(t)$ be non-parametric. Defining the cumulative hazard function as:

$$H_c(t|\mathbf{X}) \equiv \int_0^t h_c(u|\mathbf{X}) du,$$

we can show that the cumulative incidence function for cause c is given by:

$$CIF_c(t|\mathbf{X}) = \int_0^t S(u|\mathbf{X}) h_c(t|\mathbf{X}) du, \tag{15}$$

where $S(t|\mathbf{X}) = exp\left(-\sum_c H_c(t|\mathbf{X})\right)$ is the survivor function for the composite event.

We can estimate the parameters $\beta^k_{c,haz}$ for the cause-specific hazard functions by maximizing the modified partial likelihood for each cause c, which is given by:

$$L(\beta^k_{c,haz}) = \prod_i \left(\frac{exp(\mathbf{X}'_i \beta_{c,haz})}{\sum_{i' \in \mathcal{R}_i} exp(\mathbf{X}'_{i'} \beta_{c,haz})} \right)^{\mathbb{I}[C_i = c]},$$

where $\mathbb{I}[C_i = c]$ is an indicator equal to one if and only if resident i exits a nursing home due to cause c before the end of the sample period, $\mathbf{X}_i$ is the vector of covariates associated with resident i and the nursing home she went to, and $\mathcal{R}_i$ contains residents who do not exit their nursing home and are not censored before the minimum of resident i's censoring and exit times.

It should be stressed that the cause-specific hazard model is used here only to predict (counterfactual) death and discharge times, and that one should not attempt to interpret the coefficients $\beta^k_{c,haz}$.

[43] It may be difficult to think of independence of death and discharge in the present context. An example that illustrates this more clearly is a case with two totally unrelated events, e.g., individuals in Boston receiving their first dose of caffeine in the morning, and kangaroos in Australia waking up in the morning. Even in this case, the above property holds.

In fact, equation (15) reveals that the sign of the hazard ratio $\beta^k_{c,haz}$ associated with the kth covariate in $\mathbf{X}$ does not tell us whether $CIF_c(t|\mathbf{X})$ is increasing or decreasing in this covariate. This is because the $CIF_c(t|\mathbf{X})$ depends on the survivor function $S(u|\mathbf{X})$, which itself depends on the hazard functions for other causes. Hence, $CIF_c(t|\mathbf{X})$ depends on the kth covariate in $\mathbf{X}$ not only through $\beta^k_{c,haz}$ but also through the hazard ratios associated with this covariate in the *other* cause-specific hazards, $\beta^k_{c',haz}$ (which of course may have a different sign).

G.3 Simulating Exit Times from the Cause-Specific Hazard Model

I simulate event times for cause c using the formula from Bender, Augustin, and Blettner (2015):

$$T^c_{ij} = H^{-1}_{c,0}\left(-log(U^c_{ij})exp(-\mathbf{X}'_{ij}\beta_{c,haz})\right), \tag{16}$$

where U^c_{ij} is a uniformly distributed random variable, and $c \in \{death, discharge\}$.

A practical difficulty in implementing this formula is that $H_{c,0}(\cdot)$ is non-parametric in my model, and thus there is no closed form formula for $H^{-1}_{c,0}(\cdot)$. So, I linearly interpolate $H_{c,0}(t)$ for different values of t to obtain a closed form, and take its inverse.

As was mentioned briefly in the main text, I consider different assumptions about the correlation between U^c_{ij} and $U^c_{ij'}$ in my simulations. Exactly how I implement this is described in the next subsection.

G.4 Counterfactual Details

The structural model which the counterfactuals are based on includes interactions between resident characteristics and quality, as well as as triple interactions between resident characteristics, quality, and a dummy for the post-star ratings time period (2009–2010) in the demand side equation. In the supply side equation, I include nursing home quality, resident characteristics, as well as interactions between resident characteristics and a post-star ratings dummy. I draw from the sample of residents admitted in 2009 in all my simulations, abstracting away from potential changes in the pool of potential residents. Below, I describe how I implement the counterfactuals described in the main text.

- *Response Margins to Star Ratings*:
  - To simulate counterfactual outcomes for the 2009 sample under the pre-star ratings regime, I set the coefficients on the interaction terms with the post-star rating dummy to zero on both the demand and supply side (since the post-star rating dummy is always one for the 2009 sample).
  - To simulate the effect of changes in responsiveness due to the star ratings, I set the coefficients on the interaction terms with the post-star rating dummy to zero only on the supply side.
  - To simulate the effect of changes in responsiveness and changes in cream-skimming behavior due to the star ratings, I use the estimated coefficients for the model.
  - To simulate the effect of changes in responsiveness, changes in cream-skimming behavior, and quality adjustments by nursing homes due to the star ratings, I adjust nursing home quality using the pooled difference-in-difference estimates shown in Figure 7.

- *Increasing Responsiveness to Quality*: I increase responsiveness to quality for residents below the 95th percentile of the estimated distribution of responsiveness to the 95th percentile, and leave responsiveness of residents above this threshold unchanged.

- *Provision of Quality-Ranked Shortlists by Discharge Planners*: For each resident in the simulations, I consider the set of nursing homes within 15 miles that are willing to admit the resident at that point in time, and limit the choice set to the five nursing homes with highest quality.

- *Ban on Selective Admissions*: Recall that under the status quo admissions policies, nursing home j is willing to admit resident i if and only if $\pi_{ij} \geq 0$, where π_{ij} is given by:

$$\pi_{ij} = x_i'\psi^1 + w_j'\psi^2 x_i + occ_{ij}'\psi^{occ} + \omega_{ij}.$$

To simulate a ban on selective admissions, I compute the average of $x_i'\psi^1 + w_j'\psi^2 x_i$ which I denote by $\bar{\pi}_0$, and assume that a nursing home j is willing to admit resident i if and only if $\pi_{ij}^{ban} \geq 0$, where π_{ij}^{ban} is given by:

$$\pi_{ij}^{ban} = \bar{\pi}_0 + occ_{ij}'\psi^{occ} + \omega_{ij}.$$

- *No Capacity Constraints*: For these simulations, I assume that nursing homes are willing and able to admit any resident that applies.

- *Financial Incentives to Increase Staffing*: I use estimates from Gandhi, Olenski, Ruffini, and Shen (2024) who study such a scheme in policy. Their event study estimates show that the scheme increased staffing levels primarily at nursing homes with above-median Medicaid share. So, I take convert their estimates to percent increases in RN and LPN staffing, and impute counterfactual RN and LPN staffing at nursing homes with above-median Medicaid share in my data based on these percent increases. I then use the correlation between RN and LPN staffing levels with my quality measure in Table 3 to impute counterfactual quality for these nursing homes.

- *Uniform Assignment Rule*: Denote the distribution of capacity strain (as defined by the prior 7-day average of log occupancy residualized of nursing home-by-month fixed effects) conditional on $\pi_{ij} - \omega_{ij}$ (i.e., the non-stochastic component of nursing homes' admissions policies) being greater than zero by $F_{occ|\pi_{ij}-\omega_{ij}\geq 0}$. Assign each resident to the highest-quality nursing home within 15 miles of her for which capacity strain is no worse than $F^{-1}_{occ|\pi_{ij}-\omega_{ij}\geq 0}((1+0.55)/2)$. In particular, we assign resident i to the nursing home defined by:

$$\tilde{\mu}^{uniform}(i) = argmax_j \left\{ q_j | occ_{ij} \leq F^{-1}_{occ|\pi_{ij}-\omega_{ij}\geq 0}\left((1+0.55)/2\right), dist_{ij} \leq 15 \right\}.$$

The quantile $(1+0.55)/2$ is set so that the average stringency of nursing homes' admissions rules under the uniform assignment rule is the same as under the risk-stratified assignment rule, which is covered next.

- *Risk-Stratified Assignment Rule*: Define resident i's baseline mortality hazard for this counterfactual as the part of her baseline mortality hazard $exp(\mathbf{X}_{ij}'\beta_{death,haz})$ that is not due to nursing home quality, and denote the distribution of baseline mortality hazard by F_{risk}. For residents in the top decile of baseline mortality risk, assign them to the highest-quality nursing home (within 15 miles) for which capacity strain is no worse than $F^{-1}_{occ|\pi_{ij}-\omega_{ij}\geq 0}(1)$, i.e., the maximum value of $\pi_{ij} - \omega_{ij}$ for which any resident is ever admitted. For residents in the second-highest decile of risk, assign them to the highest-quality nursing home for which capacity strain is no worse than $F^{-1}_{occ|\pi_{ij}-\omega_{ij}\geq 0}(0.95)$, and so on. Note that residents in the lowest decile of risk are assigned to the highest-quality nursing home for which $occ_{ij} \leq F^{-1}_{occ|\pi_{ij}-\omega_{ij}\geq 0}(0.55)$, which explains why the quantile was chosen as $(1+0.55)/2$ for the uniform assignment rule above. More precisely, for a resident i in the kth highest decile of baseline mortality risk, we assign i to the nursing home:

$$\tilde{\mu}^{risk}(i) = argmax_j \left\{ q_j | occ_{ij} \leq F^{-1}_{occ|\pi_{ij}-\omega_{ij}\geq 0}\left(1-(k-1)(0.05)\right), dist_{ij} \leq 15 \right\}.$$

G.5 Simulation Algorithm

As described in the previous subsection, various counterfactuals may change the structural demand and supply parameters (κ and ψ), nursing home quality (q_j) to counterfactual values (which differ from their estimated values). Hence, in this subsection, I use tildes to describe the structural parameters, simulated latent variables, and simulated occupancy measures in the counterfactuals.

The simulation proceeds as follows:

1. Initialize the occupancy measures $\tilde{o}_{jt}$ and $\tilde{occ}_{jt}$ for nursing homes using the last days 30 days before the start of the sample in 2009, where $\tilde{o}_{jt}$ is the occupancy of nursing home j at time t, and:

$$\tilde{occ}_{j,t} = \left(\frac{1}{7}\sum_{s=t-6}^{t} log(\tilde{o}_{js})\right) - \left(\frac{1}{30}\sum_{s=t-29}^{t} log(\tilde{o}_{js})\right),$$

   approximates the occupancy measure used in the structural estimates (i.e., average log occupancy in the week leading up to a resident making her nursing home choice, demeaned of month fixed effects).

2. For $t = 1, ..., T^{sim}$:
   (a) For resident $i_t = 1, ..., I_t$:
      i. Draw $\bar{n} = 200$ residents from the sample of residents admitted to a nursing home in 2009.
      ii. Simulate residents' and nursing homes' counterfactual preferences, as given by:

$$\tilde{v}_{ij} = \tilde{X}'_{ij}\tilde{\kappa} + \tilde{\epsilon}_{ij},$$
$$\tilde{\pi}_{ij} = \tilde{W}'_{ij}\tilde{\psi}_{ij} + \tilde{\omega}_{ij},$$

      where $\tilde{X}_{ij}$ and $\tilde{W}_{ij}$ denote variables included in the demand and supply equations, and $\tilde{\epsilon}_{ij}$ and $\tilde{\omega}_{ij}$ are i.i.d. $N(0,1)$ draws.[44]
      iii. Find the nursing home the resident is assigned to given these counterfactual values of the latent variables, which I denote by $\tilde{\mu}(i_t)$.[45] This is given by:

$$\tilde{\mu}(i_t) = argmax\{j : \pi_{ij} \geq 0, \text{ and } \tilde{v}_{ij} \geq v_{ij'} \forall j' \text{ s.t. } \pi_{ij'} \geq 0\}.$$

[44] The matrix $\tilde{W}_{ij}$ for counterfactuals with a ban on selective admissions has different dimensions from the other simulations, since admissions policies do not vary by resident characteristics. Nonetheless, for notational simplicity I will not introduce additional notation here.

[45] I drop the small number of residents who are ineligible for any nursing home in the counterfactual.

iv. Simulate residents' event time $\tilde{T}^{c}_{i,\tilde{\mu}(i_t)}$ for cause $c \in \{death, discharge\}$ by drawing $U_{i,\tilde{\mu}(i_t)}$ from a uniform distribution on $[0,1]$ and calculating:

$$\tilde{T}^{c}_{i,\tilde{\mu}(i_t)} = \hat{H}^{-1}_{c,0}\left(-log(U^{c}_{i,\tilde{\mu}(i_t)})exp(-\tilde{\mathbf{X}}'\beta_{c,haz})\right).$$

Set residents' exit date from the nursing home as: $\tilde{T}_{i_t} = \lceil \min\{\tilde{T}^{death}_{i,\tilde{\mu}(i_t)}, \tilde{T}^{discharge}_{i,\tilde{\mu}(i_t)}\}\rceil$.

(b) Update the simulated occupancy for nursing homes at time $t+1$.

i. First, set:

$$\tilde{o}_{j,t+1} = \tilde{o}_{j,t} + f\tilde{low}_{j,t+1},$$

where $f\tilde{low}_{j,t+1}$ is the difference between the number of residents admitted to a nursing home at time t, and the number of residents whose exit date is at time t.

ii. Then, compute the simulated occupancy measure using the formula:

$$o\tilde{c}c_{j,t+1} = \left(\frac{1}{7}\sum_{s=t-5}^{t+1} log(\tilde{o}_{j,s})\right) - \left(\frac{1}{30}\sum_{s=t-28}^{t+1} log(\tilde{o}_{j,s})\right).$$

H Financial Incentives for Hospitals to Steer Patients Towards Higher-Quality Nursing Homes

To translate the abstract counterfactual of increasing residents' responsiveness to quality to the 95th percentile to an implementable policy lever, I calibrate a hospital-facing steering incentive that would have a similar effect on allocation. Specifically, the goal is to choose a payment scheme which yields the same average increase in quality of residents' chosen nursing homes as simulated in the counterfactual.

First, I quantify the change in the market share as a function of quality that is generated by increase in responsiveness in the counterfactual. In particular, denoting $Q_j \equiv 100q_j$ so that quality is in percentage point terms, I run the regression:

$$\Delta log(A_j) = \delta^{steer} Q_j + u^{steer}_j,$$

where ΔA_j is the difference in log admissions under the counterfactual that increases responsiveness to the 95th percentile relative to the counterfactual that does not change responsiveness. I estimate that $\delta^{steer} \approx 0.0988$, which implies that a 1 percentage point increase in risk-adjusted survival raises admissions by 0.0988 log-points (or 10.4 percent).

Next, I use the estimate from Cutler et al. (2020) that among vertically-integrated hospital-nursing home systems, the elasticity of self-referral with respect to profitability is:

$$\epsilon^{steer} = \frac{dlog\,(A)}{dlog(\pi^{steer})} \approx 2.5.$$

Hence, the percent increase in profitability required to increase risk-adjusted survival quality of chosen nursing homes for post-acute care residents by 1 percentage point is:

$$100\% \cdot \gamma^{unadjusted} = 100\% \cdot \frac{dlog(\pi)}{dQ} = 100\% \cdot \frac{\delta}{\epsilon^{steer}} \approx 3.95\%.$$

Given that only about 88 percent of residents in my sample are discharged from acute care hospitals, we scale up the conversion factor to $\gamma = \gamma^{unadjusted}/0.88 \approx 0.0449$ to increase the average quality of chosen nursing homes for post-acute care residents even further to make up the difference.

MedPac (2025) reports a total of 1.6 million Medicare covered stays in 2023 that cost \$30 billion in total, with an average profit margin of 22 percent. Based on these numbers, the average profit per Medicare-covered stay is:

$$\pi_0 \approx \frac{\$30,000,000,000}{1,600,000} \cdot 0.22 = \$4,125.$$

Hence, a payment scheme to hospitals which yields the same average increase in quality of chosen nursing homes as the counterfactual is approximately an additional $\$4125 \times 0.0449 \approx \$185$ per percentage point increase in risk-adjusted survival (for each patient they discharge to nursing homes).

I Details on Model of Endogenous Quality Choice

Recall from Section A.21 that nursing home j solves the following maximization problem:

$$\max_{q_j} \left[R - C_j(q_j)\right] D_j(q_j, q_{\sim j}) \text{ s.t. } D_j(q_j, q_{\sim j}) \leq \bar{N}_j,$$

where R and $C_j(q_j)$ are per-resident revenue and costs respectively, $\bar{N}_j$ is j's capacity constraint, and $D_j(q_j, q_{\sim j})$ is demand for nursing home j which depends on both j's quality choice as well as the quality choice of all other nursing homes. Denote profits by $\bar{\pi}_j(q_j, q_{\sim j}) = \left[R - C_j(q_j)\right] D_j(q_j, q_{\sim j})$.

We normalize $R = 1$ and demand to be the share of the market $D_j(q_j, q_{\sim j}) = p_j(q_j, q_{\sim j}) \in [0, 1]$, $\bar{N}_j = \bar{p}_j \in [0, 1]$. I assume that if capacity constraints do not bind, demand is given by:

$$p_j(q_j, q_{\sim j}) = \frac{e^{\bar{\kappa}_j^q q_j + \kappa^{dist} \bar{dist}_j}}{\sum_{j':m(j')=m(j)} e^{\bar{\kappa}_{j'}^q q_{j'} + \kappa^{dist} \bar{dist}_{j'}}},$$

where $\bar{dist}_j$ is the average distance between residents in j's market ($m(j)$) and j. In addition, I assume the following convex cost function:

$$C_j(q_j) = -c_j \cdot log\left(\frac{q_{max} - q_j}{q_{max} - q_{min}}\right).$$

For tractability, I abstract away from heterogeneity across residents (in both preferences and profitability).

Denote the lowest quality required by j to hit its capacity constraint by:

$$\bar{q}_j(q_{\sim j}) \equiv \inf_{q_j} \left\{ q_j : \frac{e^{\kappa^q q_j + \kappa^{dist} \bar{dist}_j}}{\sum_{j':m(j')=m(j)} e^{\kappa^q q_{j'} + \kappa^{dist} \bar{dist}_{j'}}} \geq \bar{p}_j \right\}.$$

Then, if $\partial \bar{\pi}_j(\bar{q}_j(q_{\sim j}), q_{\sim j})/\partial q_j < 0$, the optimal choice of quality q_j^* solves the following FOC:

$$\begin{aligned}\bar{\kappa}_j^q \cdot p_j(q_j^*, q_{\sim j})\left(1 - p_j(q_j^*, q_{\sim j})\right) &= \left(\frac{c_j}{q_{max} - q_j}\right) p_j(q_j^*, q_{\sim j}) \\ &\quad - c_j \cdot log\left(\frac{q_{max} - q_j}{q_{max} - q_{min}}\right) \cdot \bar{\kappa}_j^q p_j(q_j^*, q_{\sim j})\left(1 - p_j(q_j^*, q_{\sim j})\right),\end{aligned}$$

whereas if $\partial \bar{\pi}_j(\bar{q}_j(q_{\sim j}), q_{\sim j})/\partial q_j \geq 0$, then $q_j^* = \bar{q}_j(q_{\sim j})$.

