THE ILLUSION OF HEALTH CARE EXCEPTIONALISM? EVIDENCE FROM NURSING HOMES

ALDEN CHENG

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For over half a century, limited consumer responsiveness to provider quality has been viewed as a defining feature of health care markets. I show that this apparent exceptionalism partly reflects a failure to distinguish consumer preferences from provider-imposed constraints on access. Using administrative data covering the universe of nursing home residents in California, I construct quality measures based on risk-adjusted mortality that are robust to gaming of publicly provided quality measures and validate them using a distance-based IV strategy. I then use these quality measures as inputs into a structural demand model in which nursing homes may reject patients based on observable characteristics. Conventional demand estimation that treats all options as available yields precise null estimates of average demand for quality. Accounting for unobserved rejections instead reveals positive consumer demand, although average responsiveness remains lower than estimates from hospital settings and varies substantially across baseline demographic and health characteristics. The introduction of nursing home star ratings had limited effects on consumer demand, but counterfactual simulations indicate that financial steering incentives and improved hospital discharge processes may improve allocation and reduce mortality by 5 to 17 percent in spite of supply-side constraints. Finally, demand heterogeneity has important consequences for patient outcomes, explaining roughly 10 percent of the mortality-age gradient.

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* Postdoctoral Research Associate, National Bureau of Economic Research/Center for Business and Public Policy (CBPP) at Gies College of Business, University of Illinois (email: alden15@nber.org). I am incredibly grateful to Alberto Abadie, Joseph Doyle, Amy Finkelstein, Ashvin Gandhi, Jon Gruber, Ben Handel, and David Molitor for their support and advice. In addition, Jason Abaluck, Josh Angrist, Nikhil Agarwal, David Card, Yiqun Chen, Victor Chernozhukov, Jonathan Cohen, David Grabowski, Martin Hackmann, Jetson Leder-Luis, Haizhen Lin, Julian Reif, Frank Schilbach, Mark Shepard, Maggie Shi, and seminar participants at Gies College of Business, University of Illinois Urbana-Champaign, MIT, Imperial College London, Nanyang Technological University, Queens College, CUNY, University of Illinois Chicago, and the Midwest Economic Association Conference provided valuable feedback. I also thank Mohan Ramanujan at the National Bureau of Economic Research for his assistance. All mistakes are my own. Previous titles for this paper include "Demand for Quality in the Presence of Information Frictions: Evidence from the Nursing Home Market", and "Barriers to Choosing High-Quality Healthcare Providers: Evidence from the Nursing Home Market". The author is an NBER postdoctoral research associate located at the Gies College of Business at the University of Illinois, Urbana-Champaign, and was a PhD candidate in Economics at MIT when writing commenced. The author has no relevant or material financial interests that relate to the research in this paper.

I. INTRODUCTION

Consumer responsiveness to quality is central to a well-functioning market. This is particularly so in health care settings, where provider quality can have first-order consequences for patient welfare (Doyle et al., 2015; Einav, Finkelstein, and Mahoney, 2025). Government monitoring and regulation of provider quality is costly and often imperfect (Chen and Dillender, 2025; Gandhi, Olenski, and Shi, 2025), so patient demand plays a crucial role in incentivizing providers to invest in quality. Yet, despite its theoretical importance and a longstanding debate going back to Arrow (1963) which is still ongoing today (Cutler, 2011; Skinner, 2011; Chandra et al., 2016), there is a lack of consensus on whether—and the extent to which—consumers respond to quality of health care providers.

An important reason for this lack of consensus is that measurement of patient responsiveness to quality faces unique challenges in health care settings. First, quality is difficult to measure: publicly reported measures are often gamed by providers, and estimation of provider value-added based on their causal effect on patient outcomes may be complicated by selection. Second, the profitability of patients to providers varies substantially, giving rise to cream-skimming incentives. Rejections of patients by providers are rarely recorded in the data, and can bias naïve demand estimates that do not account for these unobserved choice set constraints.

In this paper, I estimate patient demand for nursing home quality, and quantify its consequences for patient mortality. To address well-known issues with publicly reported nursing home quality metrics, I estimate facility value-added based on their causal effect on 90-day survival using double machine-learning and empirical Bayes, and validate these estimates using a distance-based IV strategy. I then use these estimates as inputs into a structural demand model that accounts for unobserved choice set constraints arising from nursing home rejections. Specifically, I simultaneously estimate patient demand and nursing homes' admissions policies, using distance and high-frequency variation in capacity strain as demand and supply shifters respectively.

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.

Turning to the demand estimates, I find that accounting for provider cream-skimming is important: while naïve estimates suggest that average demand is essentially zero, the full model yields positive demand estimates. This difference is due to greater selectivity by higher-quality providers—both conditional and unconditional on occupancy rates—and explains how the absence of a quality-market share gradient is not necessarily indicative of health care exceptionalism. At the same time, the magnitude of average demand is modest, implying that residents are willing to tolerate a 5 percentage point higher probability of death (within 90 days) in exchange for a one-mile reduction in travel distance. At the same time, there is systematic heterogeneity in responsiveness to quality: relatively young, English-speaking residents with a Bachelor's degree and without dementia are three times more responsive to quality than the average resident. The introduction of star ratings by the CMS at the end of 2008 had a limited effect on consumer demand, although I find suggestive evidence of some provider responses in the form of changes in admissions policies and quality investments.

To explore the potential effects of alternative policies and to quantify the implications of consumer demand for mortality outcomes, I conduct counterfactual simulations. Improved hospital discharge processes—in the form of financial incentives for hospitals to discharge patients to higher-quality nursing homes, and the provision of quality-ranked shortlists by discharge planners—can improve allocation and reduce mortality by 5–17 percent. These reforms also appear to be highly cost-effective: a back-of-the-envelope calculation suggests that the statistical value of life-years saved by the financial incentive scheme is at least 30 times its cost, while providing quality-ranked shortlists only requires a modest amount of discharge planners' time. Finally, given that older consumers have higher mortality risk and are also less responsive to quality, I find that (heterogeneity in) demand for quality explains roughly 10 percent of the mortality-age gradient.

This paper contributes to several strands of literature. First, it contributes to a longstanding debate on whether and the extent to which patients respond to quality of health care providers. Despite the theoretical importance of patient demand for quality given its implications for providers' quality investment incentives and patient welfare, and a longstanding and ongoing debate dating back to Arrow (1963), there is still a lack of consensus. This is due in part to two challenges in estimating patient demand: challenges in the measurement of provider quality, and unobserved

choice set constraints stemming from provider cream-skimming. I address these challenges by estimating provider value-added, which I use as inputs into a structural model that accounts for provider cream-skimming. I estimate that demand is small but positive, and find that controlling for unobserved rejections by providers is important: ignoring these constraints, average demand estimates are zero, suggesting a potential explanation for contrasting estimates in the prior literature.

Second, it adds to a vast literature on why individuals experience drastically different health outcomes. Previous work has studied explanations such as differences in health capital (Grossman, 1972), the role of medical spending (Fisher et al., 2003a,b), quality of health care providers (Chandra et al., 2016; Einav, Finkelstein, and Mahoney, 2025), place effects (Finkelstein, Gentzkow, and Williams, 2016; Deryugina and Molitor, 2020; Finkelstein, Gentzkow, and Williams, 2021), and peer effects (Nakajima, 2007; Cheng and Hackmann, 2025). I add to this by highlighting a relatively understudied determinant of patient health: responsiveness to quality of health care providers, showing that it explains a significant fraction of the gradient between mortality outcomes and baseline health, even before accounting for endogenous quality responses by providers.

Finally, this paper contributes to a growing literature on the economics of nursing homes. Most prior work has focused on provider behavior—including the effects of ownership structure (Gandhi, Song, and Updrashta, 2022; Gupta et al., 2021), reimbursement rates and competition (Hackmann, 2019), and financial incentives (Gandhi et al., 2024) on nursing home quality, as well as strategic admission and discharge decisions by nursing homes (Gandhi, 2023; Hackmann, Pohl, and Ziebarth, 2024)—although there is also a smaller literature on consumer choice (Gandhi, 2023) and quality estimation (Einav, Finkelstein, and Mahoney, 2025; Olenski and Sacher, 2024). The present paper contains elements of all three, although the focus is on consumer choice.

This paper proceeds as follows. In Section II, 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 III, before using them to study residents' demand for quality in the presence of cream-skimming by providers in Section IV. I then quantify implications of residents' responsiveness to quality on allocation and health outcomes using simulations in Section V, before concluding in Section VI.

II. BACKGROUND

II.A. Nursing Home Industry

There are roughly 15,000 skilled nursing facilities (SNFs)—which I colloquially refer to in this paper as nursing homes—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 exceeding $200 billion annually (Martin et al., 2025), 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 with mixed results (Park and Stearns, 2009; Chen and Grabowski, 2015; Hackmann, 2019; Gandhi et al., 2024). The potentially severe health consequences for patients and limited success of regulations targeted at providers make consumer demand a central economic object in this setting, both for the allocation of patients to higher-quality providers, as well as for incentivizing providers to improve quality.

At the same time, residents are not always able to choose their most-preferred nursing homes, due to capacity constraints and providers' cream-skimming incentives. In particular, patients vary widely in their profitability to nursing homes, and 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

[1]More recently, the rise of private equity ownership in the nursing home sector is also believed to have contributed to lower quality (Gupta et al., 2021; Gandhi, Song, and Updrashta, 2022).

unlikely to 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 averaged less than one-third of Medicare rates in 2005 (California HealthCare Foundation, 2007). These differences in reimbursement rates—as well as expected costs of care and length of stay—give rise to severe cream-skimming incentives for nursing homes.

II.B. Data

The primary data source for this paper is the Minimum Data Set 2.0 (MDS). All nursing homes that receive federal funding—which account 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.[2] Several studies on the accuracy of MDS data have found it to be fairly reliable (Shin and Scherer, 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 Table A.1 for a finer breakdown of the different types of data collected on each resident).[3] 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

[2]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.

[3]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.

for identifying cream-skimming by nursing homes, as Section IV describes).

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.[4] 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 (based on 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. I also supplement this data with information on nursing homes' 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 already comatose or on hospice at admission, given that the survival-based quality measure may not be appropriate for them.

[4]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.

II.C. Summary Statistics

Panel A of Table I 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.[5] As a point of reference, compared to the Medicare population in 2005, the rate of dementia 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.[6] We observe that nursing homes have 105 beds on average, occupancy rates tend to be quite high (87 percent on average)[7], 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.

Table I. Summary Statistics for Residents and Nursing Homes in California

Panel A: Residents ($N = 653{,}946$)		*Panel B: Nursing Homes* ($J = 840$)	
Age	77.541	Number of beds	105.065
	(12.991)		(48.194)
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 reports summary statistics for residents and nursing homes in California between 2000 and 2010. Standard deviations are reported in parentheses.

[5]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.

[6]These statistics are weighted by years in the sample, although the general patterns for statistics that are weighted by number of admissions are qualitatively similar (see Appendix Table A.3).

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

III. QUALITY ESTIMATION

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 III.C). Hence, I use 90-day risk-adjusted survival rate as the main 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 on 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 et al., 2015; Deryugina and Molitor, 2020; Finkelstein, Gentzkow, and Williams, 2021; Abaluck et al., 2021), which makes it easier to compare the magnitude of my consumer choice estimates with estimates from other health care settings (Chandra et al., 2016; Tay, 2003). In contrast, while quality measures such as falls and different types of pressure 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.

III.A. 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 K.[8]

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 analysis.

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 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 et al. (2021), I derive the following structural equation from equation (1):

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

[8]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.

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.[9] 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/Conditional Independence). *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.,*

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

[9] 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.

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 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 region fixed effects in all IV specifications (using different definitions of region for robustness). 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 (He and Schachter, 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 et al., 2021), since it is difficult to interpret,[10] 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 region fixed effects makes it less likely that the fallback condition is violated (similar to the exclusion restriction).

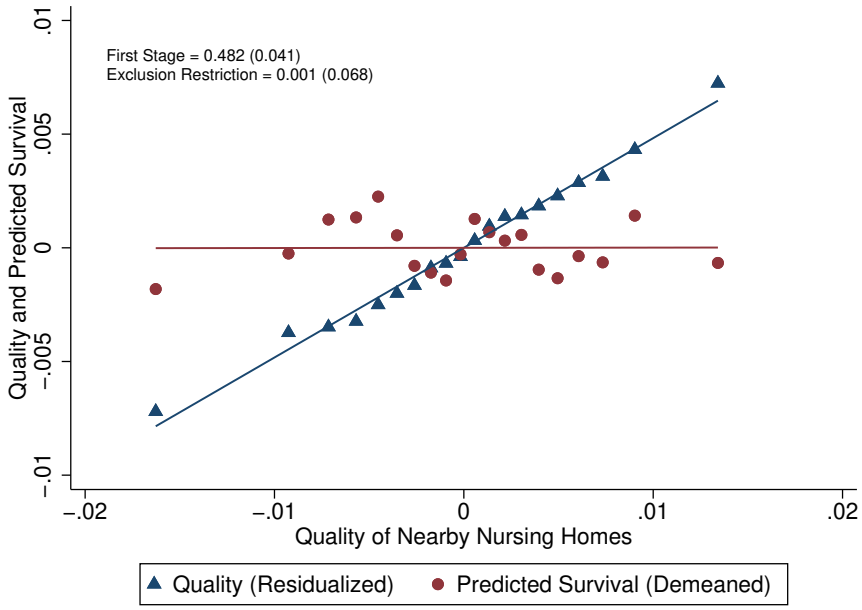
Finally, there is a positive correlation between the measurement error in the quality estimates and the instrument (which in my primary specification is an average of the quality estimates for nursing homes close to each resident), so the IV estimate may suffer from attenuation bias. In Appendix Section M, 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.

III.B. Quality Estimation Results

The standard deviation of nursing home quality is a parameter in the empirical Bayes procedure and is estimated to be 0.02, implying 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

[10] 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.

Figure I. 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).

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 I 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.[11]

[11]The balance test in Figure I 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.

Table II 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 five nearest nursing homes to each resident, using region fixed effects of increasing granularity. Across specifications, the first stage F-statistics range from 88.8 to 142.9, 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.

Table II. Instrumental Variables Estimates of the Forecast Coefficient

	(1)	(2)	(3)	(4)
Panel A. First stage: leave-year-out quality estimates				
Leave-year-out quality in five closest nursing homes	0.541	0.482	0.500	0.487
	(0.045)	(0.041)	(0.048)	(0.052)
F-statistic	142.9	136.8	108.3	88.8
Panel B. Reduced form: 90-day survival				
Leave-year-out quality in five closest nursing homes	0.567	0.457	0.510	0.467
	(0.064)	(0.066)	(0.070)	(0.077)
Panel C. 2SLS: 90-day survival				
Leave-year-out quality estimates	1.048	0.948	1.021	0.960
	(0.062)	(0.089)	(0.075)	(0.086)
Demographic and health controls	X	X	X	X
Region fixed effects	HSA	County	ZIP3	ZIP3 × Urban
Observations	632,122	632,122	632,122	632,122

Notes: This table presents first-stage, reduced-form, and two-stage least squares estimates of the forecast coefficient. The outcome in Panels B and C is 90-day survival. The endogenous variable is the leave-year-out empirical Bayes quality estimate for nursing homes, and the instrument is the average quality of the five nursing homes closest to each resident. All regressions include controls for residents' demographics and health, as well as region fixed effects of increasing granularity: Hospital Service Area, county, three-digit ZIP code, and the interaction between three-digit ZIP code and urban classification. A ZIP code is classified as urban if it is less than 50 miles from one of eight major urban centers. Standard errors, clustered at the nursing home level, are reported in parentheses.

In addition, Appendix Table A.5 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 at the beginning of Section III, 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).[12] 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.[13] Appendix Figures A.5 and A.6 show that quality estimates based on mortality over 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.4 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.

III.C. Discussion of Nursing Home Quality Estimates

1. Commonality of Quality Measures. Table III 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).[14] Appendix Table A.6 shows that the same patterns hold for the fixed effects quality estimates.

On the other hand, the R-squared of 0.04 in column 8 of Table III shows that only a small

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

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

[14] 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 III. Correlations Between Quality Estimates and Nursing Home Characteristics

	Quality estimate (s.d.)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2009 star rating (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)
Observations	9,988	9,994	9,995	9,989	9,997	9,997	9,997	9,975
R^2	0.009	0.013	0.015	0.012	0.003	0.011	0.002	0.043

Notes: This table reports correlations between nursing home quality estimates and facility characteristics. The unit of observation is a nursing home–year. Observations are weighted so that each nursing home's total weight equals its number of residents over the sample period. Standard errors, clustered by nursing home, are reported in parentheses.

fraction of the variation in my quality measure can be explained by these publicly available quality measures. In Appendix Table A.7, 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.