To obtain the nursing home-specific cost parameters c_j, I assume that nursing homes' quality choices are optimal, and use the FOC or capacity constraint to back out c_j. Given evidence from Section 4 that responsiveness to quality and nursing home quality both changed as a result of the star ratings, I use quality and demand from both periods (pre- and post-star ratings) for the calibration, but assume that c_j is time invariant. In cases where capacity constraints in both periods are not binding, I simply set c_j to be:

$$c_j = \frac{\bar{\kappa}_j^q \cdot (1-p_j)}{\dfrac{1}{q_{max}-q_j} - log\left(\frac{q_{max}-q_j}{q_{max}-q_{min}}\right) \cdot \bar{\kappa}_j^q\,(1-p_j)},$$

by rearranging the FOC (using average p_j, $\bar{\kappa}_j^q$, and q_j from the two periods). Note that if the capacity constraint binds, then $\partial\bar{\pi}_j(\bar{q}_j(q_{\sim j}), q_{\sim j})/\partial q_j \geq 0$, and generally there is a range of values of $c_j \in [0, \bar{c}_j]$ for which this inequality holds. So, if the capacity constraint binds in one period, I first consider setting c_j to the largest value consistent with the data for that period $\bar{c}_j$, and checking if it is consistent with the quality choice and capacity constraint in the other period and adjusting accordingly.[46]

I parametrize the demand-side counterfactuals by varying the level of $\bar{\kappa}^q$. In the counterfactual which increases responsiveness, I set $\bar{\kappa}_j^q$ to the average of the counterfactual distribution of responsiveness. By contrast, the counterfactual for the provision of quality-ranked shortlists does not map directly to a specific value of κ^q. To address this, I approximate this demand-side change by choosing a value of κ^q that generates the same average increase in quality of chosen nursing homes (based on the logit shares with capacity constraints) as the average increase for this corresponding counterfactual observed in panel (a) of Figure 8.

To simulate quality choices by nursing homes for a counterfactual value of average responsiveness to quality $\tilde{\bar{\kappa}}^q$, I solve for the Nash equilibrium where each nursing home's quality choice is optimal given all other nursing homes' quality choice. Denoting:

$$\begin{aligned} g_j(q_j, q_{\sim j}) \equiv\; & \tilde{\bar{\kappa}}_j^q \cdot p_j(q_j, q_{\sim j})\,(1 - p_j(q_j, q_{\sim j})) \\ & - \left[\left(\frac{c_j}{q_{max}-q_j}\right) p_j(q_j, q_{\sim j}) - c_j \cdot log\left(\frac{q_{max}-q_j}{q_{max}-q_{min}}\right) \cdot \tilde{\bar{\kappa}}_j^q p_j(q_j, q_{\sim j})\,(1 - p_j(q_j, q_{\sim j}))\right], \end{aligned}$$

we can write the equilibrium conditions as:

$$g_j(\tilde{q}_j^*, \tilde{q}_{\sim j}^*) \geq 0,$$

$$\bar{q}_j(\tilde{q}_{\sim j}^*) - \tilde{q}_j^* \geq 0,$$

$$g_j(\tilde{q}_j^*, \tilde{q}_{\sim j}^*) \cdot \left(\bar{q}_j(\tilde{q}_{\sim j}^*) - \tilde{q}_j^*\right) = 0,$$

for all nursing homes j.

I solve for the Nash equilibrium via fixed point iteration as follows:

1. I initialize nursing home quality $q_j^{(0)}$ to be equal to the estimated quality from the data for all j.
2. For iterations $k = 1, ..., K$ for some large number K:
    (a) I start by computing the predicted shares for nursing homes in each market based on the

[46] For example, suppose the capacity constraint binds in the pre-period and $\bar{c}_j^{pre}$ is the largest value of c_j consistent with the pre-period capacity constraint binding (specifically, where $\partial\bar{\pi}_j(\bar{q}_j(q_{\sim j}), q_{\sim j})/\partial q_j = 0$ in the pre-period). If the post-period capacity constraint also binds, then I set c_j to the minimum of $\bar{c}_j^{pre}$ and $\bar{c}_j^{post}$. On the other hand, if the pre-period capacity constraint does not bind, I compute the value of c_j that solves the FOC in the post period, denoting this by c_j^{post*}, and if $c_j^{post*} \leq \bar{c}_j^{pre}$, then I set $c_j = \bar{c}_j^{pre}$. There is a possibility that $c_j^{post*} > \bar{c}_j^{pre}$ which would lead to a contradiction. This may occur because of the simplifying assumptions in the model, or because of estimation noise in pre- and post-star ratings responsiveness and quality. In practice, this is very rare, and in such cases I set $c_j = \min\left\{\bar{c}_j^{pre}, c_j^{post*}\right\}$.

values of nursing home quality $q^{(k-1)}$ from the previous iteration.

i. First, I compute the share unconstrained logit share for each nursing home:

$$p_j^{(k),unconstrained} = \frac{e^{\tilde{\bar{\kappa}}_j^q q_j^{(k-1)} + \kappa^{dist} \bar{dist}_j}}{\sum_{j':m(j')=m(j)} e^{\tilde{\bar{\kappa}}_{j'}^q q_{j'}^{(k-1)} + \kappa^{dist} \bar{dist}_{j'}}}.$$

ii. Then, for nursing homes with predicted shares that exceed capacity ($p_j^{(k),unconstrained} > \bar{p}_j$), I adjust predicted share to be equal to capacity, and redistribute the excess shares among the unconstrained nursing homes within the same market proportionally (according to their shares).

iii. It is possible that the previously unconstrained nursing homes exceed capacity after receiving excess shares from other nursing homes, so I iterate the process of reallocating excess shares until convergence. I denote the final shares by $p_j^{(k)}$.

(b) Next, I compute the best-response quality choice given $p_j^{(k)}$.

i. If $p_j^{(k)} < \bar{p}_j$, then I set $\hat{q}_j^{(k)}$ as the solution to the FOC:

$$\tilde{\bar{\kappa}}_j^q \cdot p_j^{(k)} \left(1 - p_j^{(k)}\right) - \left[\left(\frac{c_j}{q_{max} - q_j}\right) p_j^{(k)} - c_j \cdot log\left(\frac{q_{max} - q_j}{q_{max} - q_{min}}\right) \cdot \tilde{\bar{\kappa}}_j^q p_j^{(k)} \left(1 - p_j^{(k)}\right)\right] = 0.$$

ii. If $p_j^{(k)} = \bar{p}_j$, then I reduce $\hat{q}_j^{(k)}$ by a small fraction of the excess share from $q_j^{(k-1)}$ to come closer to feasibility.

(c) I set nursing home for the next iteration as:

$$q^{(k)} = (1 - \lambda) q^{(k-1)} + \lambda \hat{q}^{(k)}.$$

(d) If $\|q^{(k)} - q^{(k-1)}\|_\infty < \epsilon^{tol}$ for a small tolerance $\epsilon^{tol} > 0$, convergence is achieved so I stop the loop and set $\tilde{q}^* = q^{(k)}$.[47] Otherwise, continue to the next iteration.

Note that when computing the best-response functions for constrained nursing homes, I typically do not immediately reduce quality all the way to the quality that would set the constrained nursing home's share to exactly equal to its constraint. Similarly, when updating nursing home quality in each iteration, I generally only update partially from the previous iteration's quality. I adopt this dampening procedure to avoid cycling or oscillations, at the cost of potentially longer computational times.

J Variable Selection Procedure Motivated by Double Machine Learning

The validity of my quality estimates relies on the selection on observables assumption, so it helps that my data contains more than 500 baseline resident characteristics. However, including the full set of controls may raise concerns of "overfitting", especially because many of the control variables correspond to medical conditions that are quite rare and because the sample sizes for some nursing homes are relatively small.[48] Hence, I use a variable selection method motivated by the post-double-selection

[47] In practice, ϵ^{tol} is set at 10^{-6}.

[48] An example in this context would be if some of the controls (that one need not control for to obtain consistent estimates of quality) end up being perfectly collinear with some of the nursing home choice dummies so that it becomes impossible to estimate quality for these nursing homes.

procedure used by Belloni, Chernozhukov, and Hansen (2014).

The standard post-double-selection procedure involves running Lasso regressions of both the outcome Y_i and the endogenous variable D_i on the full set of controls X_i , then taking the union of the variables selected in these two Lasso regressions for the final estimation of the treatment effect.[49] The complication with applying post-double-selection in the present setting is that the vector of treatment variables is relatively high-dimensional; specifically, it contains $J - 1 > 800$ nursing home choice dummies, in contrast to most settings where post-double-selection is used that only involve a single treatment variable (or at most, a few). Running Lasso regressions of each nursing home choice dummy D_{ij} on the full set of controls is computationally infeasible.

Hence, instead of running Lasso regressions of each nursing home choice dummy (and the outcome) on the full set of controls, I create a linear index summarizing the "type" of nursing home a resident chooses based on the leave-out mean of the outcome variable, i.e., $\bar{Y}_{\mu(i),-i} \equiv \frac{1}{N_{\mu(i)} - 1} \sum_{i' \neq i} Y_{i'} D_{i',\mu(i)}$, where $\mu(i)$ denotes the nursing home chosen by resident i, and $N_j \equiv \sum_{i=1}^{N} D_{ij}$. We can motivate the use of $\bar{Y}_{\mu(i),-i}$ in the post-double-selection procedure based on a correlated effects approach, which involves modeling the causal effects β_j as a function of observables (resident outcomes in this case), and I also use the leave-one-out mean to avoid a mechanical relationship between Y_i and $\bar{Y}_{\mu(i),-i}$. I then apply the standard post-double-selection procedure but using $\bar{Y}_{\mu(i),-i}$ in place of D_i. Finally, I take the union of the variables selected by the two Lasso regressions (of Y_i on X_i and $\bar{Y}_{\mu(i),-i}$ on X_i) and estimate an empirical Bayes model using this set of controls.

K Details on Empirical Bayes Implementation

Recall that we are estimating the model:

$$Y_i = \mu_1 + \sum_{j=2}^{J} \beta_j D_{ij} + X_i'\gamma + \epsilon_i,$$

where the parameters of interest are β_j. We can rewrite this in a more familiar form for panel data:

$$Y_{ji'} = \mu_1 + X_{ji'}'\gamma + \beta_j + \epsilon_{ji'},$$

so that nursing homes (indexed by j) correspond to the members of the (unbalanced) panel, and residents in nursing homes (indexed by i') are akin to the time dimension in panel data.

Adopting a Bayesian perspective, I treat the parameters β_j as random and as being drawn from a prior distribution $N(0, \sigma_\beta^2)$. Under the approximation that $\epsilon_{ji'}$ are drawn from a mean zero normal distribution with variance σ_ϵ^2, we can derive the likelihood function for maximum likelihood estimation

[49] Although the omitted variables bias is zero if the omitted variable is either unrelated to the endogenous variable or unrelated to the outcome, taking the union of the selected variables makes the procedure robust to "modest" errors in the variables selection process.

(MLE). In particular, the log-likelihood for the jth nursing home is given by:

$$l_j = -\frac{1}{2}\Bigg\{ \frac{1}{\sigma_\epsilon^2} \sum_{i'=1}^{N_j} (Y_{ji'} - \mu_1 - X'_{ji'}\gamma)^2 - \frac{\sigma_\beta^2}{N_j \sigma_\beta^2 + \sigma_\epsilon^2} \left[\sum_{i'=1}^{N_j} (Y_{ji'} - \mu_1 - X'_{ji'}\gamma) \right]^2 + log\left(N_j \frac{\sigma_\beta^2}{\sigma_\epsilon^2} + 1 \right) + N_j log(2\pi\sigma_\epsilon^2) \Bigg\},$$

where N_j denotes the total number of residents in nursing home j (over the sample period), and the log-likelihood is minimized over $(\mu_1, \gamma', \sigma_\beta^2, \sigma_\epsilon^2)'$. Finally, the empirical Bayes estimates of nursing home quality are given by:

$$\hat{\alpha}_j = \frac{\hat{\sigma}_\beta^2}{\hat{\sigma}_\beta^2 + \hat{\sigma}_\epsilon^2/N_j} \left[\frac{1}{N_j} \sum_{i'=1}^{N_j} (Y_{ji'} - \hat{\mu}_1 - X'_{ji'}\hat{\gamma}) \right] + \frac{\hat{\sigma}_\epsilon^2/N_j}{\hat{\sigma}_\beta^2 + \hat{\sigma}_\epsilon^2/N_j} \left[\frac{1}{N} \sum_{j=1}^{J} \sum_{i'=1}^{N_j} (Y_{ji'} - \hat{\mu}_1 - X'_{ji'}\hat{\gamma}) \right], \quad (17)$$

where N is the total number of observations.[50]

L Simple Model of Attenuation Bias in IV Due to Positively Correlated Measurement Errors

Consider IV estimation of the forecast coefficient λ. Recall that the endogenous variable is the quality estimate of resident i's chosen nursing home $\hat{\alpha}_i$, and the instrument $\hat{Z}_i$ is the quality estimate of the nursing home closest to the resident, where the "hats" emphasize that these are finite-sample estimates.[51] Define the fixed effects quality estimate by $\hat{\alpha}_j$, and its empirical Bayes counterpart by $\hat{\alpha}_j^{EB}$ (and similarly for the instruments, which are average estimated quality of nursing homes close to each resident). Given that we use a finite-sample estimate $\hat{\alpha}_j = \alpha_j + e_{\alpha,j}$ (or its empirical Bayes counterpart) in place of the estimate $\alpha_i \equiv \lim_{N_{j(i)} \to \infty} \hat{\alpha}_i$ that we will obtain in large samples, it suffers from measurement error, and similarly for $\hat{Z}_i = Z_i + e_{Z,\mathcal{N}_i}$ (or its empirical Bayes counterpart) since it is defined using the $\hat{\alpha}_j$'s, where $\mathcal{N}_i$ is the set of nursing home close to the resident and $Z_i \equiv \lim_{N_{j(i)} \to \infty} \hat{Z}_i$.

Let $\mu(i)$ denote the nursing home chosen by the resident. I assume the measurement error is classical, so that $e_{\alpha,j} \sim^{i.i.d.} N(0, Var(e_\alpha))$, and that the quality estimates are independent and normalized to have mean zero. Given that the instrument is average estimated quality of nursing homes close to each resident, the finite-sample measurement error in the instrument will be correlated with the endogenous variable, i.e., estimated quality of the actual nursing home chosen by the resident.

For simplicity, I omit the controls in my description, but this is without loss of generality since we can think of the variables as residualized of the controls due to the Frisch-Waugh theorem. I will

[50] This MLE can be implemented in Stata via the "xtreg, mle" command. However, as a sidenote, the postestimation command "predict, u" in Stata to recover the random effects is somewhat misleading. In particular, it yields the unshrunken estimates $\sum_{i'=1}^{N_j} (Y_{ji'} - \hat{\mu}_1 - X'_{ji'}\hat{\gamma})/N_j$, instead of the shrunken estimates (which confusingly is the result when one runs the same postestimation command after using a different random effects estimator "xtreg, re"). Therefore, shrinkage must be done manually after running "xtreg, mle".

[51] For simplicity, I omit the notation indicating that this is a leave-year-out estimate.

denote the population reduced form and first stage as:

$$Y_i = a_0 + \delta_r Z_i + e_i^r,$$
$$\alpha_i = b_0 + \delta_f Z_i + e_i^f,$$

respectively. Similarly, I will use "hats" for all of these variables for the finite-sample reduced form and first stage regressions.

In this section, I derive the attenuation bias in finite samples due to positively correlated measurement errors. I do so for the two types of value-added quality estimates — fixed effects quality estimates, and empirical Bayes quality estimates. I then derive a correction factor for IV estimation based on the fixed effects quality estimates, and show that this IV correction factor is already implicitly accounted for in the shrinkage procedure underlying the empirical Bayes estimates.

L.1 IV Using the Fixed Effects Quality Estimates

I start with the fixed effects quality estimates. First, we have:

$$\begin{aligned} Cov(Y_i, \hat{Z}_i) &= Cov(a_0 + \delta_r Z_i + e_i^r, \hat{Z}_i) \\ &= \delta_r \cdot Cov(Z_i, Z_i + e_{Z,\mathcal{N}_i}) \\ &= \delta_r \cdot Var(Z_i), \end{aligned}$$

and:

$$\begin{aligned} Cov(\hat{\alpha}_i, \hat{Z}_i) &= Cov(\alpha_i + e_{\alpha,\mu(i)}, Z_i + e_{Z\mathcal{N}_i}) \\ &= Cov(b_0 + \delta_f Z_i + e_i^f + e_{\alpha,\mu(i)}, Z_i + e_{Z\mathcal{N}_i}) \\ &= \delta_f Var(Z_i) + Cov(e_{\alpha,\mu(i)}, e_{Z\mathcal{N}_i}) \\ &= \delta_f \left(Var(Z_i) + Cov(e_{\alpha,\mu(i)}, e_{Z\mathcal{N}_i})/\delta_f \right) \end{aligned}$$

So, the IV estimate $\hat{\lambda}$ is given by:

$$\begin{aligned} \hat{\lambda} &= \frac{\delta_r \cdot Var(Z_i)/Var(\hat{Z}_i)}{\delta_f \left(1 + Cov(e_{\alpha,\mu(i)}, e_{Z\mathcal{N}_i})/\delta_f\right)/Var(\hat{Z}_i)} \\ &= \lambda \cdot \frac{Var(Z_i)}{Var(Z_i) + Cov(e_{\alpha,\mu(i)}, e_{Z\mathcal{N}_i})/\delta_f}, \end{aligned}$$

where λ is the population IV estimate.

Since:

$$\begin{aligned} \hat{Z}_i &= \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} (\alpha_j + e_{\alpha,j}) \\ &= \underbrace{\frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} \alpha_j}_{\equiv Z_i} + \underbrace{\frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} e_{\alpha,j}}_{\equiv e_{Z,\mathcal{N}_i}}, \end{aligned}$$

we also have:

$$\begin{aligned}Cov(e_{\alpha,\mu(i)}, e_{Z,\mathcal{N}_i}) &= \mathbb{E}[e_{\alpha,\mu(i)} e_{Z,\mathcal{N}_i}] \\ &= Pr\left(\mu(i) \in \mathcal{N}_i\right) \mathbb{E}[e_{\alpha,\mu(i)} e_{Z,\mathcal{N}_i} | \mu(i) \in \mathcal{N}_i] \\ &= \frac{Pr\left(\mu(i) \in \mathcal{N}_i\right) \mathbb{E}[e^2_{\alpha,\mu(i)}]}{|\mathcal{N}_i|} \\ &= \frac{Pr\left(\mu(i) \in \mathcal{N}_i\right) Var(e_{\alpha,j})}{|\mathcal{N}_i|}.\end{aligned}$$

In addition, we have:

$$\begin{aligned}\delta_f &= Cov(\alpha_i, Z_i)/Var(Z_i) \\ &= \mathbb{E}[\alpha_i Z_i]/Var(Z_i) \\ &= Pr\left(\mu(i) \in \mathcal{N}_i\right) \mathbb{E}[\alpha_i Z_i | \mu(i) \in \mathcal{N}_i]/Var(Z_i) \\ &= \frac{Pr\left(\mu(i) \in \mathcal{N}_i\right) Var(\alpha_j)}{|\mathcal{N}_i| \cdot Var(Z_j)}\end{aligned}$$

Hence, we find that:

$$\begin{aligned}Cov(e_{\alpha,\mu(i)}, e_{Z\mathcal{N}_i})/\delta_f &= \frac{Pr\left(\mu(i) \in \mathcal{N}_i\right) Var(e_{\alpha,j})}{|\mathcal{N}_i|} \cdot \frac{|\mathcal{N}_i| \cdot Var(Z_j)}{Pr\left(\mu(i) \in \mathcal{N}_i\right) Var(\alpha_j)} \\ &= \frac{Var(e_{\alpha,j}) \cdot Var(Z_j)}{Var(\alpha_j)},\end{aligned}$$

assuming that $Pr\left(\mu(i) \in \mathcal{N}_i\right) > 0$ (i.e., that the first stage exists).

Substituting back into the formula for the finite-sample IV estimate: we obtain:

$$\begin{aligned}\hat{\lambda} &= \lambda \cdot \frac{Var(Z_i)}{Var(Z_i) + Cov(e_{\alpha,\mu(i)}, e_{Z\mathcal{N}_i})/\delta_f} \\ &= \lambda \cdot \frac{Var(Z_i)}{Var(Z_i) + \dfrac{Var(e_{\alpha,j}) \cdot Var(Z_j)}{Var(\alpha_j)}} \\ &= \lambda \cdot \frac{Var(Z_i)}{Var(Z_i)\left(1 + \dfrac{Var(e_{\alpha,j})}{Var(\alpha_j)}\right)} \\ &= \lambda \cdot \frac{Var(\alpha_j)}{Var(\alpha_j) + Var(e_{\alpha,j})}.\end{aligned}$$

From this, we see that the finite-sample IV estimate is attenuated by a factor $\frac{Var(\alpha_j)}{Var(\alpha_j) + Var(e_{\alpha,j})}$. Therefore, we need to multiply $\hat{\lambda}$ by a correction factor $\frac{Var(\alpha_j) + Var(e_{\alpha,j})}{Var(\alpha_j)}$, where both $Var(\alpha_j)$ and $Var(e_{\alpha,j})$ are available from the fixed effects quality estimation procedure.

L.2 IV Using the Empirical Bayes Quality Estimates

Recall that the empirical Bayes estimate of a nursing home quality is given by:

$$\hat{\alpha}_j^{EB} = \frac{Var(\alpha_j)}{Var(\alpha_j) + s^2/N_j} \hat{\alpha}_j = \frac{Var(\alpha_j)}{Var(\alpha_j) + Var(e_{\alpha,j})} \hat{\alpha}_j,$$

where s^2 is the variance of the error term in the value-added estimation equation, and N_j is the number of observations for nursing home j (i.e., the number of residents admitted to nursing home j for the first time during the sample period).

Assuming that $\alpha_j \perp N_j$ (which is a reasonable approximation given that occupancy rates at nursing homes are relatively high and that estimated responsiveness to nursing home quality is quite low on average), we find that:

$$\begin{aligned}
Cov(Y_i, \hat{Z}_i^{EB}) &= Cov\left(Y_i, \frac{1}{|\mathcal{N}_i|}\sum_{j\in\mathcal{N}_i}\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}\hat{\alpha}_j\right)\\
&= Cov\left(a_0 + \delta_r Z_i + e_i^r, \frac{1}{|\mathcal{N}_i|}\sum_{j\in\mathcal{N}_i}\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}(\alpha_j + e_{\alpha,j})\right)\\
&= \mathbb{E}\left[(\delta_r Z_i)\left(\frac{1}{|\mathcal{N}_i|}\sum_{j\in\mathcal{N}_i}\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}(\alpha_j + e_{\alpha,j})\right)\right]\\
&= \delta_r \cdot \mathbb{E}\left[(Z_i)\left(\frac{1}{|\mathcal{N}_i|}\sum_{j\in\mathcal{N}_i}\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}\alpha_j\right)\right]\\
&= \delta_r \cdot Var(Z_i)\mathbb{E}\left[\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}\right]
\end{aligned}$$

Next, we also have:

$$\begin{aligned}
Cov(\hat{\alpha}_i^{EB}, \hat{Z}_i^{EB}) &= Cov\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\hat{\alpha}_{\mu(i)}, \frac{1}{|\mathcal{N}_i|}\sum_{j\in\mathcal{N}_i}\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}\hat{\alpha}_j\right)\\
&= \mathbb{E}\left[\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\hat{\alpha}_{\mu(i)}\right)\left(\frac{1}{|\mathcal{N}_i|}\sum_{j\in\mathcal{N}_i}\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}\hat{\alpha}_j\right)\right]\\
&= Pr\left(\mu(i)\in\mathcal{N}_i\right)\mathbb{E}\left[\frac{1}{|\mathcal{N}_i|}\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\right)^2\hat{\alpha}_{\mu(i)}^2\right]\\
&= Pr\left(\mu(i)\in\mathcal{N}_i\right)\mathbb{E}\left[\frac{1}{|\mathcal{N}_i|}\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\right)^2\alpha_{\mu(i)}^2\right]\\
&\quad + Pr\left(\mu(i)\in\mathcal{N}_i\right)\mathbb{E}\left[\frac{1}{|\mathcal{N}_i|}\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\right)^2\left(e_{\alpha,\mu(i)}\right)^2\right]\\
&= \frac{Pr\left(\mu(i)\in\mathcal{N}_i\right)}{|\mathcal{N}_i|}\cdot\mathbb{E}\left[\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\right)^2\right]\cdot\left(Var(\alpha_j)+Var(e_{\alpha,j})\right)
\end{aligned}$$

In addition, note that we can write the variance of the quality estimate $\hat{\alpha}_{\mu(i)}$ for the nursing home chosen by i as:

$$\begin{aligned}
Var(e_{\alpha,\mu(i)}) &= \mathbb{E}\left[s^2/N_{\mu(i)}\right] \\
&= \sum_j Pr\left(\mu(i)=j\right)\mathbb{E}\left[s^2/N_j\right] \\
&\approx \sum_j \left(\frac{N_j}{N}\right)\left(\frac{s^2}{N_j}\right) \\
&= \sum_j \frac{s^2}{N} \\
&= \frac{J}{N}s^2
\end{aligned}$$

Now, taking a first-order Taylor expansion for $\mathbb{E}\left[\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\right)^2\right]$ as a function of $s^2/N_{\mu(i)}$ around its mean $\mathbb{E}\left[s^2/N_{\mu(i)}\right] = (J/N)\cdot s^2$, we obtain:

$$\begin{aligned}
\mathbb{E}\left[\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_{\mu(i)}}\right)^2\right] &\approx \left(\frac{Var(\alpha_j)}{Var(\alpha_j)+(J/N)\cdot s^2}\right)^2 - 2\cdot\frac{Var(\alpha_j)^2}{\left(Var(\alpha_j)+(J/N)\cdot s^2\right)^3}\underbrace{\mathbb{E}\left[\frac{s^2}{N_{\mu(i)}}-\frac{J}{N}s^2\right]}_{=0} \\
&= \left(\frac{Var(\alpha_j)}{Var(\alpha_j)+(J/N)\cdot s^2}\right)^2,
\end{aligned}$$

and similarly, $\mathbb{E}\left[\frac{Var(\alpha_j)}{Var(\alpha_j)+s^2/N_j}\right] \approx \frac{Var(\alpha_j)}{Var(\alpha_j)+(J/N)\cdot s^2}$.

So, we can write:

$$\begin{aligned}
Cov(\hat{\alpha}_i^{EB},\hat{Z}_i^{EB}) &\approx \frac{Pr\left(\mu(i)\in\mathcal{N}_i\right)}{|\mathcal{N}_i|}\cdot\mathbb{E}\left[\left(\frac{Var(\alpha_j)}{Var(\alpha_j)+(J/N)\cdot s^2}\right)^2\right]\cdot\left(Var(\alpha_j)+\frac{J}{N}s^2\right) \\
&= \frac{Pr\left(\mu(i)\in\mathcal{N}_i\right)}{|\mathcal{N}_i|}\cdot\frac{Var(\alpha_j)^2}{Var(\alpha_j)+(J/N)\cdot s^2} \\
&= \underbrace{\left(\frac{Pr\left(\mu(i)\in\mathcal{N}_i\right)}{|\mathcal{N}_i|}\cdot\frac{Var(\alpha_j)}{Var(Z_i)}\right)}_{=\delta_f}\cdot Var(Z_i)\cdot\frac{Var(\alpha_j)}{Var(\alpha_j)+(J/N)\cdot s^2}
\end{aligned}$$

Therefore, the IV estimate using empirical Bayes quality estimates is (to a first order) given by:

$$\begin{aligned}
\hat{\lambda}^{EB} &\approx \frac{\delta_r\cdot Var(Z_i)\cdot\frac{Var(\alpha_j)}{Var(\alpha_j)+(J/N)\cdot s^2}}{\delta_f\cdot Var(Z_i)\cdot\frac{Var(\alpha_j)}{Var(\alpha_j)+(J/N)\cdot s^2}} \\
&= \frac{\delta_r}{\delta_f} \\
&= \lambda.
\end{aligned}$$

M Simple Model of Imperfect Information About Quality

Suppose that residents do not directly observe nursing home quality β_j, but only a noisy signal of it, $\check{\beta}_j = \beta_j + e_j^{\beta}$, as well as publicly available information about the nursing home $w_{\sim\beta,j}$, which includes reported staffing levels, ownership status, and number of cited deficiencies.[52] Assume also that $e^{\beta}_{j} \sim^{i.i.d.} N(0, \sigma^2_{e^{\beta}})$, and is independent of everything else.

Suppose that nursing home quality is drawn from a normal distribution, with a mean that is linear in publicly available information about nursing homes, specifically, $w'_{\sim\beta,j}\beta^{w_{\sim\beta}}_{\beta}$. In this case, residents' conditional expectation of nursing home j's quality given the signal is:

$$\tilde{\beta}_j \equiv \mathbb{E}[\beta_j|\check{\beta}_j] = \frac{\sigma^2_{e^{\beta}}}{\sigma^2_{e^{\beta}} + \sigma^2_{\beta}} w'_{\sim\beta,j}\beta^{w_{\sim\beta}}_{\beta} + \frac{\sigma^2_{\beta}}{\sigma^2_{e^{\beta}} + \sigma^2_{\beta}}\check{\beta}. \tag{18}$$

If we assume that residents' decision utility is given by $v_{ij} = \kappa^{\tilde{\beta}}\tilde{\beta}_j + \kappa^{dist}dist_{ij} + \epsilon_{ij}$, then substituting in the expression for $\tilde{\beta}_j$ derived above, we obtain:

$$v_{ij} = w'_{\sim\beta,j}\overbrace{\left[\left(\frac{\kappa^{\tilde{\beta}}\sigma^2_{e^{\beta}}}{\sigma^2_{e^{\beta}} + \sigma^2_{\beta}}\right) \cdot \beta^{w_{\sim\beta}}_{\beta}\right]}^{\equiv \kappa^{\tilde{\beta}}_{w_{\sim\beta}}} + \overbrace{\left[\frac{\sigma^2_{\beta}}{\sigma^2_{e^{\beta}} + \sigma^2_{\beta}} \cdot \kappa^{\tilde{\beta}}\right]}^{\equiv \kappa^{\tilde{\beta}}_{\beta}}\beta_j + \kappa^{dist}dist_{ij} + \tilde{\epsilon}_{ij}, \tag{19}$$

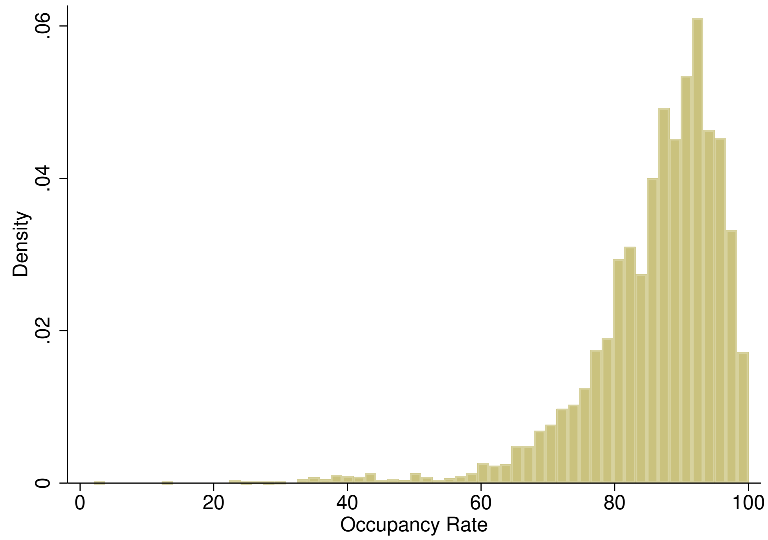
where $\tilde{\epsilon}_{ij} \equiv \kappa^{\tilde{\beta}}_{\beta}e^{\beta}_{j} + \epsilon_{ij}$ is a composite error term that is conditionally independent of the instruments given the covariates. Then, it is clear from the expression for $\kappa^{\tilde{\beta}}_{w_{\sim\beta}}$ that if residents have positive demand for expected quality ($\kappa^{\tilde{\beta}} > 0$), each component of $\kappa^{\tilde{\beta}}_{w_{\sim\beta}}$ should have the same sign as the corresponding component in $\beta^{w_{\sim\beta}}_{\beta}$. Therefore, when we estimate residents' preferences as a linear function of $w_{\sim\beta,j}$, β_j, and $dist_{ij}$, we should estimate that residents place positive weight on nursing home characteristics in $w_{\tilde{\beta},j}$ that positively predict quality β_j, and negative weight on those that negatively predict β_j.

The results are qualitatively similar if we allow for noise in the estimated quality measure β_j. It is easy to show that residents' preferences for components of $w_{\sim\beta,j}$ have the same sign as above: the only difference is that the weights that residents put on the quality signal and prior based on observables will now include a term for the variance of the estimation noise for β_j.

[52]For purposes of exposition, I initially assume that estimation noise in nursing home j is negligible, at least relative to the noise in the residents' signal e^{β}_{j}. I will also explain at the end of this section that relaxing this assumption does not change the model's predictions.

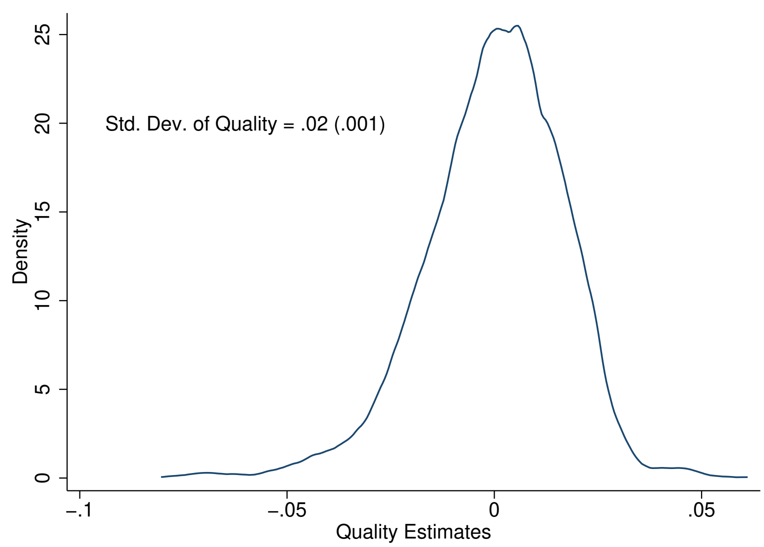
A Appendix Figures and Tables

Figure A.1: Nursing Home Occupancy Rates



Notes: This figure contains a histogram of nursing home occupancy rates, based on data from the OSCAR data set. The unit of observation is a nursing home-year, and observations are weighted by the number of residents admitted to the nursing home for their first stay during that year.

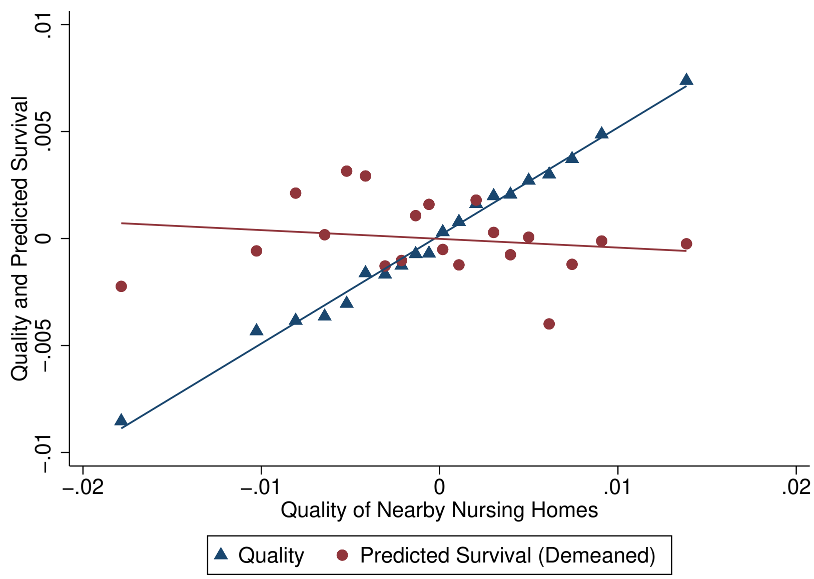
Figure A.2: Kernel Density Plot of Nursing Home Quality Estimates



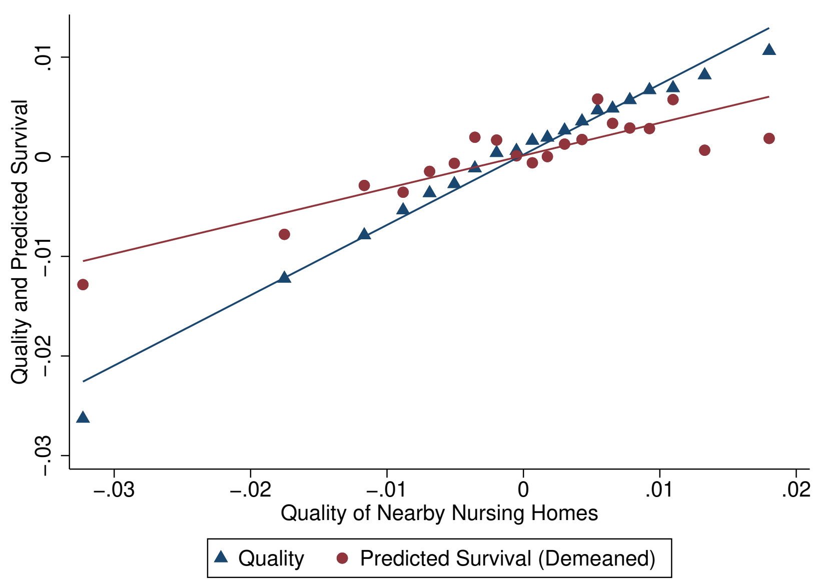
Notes: This figure contains a kernel density plot of the main quality estimates, using an Epanechnikov kernel. The standard error for the standard deviation of nursing home quality displayed in the figure is calculated based on the square root of the variance from the inverse of the Fisher information matrix from the maximum likelihood estimation of the empirical Bayes model in equation (1).