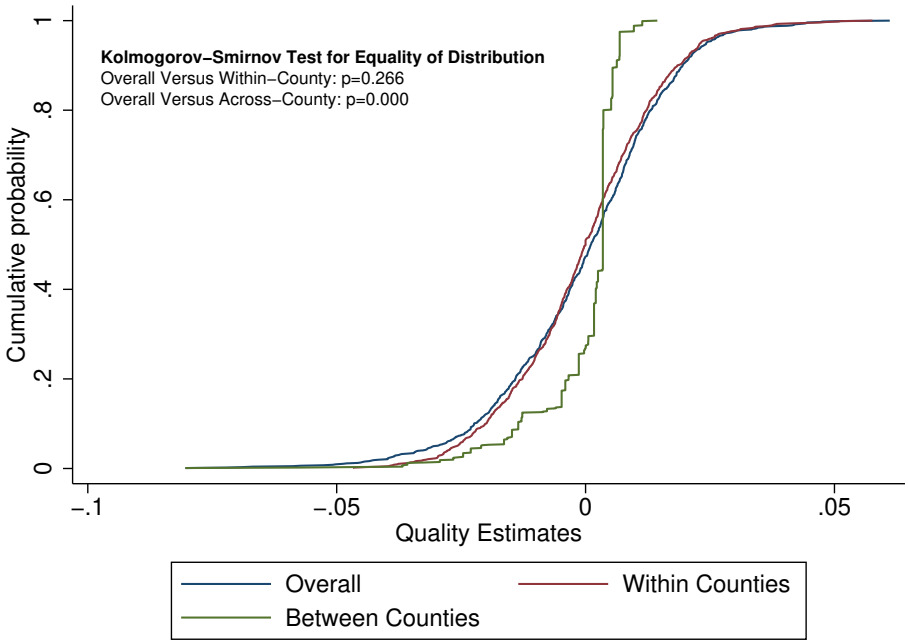
2. Geographical Variation in Nursing Home Quality. Finally, while the quality estimates indicate substantial variation in nursing home quality across California, the degree of local variation is also important for consumer choice; in particular, if quality is highly geographically concentrated, then residents living in certain areas may not have access to high-quality nursing homes. To shed light on whether this is the case, Figure II 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 are equal 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 take advantage of this variation is the topic of the next section.

IV. STRUCTURAL ESTIMATION

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 IV.A 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 IV.B, I present and estimate a structural model of consumer choice

Figure II. ECDF of Empirical Bayes Quality Estimates



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.

and provider cream-skimming using recent advancements in the empirical matching literature (Agarwal and Somaini, 2026). Finally, I present the structural estimates in Section IV.C, and conduct robustness checks in Section IV.D.

IV.A. 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 condi-

tional 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 she was choosing her nursing home—i.e., the occupancy-quality gradient, Δ_i is positive—she may be "forced" to choose a lower-quality nursing home than she would like. Hence, we may expect naïve demand estimates to vary negatively with Δ_i, even though there is little reason to believe that true demand is a function of Δ_i.

To operationalize this, I measure the occupancy-quality gradient by regressing a measure of capacity strain faced by these nursing homes on their quality, and denote the estimated coefficient by $\hat{\Delta}_i$.[15] I then estimate conditional logit models where I allow responsiveness to quality to vary as a quartic function of $\hat{\Delta}_i$:

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

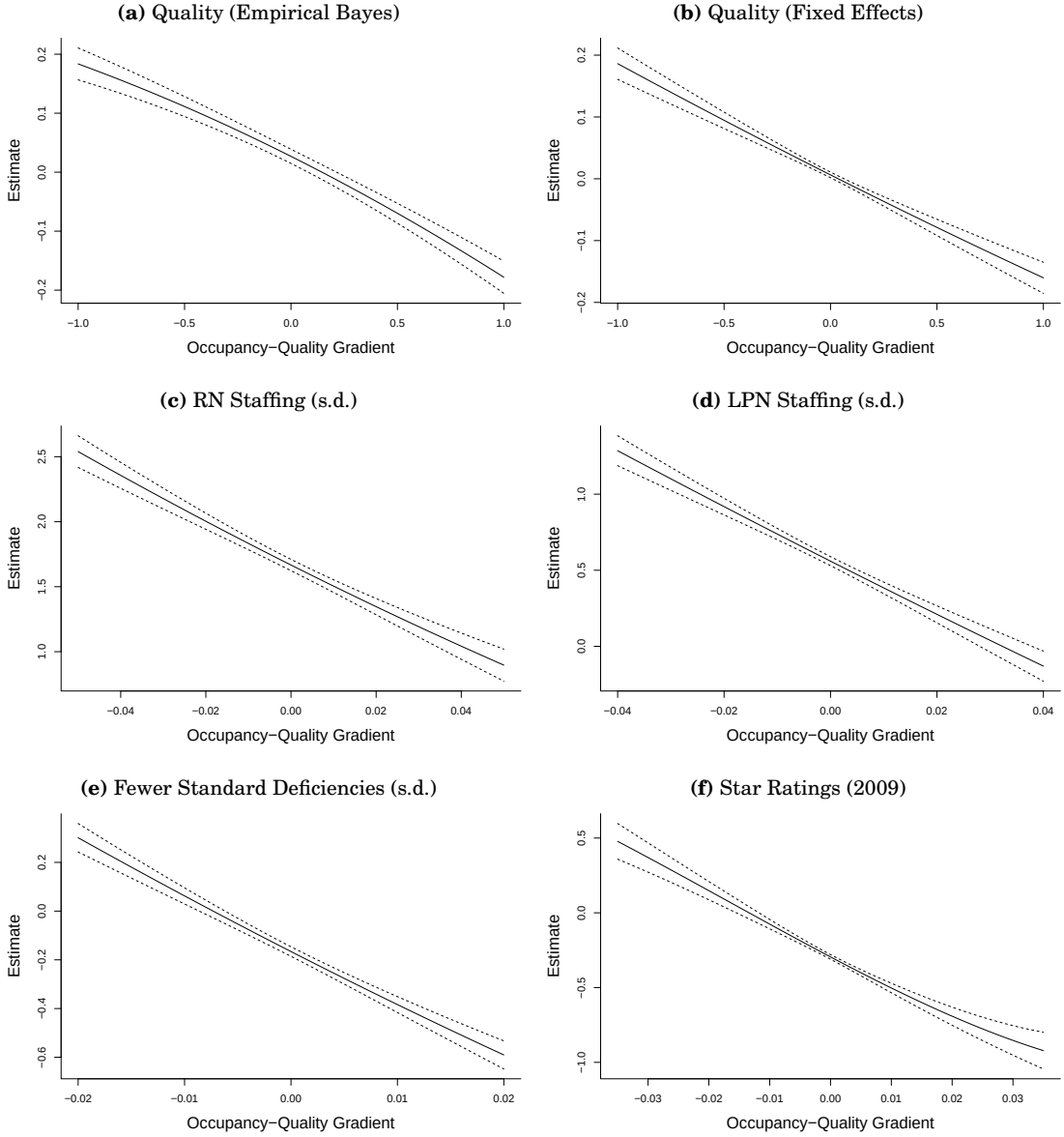
Figure III shows that conditional logit estimates of responsiveness to quality are indeed decreasing in the occupancy-quality gradient across a range of different quality measures: the causal mortality-based (empirical Bayes or fixed effects) quality estimates from the previous section, RN staffing, LPN staffing, (fewer) deficiency citations, and star ratings. This implies that failing to account for capacity 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.[16] 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

[15] 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.

[16] 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.

Figure III. Relationship Between Naïve Demand Estimates and the Occupancy-Quality Gradient



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.

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.[17] 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 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., staffing constraints) is often more relevant than spare beds, and this varies across nursing homes. For these reasons, deviations from average occupancy patterns at each nursing home is a more appropriate measure of capacity strain.

Table IV shows results supporting prediction 1 based on regressions at the nursing home-day level: conditional on nursing home-month fixed effects, nursing homes admit fewer new residents

[17] 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.

on days when occupancy is higher than usual. This finding is robust to different measures of nursing homes' admissions decisions—such as an indicator for any new admissions and net admissions (i.e., admissions minus discharges)—and is not sensitive to the functional form used for occupancy.

Figure IV 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).[18] 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 et al., 2023).[19] Appendix Figures A.11 and A.12 show that these results remain qualitatively similar if we use occupancy in levels or occupancy percentile instead of log occupancy, while Appendix Table A.8 shows that these results are also robust to using nursing home-month fixed effects instead of nursing home-year fixed effects.

IV.B. Structural Model

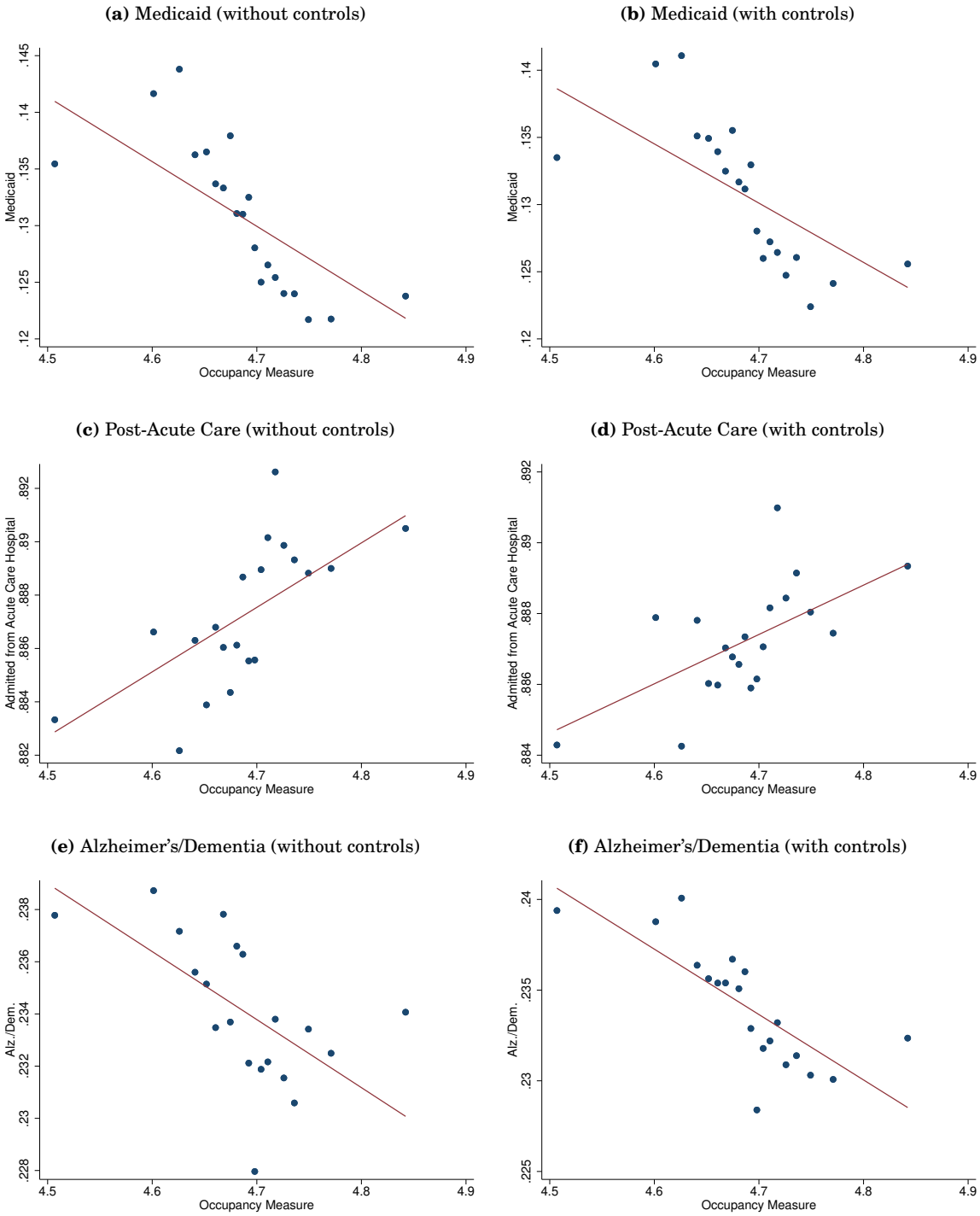
Having documented cream-skimming behavior by nursing homes, in this subsection I describe a structural model and estimation procedure that accounts for unobserved choice set constraints arising from selective admissions.

1. Identification of the 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

[18] While I used nursing home-month fixed effects for the nursing home-day level regressions in Table IV, 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.8 shows that the results are still robust to the inclusion of nursing home-month fixed effects.

[19] 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 IV. Reduced Form Evidence of Selective Admissions



Notes: These bin scatters show indicators for Medicaid status, admission from an acute care hospital, 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.

Table IV. Lagged Occupancy and Daily Resident Flows

	(1)	(2)	(3)
Panel A: Number of New Residents			
Lagged 7-day avg. log occupancy	-0.857^{***}		
	(0.0466)		
Lagged 7-day avg. occupancy		-0.0197^{***}	
		(0.000437)	
Lagged 7-day avg. occupancy percentile			-0.00574^{***}
			(0.000131)
Nursing home × month fixed effects	X	X	X
Observations	3,426,363	3,426,363	3,426,363
Panel B: Any New Residents			
Lagged 7-day avg. log occupancy	-0.619^{***}		
	(0.0330)		
Lagged 7-day avg. occupancy		-0.0133^{***}	
		(0.000323)	
Lagged 7-day avg. occupancy percentile			-0.00420^{***}
			(7.54×10^{-5})
Nursing home × month fixed effects	X	X	X
Observations	3,426,363	3,426,363	3,426,363
Panel C: Flow of Residents			
Lagged 7-day avg. log occupancy	-3.698^{***}		
	(0.191)		
Lagged 7-day avg. occupancy		-0.0829^{***}	
		(0.00238)	
Lagged 7-day avg. occupancy percentile			-0.0233^{***}
			(0.000457)
Nursing home × month fixed effects	X	X	X
Observations	3,426,363	3,426,363	3,426,363

Notes: This table reports nursing home-day regressions of resident flows on different measures of recent occupancy. The dependent variables are the number of new residents in Panel A, an indicator for any new residents in Panel B, and the change in the number of residents from the previous day in Panel C. Standard errors, clustered at the nursing home level, are reported in parentheses.

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 (2026) 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,[20] 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.[21]

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 IV. 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.

The assumption that merits most discussion is the exclusion restriction for temporary occupancy fluctuations as the supply instrument. To discuss this assumption, first consider why simply using occupancy (rather than fluctuations in occupancy) as the supply instrument is likely to violate the exclusion restriction, and how this will affect the demand estimate. Suppose that

[20] 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.

[21] 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 finds low responsiveness by residents to this price.

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 IV), 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.

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 (includ-

ing 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,[22] 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.

I define each resident i's choice set as the set of all nursing homes within 15 miles of her prior address, $\mathcal{J}_i$.[23] 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 $2^{|\mathcal{J}_i|} - 1$.[24] 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.[25]

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, 2026). At a

[22] 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.

[23] 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.

[24] 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.

[25] 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.

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 the posterior distribution is updated in each iteration. In each iteration, I draw the structural error terms $(\epsilon', \omega')'$ 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 (Roberts 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 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.

IV.C. Structural Estimation Results

Table V presents estimates of the structural model. Estimates from the preferred specification—which account for unobserved choice set constraints—are shown in columns 1 and 2, whereas naïve estimates that ignore these constraints are shown in columns 3 and 4. In addition, given the potential concern that some residents may be able to wait until capacity at their preferred nursing home is less strained, I show results for the full sample (in columns 1 and 3), and also for the subsample of post-acute care residents (columns 2 and 4) who face greater time constraints when choosing nursing homes.[26]

First, we observe that in our preferred specification, the coefficients on the demand- and

[26] In particular, post-acute care patients often report having only one or two days to choose a nursing home before they are discharged from the hospital (Shugarman and Brown, 2006).