Figure A.3: Robustness of First Stage Assumption and Exclusion Restriction

(a) County Fixed Effects



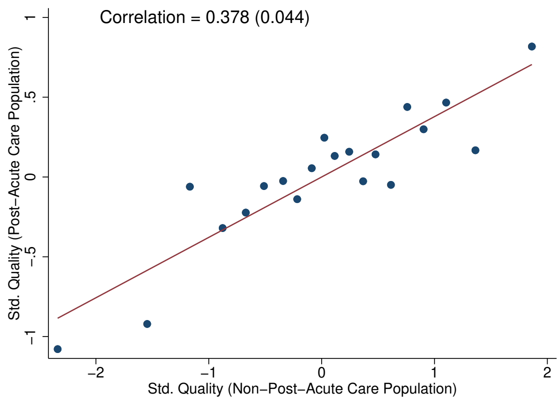
(b) No County Fixed Effects



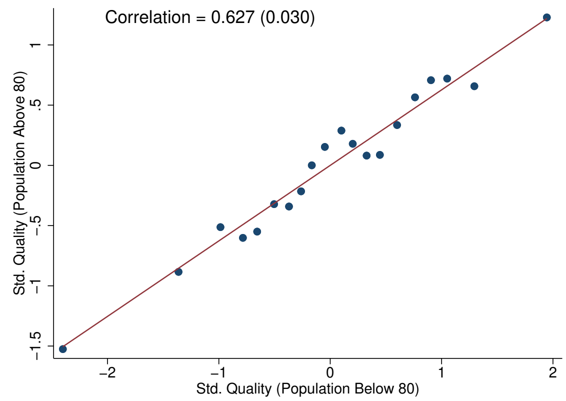
Notes: The x-axis in these figures correspond to the average quality of the five nearest nursing homes to each resident. Variables in panel A are residualized of county fixed effects, whereas variables in panel B are not residualized of county fixed effects.

Figure A.4: Bin Scatters of Quality Estimates for Different Subpopulations

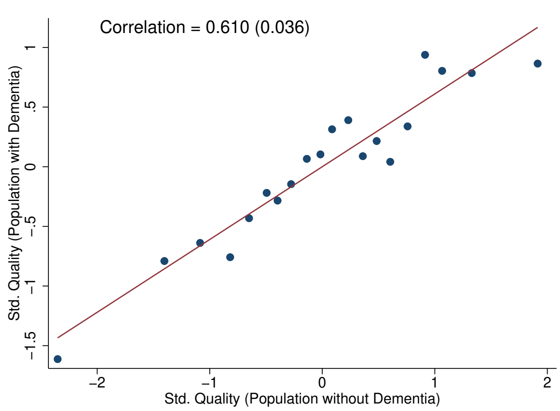
(a) Whether the Resident was Post-Acute Care



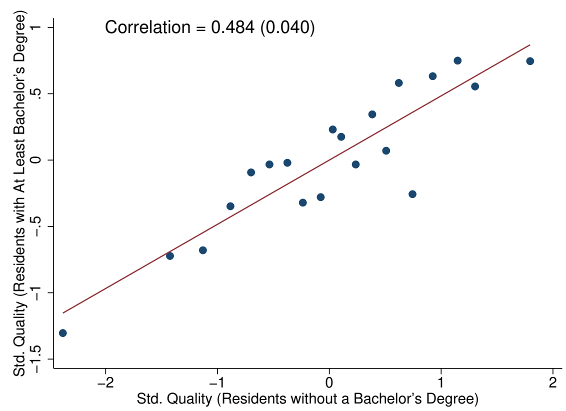
(b) Whether the Resident was Above 80



(c) Whether the Resident has Dementia



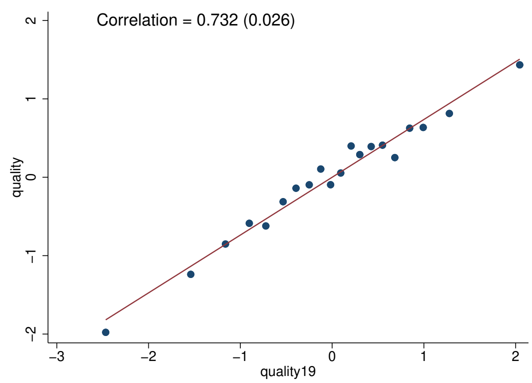
(d) Whether the Resident has Bachelor's Degree



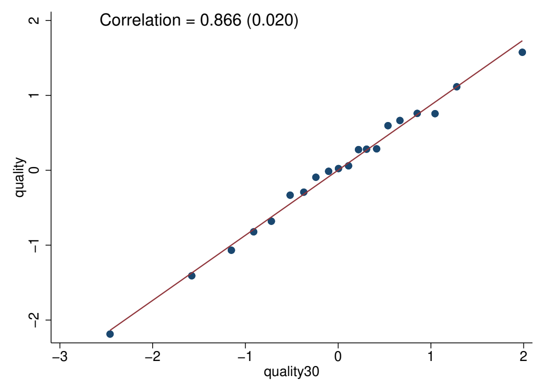
Notes: For each plot, I partition the resident population based on the resident characteristic in the sub-figure title, estimate quality separately for the two subsamples, and then plot these two sets of coefficients against each other.

Figure A.5: Relationship Between Empirical Bayes Quality Estimates Based on Mortality Over Different Time Horizons

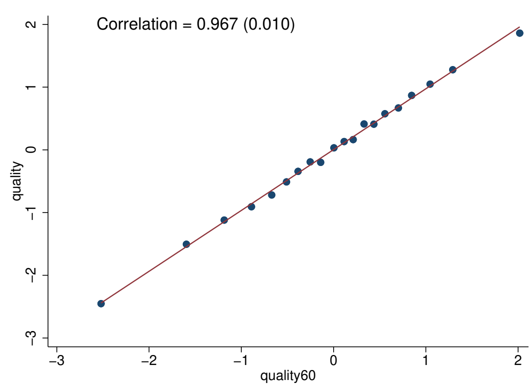
(a) 19-Day Versus 90-Day Mortality



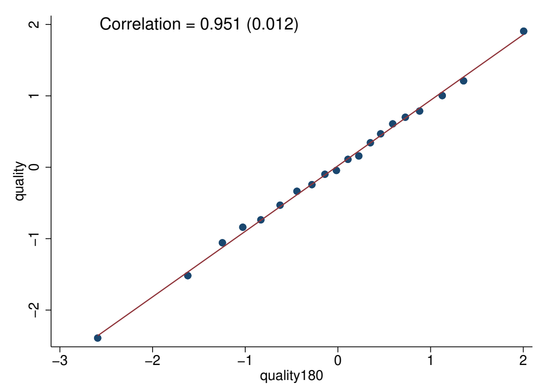
(b) 30-Day Versus 90-Day Mortality



(c) 60-Day Versus 90-Day Mortality



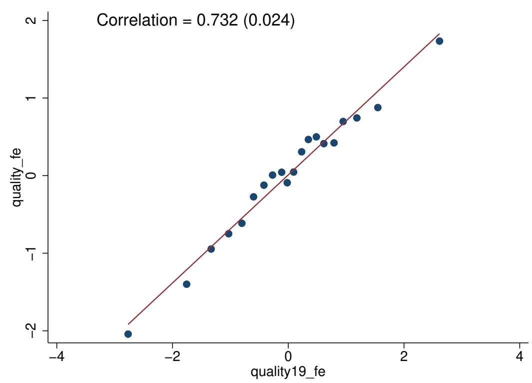
(d) 180-Day Versus 90-Day Mortality



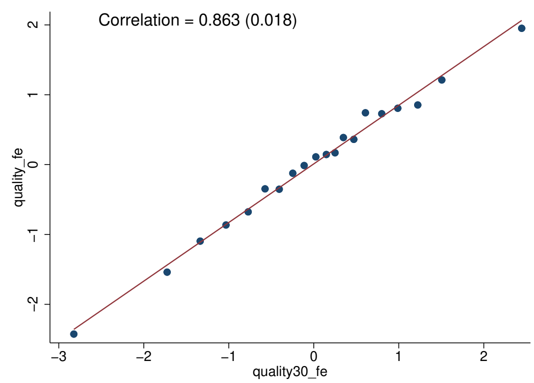
Notes: The x-axis of these figures correspond to empirical Bayes quality estimates using survival for at least 19, 30, 60, or 180 days as the outcome (standardized to have mean zero and standard deviation one). The bin scatters are weighted by the number of observations for each nursing home, and robust standard errors are used.

Figure A.6: Relationship Between Fixed Effects Quality Estimates Based on Mortality Over Different Time Horizons

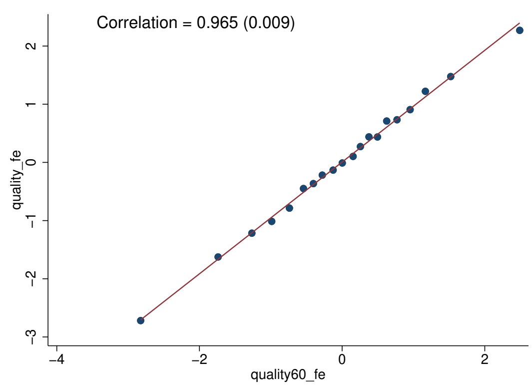
(a) 19-Day Versus 90-Day Mortality



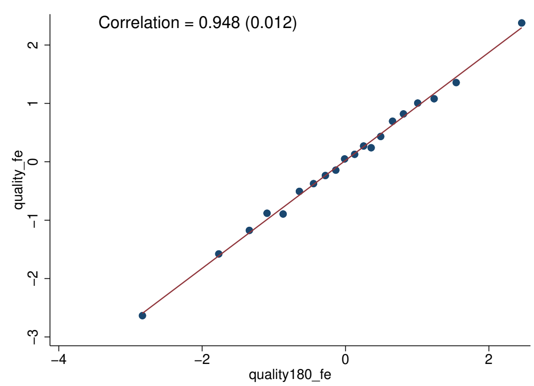
(b) 30-Day Versus 90-Day Mortality



(c) 60-Day Versus 90-Day Mortality

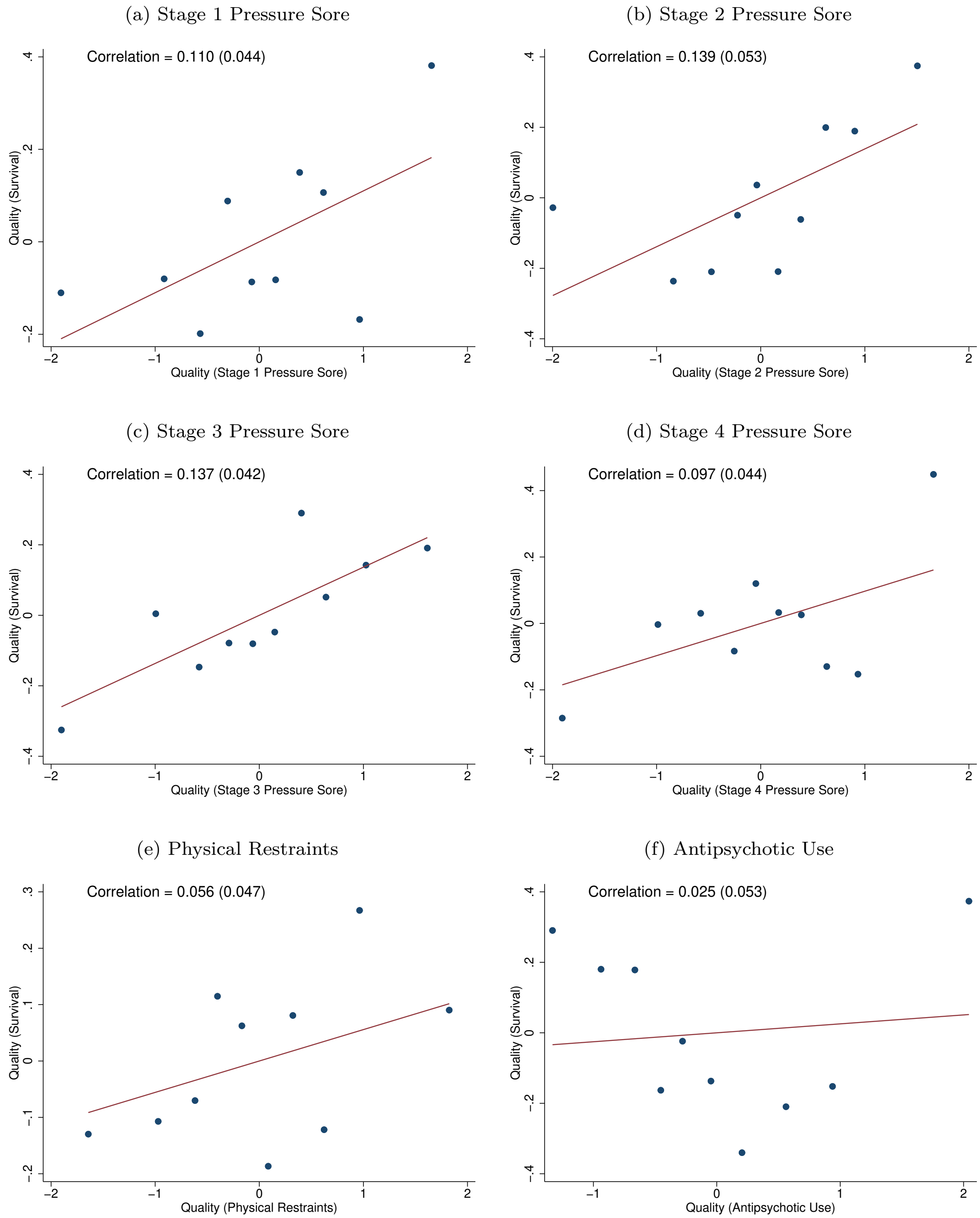


(d) 180-Day Versus 90-Day Mortality



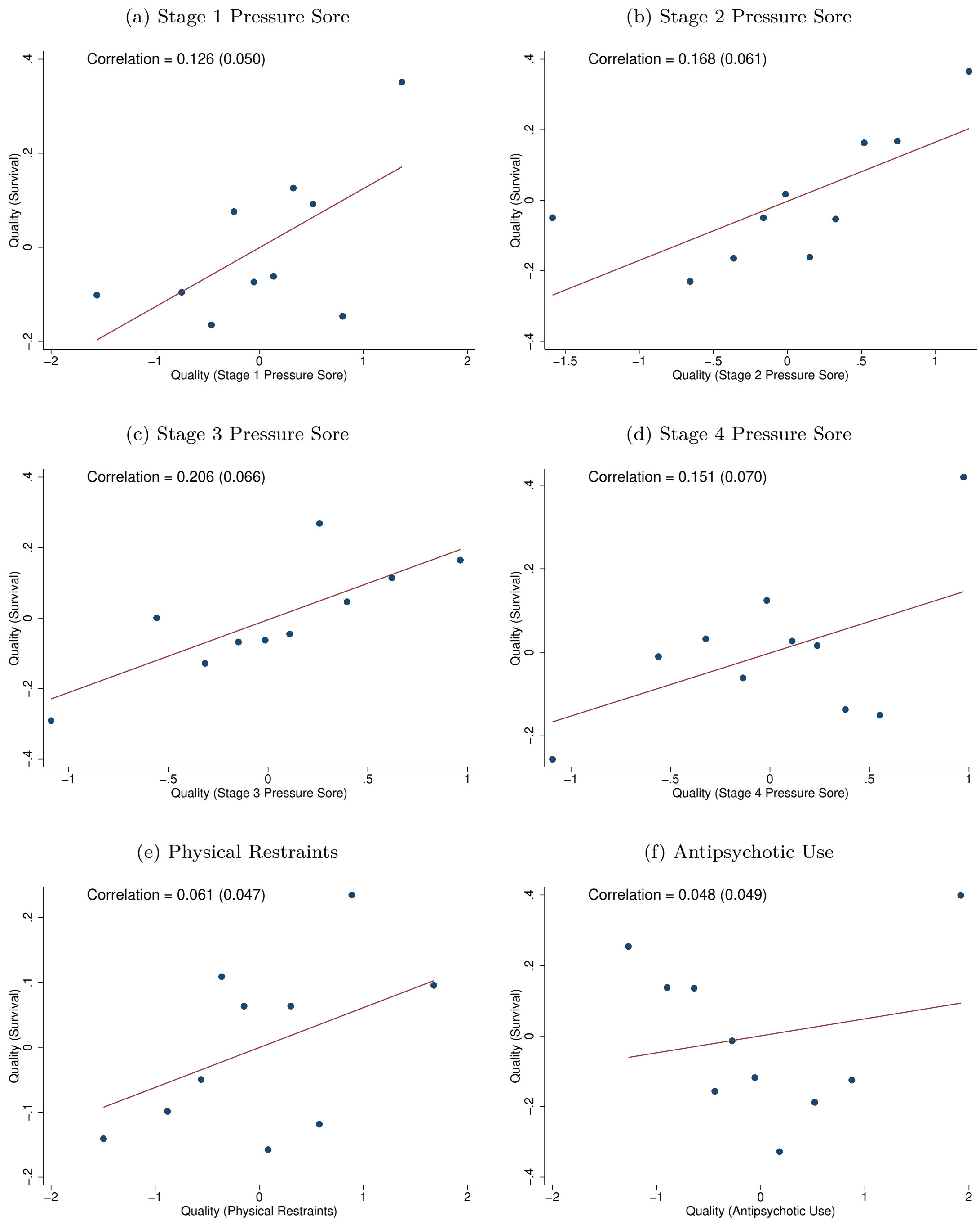
Notes: The x-axis of these figures correspond to fixed effects quality estimates using survival for at least 19, 30, 60, or 180 days as the outcome (standardized to have mean zero and standard deviation one). The bin scatters are weighted by the number of observations for each nursing home, and robust standard errors are used.

Figure A.7: Relationship Between Empirical Bayes Quality Estimates and Quality Estimates Based on Other Outcomes



Notes: The x-axis of these figures correspond to quality estimates using other resident outcomes (instead of 90-day survival rate) as the dependent variable. The estimation procedure is the same as for my main quality estimates, except that I use a different outcome variable, and I do not use double machine-learning to select controls for computational reasons. The outcome variables I use are dummies for not developing a stage S or higher pressure sore (for $S \in \{1, 2, 3, 4\}$), no use of physical restraints, and no use of antipsychotics during the first 90 days after admission. The bin scatters are weighted by the number of observations for each nursing home, and the standard errors are clustered by nursing home.