Table V. Structural Estimates

	Full Model		Demand Only	
	Full Sample (1)	Post-Acute Care (2)	Full Sample (3)	Post-Acute Care (4)
Resident Preferences				
Distance to Nursing Homes (in Miles)	-0.171^{***}	-0.172^{***}	-0.158^{***}	-0.160^{***}
	(0.001)	(0.001)	(0.0004)	(0.0004)
Quality	18.213^{***}	17.184^{***}	3.359^{***}	-0.020
	(1.050)	(1.616)	(0.732)	(0.749)
Quality × Alzheimer's/Dementia	-1.014^{***}	-0.851^{***}	-1.419^{***}	-1.362^{***}
	(0.278)	(0.309)	(0.279)	(0.270)
Quality × Age	-0.218^{***}	-0.203^{***}	-0.063^{***}	-0.019^{**}
	(0.010)	(0.019)	(0.008)	(0.009)
Quality × At Least Bachelor's Degree	2.685^{***}	3.060^{***}	2.383^{***}	2.410^{***}
	(0.342)	(0.373)	(0.302)	(0.321)
Quality × English as Primary Language	2.141^{***}	2.338^{***}	1.659^{***}	1.594^{***}
	(0.335)	(0.330)	(0.287)	(0.289)
Quality × Black	-0.025	-0.219	-1.165^{***}	-1.244^{***}
	(0.500)	(0.407)	(0.360)	(0.369)
Quality × Hispanic	-0.412	-0.298	-0.285	-0.592^{*}
	(0.384)	(0.357)	(0.343)	(0.340)
Quality × Post-Star Ratings	0.239	0.284	0.538^{***}	0.492^{**}
	(0.249)	(0.262)	(0.206)	(0.229)
Nursing Homes' Admissions Policies				
Capacity Strain	-10.129^{***}	-9.829^{***}		
	(0.192)	(0.158)		
Quality	-14.776^{***}	-17.507^{***}		
	(0.605)	(1.684)		
Medicaid	-0.126^{***}	-0.113^{***}		
	(0.022)	(0.019)		
Post-Acute Care	0.075			
	(0.049)			
Alzheimer's/Dementia	-0.113^{***}	-0.137^{***}		
	(0.033)	(0.024)		
Age	0.032^{***}	0.034^{***}		
	(0.001)	(0.001)		
At Least Bachelor's Degree	-0.029	-0.092^{**}		
	(0.019)	(0.039)		
English as Primary Language	-0.030	-0.090^{***}		
	(0.024)	(0.018)		
Black	-0.401^{***}	-0.372^{***}		
	(0.031)	(0.029)		
Hispanic	0.012	-0.091^{***}		
	(0.024)	(0.014)		
Average Demand for Quality	0.198 (0.015)	0.219 (0.013)	-0.003 (0.007)	-0.009 (0.008)
10th Percentile of Demand for Quality	-0.025 (0.014)	0.010 (0.012)	-0.132 (0.013)	-0.115 (0.015)
90th Percentile of Demand for Quality	0.465 (0.021)	0.467 (0.030)	0.141 (0.011)	0.098 (0.019)
Year fixed effects in supply equation	X	X		
Observations	5,492,614	5,124,314	5,492,614	5,124,314

Notes: This table reports estimates from the structural model. Coefficient estimates and their standard errors are based on the posterior mean and standard deviation of the Gibbs chain respectively, with standard errors reported in parentheses. Demand for quality is defined as the marginal rate of substitution between quality (in percentage points) and distance (in miles). To compute the average, 10th percentile, and 90th percentile of demand for quality over the sample and their standard errors, I take 1,000 draws of the coefficient estimates from the posterior distribution, computing individual-specific demand for each draw as well as the mean, 10th percentile, and 90th percentile across individuals in each draw, and then take the mean and standard deviations of these statistics across draws. The full-sample specifications include all residents, while the post-acute care specifications restrict the sample to residents admitted from acute care hospitals. A burn-in period corresponding to the first half of the chain was used.

supply-side instruments—distance to nursing home and capacity strain respectively—are highly statistically significant, indicating that the model is unlikely to suffer from weak identification. Moreover, estimates of nursing homes' admissions policies are consistent with the reduced form evidence shown in Figure IV, with facilities being less likely to admit patients who are on Medicaid or suffer from dementia, and more likely to admit patients from acute care hospitals (who tend to be covered by Medicare).

Turning to the demand estimates, we observe in columns 1 and 2 that estimates of average demand for quality from the preferred specification are positive and highly statistically significant. The magnitude of average demand is similar in the full and post-acute care samples, with a marginal rate of substitution (MRS) between quality (in percentage points of risk-adjusted 90-day survival) and distance (in miles) of roughly 0.2. By contrast, columns 3 and 4 show that specifications that do not account for unobserved choice set constraints stemming from nursing homes' admissions policies yield precise, near-zero estimates of average demand for quality.

The null demand estimates in the naïve specification are due to the model misattributing rejections by high-quality nursing homes to weak demand for quality from patients. This bias is compounded by the fact that higher-quality nursing homes are more selective in their admissions policies (holding capacity strain fixed), as indicated by the negative and highly statistically significant coefficient estimate on quality on the supply side in columns 1 and 2. This behavior is consistent with the dynamic model of selective admissions outlined above: if residents value quality, higher-quality nursing homes anticipate a higher future stream of applications and can thus impose a higher profitability threshold for admission. The combination of these two forces—unobserved rejections by health care providers, and greater selectivity among higher-quality providers—help explain how the absence of a quality-market share gradient can be mistaken for health care exceptionalism.

To put the magnitude of these unobserved choice set constraints into perspective, Appendix Table A.9 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 21.3 percent, and that it is considerably higher at above-median quality nursing homes (25.8 percent), and lower at below-median quality nursing homes (16.9 percent). In addition, the variation in rejection rates by resident characteristics is substantial: for instance, residents on Medicaid are 3.8–3.9

percentage points more likely to be rejected than those not on Medicaid across all nursing homes (18 percent of the overall rejection rate), while residents with Alzheimer's/dementia are 2.6–2.7 percentage points more likely to be rejected (12–13 percent of the average rejection rate).

While average demand is positive, columns 1 and 2 show that there is also systematic demand heterogeneity along patient characteristics. Patients who are older and suffer from dementia are less responsive to nursing home quality, while demand is greater among patients with more education and with English as their primary language. Patients choosing a nursing home after the introduction of star ratings—a high-profile information intervention by the CMS—are also slightly more responsive, although the estimate is not statistically significant. This demand heterogeneity is quantitatively meaningful: the 10th percentile of the demand distribution is not statistically different from zero, while the 90th percentile is roughly 2.5 times average demand.

The naïve model in columns 3 and 4 produces qualitatively similar patterns of demand heterogeneity for most patient characteristics. A notable exception is race, where the demand-only model (but not the full model) suggests that Black patients are less responsive to quality than White patients are (conditional on other non-race patient characteristics in the model). This discrepancy can be explained by the estimates of nursing homes' admissions policies in columns 1 and 2: we observe that nursing homes reject Black residents at significantly higher rates, which the restricted model misinterprets as Black residents being less responsive to quality. In addition, we observe that the distribution of demand for quality from the misspecified model is roughly symmetric around zero, with the 10th percentile being negative and highly statistically significant. While quality may be negatively correlated with other nursing home characteristics that residents value in theory, it seems implausible in practice that a substantial share of residents derive disutility from quality.

Finally, although the preferred specification shows that most residents exhibit positive demand for quality, the implied magnitudes are modest. Even at the 90th percentile, the MRS is approximately 0.5, which assuming full information on the part of patients, implies that patients are willing to tolerate a $1/0.5 \approx 2$ percentage point higher probability of dying within 90 days in exchange for a one-mile reduction in travel distance. This is also lower than MRS estimates from hospital settings, which range from 1.8 at the low end (Chandra et al., 2016) to 8 at the high end (Tay, 2003). Evidently, modest consumer demand for quality in this market has also been an issue of concern to the CMS, leading to the introduction of the star ratings at the end of 2008. However,

the statistically insignificant coefficient estimates on the indicator for post-star ratings in columns 1 and 2 suggest that the star ratings had only a modest effect on consumer demand.

Appendix Section G studies the star ratings' effects in greater detail, using a more flexible specification of the structural model which allows both consumer demand and nursing homes' admissions policies to differ pre- and post-star ratings, and for heterogeneity in admissions policies by quality. Model estimates indicate that increases in demand for quality were concentrated among residents who were already relatively responsive to quality pre-star ratings, suggesting a regressive demand-side effect. On the other hand, lower-quality nursing homes became more selective post-star ratings, consistent with an attempt to pool with higher-quality providers when risk adjustment is imperfect (Dranove et al., 2003). Lastly, using an event study design, I find larger investments in quality among nursing homes that were more exposed to increases in consumer demand for quality, particularly if they were low-quality pre-star ratings.

IV.D. Robustness Checks

In this subsection, I address the main threats to the validity of the structural estimates.

1. Omitted Attributes Correlated with Quality. The first concern is that nursing home quality may be endogenous because facilities with high or lower estimated quality may also have certain attributes that are valued by residents, such as reputation, management quality, or referral relationships. This has different implications depending on whether quality is positively or negatively correlated with the omitted attributes that residents value. If they are negatively correlated, then "true" demand for quality would be larger than implied by the estimates in Table V. However, this seems unlikely, especially given the positive correlations between quality and other positive nursing home attributes shown in Table III.

On the other hand, if quality is positively correlated with omitted attributes that are valued by residents, then estimated demand for quality may be biased upwards. I address this possibility in three ways. First, I adopt a control function approach using average quality of other nursing homes nearby as an instrument. I implement this following the approach in Petrin and Train (2010), by including the residual from a first stage regression of quality on the instrument—which proxies for the endogenous component of quality—in the indirect utility equation. Appendix Table A.10 shows full-sample estimates from the baseline specification and based on the control function approach in columns 1 and 2 respectively, and similarly, for the post-acute care sample in columns 3 and 4. We observe that the F-statistic from the first stage regression is 88, indicating that the

instrument holds strong predictive power. Importantly, estimates of average demand, as well as the 10th and 90th percentiles of demand, are similar and not statistically distinguishable from the estimates from the main specification at the 5 percent level.

Second, I include other nursing home characteristics in the demand equation. This is tricky, since facility characteristics such as star ratings, staffing levels and deficiency citations reflect inputs or components of quality, and adding these variables to the utility equation would change the interpretation of the coefficient on quality. Therefore, I only include nursing home characteristics that are not clearly components of quality—such as for-profit status and chain ownership—in the demand equation. Although Table III shows that for-profit status and chain ownership are negatively correlated with nursing home value-added, patients may still exhibit a tendency to choose these nursing homes due to other reasons, such as better brand recognition, marketing, and hospital referral relationships. Appendix Table A.11 shows structural estimates that include for-profit status and chain ownership in the demand side, with the preferred specification presented in columns 1 and 2, and the naïve specification shown in columns 3 and 4. We observe a similar pattern to our main results in Table V: estimates of average demand for quality (conditional on for-profit and chain status) is positive and highly statistically significant under the full model, but small and statistically indistinguishable from zero under the naïve specification.

Third, 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 results that (i) average demand for quality is positive, and (ii) average demand for quality is lower than in hospital settings. 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 positive demand estimate (respectively, the discrepancy between my demand estimate and previous estimates from the hospital setting), residents need to value the omitted variable more than 7 times (70 times) they do nursing homes' for-profit and chain ownership, based on a similar assumption on the proportional selection relationship adopted by Oster (2019).

2. Heterogeneity in Admissions Policies. A separate concern is that the demand estimates may partly capture heterogeneity in admissions policies: for instance, even conditional on quality, nursing homes with higher average occupancy rates may be more selective. To address this, columns 2 and 5 of Appendix Table A.12 shows structural estimates that control for annual

occupancy rates in nursing homes' admissions policies. Indeed, we observe that nursing homes with higher average occupancy rates are indeed more selective. Nonetheless, a comparison with the estimates from the main specification in columns 1 and 4 of the same table reveals that controlling for annual occupancy hardly affects the demand estimates.

Relatedly, differences in health production technology, profitability, or specialization may generate heterogeneity in admissions policies across nursing homes. In particular, although Table V showed that higher-quality nursing homes are more selective *on average*, they may also have different preferences over patient types. If this is the case, estimates of demand heterogeneity may in part reflect differences in admissions policies. To test whether such heterogeneity affects the demand-side estimates, columns 3 and 6 of Appendix Table A.12 shows structural estimates that include interactions between quality and patient characteristics in nursing homes' admissions policies. Again, a comparison with the estimates from the main specification in columns 1 and 4 shows that estimates of average demand and patterns of demand heterogeneity remain similar even after controlling for heterogeneity in admissions policies.

Taken together, the results in this section reconcile two facts. Residents place positive value on nursing home quality on average, but this demand is modest and partly obscured by supply-side constraints: nursing homes—particularly higher-quality ones—admit fewer residents when capacity is strained, weakening the link between quality and realized market shares. This raises a natural question: even if residents could be induced to place greater weight on quality, would such demand-side changes alone be sufficient to improve allocation and health outcomes in the presence of capacity constraints and selective admissions? I address this question in the next section in counterfactual simulations.

V. COUNTERFACTUAL SIMULATIONS

In this section, I conduct counterfactual simulations to study the effect of demand on allocation and health outcomes in the presence of selective admissions by nursing homes. Given the limited effect the star ratings had on consumer demand, a natural concern is whether counterfactual increases in demand are realistic. I therefore focus on demand-side counterfactuals that are grounded in institutional details of the nursing home placement process. Specifically, I focus on the discharge process from hospitals to nursing homes, given that most residents in my sample are post-acute care, this is the margin that is most amenable to policy intervention.

V.A. Main Counterfactuals

The first counterfactual considers the effect of increasing demand for quality to the 95th percentile of the estimated distribution. To anchor this to a plausible real-world policy, I consider financial schemes which incentivize hospitals to discharge patients to higher-quality nursing homes. Specifically, I calibrate a financial incentive scheme that achieves an equivalent effect to the increase in demand, using the steering elasticity with respect to profits estimated by Cutler et al. (2021).

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). Post-acute care patients often only have one or two days to choose a nursing home before being discharged from the hospital (Shugarman and Brown, 2006), yet discharge planners often provide them with a (potentially very long) undifferentiated list of nursing homes to choose from, with little additional guidance. Indeed, only 4 percent of patients report receiving any information about nursing home quality (Tyler et al., 2017).[27] Hence, in this counterfactual, I simulate an alternative discharge planning process where planners provide residents with a quality-ranked shortlist of five available nursing homes.

Finally, I benchmark the magnitudes of the effects from these demand-side exercises in two ways: (i) by comparing them to the simulated effects from a supply-side counterfactual in which nursing homes are given financial incentives to increase staffing using estimates from Gandhi et al. (2024), and (ii) by showing the effect of demand heterogeneity on the mortality-age gradient. Appendix Section H.D describes these counterfactuals in greater detail.

Having defined the main counterfactuals, I next describe how I combine the structural estimates from the previous section with a competing risks model of deaths and discharges to simulate the dynamic evolution of patient allocation and outcomes.

V.B. Simulation Procedure

1. Competing Risks Model of Deaths and Discharges. For a given level of occupancy across nursing homes, estimates from the structural model in Section IV 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

[27] 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.

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,[28] standard hazard methods that do not account for this codependency will typically produce misleading estimates.[29] Therefore, in order to realistically simulate the evolution of occupancy and mortality outcomes in different counterfactuals, I combine 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 H describes the competing risks model and its estimation in greater detail.

2. Outline of Simulation Algorithm. For each day of the simulation, I draw $\bar{n}$ residents from the data. First, I simulate admissions using a more flexible version of the structural model in Section IV which allows both consumer demand and nursing homes' admissions policies to differ pre- and post-star ratings, and admissions policies to vary as a function of facility quality. In particular, 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 counterfactual 100 times based on independent draws of the structural parameters from the posterior distribution of the Gibbs sampler, and take the average over these replications. For the full simulation algorithm and assumptions underlying the counterfactual simulations, see Appendix Sections H.E and H.A respectively.

[28] 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.

[29] 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.

V.C. Simulation Results

Figure V shows simulation results for the three counterfactuals described in Section V.A. Panel (a) shows effects on patient allocation—specifically, the change in the average quality of nursing homes that patients are admitted to relative to the status quo—while panel (b) shows effects on patient outcomes—in terms of percent reduction in mortality. In addition, to better understand the role of provider cream-skimming in determining equilibrium allocations and outcomes, for each counterfactual I consider three different types of admissions policies: (i) status quo admissions policies based on the estimated parameters (in light blue), (ii) admissions policies that treat all residents equally (in medium blue), and (iii) a counterfactual where nursing homes admit all patients who apply (in dark blue). Error bars representing 95 percent confidence intervals that account for both the uncertainty of the structural estimates and the randomness of the simulations (including stochastic arrivals, discharges, and deaths) are included.

Focusing first on the simulations based on status quo admissions policies, we observe that even in the presence of supply-side constraints, demand-side policies hold the potential to improve allocation and patient outcomes. An increase in demand to the 95th percentile of the estimated distribution leads to a 0.16 s.d. increase in the average quality of nursing homes that residents are admitted to, and a 5 percent reduction in 90-day mortality. Based on the estimated elasticity of hospital steering with respect to profits in Cutler et al. (2021), I estimate that a linear incentive scheme reimbursing hospitals an additional $217 per percentage point increase in risk-adjusted value-added of the nursing home it discharges patients to would approximate the effects of this counterfactual.[30] Even under conservative assumptions on the increase in lifespan from each death within 90 days that is averted and the statistical value of a life-year, a back-of-the-envelope calculation suggests that the monetized value of life-years saved is at least 30 times the cost of this incentive scheme.[31]

[30] In particular, Cutler et al. (2021) 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. I combine this elasticity with my model's simulated responsiveness-quality share gradient and average Medicaid reimbursement amounts to estimate the linear incentive scheme that approximates an increase in demand to the 95th percentile. Appendix Section I describes this back-of-the-envelope calculation in detail.

[31] Specifically, consider a conservative statistical value of a life-year of $100,000. To obtain a back-of-the-envelope estimate of the life-years saved by each 90-day mortality averted, for patients admitted to a nursing home in 2000, I regress the number of days each patient remained alive following admission on an indicator for surviving at least 90 days, controlling for the large set of baseline demographic and health characteristics included in the value-added estimation. Moreover, given that more than half of patients admitted in 2000 remain alive even at the end of the sample (in 2010), I assume that each of these patients died immediately after the end of the sample to define the dependent variable in the regression as a conservative benchmark, since this truncation biases the estimated life-days saved downwards. I estimate that patients who avoid dying within 90 days of admission live 2617 days longer (i.e., more than 7 years longer) than patients who die within 90 days with similar baseline characteristics. This suggests that discharging a

The simulated effects of providing patients with a quality-ranked shortlist of nursing homes during discharge are even larger. Under this counterfactual, patients are admitted to nursing homes with 0.62 s.d. higher quality on average, reducing mortality by 17 percent. These substantial improvements are consistent with the lack of guidance on facility quality during the discharge process under the status quo, and the large number of facilities patients live close to (with an average of about 50 nursing homes within 15 miles).

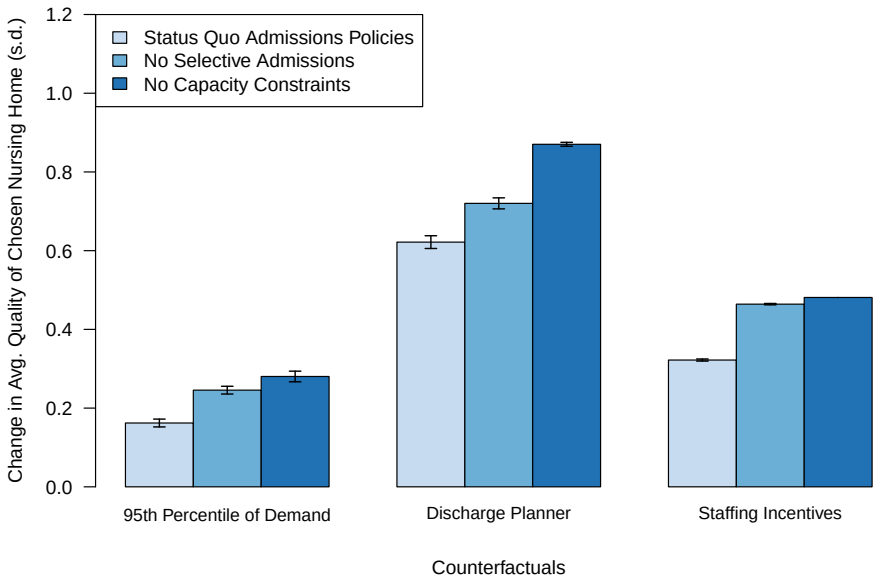
Additionally, I benchmark the magnitude of the effects from these demand-side counterfactuals in two ways. First, I compare them to the simulated effects of a 2022 policy in Illinois that offered financial incentives for facilities to increase staffing. Based on simulations that combine the estimated effects of the policy on staffing from Gandhi et al. (2024) with the correlation between staffing and nursing home value-added from Table III, I find that the simulated effects of these staffing incentives lie between the two demand-side counterfactuals, increasing quality of residents' chosen facilities by 0.32 s.d. and reducing mortality by 8.6 percent. Second, I consider the contribution of demand heterogeneity to the mortality-age gradient. I find that under the first demand-side counterfactual—which increases demand for quality to the 95th percentile, thereby eliminating most heterogeneity in demand—the mortality-age gradient is about 10 percent smaller compared to the status quo.

Finally, comparing the light-blue bars to the medium- and dark-blue bars, we observe that the gains from these demand-side counterfactuals are limited by supply-side constraints. In particular, the simulated effects of the demand-side counterfactuals on the quality of nursing homes that residents are admitted to (respectively, on patient survival) would be 16–51 percent (6–31 percent) higher in the absence of selective admissions, and 40–73 percent (28–52 percent) higher without capacity constraints (i.e., assuming that residents are always admitted to their most-preferred nursing home). While the reason that eliminating capacity constraints improves allocation and outcomes is evident given the positive demand for quality on average, the explanation for why removing selective admissions leads to improvements is more subtle. This is primarily because higher-quality nursing homes are estimated to be more selective on average; hence, by forcing admissions policies to be homogeneous across nursing homes and residents in the counterfactuals without selective admissions, barriers to access for higher-quality nursing homes are lowered.

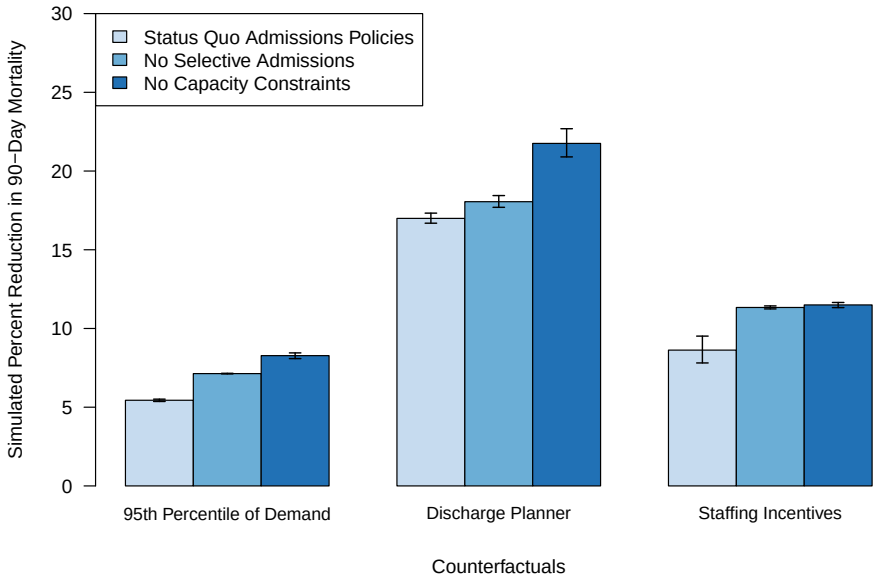
patient to a nursing home with one percentage point higher risk-adjusted 90-day survival may yield societal benefits of 0.01×7 life-years $\times$ \$100,000/life-year $\approx$ \$7000 on average, which is much larger than the cost of the incentive scheme of \$217.

Figure V. 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 three counterfactuals: (i) an increase in responsiveness to quality to the 95th percentile of the distribution of demand for quality (for residents with responsiveness below the 95th percentile), (ii) the provision of a shortlist of the five highest-quality available nursing homes by discharge planners to post-acute care residents, and (iii) financial incentives for nursing homes to increase staffing. 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 the status quo. The light-blue bars shows simulations based on 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.

I consider additional counterfactuals in the appendix. First, I consider the potential for endogenous quality responses by nursing homes in the demand-side counterfactuals. To do so, in Appendix Section J, I develop a stylized model of endogenous quality choice that accounts for capacity constraints. I calibrate nursing home-specific cost parameters under the model based on nursing homes' quality responses to the star ratings, and simulate the Nash equilibrium in facility quality under counterfactual demand levels using fixed point iteration. Simulation results suggest that allowing for endogenous quality adjustments leads to substantially greater improvements in allocation and survival. 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.

Second, I consider two simple approximations to the optimal assignment rule: (i) a "uniform" assignment rule that assigns all residents to the highest-quality nursing home below a fixed threshold of capacity strain, and (ii) a "risk-stratified" assignment rule that allows this threshold to vary by residents' baseline mortality risk. The results in Appendix Figure A.22 shows that while the average quality of residents' assigned nursing homes is similar under the two rules, the reduction in mortality is substantially higher under the risk-stratified assignment rule, suggesting that assignment rules that take into account patient characteristics can improve average outcomes.

VI. CONCLUSION

Since Arrow (1963), economists have viewed limited consumer responsiveness to provider quality as central to what makes health care different from other economic markets. If patients are unable to identify high-quality providers, competition does not reliably reward quality, and regulation can improve welfare. However, whether and the extent to which consumers respond to quality remains unresolved. A weak correlation between consumer choice and provider quality may not only reflect low demand: it may also reflect poor measurement of quality, or supply-side constraints that limit patients' choice sets.

This paper studies this question in the nursing home setting, where quality differences between providers are large, stakes for consumers are high, and the choice process is highly constrained. I first estimate nursing home quality using risk-adjusted 90-day survival, and validate these

estimates using quasi-random variation in distance to nursing homes. I then use these estimates as inputs to a structural demand model that allows for unobserved choice set constraints stemming from nursing homes' admissions decisions.

The results show that quality varies substantially across nursing homes, even within local markets, and that this variation has meaningful consequences for patient mortality. Yet, observed market shares alone are misleading. A model that ignores provider rejections yields precise estimates suggesting no demand for quality on average. By contrast, after accounting for unobserved choice set constraints, I find that residents do respond to quality. Average demand is modest but economically meaningful, with systematic variation across patients: residents who are younger, more educated, English-speaking, and without dementia are substantially more responsive to quality than the average resident.

These findings help reconcile the mixed evidence on demand for quality in health care. In a market with capacity constraints, the absence of a quality-market share gradient need not imply a lack of consumer demand for quality. Instead, it may reflect cream-skimming behavior by providers, who selectively admit patients based on expected profitability or care needs. In this case, observed choices combine consumer preferences with supply-side rationing, making demand look weaker than it is in reality.

I consider policy implications of consumer demand in counterfactual simulations. Despite the limited effects of star ratings on consumer demand, I find that improved discharge processes from hospitals to nursing homes can improve allocative efficiency and patient outcomes substantially, even if these gains are limited by supply-side constraints. In addition, demand heterogeneity has consequences for health inequality. Older residents face higher baseline mortality risk but are also less responsive to quality, and accounting for demand heterogeneity reduces the mortality-age gradient by about 10 percent. This mechanism operates through patient allocation holding provider quality fixed, and therefore complements explanation of variations in health outcomes based on socioeconomic background, medical spending, place effects, and provider behavior.

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Appendix

A. ADDITIONAL BACKGROUND ON NURSING HOMES

A.A. Brief History of the Nursing Home Industry

The growth and development of the nursing home industry in its early days were 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.[32] 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.B. 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

[32]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.

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).

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.[33]

[33]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).

B. DATA APPENDIX

B.A. 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 et al., 2015; Guo and Zhang, 2019), and given 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.B. 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.[34] 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.C. 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

[34] 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.

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 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 et al. (2021). Suppose that:

$$Y_{ij} = \mu_j + a_i, \tag{7}$$

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 (7) to obtain:

$$\begin{aligned} Y_i &= Y_{i1} + \sum_{j=2}^{J} (Y_{ij} - Y_{i1}) D_{ij} \\ &= \mu_1 + \sum_{j=2}^{J} \beta_j D_{ij} + a_i, \end{aligned} \tag{8}$$

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:

$$a_i = X_i'\gamma + u_i, \ \mathbb{E}[X_i u_i] = 0, \tag{9}$$

and substitute this into equation (8) 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:

$$\beta_j = \lambda\alpha_j + \eta_j,\ \mathbb{E}[\alpha_j\eta_j] = 0. \tag{10}$$

Substituting equation (10) 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:

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

where $\lambda_{j\phi}^A \equiv Pr(j \in J_i, \phi_i = \phi)$, and $F_{j\phi}^\Pi(\Pi) = \int_{\{c:\Pi_{ij} \leq \Pi\}} \hat{p}(c_i) dF_c(c | j \in J_i, \phi_i = \phi)$. 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 (2026), and the formal assumptions required for identification. I also briefly comment on how these assumptions relate to the setting in this paper.[35]

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

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

where I denote resident-specific preference heterogeneity by ζ_i. We can set $|v_j^2(x_i, dist_{ij})| = 1$ 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:

$$\begin{aligned} \sigma_{ij} &= \sigma_j(x_{i,}\zeta_i, occ_{ij}) \\ &= \mathbb{I}[\pi(x_i, \zeta_i, occ_{ij}) \geq 0]. \end{aligned}$$

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

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

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.

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 non-parametrically identified.

Theorem 1 *(Agarwal and Somaini 2026). 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,[36] 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: $(\kappa', \psi')' \sim N(0, 100I)$.

[36] 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.

(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 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:

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

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

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:

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

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

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

G. 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.

G.A. 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,[37] whether

[37]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.

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 A.16. 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.19, 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 residents with poorer health at baseline,[38] so we do not find evidence supporting the second and third hypotheses.

G.B. 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 A.16 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 III but at the annual level, using this as the outcome for the event studies. I consider two versions of the event study: (i) using the average change in responsiveness among residents living within 15 miles of a nursing home as a continuous treatment variable, or (ii) partitioning nursing homes into four quartiles based on average change in responsiveness of residents and using these quartiles to define the treatment groups, denoting quartiles 1 to 4 by $D_j^{\Delta\kappa\in Q1}$, $D_j^{\Delta\kappa\in Q2}$, $D_j^{\Delta\kappa\in Q3}$, and $D_j^{\Delta\kappa\in Q4}$ respectively. 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 specifications can thus be written as:

$$q_{jt} = \sum_{m=-5}^{2} \left(\beta_{\Delta\kappa}^{(m)} \Delta\kappa_j \cdot \mathbb{I}[t - 2008 = m] \right) + \delta_t^{cts,es} + \gamma_j^{cts,es} + \epsilon_{jt}^{cts,es}, \tag{11}$$

$$q_{jt} = \sum_{m=-5}^{2} \left[\left(\beta_{Q2}^{(m)} \times \Delta D_j^{\Delta\kappa\in Q2} + \beta_{Q3}^{(m)} \times D_j^{\Delta\kappa\in Q3} + \beta_{Q4}^{(m)} \times D_j^{\Delta\kappa\in Q4} \right) \cdot \mathbb{I}[t - 2008 = m] \right] + \delta_t^{es} + \gamma_j^{es} + \epsilon_{jt}^{es}, \tag{12}$$

where I use the lowest quartile of change in responsiveness as the reference group for the second specification. 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.

Figures A.17 and A.18 plots event study estimates of equations (11) and (12) respectively with 95 percent confidence intervals, for nursing homes with below-median and above-median pre-star

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

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 there are hardly any pre-trends regardless of the specification, supporting the parallel trends assumption. In panel (a) of both figures, 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, regardless of whether treatment is defined based on the continuous change in average responsiveness of residents close to each nursing home, or quartiles of the changes in responsiveness. 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.

G.C. Effects of Different Response Margins to the Star Ratings

Figure A.24 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 A.16, 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 A.24 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.19. 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 the resident level. Reassuringly, the estimated discontinuity of -0.00287 (0.00100) — shown graphically in Appendix Figure A.20 — 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.

G.D. 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 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. Putting this together, the counterfactual simulations show that the star ratings improved patient allocation and outcomes, with most of these improvements coming from changes in nursing homes' admissions policies and endogenous quality responses, rather than from the direct effect on consumer demand.

H. SIMULATION DETAILS

H.A. 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.28 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.28 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.

H.B. 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

[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.

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 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:

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

[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.

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

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

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 $\beta^k_{c,haz}$. 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).

H.C. Simulating Exit Times from the Cause-Specific Hazard Model

I simulate event times for cause c using the formula from Bender, Augustin, and Blettner (2005):

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

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.

H.D. Counterfactual Details

The structural model which the counterfactuals are based on includes interactions between resident characteristics and quality, as well 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 Appendix Figure A.18.
- *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 et al. (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 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 III 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 $F^{-1}_{occ|\pi_{ij}-\omega_{ij}\geq 0}\left((1+0.55)/2\right)$. 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:

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

H.E. 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 $o\tilde{c}c_{jt}$ for nursing homes using the last 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:
$$o\tilde{c}c_{j,t} = \left(\frac{1}{7}\sum_{s=t-6}^{t} log(\tilde{o}_{js})\right) - \left(\frac{1}{30}\sum_{s=t-29}^{t} log(\tilde{o}_{js})\right),$$
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) Draw $\bar{n} = 200$ residents from the sample of residents admitted to a nursing home in 2009.
   (b) For resident $i_t = 1, ..., \bar{n}$:

i. Simulate residents' and nursing homes' counterfactual preferences, as given by:

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

where $\tilde{X}_{i_t j}$ and $\tilde{W}_{i_t j}$ denote variables included in the demand and supply equations, and $\tilde{\epsilon}_{i_t j}$ and $\tilde{\omega}_{i_t j}$ are i.i.d. $N(0,1)$ draws.[44]

ii. 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:

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

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

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

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

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

i. First, set:

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

where $\tilde{flow}_{j,t+1}$ 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:

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

I. 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

[44] The matrix $\tilde{W}_{i_t j}$ 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.

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:

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

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 $\delta^{steer} \approx 0.116$, which implies that a 1 percentage point increase in risk-adjusted survival raises admissions by 0.116 log-points (or 12.3 percent).

Next, I use the estimate from Cutler et al. (2021) 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:

$$100\% \cdot \gamma^{unadjusted} = 100\% \cdot \frac{dlog(\pi)}{dQ} = 100\% \cdot \frac{\delta^{steer}}{\epsilon^{steer}} \approx 4.64\%.$$

Given that only about 88 percent of residents in my sample are discharged from acute care hospitals, we scale up the conversion factor to $\gamma = \gamma^{unadjusted}/0.88 \approx 0.0527$ to increase the average quality of chosen nursing homes for post-acute care residents even further to make up the difference.

Medicare Payment Advisory Commission (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 $\$4125 \times 0.0527 \approx \$217$ per

percentage point increase in risk-adjusted survival (for each patient they discharge to nursing homes).

J. DETAILS ON MODEL OF ENDOGENOUS QUALITY CHOICE

J.A. Endogenous Quality Choice

The main 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. 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 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 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.[46] On the supply side, I assume the following convex cost function:

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

[46]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.

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

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

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

and denote profits by $\bar{\pi}_j(q_j, q_{\sim j}) = [R - C_j(q_j)]\, D_j(q_j, q_{\sim j})$. 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:

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

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. 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:

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

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.[47] Appendix Figure A.21 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 $\bar{\kappa}^q$. In the counterfactual

[47] 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 post-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 $c_j = \min\left\{\bar{c}_j^{pre}, c_j^{post*}\right\}$.

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 V.