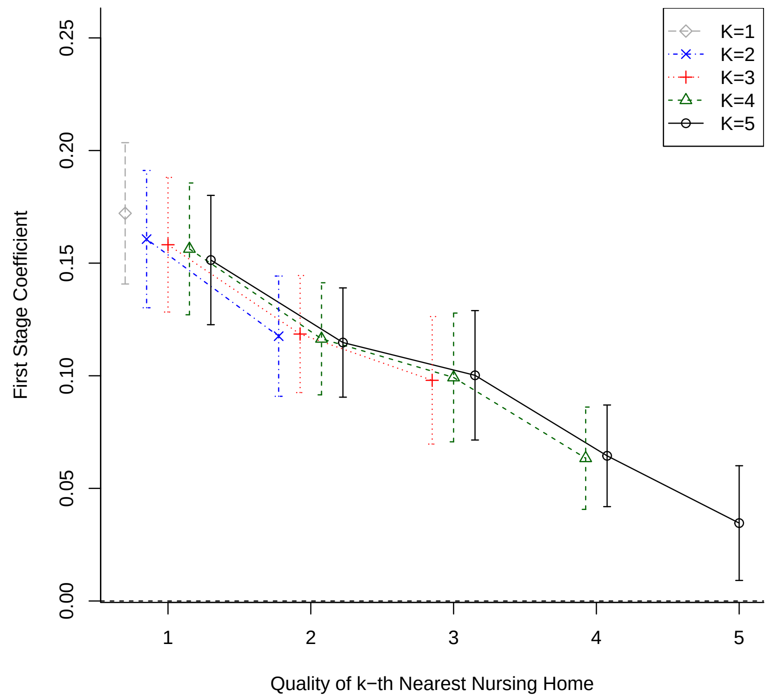
Figure A.8: Relationship Between Fixed Effects Quality Estimates and Quality Estimates Based on Other Outcomes



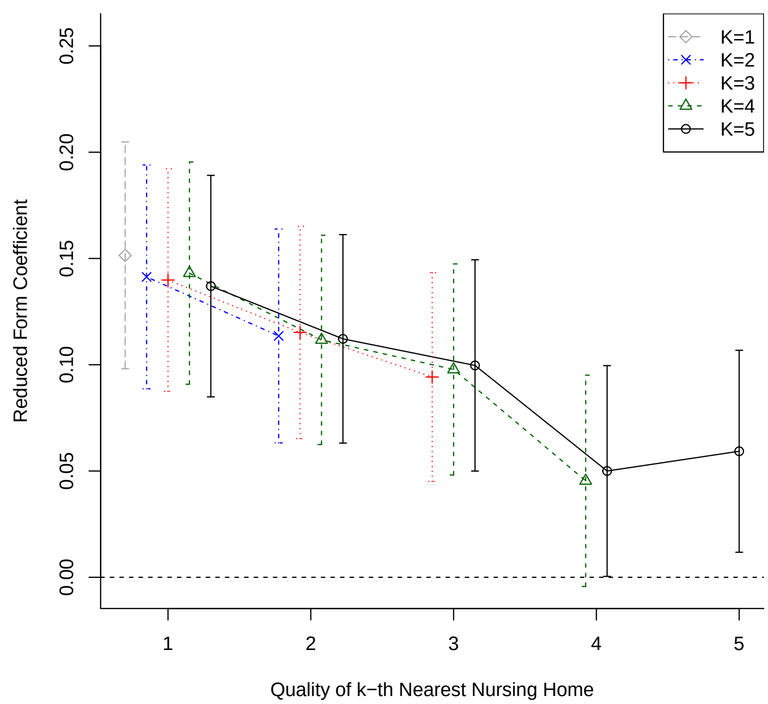
Notes: The x-axis of these figures correspond to quality estimates using other resident outcomes (instead of 90-day survival rate) as the dependent variable. The estimation procedure is the same as for my main quality estimates, except that I use a different outcome variable, and I do not use double machine-learning to select controls for computational reasons. The outcome variables I use are dummies for not developing a stage S or higher pressure sore (for $S \in \{1, 2, 3, 4\}$), no use of physical restraints, and no use of antipsychotics during the first 90 days after admission. The bin scatters are weighted by the number of observations for each nursing home, and the standard errors are clustered by nursing home.

Figure A.9: First Stage and Reduced Form for Different IV Specifications

(a) First Stage

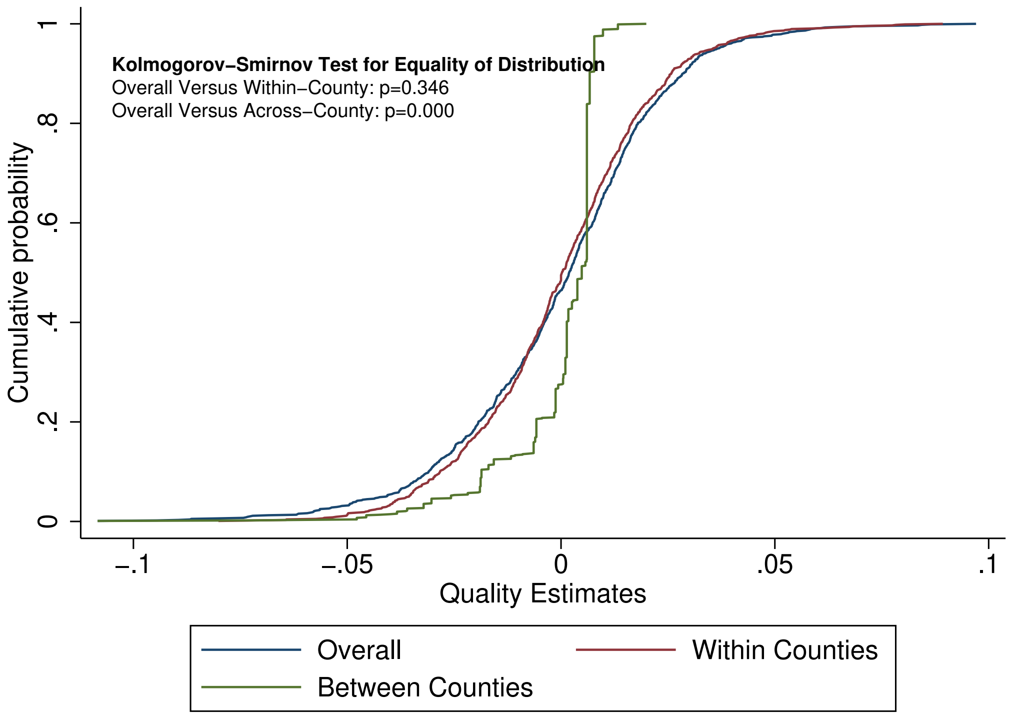


(b) Reduced Form



Notes: These figures plot the first-stage and reduced-form coefficients and the associated 95 percent confidence intervals for IV specifications that use the quality of the K nearest nursing homes to each resident as the instrument(s), for K ranging from one to five.

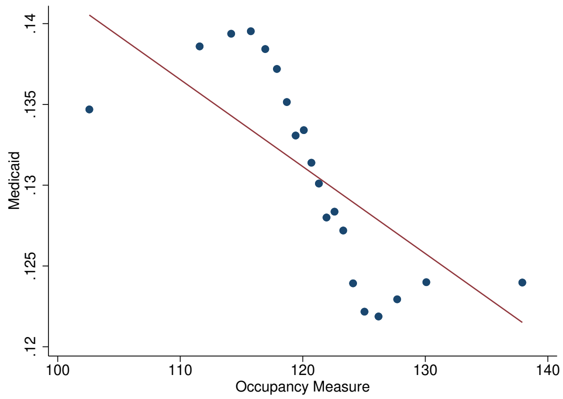
Figure A.10: ECDF of Fixed Effects Quality Estimates (Overall, Within Counties, and Between Counties)



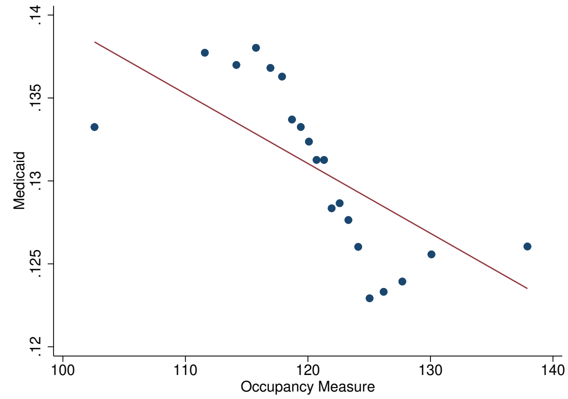
Notes: This figure plots the empirical CDFs showing the overall variation in nursing home quality, as well as the within-county and across-county variations in quality in blue, red, and green respectively. Within-county variation is plotted using the residuals from a regression of the quality estimates on county fixed effects, and across-county variation is plotted using the averages of the quality estimates within each county. The p-values from two-sample Kolmogorov-Smirnov tests for equality of distributions comparing the overall distribution of quality to the within-county and across-county distributions of quality are also shown in the figure.

Figure A.11: Reduced Form Evidence of Selective Admissions Using Lagged 7-day Average of Occupancy as Measure of Capacity Strain

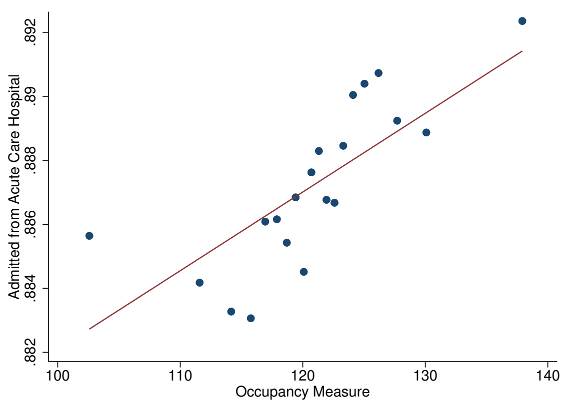
(a) Medicaid (without controls)



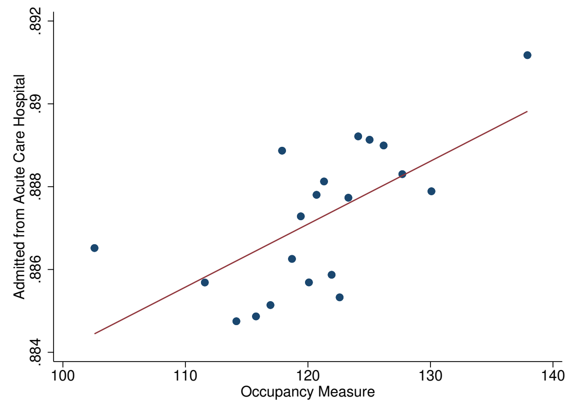
(b) Medicaid (with controls)



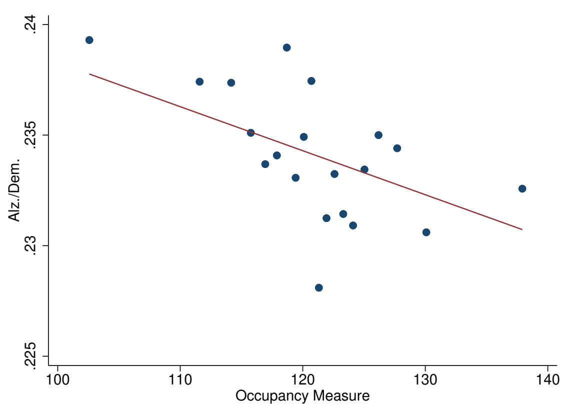
(c) Post-Acute Care (without controls)



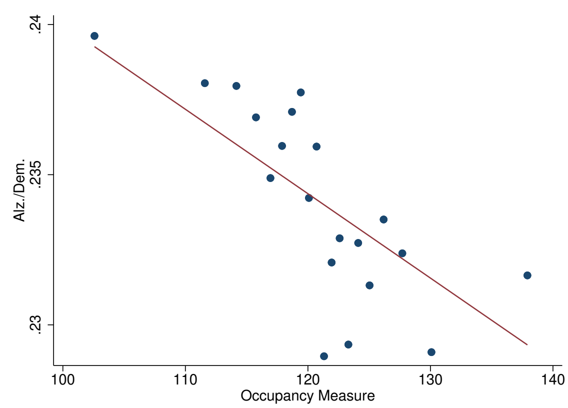
(d) Post-Acute Care (with controls)



(e) Alzheimer’s/Dementia (without controls)



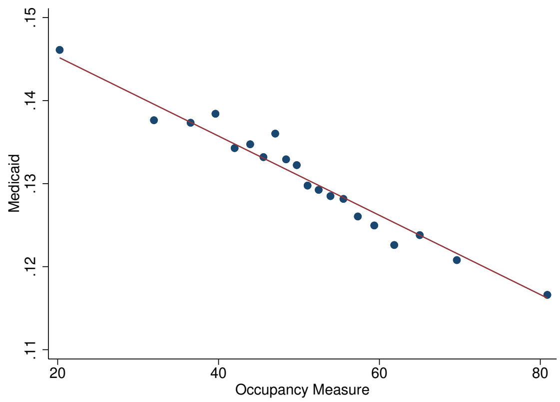
(f) Alzheimer’s/Dementia (with controls)



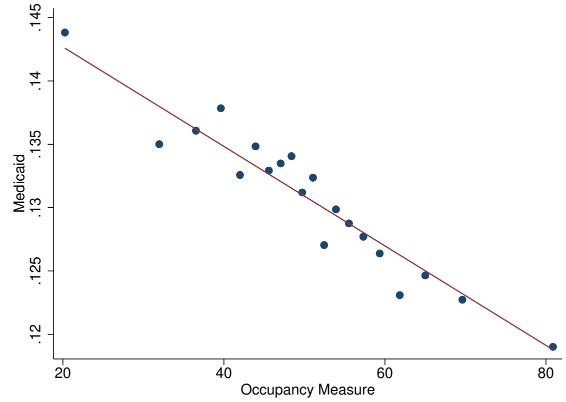
Notes: These bin scatters show indicators for Medicaid status and Alzheimer’s/dementia of admitted residents as a function of lagged seven-day average occupancy for the nursing home as of the date of admission for the resident. The bin scatters include nursing home-year fixed effects, and in some specifications, controls for Medicaid status, post-acute care, Alzheimer’s/dementia, age, education, primary language, and race, omitting the control that matches the outcome (e.g., Medicaid is not included as a control when Medicaid is the outcome in the bin scatter). The unit of observation is a resident.

Figure A.12: Reduced Form Evidence of Selective Admissions Using Lagged 7-day Average of Occupancy Percentile as Measure of Capacity Strain

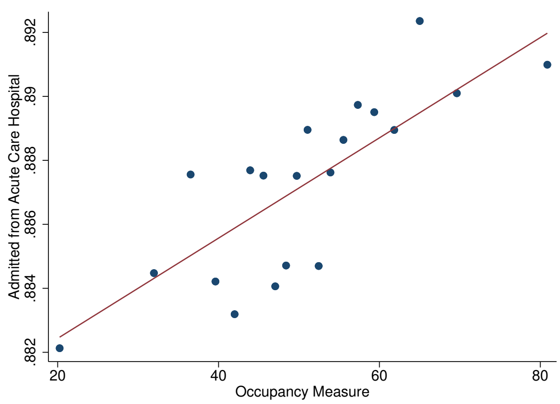
(a) Medicaid (without controls)



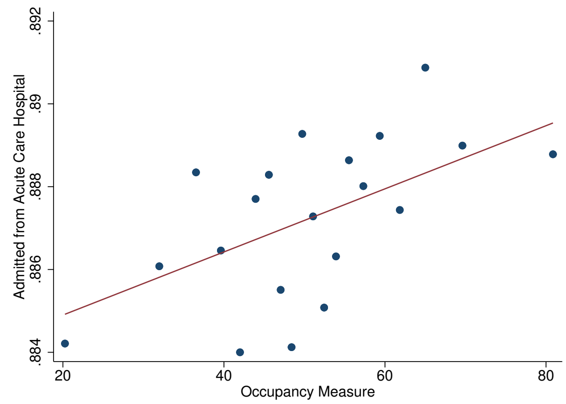
(b) Medicaid (with controls)



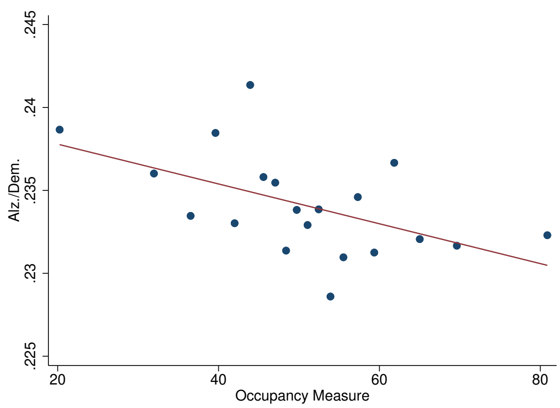
(c) Post-Acute Care (without controls)



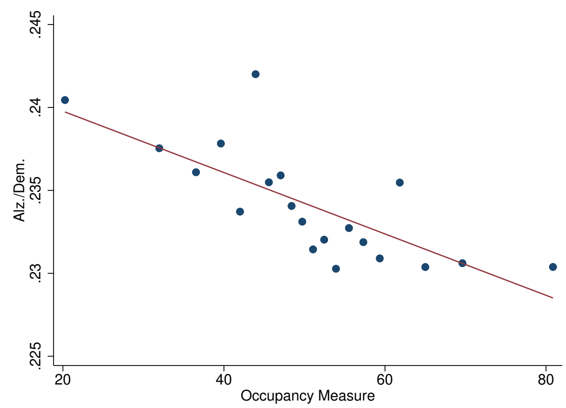
(d) Post-Acute Care (with controls)



(e) Alzheimer's/Dementia (without controls)

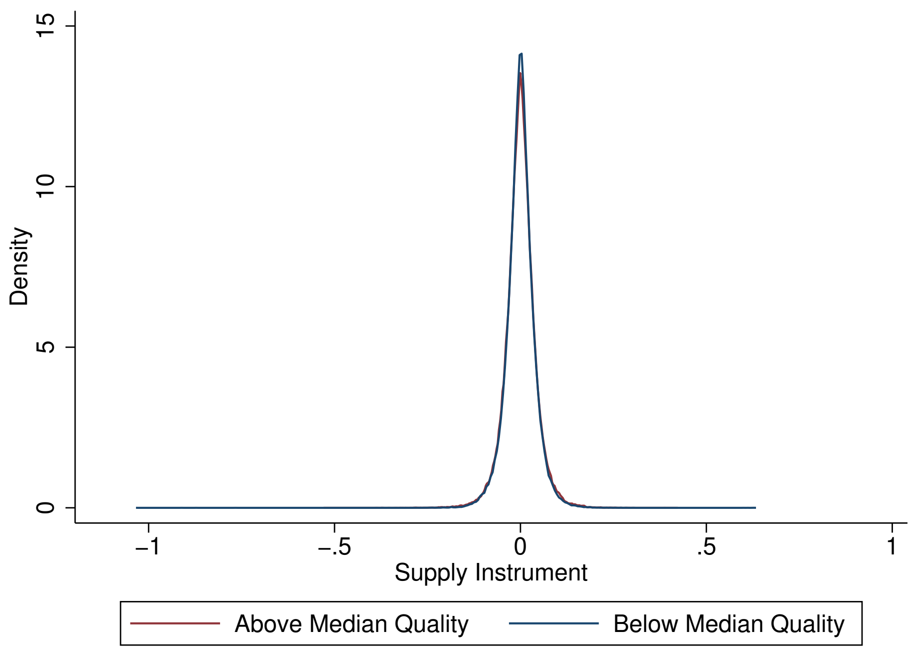


(f) Alzheimer's/Dementia (with controls)



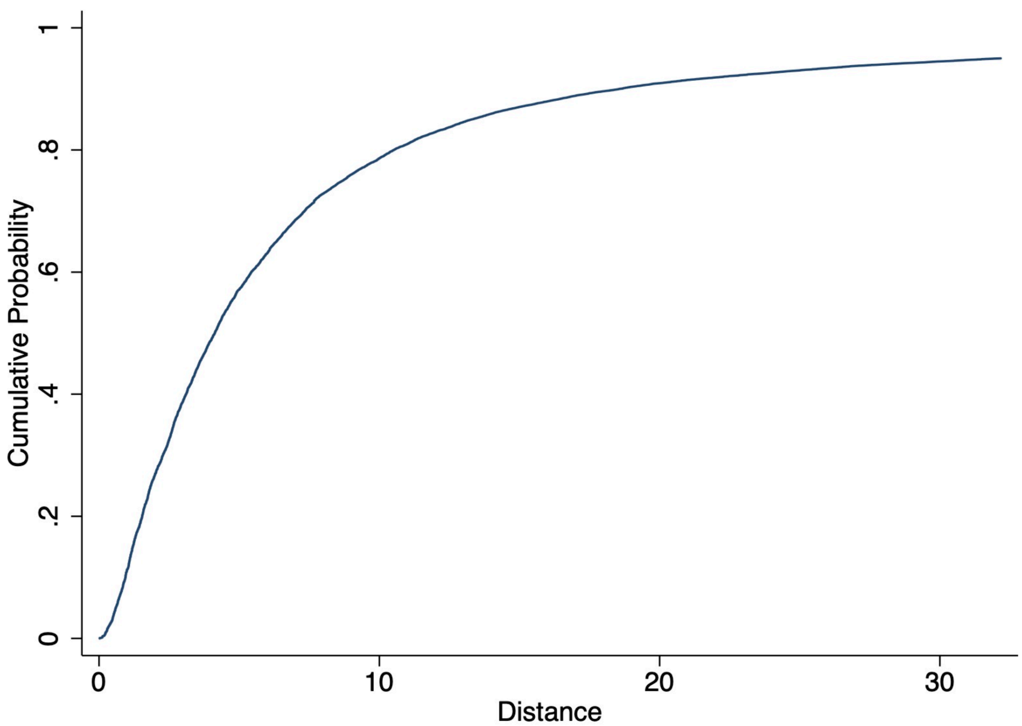
Notes: These bin scatters show indicators for Medicaid status and Alzheimer's/dementia of admitted residents as a function of lagged seven-day average occupancy percentile for the nursing home as of the date of admission for the resident. The bin scatters include nursing home-year fixed effects, and in some specifications, controls for Medicaid status, post-acute care, Alzheimer's/dementia, age, education, primary language, and race, omitting the control that matches the outcome (e.g., Medicaid is not included as a control when Medicaid is the outcome in the bin scatter). The unit of observation is a resident.