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:

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

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 values of nursing home quality $q^{(k-1)}$ from the previous iteration.
      i. First, I compute the 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:

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

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 $\tilde{q}^* = q^{(k)}$.[48] 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.

Appendix Figure A.23 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 survival. 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.

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

K. 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.[49] Hence, I use a variable selection method motivated by the post-double-selection 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.[50] 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.

[49] 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.

[50] 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.

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

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

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.[51]

[51]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".

M. 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.[52] 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 $e_{\alpha,j} \sim^{i.i.d.} N\left(0, Var(e_\alpha)\right)$, 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 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

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

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.

M.A. 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:

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

Hence, we find that:

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

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:

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

From this, we see that the finite-sample IV estimate is attenuated by a factor $\dfrac{Var(\alpha_j)}{Var(\alpha_j) + Var(e_{\alpha,j})}$. Therefore, we need to multiply $\hat{\lambda}$ by a correction factor $\dfrac{Var(\alpha_j) + Var(e_{\alpha,j})}{Var(\alpha_j)}$, where both $Var(\alpha_j)$

and $Var(e_{\alpha,j})$ are available from the fixed effects quality estimation procedure.

M.B. 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:

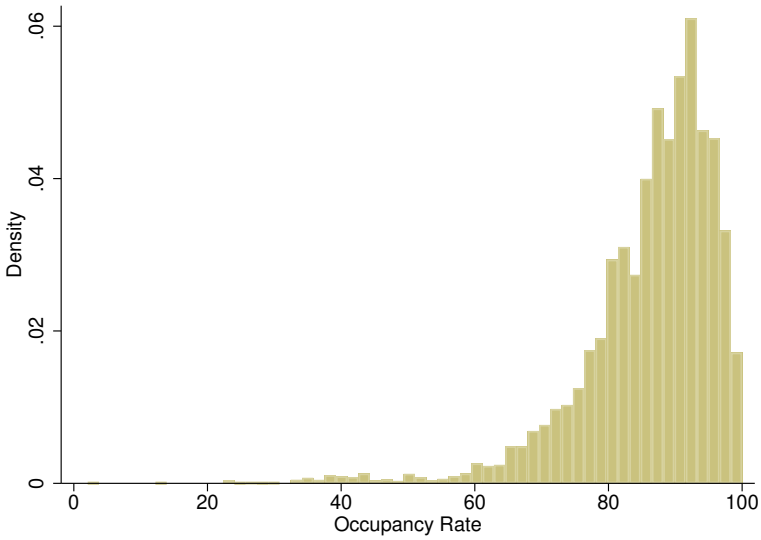
$$\begin{aligned}
Cov(\hat{\alpha}_i^{EB}, \hat{Z}_i^{EB}) &\approx \frac{Pr\left(\mu(i) \in \mathcal{N}_i\right)}{|\mathcal{N}_i|} \cdot \mathbb{E}\left[\left(\frac{Var(\alpha_j)}{Var(\alpha_j) + (J/N) \cdot s^2}\right)^2\right] \cdot \left(Var(\alpha_j) + \frac{J}{N} s^2\right) \\
&= \frac{Pr\left(\mu(i)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

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

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

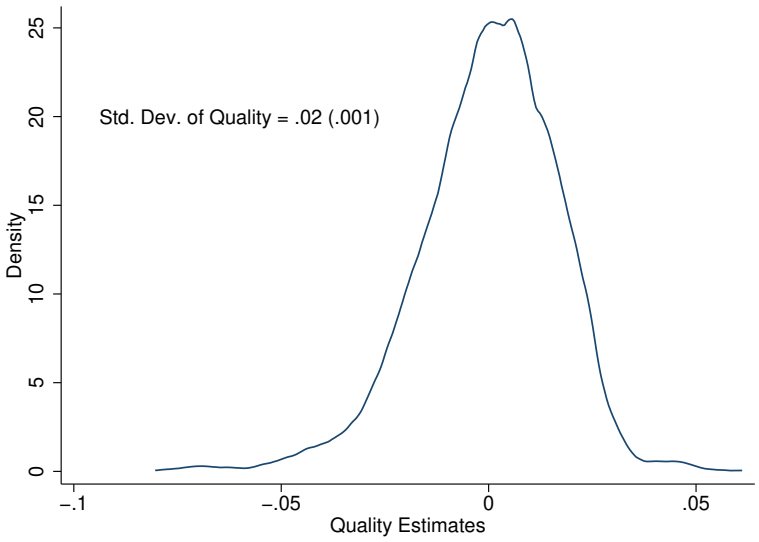
A. APPENDIX FIGURES AND TABLES

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.

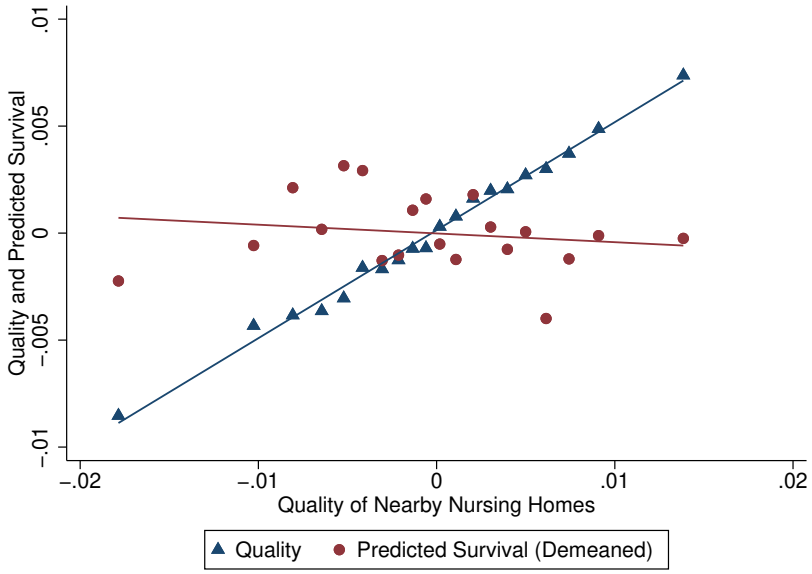
Figure A.2. Kernel Density Plot of Nursing Home Quality Estimates



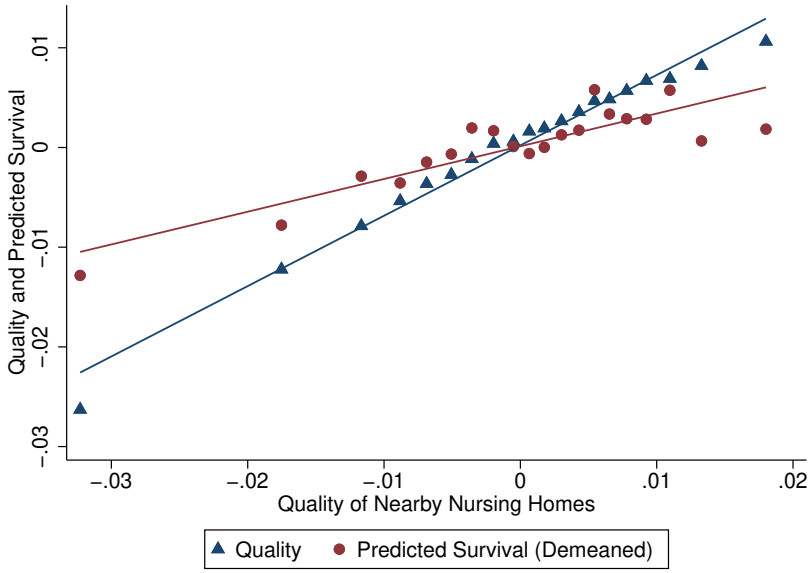
Notes: This figure contains a kernel density plot of the main quality estimates, using an Epanechnikov kernel. The standard error for the standard deviation of nursing home quality displayed in the figure is calculated based on the square root of the variance from the inverse of the Fisher information 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



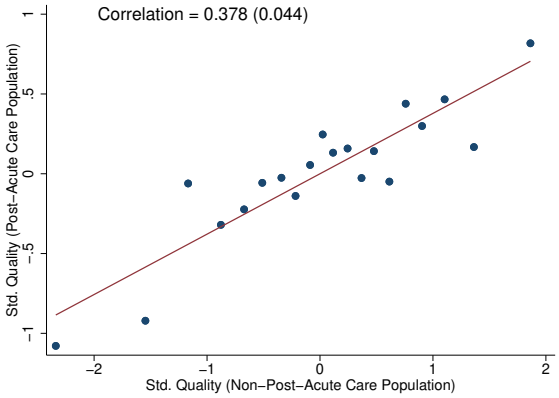
(b) No County Fixed Effects



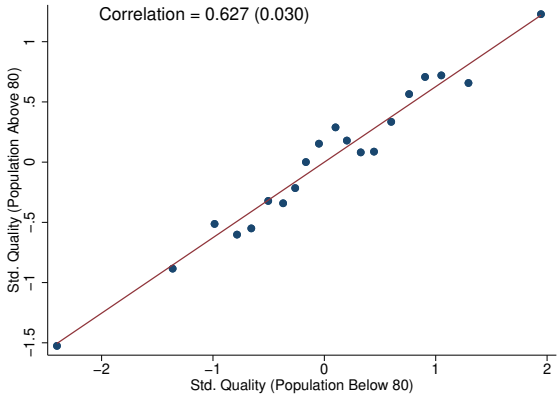
Notes: The x-axis in these figures correspond to the average quality of the five nearest nursing homes to each resident. Variables in panel A are residualized of county fixed effects, whereas variables in panel B are not residualized of county fixed effects.

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

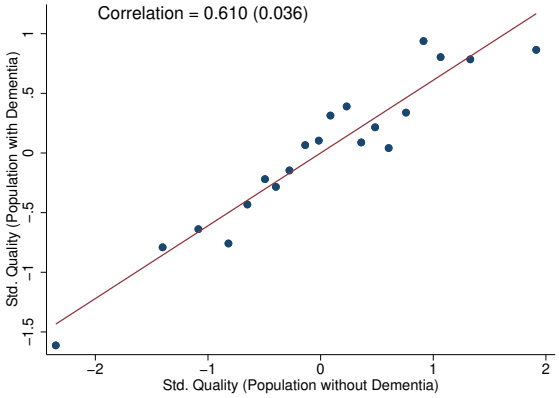
(a) Whether the Resident was Post-Acute Care



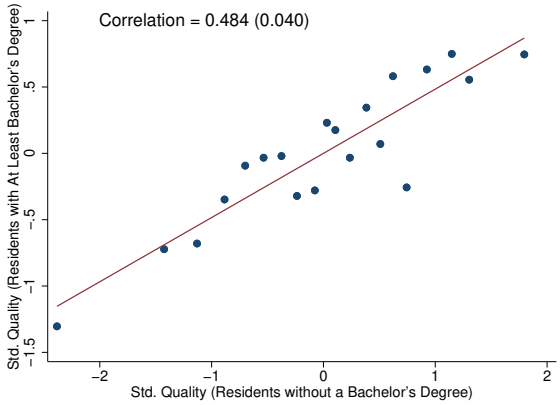
(b) Whether the Resident was Above 80



(c) Whether the Resident has Dementia

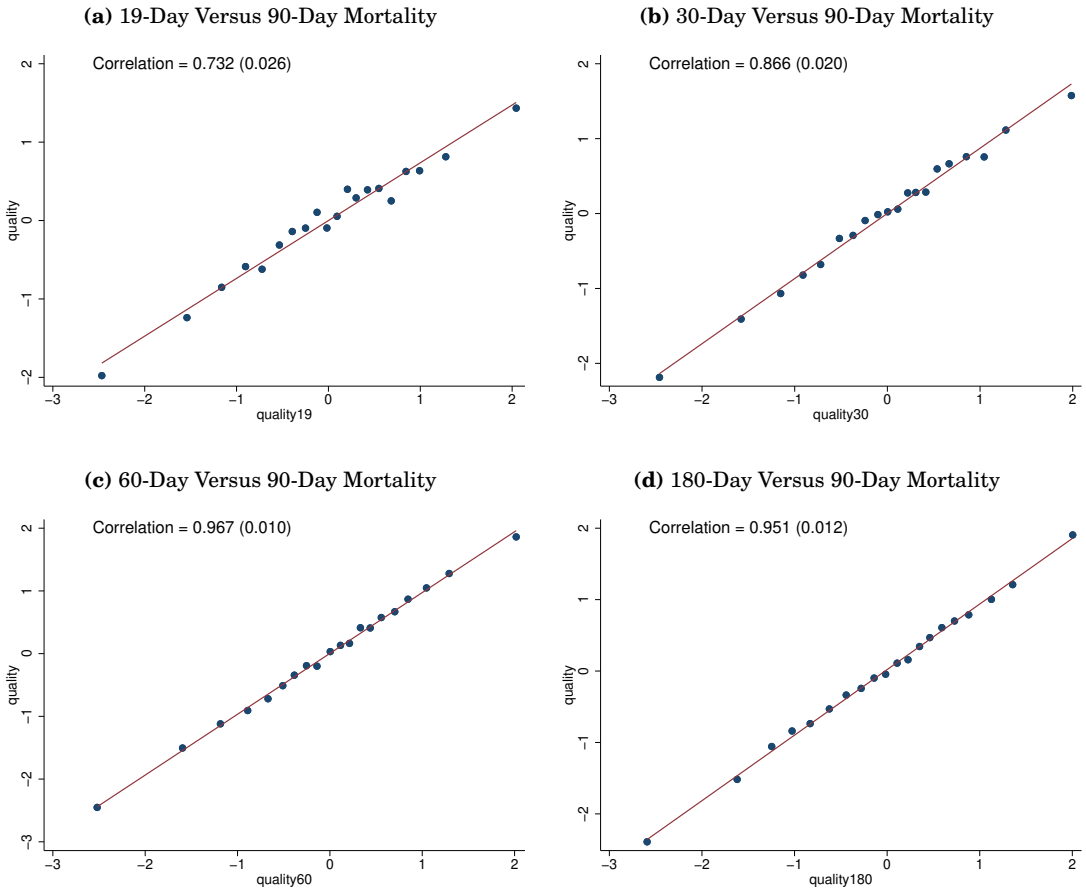


(d) Whether the Resident has Bachelor's Degree



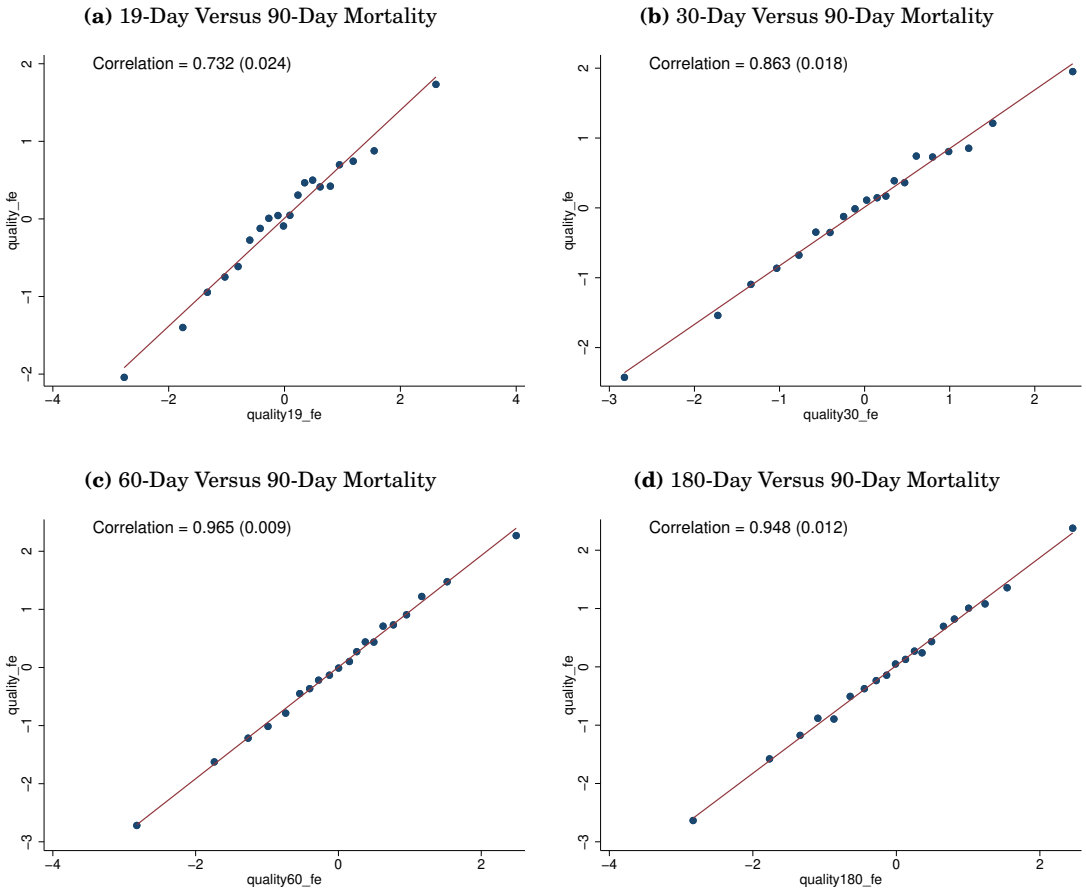
Notes: For each plot, I partition the resident population based on the resident characteristic in the sub-figure title, estimate quality separately for the two subsamples, and then plot these two sets of coefficients against each other.

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



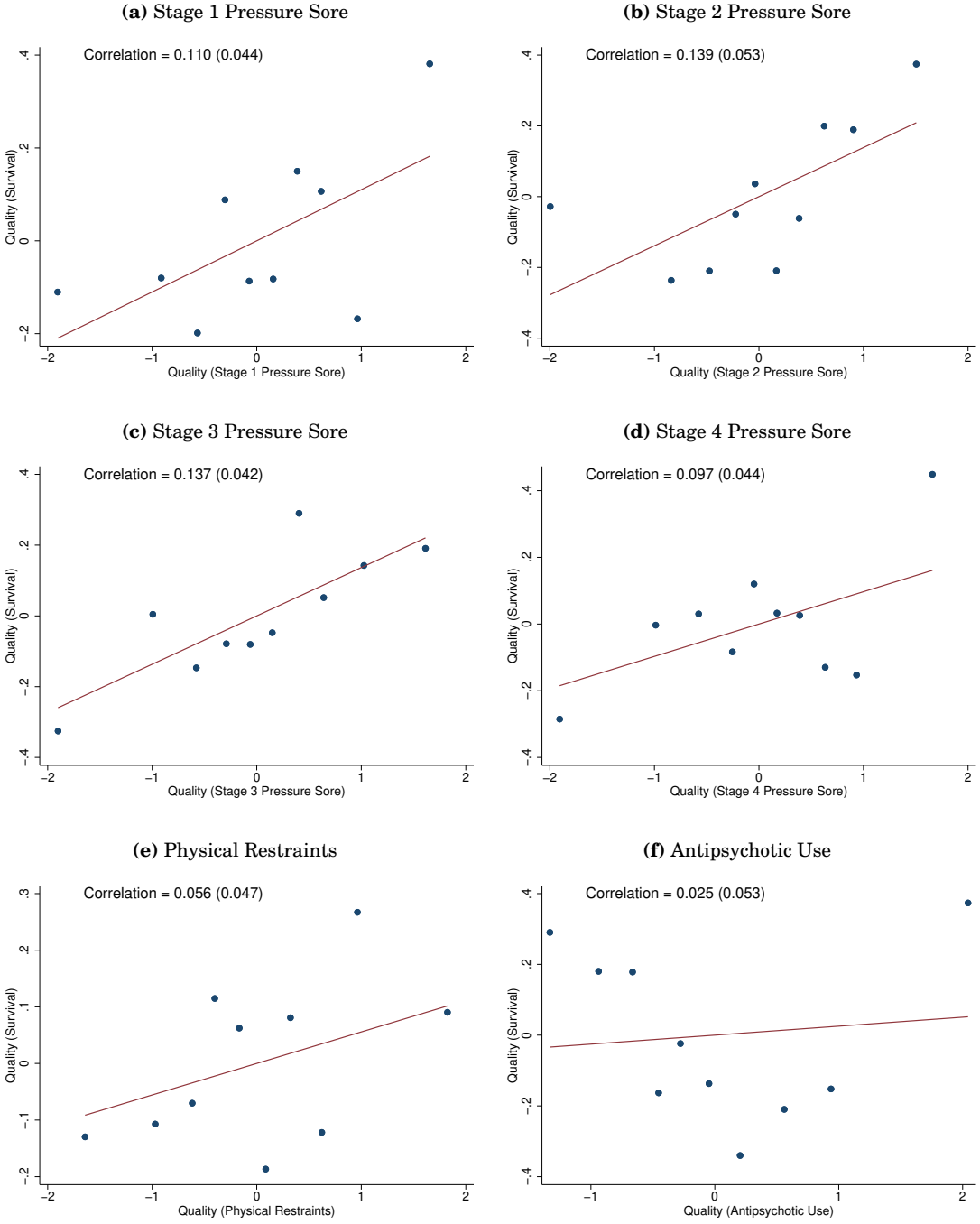
Notes: The x-axis of these figures correspond to empirical Bayes quality estimates using survival for at least 19, 30, 60, or 180 days as the outcome (standardized to have mean zero and standard deviation one). The bin scatters are weighted by the number of observations for each nursing home, and robust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

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



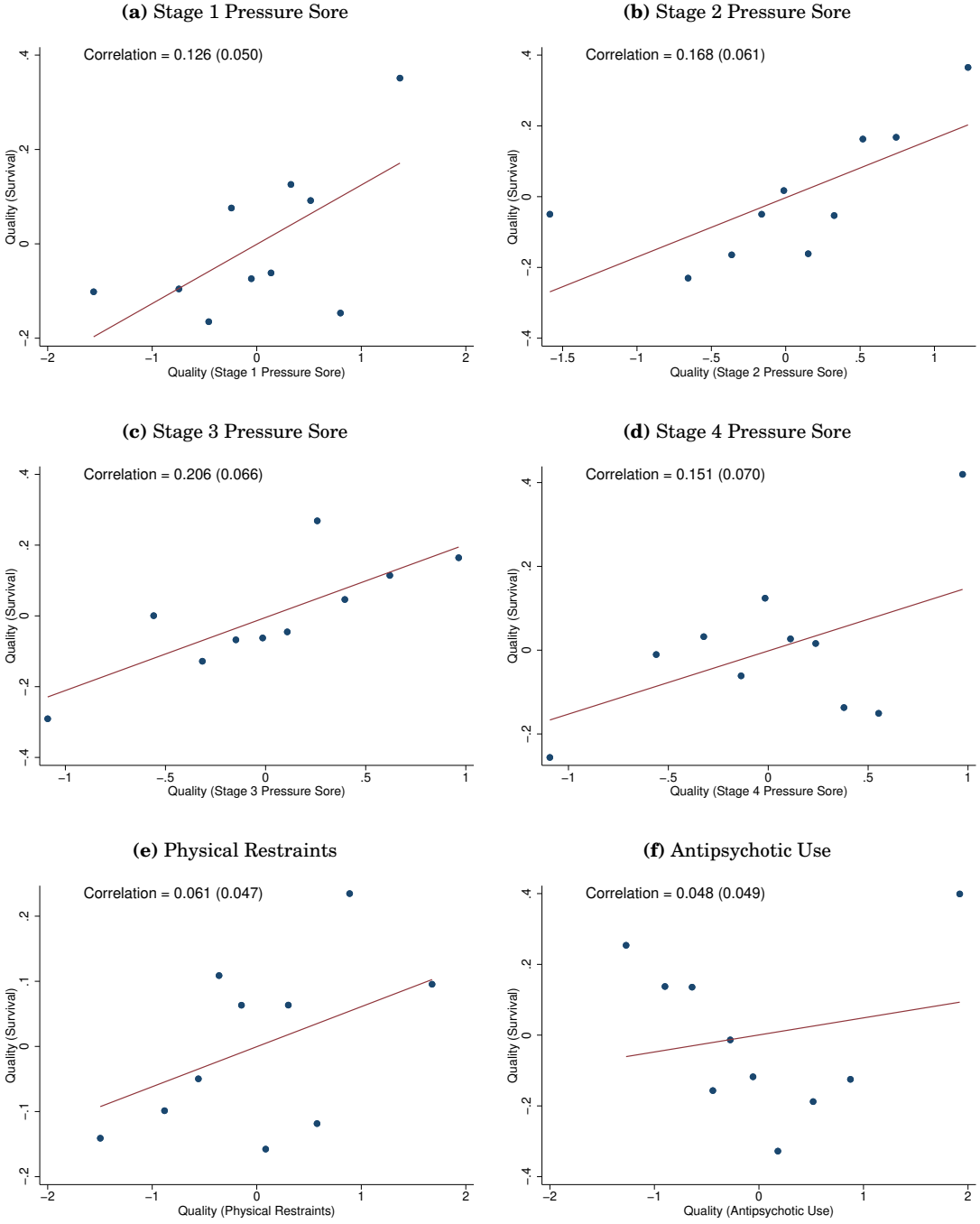
Notes: The x-axis of these figures correspond to fixed effects quality estimates using survival for at least 19, 30, 60, or 180 days as the outcome (standardized to have mean zero and standard deviation one). The bin scatters are weighted by the number of observations for each nursing home, and robust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

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



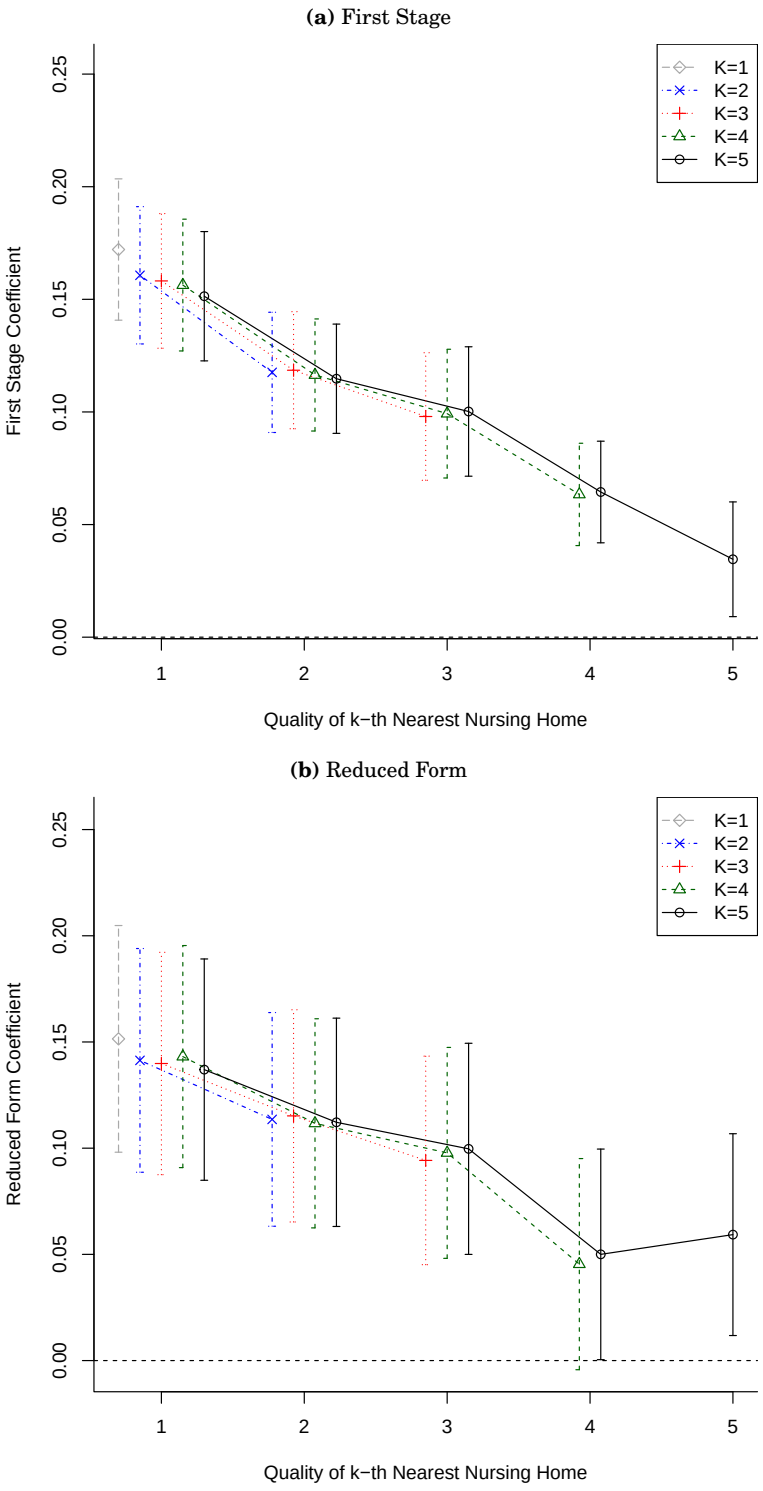
Notes: The x-axis of these figures correspond to quality estimates using other resident outcomes (instead of 90-day survival rate) as the dependent variable. The estimation procedure is the same as for my main quality estimates, except that I use a different outcome variable, and I do not use double 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



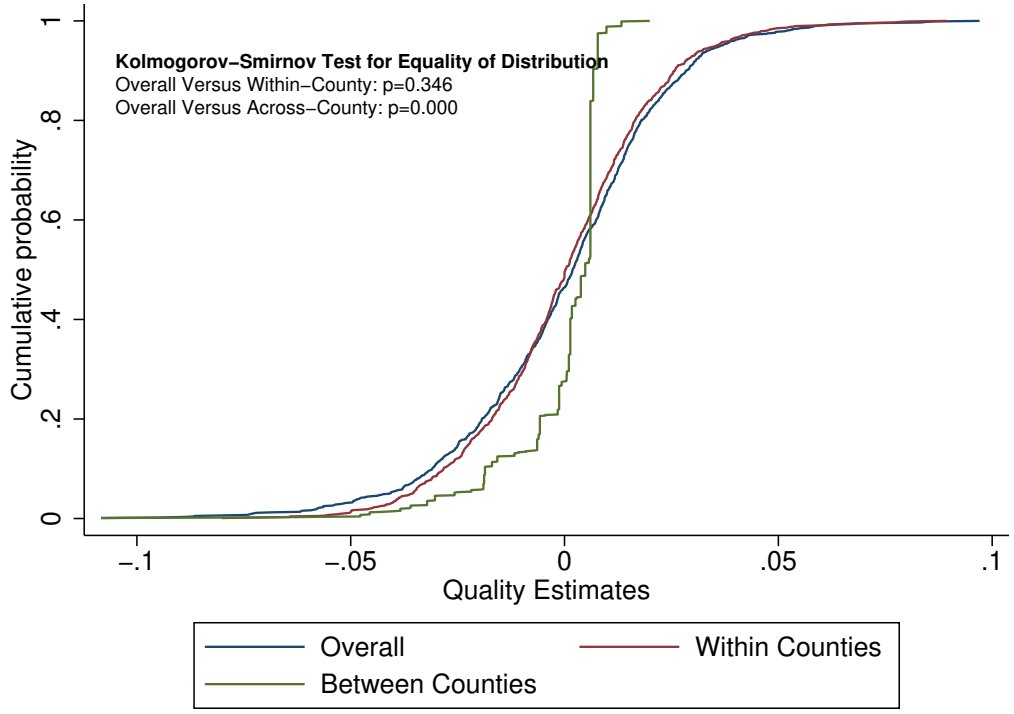
Notes: The x-axis of these figures correspond to quality estimates using other resident outcomes (instead of 90-day survival rate) as the dependent variable. The estimation procedure is the same as for my main quality estimates, except that I use a different outcome variable, and I do not use double 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



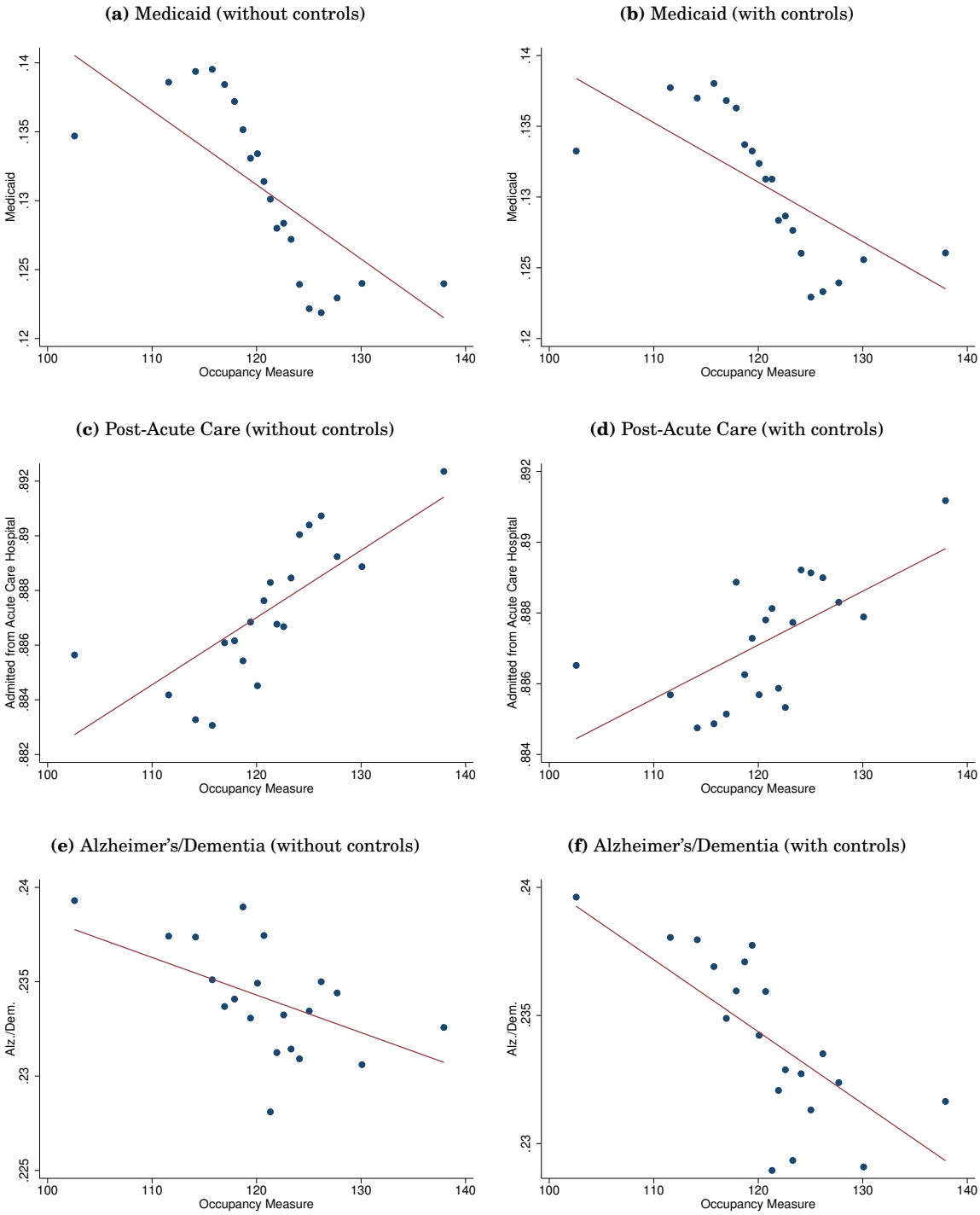
Notes: These figures plot the first-stage and reduced-form coefficients and the associated 95 percent confidence intervals for IV specifications that use the quality of the K nearest nursing homes to each resident as the instrument(s), for K ranging from one to five.