Figure A.13: Kernel Density Plot of occ_{ij} for Nursing Homes with Above-Median and Below-Median Quality



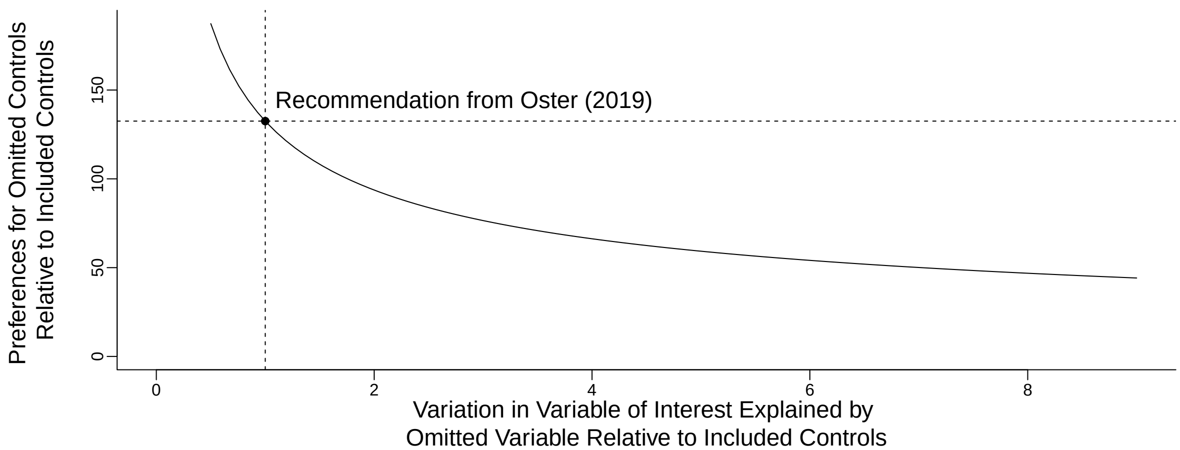
Notes: This figure contains the kernel density plot for the distributions of the supply side instrument occ_{ij} at above-median and below-median quality nursing homes, based on the Epanechnikov kernel. The unit of observation is a resident-nursing home pair (for nursing homes within 15 miles of each resident).

Figure A.14: Empirical CDF of Distance Between Residents and Their Chosen Nursing Homes



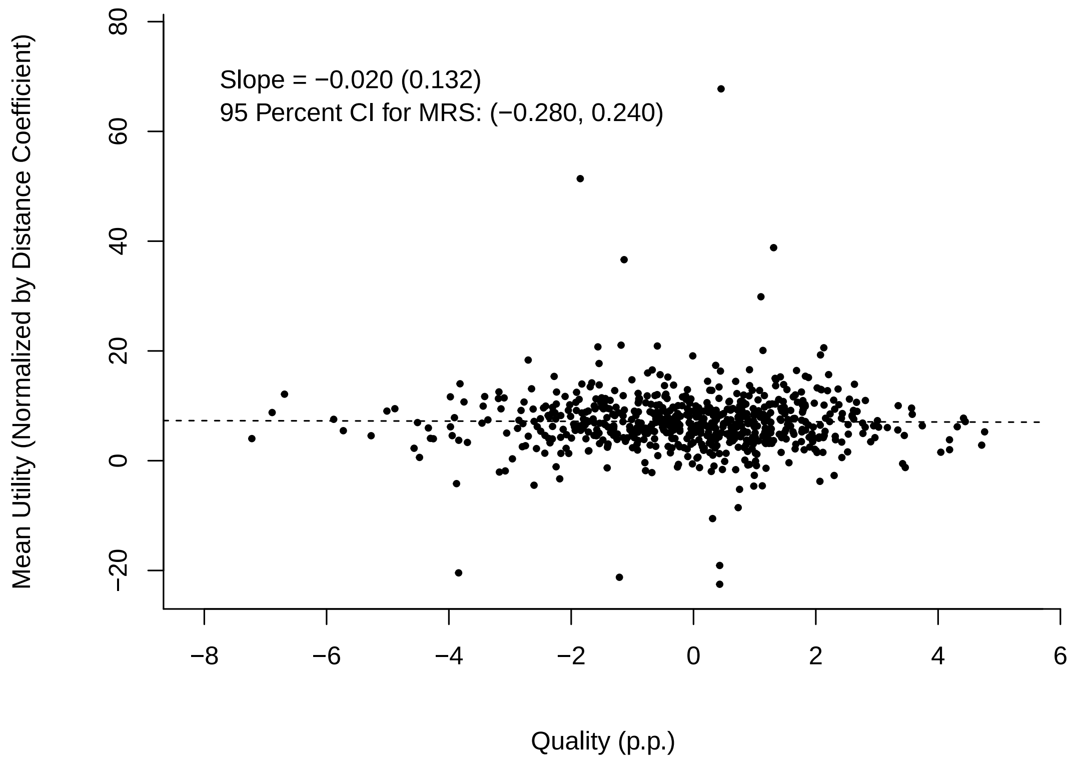
Notes: This figure shows the empirical CDF of distances between residents and their chosen nursing homes. The unit of observation is a resident.

Figure A.15: Conditions Under Which Selection on Unobservables Can Explain the Low Demand Estimate



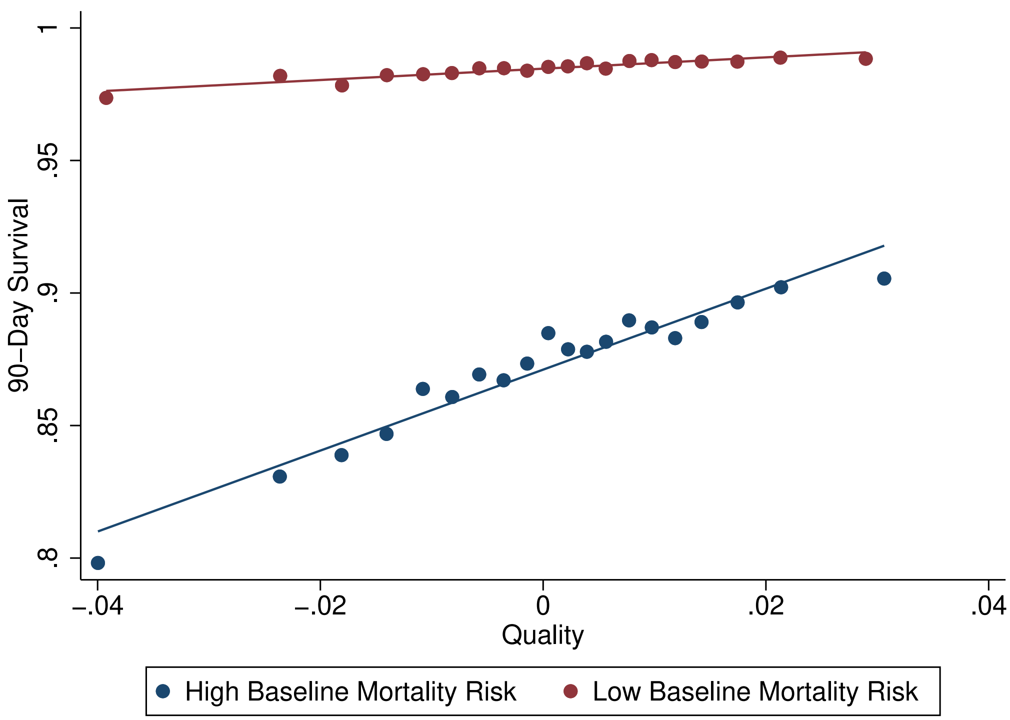
Notes: This figure shows conditions under which omitted variables bias can completely account for the low demand estimate in this paper, using methods from Cheng (2023). The x-axis represents hypothetical values of the proportional selection relationship (Oster 2019), i.e., the omitted variable's importance for explaining the explanatory variable of interest (quality β_j in this case) relative to the included controls (observable nursing home characteristics $w_{\sim\beta,j}$ in this setting) as measured by an R-squared from a hypothetical regression of β_j on $w_{\sim\beta,j}$ and the omitted variable, whereas the y-axis corresponds to hypothetical values for how much more the resident values the omitted variable relative to the included controls. The area to the northeast of the curve corresponds to combinations of these values under which omitted variables bias alone can explain the difference between my MRS estimate and the one from Chandra, Finkelstein, Sacarny, and Syverson (2016). Oster suggests that in many empirical applications, it is reasonable to assume that the omitted variable explains at most as much of the variation in the explanatory variable of interest as the omitted variable does, and the dashed lines in this figure show that under this assumption, the resident must value the omitted variable more than 100 times as much as she values nursing home characteristics $w_{\sim\beta,j}$, in order for omitted variables bias to completely explain my low demand estimate.

Figure A.16: Scatterplot of Mean Utility Against Quality



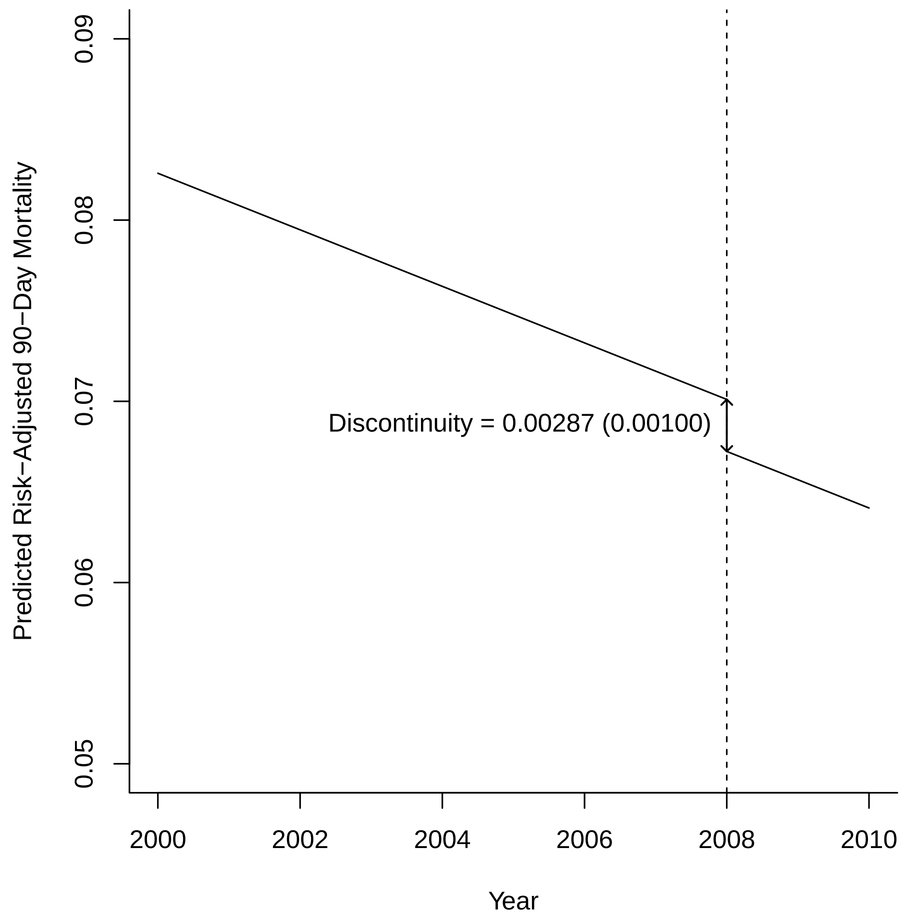
Notes: This figure plots mean utilities (divided by the coefficient for distance and multiplied by negative one) from the structural estimates with nursing home fixed effects in indirect utility against the quality estimates (in percentage points) on the x-axis. The unit of observation is a nursing home, and the regression for the best fit line is weighted by the number of observations corresponding to the nursing home in the entire sample. The slope of the line corresponds to the implied marginal rate of substitution (MRS) between quality and distance.

Figure A.17: Survival-Quality Gradient by Baseline Health



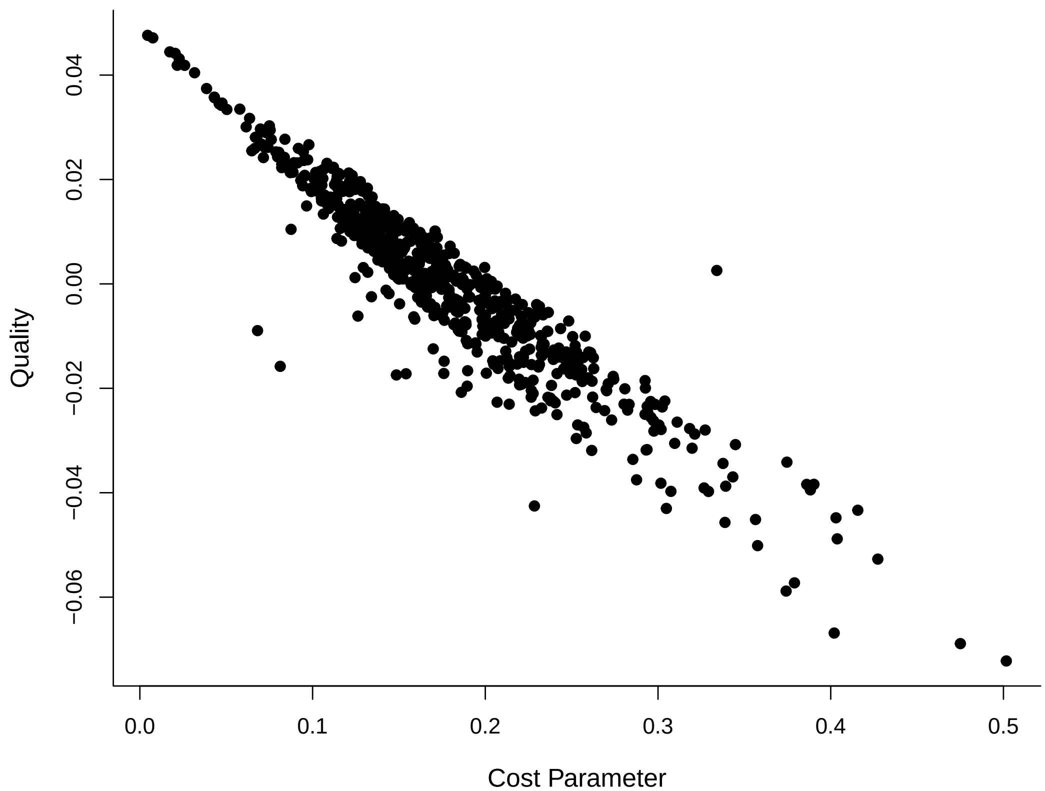
Notes: This figure shows bin scatters of 90-day survival on leave-year-out quality of the nursing home that the resident was admitted to, separately for residents with above-median and below-median baseline health respectively. Baseline health is defined as the probability of surviving at least 90 days based on baseline demographic and health characteristics, net of nursing home effects.

Figure A.18: Reduced Form Estimate of the Effect of Star Ratings on Mortality



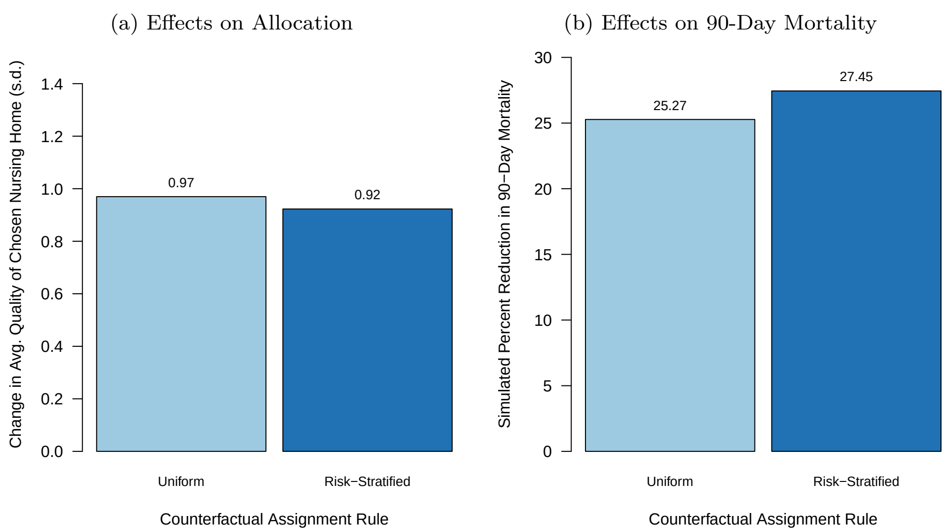
Notes: This figure shows predicted 90-mortality from a regression of 90-day mortality on a rich set of baseline demographic and health characteristics, a linear time trend, and a post-star ratings indicator. The discontinuity illustrated in the figure is the estimated effect of star ratings on 90-day mortality.

Figure A.19: Scatterplot of Quality Against Cost Parameter



Notes: This figure shows a scatterplot of quality q_j against the calibrated cost parameter c_j for the endogenous quality choice model.