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



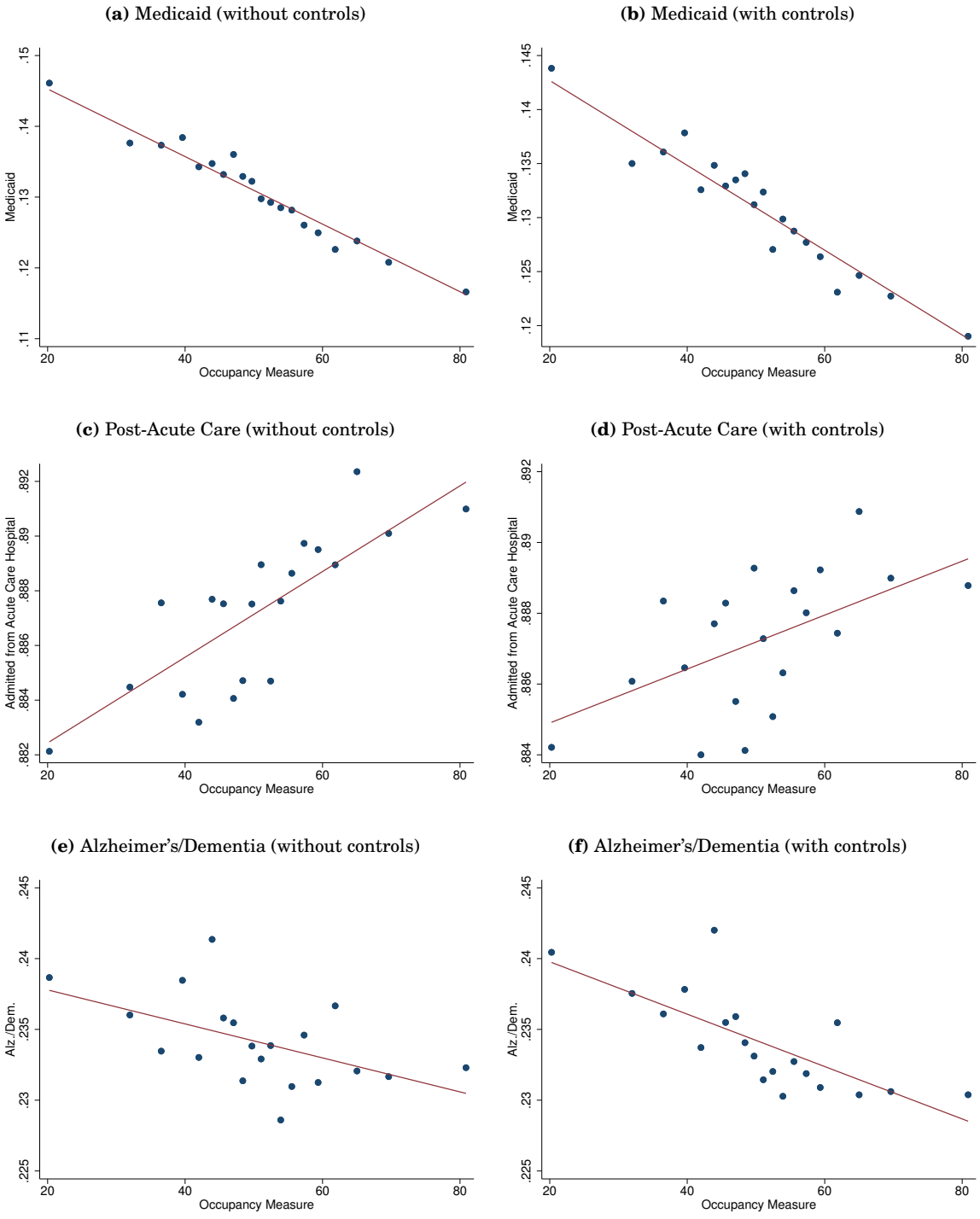
Notes: This figure plots the empirical CDFs showing the overall variation in nursing home quality, as well as the within-county and across-county variations in quality in blue, red, and green respectively. Within-county variation is plotted using the residuals from a regression of the quality estimates 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



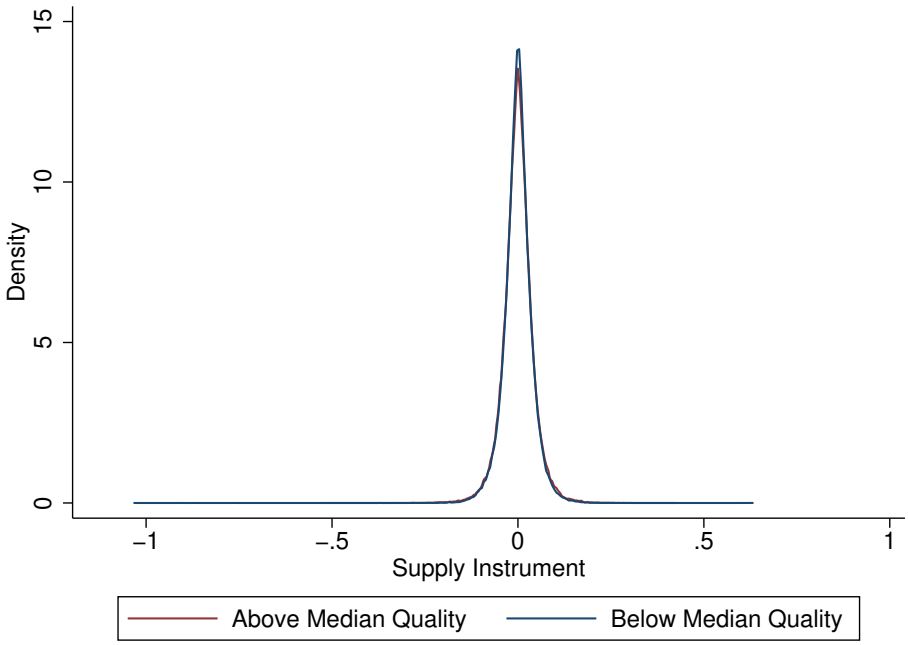
Notes: These bin scatters show indicators for Medicaid status, admission from an acute care hospital, and Alzheimer's/dementia of admitted residents as a function of lagged seven-day average occupancy for the nursing home as of the date of admission for the resident. The bin scatters include nursing 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



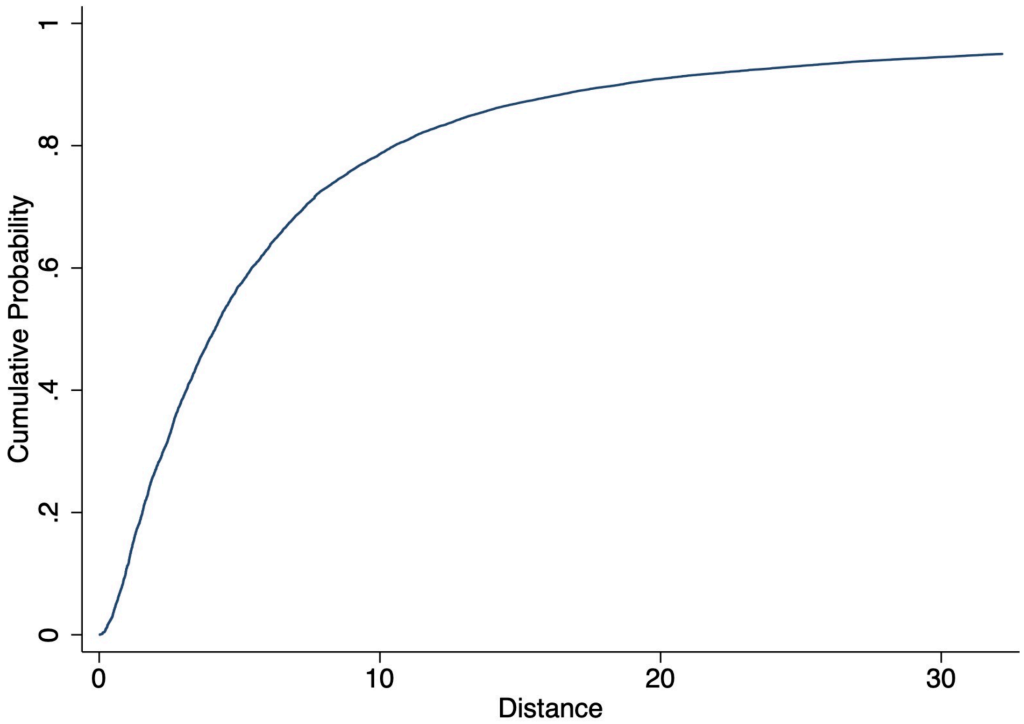
Notes: These bin scatters show indicators for Medicaid status, admission from an acute care hospital, and Alzheimer's/dementia of admitted residents as a function of lagged seven-day average occupancy percentile for the nursing home as of the date of admission for the resident. The bin scatters include 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).

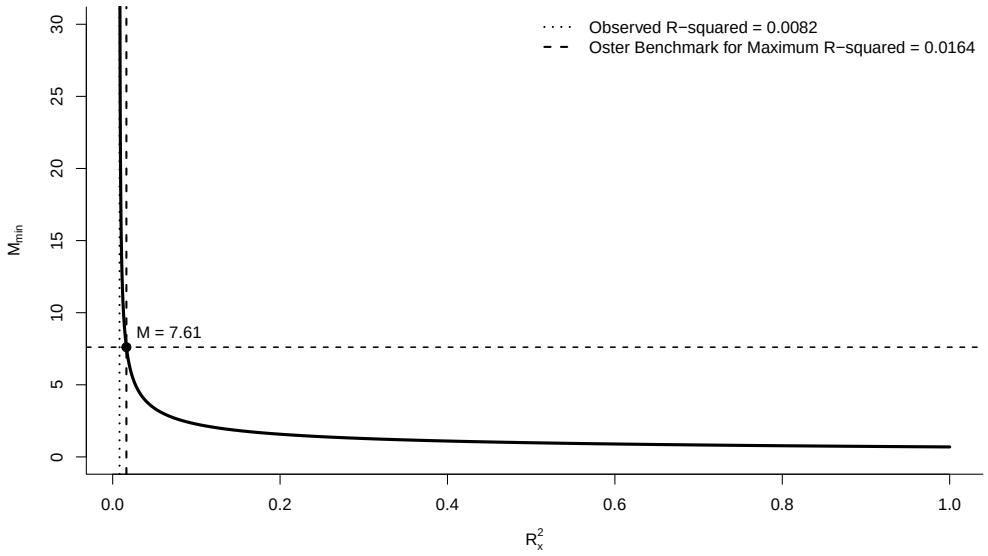
Figure A.14. Empirical CDF of Distance Between Residents and Their Chosen Nursing Homes



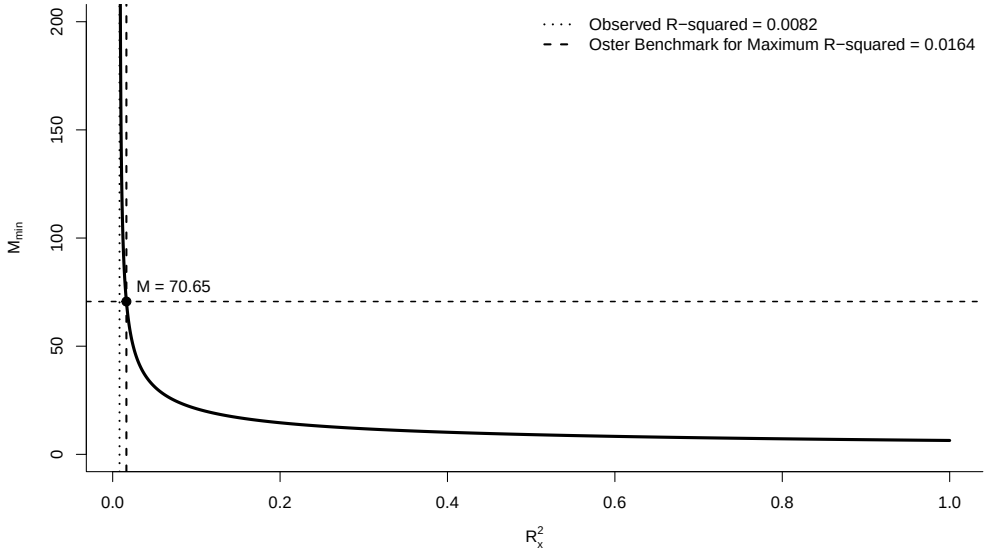
Notes: This figure shows the empirical CDF of distances between residents and their chosen nursing homes. The unit of observation is a resident.

Figure A.15. Conditions Under Which Selection on Unobservables Can Explain Discrepancy Between Demand Estimate and Target

(a) Discrepancy Between Demand Estimate and Zero

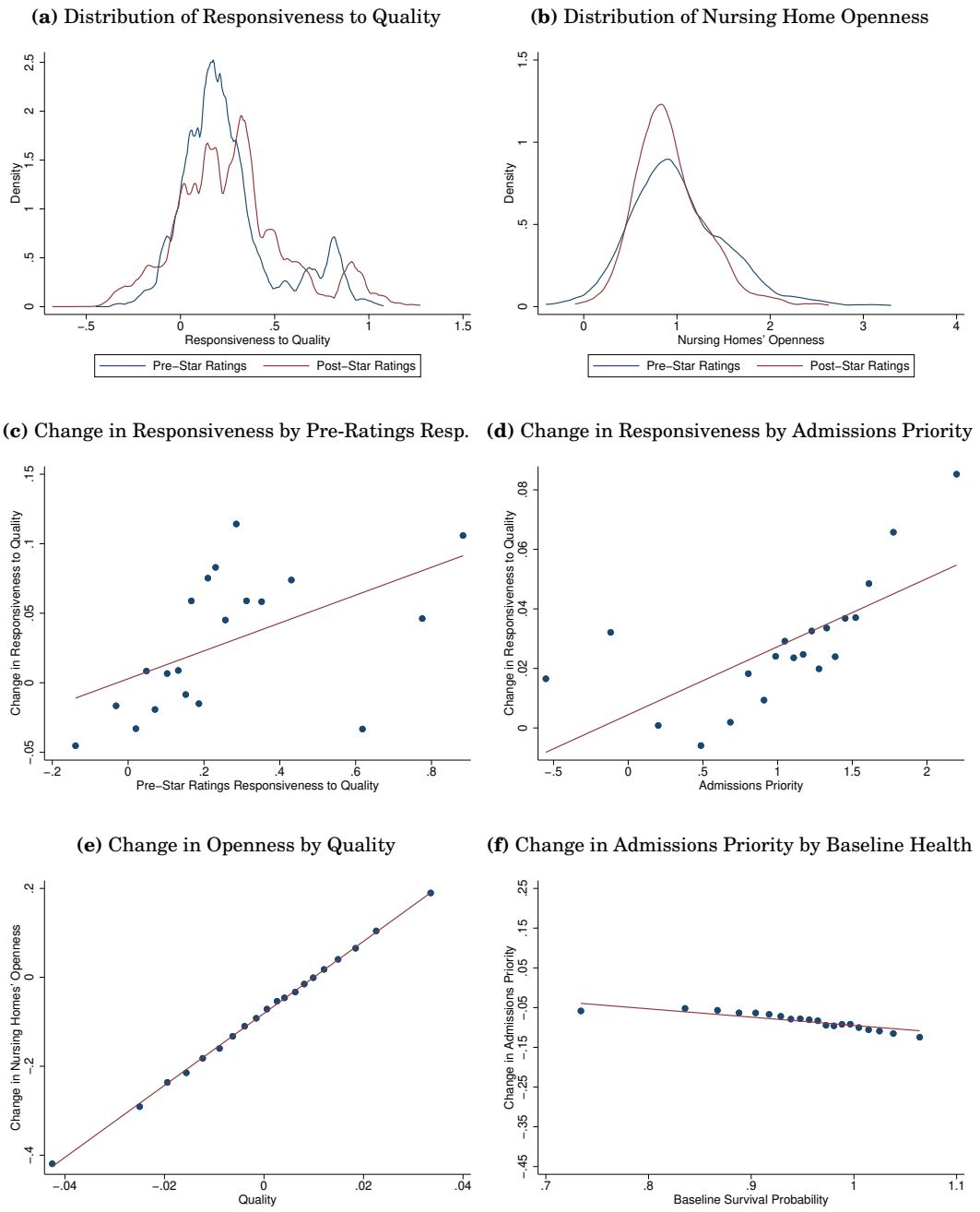


(b) Discrepancy Between Demand Estimate and MRS Estimate in Chandra, Finkelstein, Sacarny, and Syverson (2016)