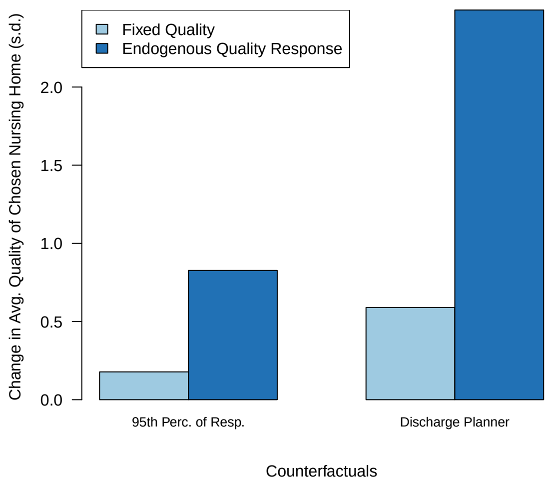
Figure A.20: Simulated Effect of Uniform and Risk-Stratified Assignment Rules



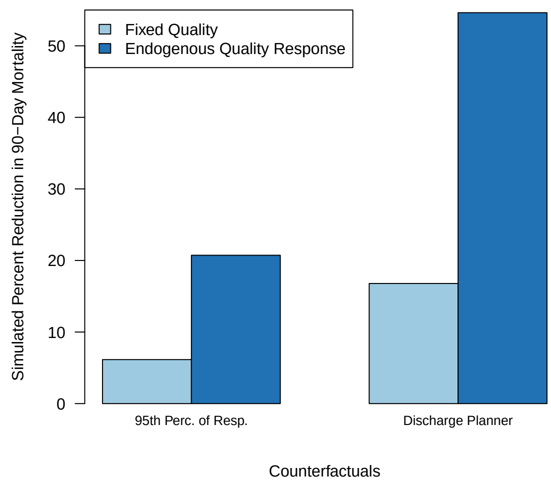
Notes: This figure shows the simulated effects of uniform and risk-stratified assignment rules. Panel (a) plots the simulated average change in quality of nursing homes chosen by residents (in standard deviations), and panel (b) plots the percent reduction in simulated 90-day mortality relative to pre-star ratings.

Figure A.21: Simulated Effect of Demand-Side Counterfactuals on Allocation and Mortality Accounting for Endogenous Quality Responses

(a) Effects on Allocation

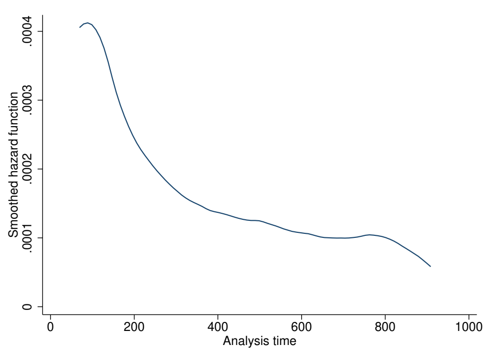


(b) Effects on 90-Day Mortality

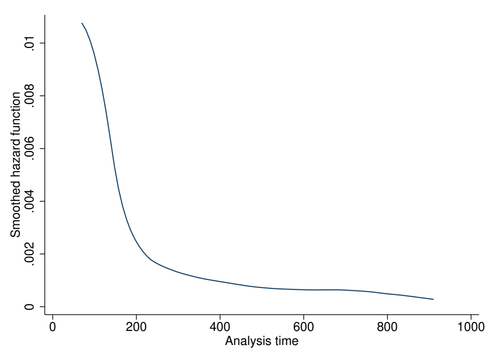


Notes: This figure shows the simulated effects of increasing residents' responsiveness to quality the 95th percentile and the provision of quality-ranked shortlists of available nursing homes by discharge planners, holding quality fixed in the light-blue bars or allowing for endogenous quality responses by nursing homes in the dark-blue bars. Panel (a) plots the simulated average change in quality of nursing homes chosen by residents (in standard deviations), and panel (b) plots the percent reduction in simulated 90-day mortality relative to pre-star ratings.

Figure A.22: Cause-Specific Baseline Hazard Functions, $h_{c,0}(t)$



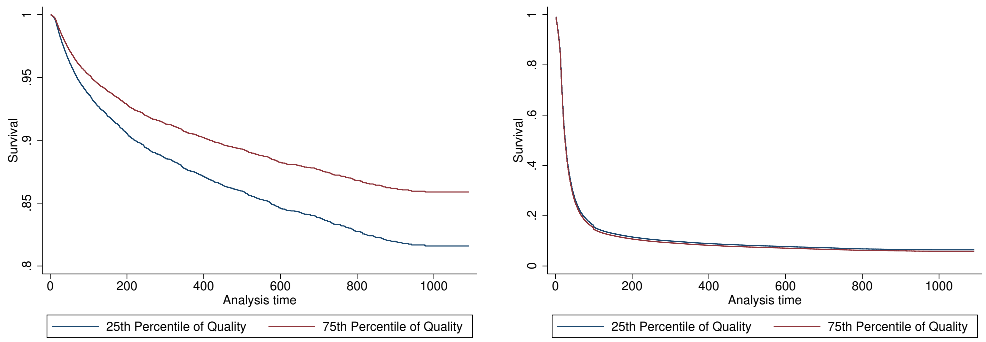
(a) Death



(b) Discharge

Notes: These figures plot the estimated cause-specific baseline hazard functions for death in panel A, and discharge in panel B.

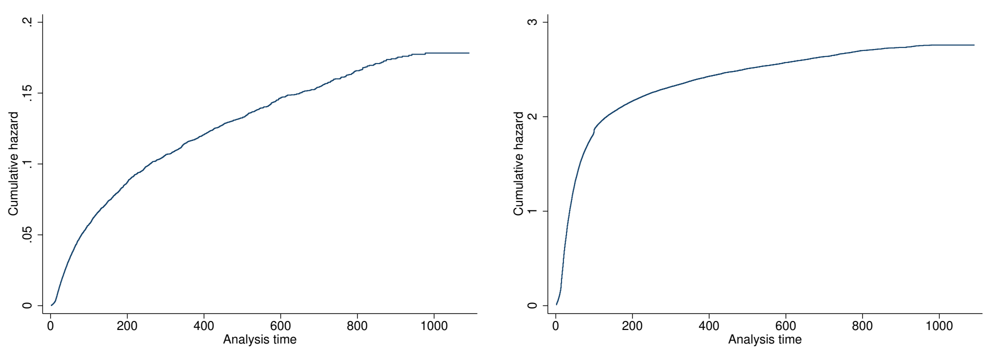
Figure A.23: Survival Curves for Cause-Specific Hazard Model (Split by Nursing Home Quality)



(a) Death (b) Discharge

Notes: These figures plot the estimated cause-specific survival curves for a resident at a nursing home at the 25th and 75th percentiles of the quality distribution, for death in panel A, and discharge in panel B (where the "survival" curve is defined based on discharge status, rather than death).

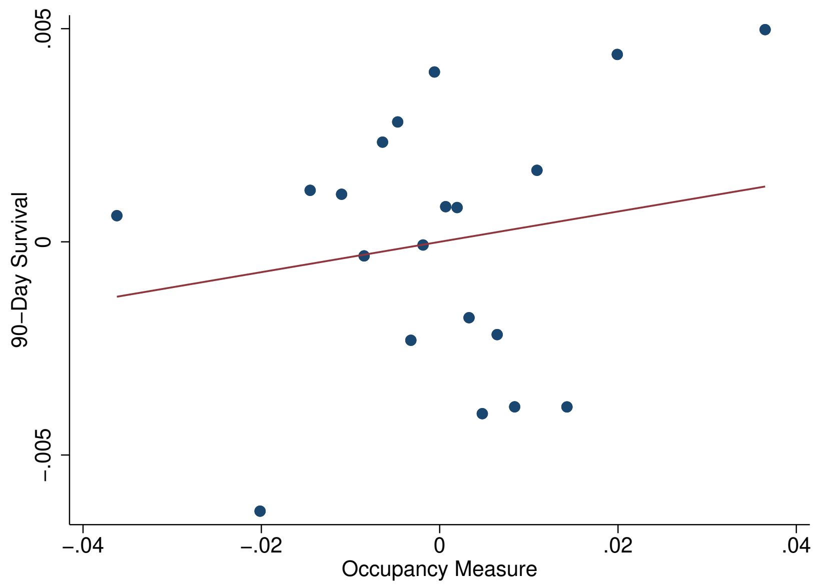
Figure A.24: Cause-Specific Cumulative Baseline Hazard Functions, $H_{c,0}(t)$



(a) Death (b) Discharge

Notes: These figures plot the estimated cause-specific cumulative baseline hazard functions for death in panel A, and discharge in panel B.

Figure A.25: Relationship Between Occupancy Fluctuations and Resident Outcomes



Notes: This figure shows a bin scatter of 90-day resident survival against my occupancy measure, controlling for resident characteristics and nursing home fixed effects. My occupancy measure is defined as the average log occupancy over the 7 days preceding admission residualized of nursing home-month fixed effects, and the sample is limited to California and the year 2009. The unit of observation is a resident.

Table A.1: Controls for Resident Characteristics at Admission

Basic demographics:	**Psychosocial well-being:**
Age, race, gender, and marital status	Sense of initiative/involvement
Insurance status	Unsettled relationships
Cognitive patterns:	Feelings about past roles
Whether resident is comatose	**Physical functioning and structural problems:**
Short-term and long-term memory	ADL self-performance and support provided: walking, dressing, eating, etc.
Memory/recall ability:	Walking
Current season, location of own room, staff names/faces, etc.	Dressing
Cognitive skills for daily decision-making	Eating, etc.
Disordered thinking/awareness	Independence in bathing
Change in cognitive patterns	Test for balance
Communication/hearing patterns:	Functional limitation in range of motion
Hearing	Modes of locomotion
Communication devices/techniques	Modes of transfer
Modes of expression	Task segmentation
Ability to make self understood	ADL functinoal rehabilitation potential
Speech clarity	Change in ADL function
Ability to understand others	**Continence:**
Change in communication/hearing	Continence self-control
Vision patterns:	Bowel elimination pattern
Vision adequacy	Appliances and programs
Visual limitations/difficulties	Change in urinary continence
Use of visual appliances	**Disease diagnoses:**
Mood and behavioral Patterns:	Indicators for various diseases
Indicators of depression, anxiety, and sad mood;	Indicators for various infections infections
Mood persistence	ICD-9 codes for other diagnoses
Change in mood	
Behavioral symptoms:	
Wandering, verbally/physically abusive, etc.	
Recent change in behavioral symptoms	

Table A.2: Controls for Resident Characteristics at Admission (continued)

Health conditions:
- Fluid condition:
  - Rapid weight gain/loss
  - Dehydration, etc.
- Pain symptoms
- Pain site
- Accidents
- Stability of conditions

Oral/nutritional status:
- Oral problems:
  - Chewing
  - Swallowing
  - Pain
- Height and weight
- Weight change
- Nutritional problems:
  - Complaints about taste and/or hunger
  - Leftover food
- Nutritional approaches:
  - Parental/IV
  - Feeding tube, etc.
- Parenteral or enteral intake

Oral/dental status:
- Oral status and disease prevention:
  - Dentures
  - Problems with teeth
  - Inflamed gums, etc.

Skin condition:
- Ulcers
- Type of Ulcer
- History of resolved ulcers
- Other skin problems or lesions present
- Skin treatments
- Foot problems and care

Activity pursuit patterns:
- Time awake
- Time involved in activities
- Preferred activity settings
- General activity preferences:
  - Cards/other games
  - Crafts/arts
  - Exercise/sports
  - Music
  - Reading/writing, etc.
- Preferences on change in daily routine

Medications:
- Number of medications
- New medications
- Injections
- Days receiving various medications (antipsychotic, antidepressant, etc.)

Special treatments and procedures:
- Special care:
  - Chemotherapy
  - Dialysis
  - IV medication, etc.
- Intervention programs for mood, behavior, cognitive loss
- Nursing rehabilitation/restorative care
- Devices and restraints
- Hospital stay(s)
- ER visit(s)
- Physician visits
- Physician orders
- Abnormal lab values

Table A.3: Additional Summary Statistics

Residents (N=653,946)			
Age	77.541	Medicare	0.618
	(12.991)		(0.486)
Female	0.611	Medicaid	0.128
	(0.488)		(0.334)
Married	0.329	Admitted from Acute Care Hospital	0.889
	(0.470)		(0.314)
White	0.735	Admitted from Home	0.081
	(0.441)		(0.273)
Black	0.068	Death Within 90 Days	0.075
	(0.252)		(0.264)
Hispanic	0.113	Short Term Memory Issues	0.476
	(0.317)		(0.499)
High School/Some College	0.634	Long Term Memory Issues	0.278
	(0.482)		(0.448)
At Least Bachelor's Degree	0.131	Dementia	0.233
	(0.338)		(0.423)

Notes: This table contains summary statistics for residents who had their first stays in a nursing home in California between 2000 and 2010.

Table A.4: Summary Statistics for Nursing Homes (Weighted by Admissions)

Nursing Homes (J=840)	
Number of Beds	123.989
	(51.812)
Occupancy Rate	86.198
	(10.171)
Chain	0.641
	(0.480)
For-Profit	0.913
	(0.282)
Deficiencies	6.573
	(8.156)
RN hours per resident day	0.387
	(0.354)

Nursing homes are weighted by number of years that the nursing home was in the sample for.

Table A.5: IV Estimates of the Forecast Coefficient for the Fixed Effects Quality Estimates

Panel A: 1st Stage, Dep Var: Leave-Year-Out Quality E:	(1)	(2)	(3)	(4)
Instrument	0.145	0.322	0.403	0.495
	(0.013)	(0.027)	(0.036)	(0.051)
F-statistic	116.2	141.4	126.5	94.3
Panel B: Reduced form, Dep Var: 90-day Survival	(1)	(2)	(3)	(4)
Instrument	0.117	0.291	0.365	0.477
	(0.023)	(0.043)	(0.056)	(0.076)
Panel C: 2SLS, Dep Var: 90-day Survival	(1)	(2)	(3)	(4)
Leave-Year-Out Fixed Effects Quality Estimates	0.808	0.906	0.907	0.963
	(0.119)	(0.090)	(0.090)	(0.092)
Instrument: Avg. Quality of K Nearest Nursing Homes	K=1	K=3	K=5	K=10
Demographic and Health Controls	X	X	X	X
County Fixed Effects	X	X	X	X
Number of Observations	632,162	632,207	632,207	632,207

Notes: This table presents the first stage, reduced form, and IV results for the estimates of the forecast coefficient. The outcome variable is 90-day mortality, the endogenous variable is the leave-year-out fixed effects quality estimates for nursing homes, and the instrument is average quality of the K nursing homes closest to each resident, with the value of K ranging across specifications. All regressions include the controls for residents' demographics and health, as well as county fixed effects. Standard errors clustered at the nursing home level are displayed in parentheses.

Table A.6: Over-Identified IV Estimates of the Forecast Coefficient

					Dependent Variable: 90-Day Survival					
Panel A: Empirical Bayes Quality Estimates										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Forecast Coefficient, λ	0.908	0.936	0.946	0.946	0.979	1.006	1.004	1.013	1.032	1.048
	(0.120)	(0.101)	(0.091)	(0.088)	(0.086)	(0.084)	(0.083)	(0.083)	(0.082)	(0.083)
Controls for Health and Demographic	X	X	X	X	X	X	X	X	X	X
County Fixed Effects	X	X	X	X	X	X	X	X	X	X
Number of Nearest Nursing Homes	1	2	3	4	5	6	7	8	9	10
Kleibergen-Paap rk Wald F statistic	109.9	67.8	49.2	37.9	31.2	26.3	22.3	19.4	17.4	15
Number of Observations	632,162	625,358	619,829	614,307	607,502	599,393	589,741	584,472	573,360	561,820
					Dependent Variable: 90-Day Survival					
Panel B: Fixed Effects Quality Estimates										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Forecast Coefficient, λ	0.808	0.870	0.900	0.903	0.932	0.966	0.963	0.976	0.995	1.013
	(0.119)	(0.102)	(0.092)	(0.089)	(0.088)	(0.085)	(0.084)	(0.084)	(0.083)	(0.085)
Adjusted for Attenuation Bias	X	X	X	X	X					
Demographic and Health Controls	X	X	X	X	X	X	X	X	X	X
County Fixed Effects	X	X	X	X	X	X	X	X	X	X
Number of Nearest Nursing Homes	1	2	3	4	5	6	7	8	9	10
Kleibergen-Paap rk Wald F statistic	116.2	68.3	48.6	37	30.4	25.7	21.9	19	16.8	14.4
Number of Observations	632,162	625,358	619,829	614,307	607,502	599,393	589,741	584,472	573,360	561,820

Notes: This table presents IV estimates of the effect of the nursing home quality estimate on resident outcomes, instrumenting quality of chosen nursing home with the K instruments for the quality of the K nearest nursing homes to the resident's prior address, for K ranging from 1 to 10. Standard errors clustered at the nursing home level are shown in parentheses.

Table A.7: Relationship Between Fixed Effects Quality Estimates and Nursing Home Characteristics

	Quality Estimates (s.d.)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2009 Star Ratings (s.d.)	0.0816							0.0491
	(0.0347)							(0.0355)
RN hours per resident day (s.d.)		0.0988						0.230
		(0.0377)						(0.0536)
LPN hours per resident day (s.d.)			0.109					0.126
			(0.0231)					(0.0362)
CNA hours per resident day (s.d.)				0.0971				-0.0436
				(0.0181)				(0.0293)
Deficiencies (s.d.)					-0.0497			-0.0226
					(0.0174)			(0.0148)
For-Profit (s.d.)						-0.0861		-0.0642
						(0.0328)		(0.0292)
Chain (s.d.)							-0.0584	-0.0390
							(0.0309)	(0.0297)
N	9,988	9,994	9,995	9,989	9,997	9,997	9,997	9,975
R-squared	0.007	0.010	0.012	0.010	0.003	0.007	0.003	0.034

Notes: This table shows correlations between the nursing home quality estimates and various nursing home characteristics. The unit of observation is a nursing home-year. Observations are weighted such that the total weight each nursing home receives is equal to the number of residents it has over the sample period. Standard errors are clustered by nursing home.

Table A.8: Predictivity of Quality and Nursing Home Characteristics for Resident Outcomes

	Indicator for Resident Surviving At Least 90 Days After Admission x 100			
Quality Measure:	Empirical Bayes		Fixed Effects	
	(1)	(2)	(3)	(4)
Leave-Year-Out Quality Estimate (s.d.)	1.325	1.306	1.340	1.320
	(0.0383)	(0.0394)	(0.0397)	(0.0404)
2009 Star Ratings (s.d.)		0.0129		0.0291
		(0.0298)		(0.0311)
RN hours per resident day (s.d.)		0.0454		0.0579
		(0.0380)		(0.0378)
LPN hours per resident day (s.d.)		0.0752		0.0874
		(0.0395)		(0.0398)
CNA hours per resident day (s.d.)		0.0215		0.0207
		(0.0407)		(0.0408)
Deficiencies (s.d.)		-0.00459		-0.00582
		(0.0405)		(0.0404)
Chain (s.d.)		-0.0178		-0.0256
		(0.0300)		(0.0306)
For-Profit (s.d.)		0.0457		0.0587
		(0.0334)		(0.0339)
N	632,122	632,122	632,122	632,122
R-squared	0.140	0.140	0.140	0.140

Notes: This table shows results from regressions of resident survival on leave-year-out quality estimates and nursing home characteristics. Independent variables are standardized and the coefficients are multiplied by 100 for legibiltiy. The unit of observation is a resident, and standard errors are clustered at the nursing home level.

Table A.9: Effect of Occupancy on Admissions (Other Measures of New Admissions)

(a) Dependent Variable: Any New Residents

	Any New Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.619		
	(0.0330)		
Lagged 7-Day Avg. Occupancy		-0.0133	
		(0.000323)	
Lagged 7-Day Avg. Occ. Percentile			-0.00420
			(7.54e-05)
Nursing Home x Month Fixed Effects	X	X	X
Number of Observations	3,426,363	3,426,363	3,426,363

Notes: This table shows regression results at the nursing home-day level wherein the dependent variable is an indicator for any new residents, and the independent variables are various measures of nursing home occupancy. Standard errors are clustered at the nursing home level.

(b) Dependent Variable: Flow of Residents

	Flow of Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-3.698		
	(0.191)		
Lagged 7-Day Avg. Occupancy		-0.0829	
		(0.00238)	
Lagged 7-Day Avg. Occ. Percentile			-0.0233
			(0.000457)
Nursing Home x Month Fixed Effects	X	X	X
Number of Observations	3,426,363	3,426,363	3,426,363

Notes: This table shows regression results at the nursing home-day level wherein the dependent variable is the flow of residents (difference between number of residents today and yesterday), and the independent variables are various measures of nursing home occupancy. Standard errors are clustered at the nursing home level.

Table A.10: Reduced Form Evidence of Selective Admissions with Nursing Home x Month Fixed Effects

	Medicaid		Post-Acute Care		Alzheimer's/Dementia	
Panel A: Lagged 7-Day Avg. Log Occupancy						
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged 7-Day Avg. Log Occupancy	-0.134	-0.112	0.0397	0.0165	-0.0485	-0.0627
	(0.0179)	(0.0166)	(0.0144)	(0.0144)	(0.0259)	(0.0241)
Nursing Home x Month Fixed Effects	X	X	X	X	X	X
Controls		X		X		X
Number of Observations	614,178	614,172	614,178	614,172	614,178	614,172
Panel B: Lagged 7-Day Avg. Occupancy						
	Medicaid		Post-Acute Care		Alzheimer's/Dementia	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged 7-Day Avg. Occupancy	-0.00116	-0.000980	0.000279	7.55e-05	-0.000471	-0.000590
	(0.000153)	(0.000142)	(0.000141)	(0.000138)	(0.000221)	(0.000201)
Nursing Home x Month Fixed Effects	X	X	X	X	X	X
Controls		X		X		X
Number of Observations	614,178	614,172	614,178	614,172	614,178	614,172
Panel C: Lagged 7-Day Avg. Occupancy Percentile						
	Medicaid		Post-Acute Care		Alzheimer's/Dementia	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged 7-Day Avg. Log Occupancy Percentile	-0.000654	-0.000560	0.000151	4.65e-05	-0.000105	-0.000185
	(7.31e-05)	(7.04e-05)	(6.42e-05)	(6.30e-05)	(9.99e-05)	(9.19e-05)
Nursing Home x Month Fixed Effects	X	X	X	X	X	X
Controls		X		X		X
Number of Observations	614,178	614,172	614,178	614,172	614,178	614,172

Notes: This table shows regression results at the resident level wherein the dependent variables are various resident characteristics, and the independent variable is the lagged 7-day average of some occupancy measure of the nursing home at the time of the resident's admission. All regressions include nursing home-month fixed effects. Controls include Medicaid, post-acute care, Alzheimer's/dementia, age, education, primary language, and race. Standard errors are clustered at the nursing home level.

Table A.11: Rejection Rates from Structural Model

	Nursing Home Rejects Resident					
	(1)	(2)	(3)	(4)	(5)	(6)
	All Nursing Homes		Above-Median Quality		Below-Median Quality	
Medicaid	0.063	0.063	0.067	0.067	0.058	0.059
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-Acute Care	-0.023	-0.023	-0.023	-0.023	-0.024	-0.024
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Alzheimer's/Dementia	0.039	0.039	0.044	0.044	0.033	0.033
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls for Other Resident Characteristics	X	X	X	X	X	X
Control for Capacity Strain	X	X	X	X	X	X
Nursing Home Fixed Effects		X		X		X
Dependent Variable Mean	0.217	0.217	0.262	0.262	0.173	0.173
Number of Observations	1,923,155	1,923,155	960,942	960,942	962,213	962,213
R-squared	0.132	0.150	0.139	0.147	0.126	0.132

Notes: This table shows results from regressions of an indicator for whether a nursing home would reject a resident on various resident characteristics. Controls for other resident characteristics include age, having at least a bachelor's degree, primary language being English, and race indicators for black and hispanic. The sample consists of all resident-nursing home pairs, for nursing homes within 15 miles of the resident. Standard errors are clustered at the nursing home level.

Table A.12: Relationship Between Rejection Rates and Nursing Home Characteristics

	Rejection Rate of Nursing Home						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Quality	3.620						
	(0.102)						
RN Staffing (s.d.)		0.004					
		(0.004)					
LPN Staffing (s.d.)			0.012				
			(0.004)				
CNA Staffing (s.d.)				0.008			
				(0.003)			
Fewer Deficiencies (s.d.)					0.014		
					(0.006)		
For-Profit						-0.005	
						(0.008)	
Chain							-0.017
							(0.006)
Dependent Variable Mean	0.189	0.189	0.189	0.189	0.189	0.189	0.189
Number of Observations	674	674	674	674	674	674	674
R-squared	0.733	0.002	0.015	0.011	0.008	0.001	0.012

Notes: This table shows results from regressions of nursing homes' rejection rates on nursing home characteristics. Robust standard errors in parentheses.

Table A.13: Relationship Between Rejection Rates and Characteristics of Residents Living Within 5 Miles

	Rejection Rate of Nursing Home							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fraction Medicaid	0.236							
	(0.048)							
Fraction Post-Acute Care		0.339						
		(0.089)						
Fraction Alzheimer's/Dementia			-0.211					
			(0.082)					
Average Age				-0.011				
				(0.001)				
Fraction Bachelor's Degree					0.050			
					(0.040)			
Fraction English as Primary Language						-0.191		
						(0.029)		
Fraction Race: Black							0.193	
							(0.022)	
Fraction Race: Hispanic								0.146
								(0.038)
Dependent Variable Mean	0.189	0.189	0.189	0.189	0.189	0.189	0.189	0.189
Number of Observations	673	673	673	673	673	673	673	673
R-squared	0.057	0.034	0.019	0.135	0.002	0.099	0.081	0.045

Notes: This table shows results from regressions of nursing homes' rejection rates on average characteristics of potential residents within 5 miles. Robust standard errors in parentheses.

Table A.14: Structural Estimates Without Accounting for Admissions Policies

	Full Sample	Post-Acute Care	Full Sample	Post-Acute Care
Resident Preferences	(1)	(2)	(3)	(4)
Distance to Nursing Homes (in Miles)	-0.158	-0.159	-0.158	-0.159
	(0.000)	(0.000)	(0.000)	(0.001)
Quality	0.077	-0.008	3.729	0.468
	(0.116)	(0.108)	(0.810)	(0.715)
Quality x Alzheimer's/Dementia			-1.400	-1.349
			(0.261)	(0.258)
Quality x Age			-0.064	-0.021
			(0.009)	(0.009)
Quality x At Least Bachelor's Degree			2.333	2.420
			(0.301)	(0.299)
Quality x English as Primary Language			1.687	1.548
			(0.299)	(0.327)
Quality x Black			-1.150	-1.340
			(0.370)	(0.392)
Quality x Hispanic			-0.222	-0.582
			(0.319)	(0.329)
Number of Observations	5,492,614	5,124,314	5,492,614	5,124,314

Notes: This table shows estimates from the structural estimation using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used.

Table A.15: Structural Estimates: Residents' Responsiveness to Other Nursing Home Characteristics

	Full Sample		Post-Acute Care Sample	
Resident Preferences	(1)	(2)	(3)	(4)
Distance to Nursing Homes (in Miles)	-0.172	-0.171	-0.173	-0.173
	(0.001)	(0.001)	(0.001)	(0.001)
Quality	-0.672		-0.470	
	(0.339)		(0.170)	
RN Staffing (s.d.)	0.160	0.159	0.167	0.168
	(0.002)	(0.002)	(0.002)	(0.002)
LPN Staffing (s.d.)	0.080	0.079	0.088	0.087
	(0.002)	(0.002)	(0.002)	(0.002)
CNA Staffing (s.d.)	-0.082	-0.082	-0.080	-0.080
	(0.002)	(0.002)	(0.002)	(0.002)
Fewer Deficiencies (s.d.)	-0.021	-0.020	-0.021	-0.021
	(0.002)	(0.002)	(0.002)	(0.002)
Fewer Complaint Deficiencies (s.d.)	0.000	-0.000	0.002	0.001
	(0.002)	(0.003)	(0.003)	(0.003)
For-Profit	0.093	0.095	0.120	0.118
	(0.005)	(0.005)	(0.006)	(0.004)
Chain	0.120	0.120	0.138	0.138
	(0.003)	(0.004)	(0.004)	(0.003)
Nursing Homes' Admissions Policies				
Capacity Strain	-11.503	-11.554	-11.413	-11.102
	(0.244)	(0.270)	(0.197)	(0.207)
Quality	-1.029	-2.730	-2.732	-3.985
	(1.334)	(0.414)	(0.554)	(0.475)
Medicaid	-0.264	-0.319	-0.369	-0.369
	(0.021)	(0.032)	(0.028)	(0.032)
Post-Acute Care	0.373	0.327		
	(0.043)	(0.042)		
Alzheimer's/Dementia	-0.166	-0.181	-0.195	-0.135
	(0.026)	(0.017)	(0.026)	(0.016)
Age	0.029	0.029	0.028	0.029
	(0.001)	(0.001)	(0.001)	(0.001)
At Least Bachelor's Degree	-0.013	-0.061	-0.053	-0.104
	(0.026)	(0.021)	(0.026)	(0.016)
English as Primary Language	0.141	0.091	0.088	0.081
	(0.022)	(0.033)	(0.017)	(0.047)
Black	-0.532	-0.547	-0.511	-0.494
	(0.029)	(0.024)	(0.030)	(0.020)
Hispanic	0.004	-0.053	-0.119	-0.063
	(0.025)	(0.019)	(0.025)	(0.022)
Year Fixed Effects in Supply Equation	X	X	X	X
Number of Observations	5,492,614	5,492,614	5,124,314	5,124,314

Notes: This table shows estimates from the structural estimation using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used.

Table A.16: Structural Estimates: Instrumenting for Nursing Home Quality

	Full Sample		Post-Acute Care Sample	
Resident Preferences	(1)	(2)	(3)	(4)
Distance to Nursing Homes (in Miles)	-0.171	-0.170	-0.172	-0.171
	(0.001)	(0.001)	(0.001)	(0.001)
Quality	0.222	1.490	0.850	0.244
	(0.325)	(1.172)	(0.339)	(1.110)
Quality Residual		-1.338		0.386
		(1.234)		(1.096)
Nursing Homes' Admissions Policies				
Capacity Strain	-10.729	-10.784	-10.547	-10.690
	(0.260)	(0.335)	(0.253)	(0.283)
Quality	-0.968	-0.540	-4.055	-3.186
	(1.361)	(0.822)	(1.244)	(1.352)
Medicaid	-0.070	-0.075	-0.201	-0.119
	(0.022)	(0.024)	(0.016)	(0.032)
Post-Acute Care	0.243	0.213		
	(0.044)	(0.035)		
Alzheimer's/Dementia	-0.145	-0.120	-0.180	-0.139
	(0.017)	(0.019)	(0.020)	(0.015)
Age	0.032	0.032	0.030	0.031
	(0.001)	(0.001)	(0.001)	(0.001)
At Least Bachelor's Degree	-0.008	-0.075	-0.024	-0.004
	(0.028)	(0.023)	(0.014)	(0.036)
English as Primary Language	0.054	-0.002	0.036	0.070
	(0.041)	(0.034)	(0.019)	(0.021)
Black	-0.537	-0.573	-0.490	-0.549
	(0.033)	(0.026)	(0.014)	(0.055)
Hispanic	-0.012	-0.086	-0.017	-0.086
	(0.040)	(0.028)	(0.043)	(0.038)
Year Fixed Effects in Supply Equation	X	X	X	X
First-Stage F-Statistic	-	88	-	88
Number of Observations	5,492,614	5,492,614	5,124,314	5,124,314

Notes: This table shows estimates from the structural estimation using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used.

Table A.17: Structural Estimates: Robustness Checks for Heterogeneity in Responsiveness

	Full Sample		Post-Acute Care Sample	
Resident Preferences	(1)	(2)	(3)	(4)
Distance to Nursing Homes (in Miles)	-0.171	-0.171	-0.172	-0.172
	(0.001)	(0.001)	(0.001)	(0.001)
Quality	18.261	16.025	18.727	17.210
	(1.055)	(1.141)	(1.215)	(1.168)
Quality x Alzheimer's/Dementia	-0.967	-1.329	-1.101	-1.864
	(0.289)	(0.351)	(0.299)	(0.441)
Quality x Age	-0.218	-0.200	-0.215	-0.212
	(0.013)	(0.013)	(0.015)	(0.014)
Quality x At Least Bachelor's Degree	2.884	4.075	3.101	3.772
	(0.356)	(0.619)	(0.375)	(0.388)
Quality x English as Primary Language	2.200	4.068	2.180	4.215
	(0.321)	(0.392)	(0.347)	(0.495)
Quality x Black	0.088	-4.735	0.001	-7.886
	(0.546)	(0.738)	(0.439)	(0.986)
Quality x Hispanic	-0.096	0.759	-0.339	0.808
	(0.372)	(0.611)	(0.394)	(0.564)
Nursing Homes' Admissions Policies				
Capacity Strain	-10.159	-9.952	-9.567	-9.571
	(0.238)	(0.268)	(0.211)	(0.204)
Quality	-15.121	2.549	-18.446	-13.241
	(0.689)	(1.750)	(1.172)	(2.598)
Medicaid	-0.166	-0.160	-0.108	-0.144
	(0.031)	(0.024)	(0.033)	(0.030)
Post-Acute Care	0.014	0.056		
	(0.036)	(0.033)		
Alzheimer's/Dementia	-0.137	-0.209	-0.068	-0.151
	(0.019)	(0.013)	(0.020)	(0.025)
Age	0.032	0.034	0.034	0.033
	(0.001)	(0.001)	(0.001)	(0.001)
At Least Bachelor's Degree	-0.075	0.029	-0.096	-0.063
	(0.039)	(0.028)	(0.023)	(0.025)
English as Primary Language	-0.047	0.044	-0.059	0.003
	(0.025)	(0.020)	(0.038)	(0.028)
Black	-0.424	-0.521	-0.395	-0.578
	(0.042)	(0.035)	(0.012)	(0.036)
Hispanic	-0.085	0.039	-0.092	-0.006
	(0.022)	(0.021)	(0.037)	(0.048)
Year Fixed Effects in Supply Equation	X	X	X	X
Quality x Resident Characteristics in Supply Equation		X		X
Number of Observations	5,492,614	5,492,614	5,124,314	5,124,314

Notes: This table shows estimates from the structural estimation using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used.

Table A.18: Structural Estimates: Heterogeneity in Responsiveness to Different Quality Measures (QMs)

	Full Sample			Post-Acute Care Sample		
	QM: Quality Estimates	*QM: RN (s.d.)*	*QM: LPN (s.d.)*	*QM: Quality Estimates*	*QM: RN (s.d.)*	*QM: LPN (s.d.)*
Resident Preferences	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Nursing Homes (in Miles)	-0.171	-0.170	-0.171	-0.172	-0.172	-0.173
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
QM	18.261	-0.289	0.199	18.727	-0.272	0.233
	(1.055)	(0.014)	(0.018)	(1.215)	(0.018)	(0.021)
QM x Alzheimer's/Dementia	-0.967	-0.071	-0.044	-1.101	-0.050	-0.039
	(0.289)	(0.007)	(0.005)	(0.299)	(0.006)	(0.006)
QM x Age	-0.218	0.004	-0.002	-0.215	0.003	-0.002
	(0.013)	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)
QM x At Least Bachelor's Degree	2.884	0.025	0.041	3.101	0.017	0.042
	(0.356)	(0.006)	(0.005)	(0.375)	(0.006)	(0.006)
QM x English as Primary Language	2.200	0.091	0.106	2.180	0.090	0.098
	(0.321)	(0.006)	(0.006)	(0.347)	(0.008)	(0.006)
QM x Black	0.088	-0.107	-0.001	0.001	-0.114	0.005
	(0.546)	(0.009)	(0.008)	(0.439)	(0.008)	(0.010)
QM x Hispanic	-0.096	0.002	0.001	-0.339	0.002	-0.002
	(0.372)	(0.007)	(0.007)	(0.394)	(0.008)	(0.007)
Nursing Homes' Admissions Policies						
Capacity Strain	-10.159	-10.642	-10.218	-9.567	-10.364	-10.019
	(0.238)	(0.218)	(0.207)	(0.211)	(0.217)	(0.265)
QM	-15.121	0.887	-0.192	-18.446	0.876	-0.183
	(0.689)	(0.044)	(0.008)	(1.172)	(0.043)	(0.010)
Medicaid	-0.166	0.444	-0.160	-0.108	0.403	-0.271
	(0.031)	(0.031)	(0.029)	(0.033)	(0.051)	(0.025)
Post-Acute Care	0.014	-0.346	0.460			
	(0.036)	(0.085)	(0.032)			
Alzheimer's/Dementia	-0.137	-0.077	-0.098	-0.068	-0.036	-0.087
	(0.019)	(0.043)	(0.043)	(0.020)	(0.031)	(0.036)
Age	0.032	0.029	0.029	0.034	0.029	0.028
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
At Least Bachelor's Degree	-0.075	-0.196	-0.079	-0.096	-0.235	-0.108
	(0.039)	(0.033)	(0.034)	(0.023)	(0.025)	(0.021)
English as Primary Language	-0.047	0.177	0.046	-0.059	0.133	0.008
	(0.025)	(0.024)	(0.031)	(0.038)	(0.051)	(0.060)
Black	-0.424	-0.595	-0.453	-0.395	-0.655	-0.532
	(0.042)	(0.022)	(0.038)	(0.012)	(0.013)	(0.026)
Hispanic	-0.085	0.007	-0.043	-0.092	-0.019	-0.033
	(0.022)	(0.021)	(0.018)	(0.037)	(0.033)	(0.028)
Year Fixed Effects in Supply Equation	X	X	X	X	X	X
Number of Observations	5,492,614	5,492,614	5,492,614	5,124,314	5,124,314	5,124,314

Notes: This table shows estimates from the structural estimation using Gibbs sampling. A burn-in period corresponding to the first half of the chain was used.