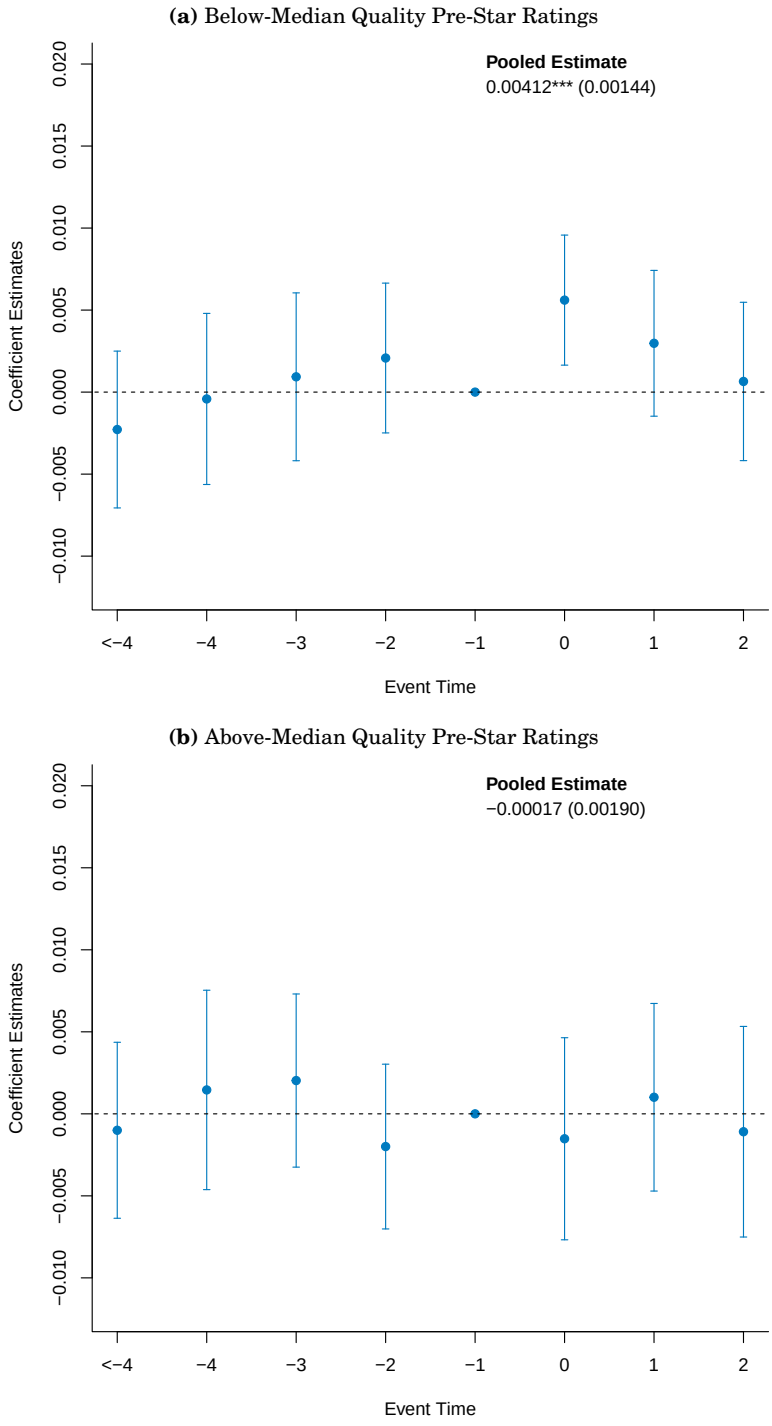
Notes: This figure shows conditions under which omitted variables bias can completely account for the low demand estimate in this paper, using methods from Cheng (2023). The x-axis represents hypothetical values of the proportional selection relationship (Oster 2019), i.e., the omitted variable's importance for explaining the explanatory variable of interest (quality β_j in this case) relative to the included controls (for-profit status and chain ownership $w_{\sim\beta,j}$ 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 zero in panel (a), or the one from Chandra, Finkelstein, Sacarny, and Syverson (2016) in panel (b). 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 7 times (respectively, 70 times) as much as she values for-profit status and chain ownership $w_{\sim\beta,j}$, in order for omitted variables bias to completely explain the discrepancy between my demand estimate and zero (the MRS estimate in Chandra, Finkelstein, Sacarny, and Syverson (2016)).

Figure A.16. Responsiveness to Quality and Admissions Policies Pre- and Post-Star Ratings



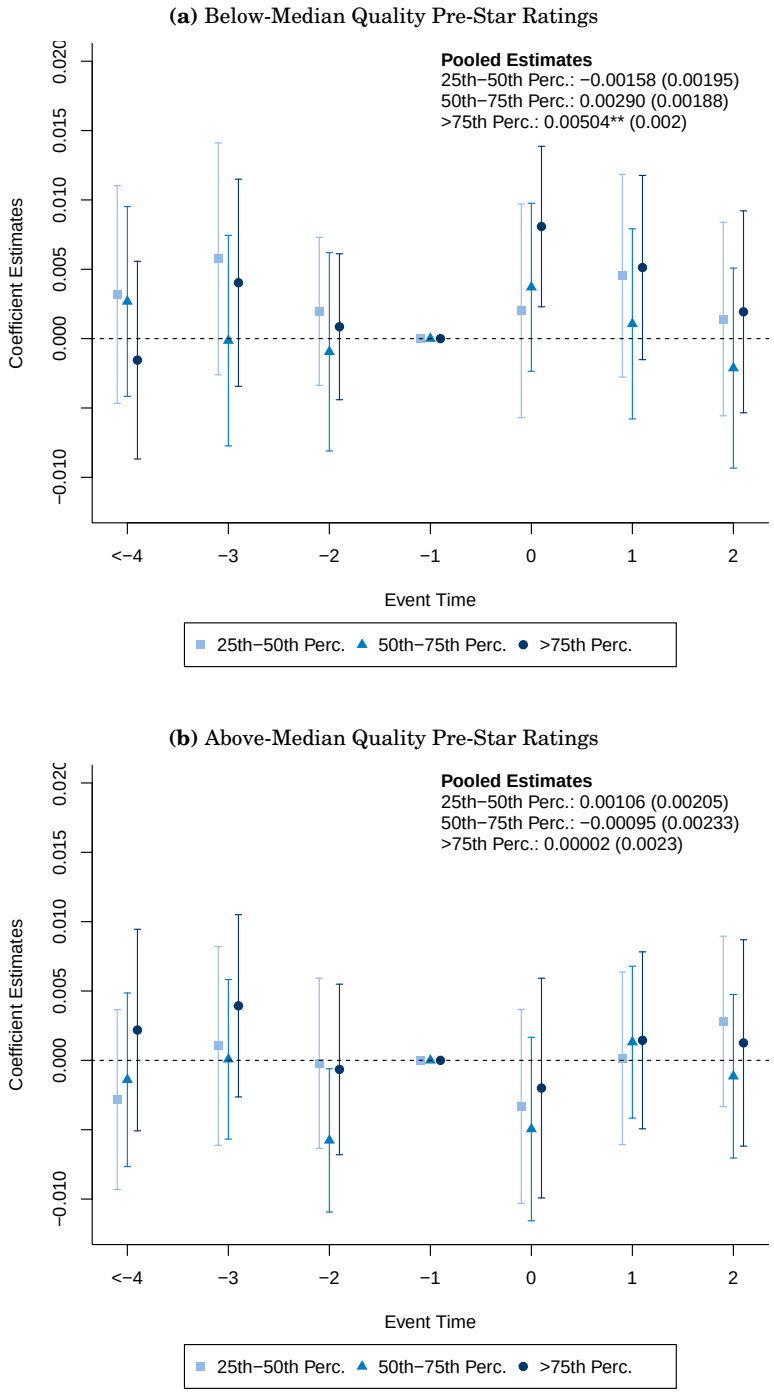
Notes: Panels (a) shows a kernel density plot of the estimated pre- and post-star ratings distributions of responsiveness to quality, where the unit of observation is a resident. Panel (b) shows a kernel density plot of the estimated pre- and post-star ratings distributions of nursing home openness, 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 I), 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 A.17. Continuous Event Study Estimates of the Effect of Star Ratings on Nursing Homes Quality



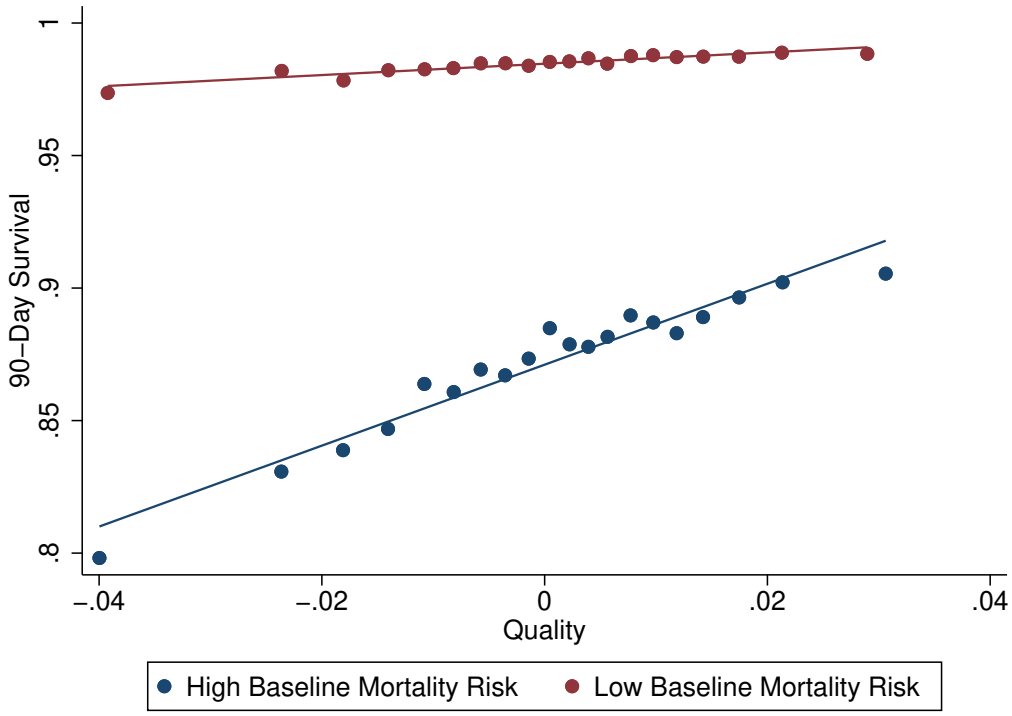
Notes: Panels (a) and (b) show event study estimates of equation (11) for nursing homes with below-median quality pre-star ratings and above-median quality pre-star ratings respectively. The top-right of each panel shows the pooled two-way fixed effects estimates. The unit of observation is a nursing 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.

Figure A.18. Event Study Estimates of the Effect of Star Ratings on Nursing Homes Quality



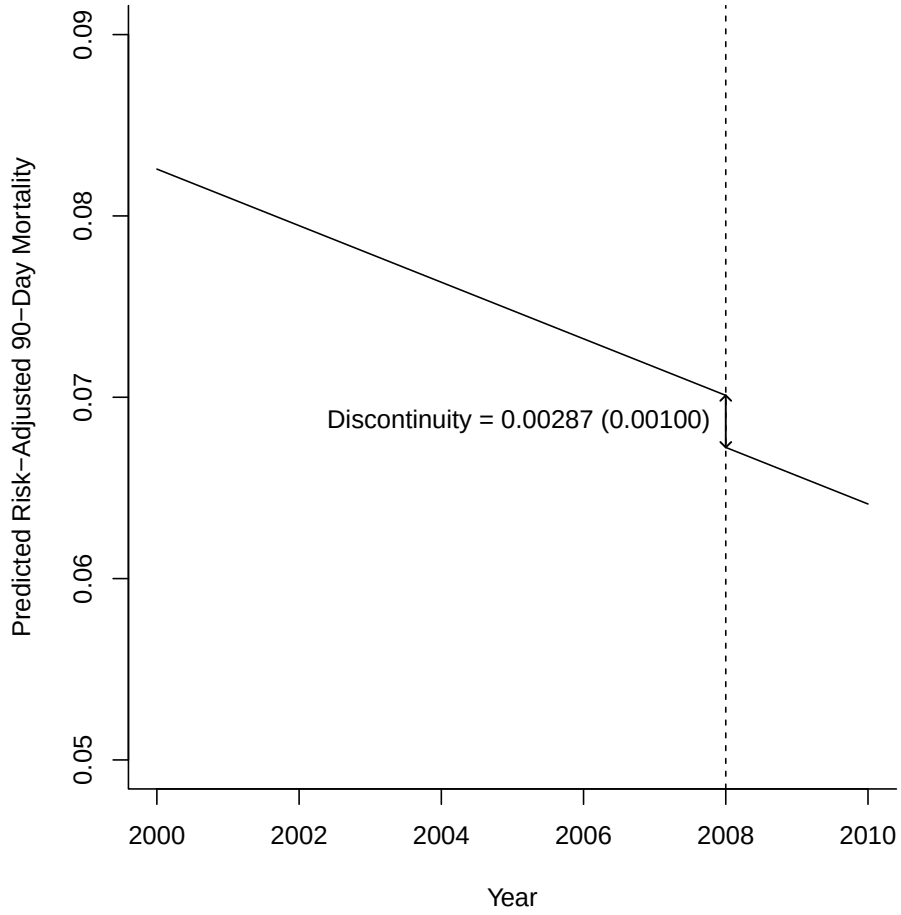
Notes: Panels (a) and (b) show event study estimates of equation (12) for nursing homes with below-median quality pre-star ratings and above-median quality pre-star ratings respectively. Nursing homes are grouped into quartiles based on the average change in responsiveness to quality for residents within 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.

Figure A.19. Survival-Quality Gradient by Baseline Health



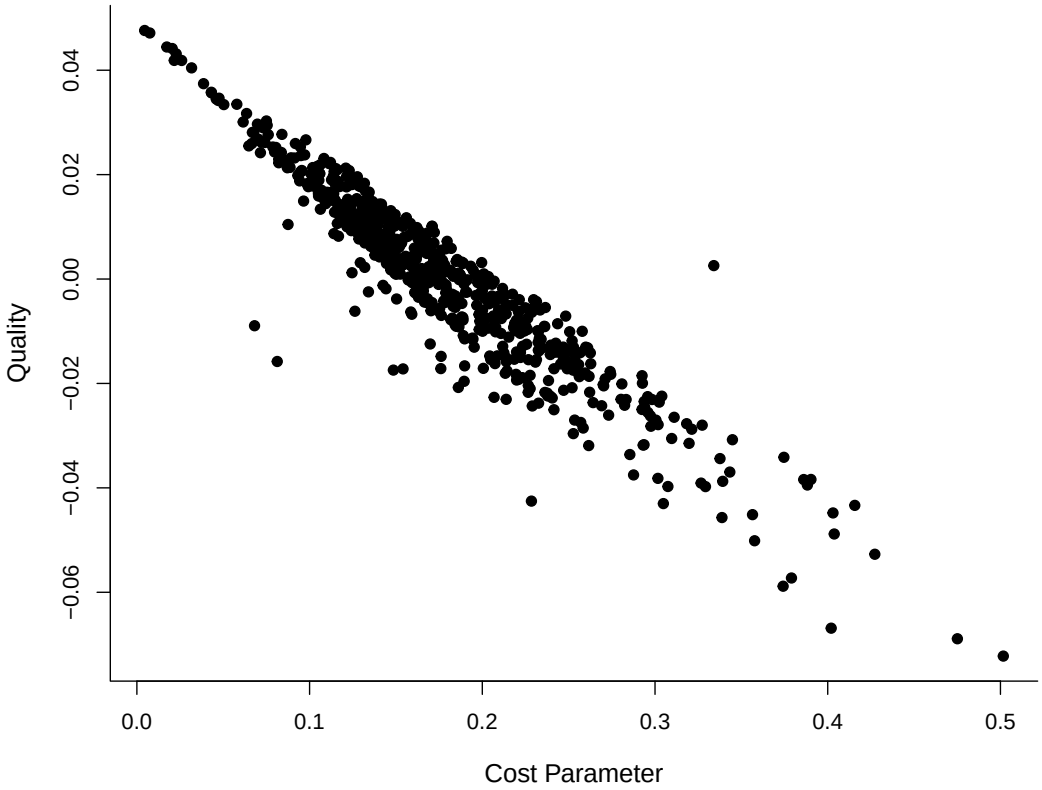
Notes: This figure shows bin scatters of 90-day survival on leave-year-out quality of the nursing home that the resident was admitted to, separately for residents with above-median and below-median baseline health respectively. Baseline health is defined as the probability of surviving at least 90 days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

Figure A.20. Reduced Form Estimate of the Effect of Star Ratings on Mortality



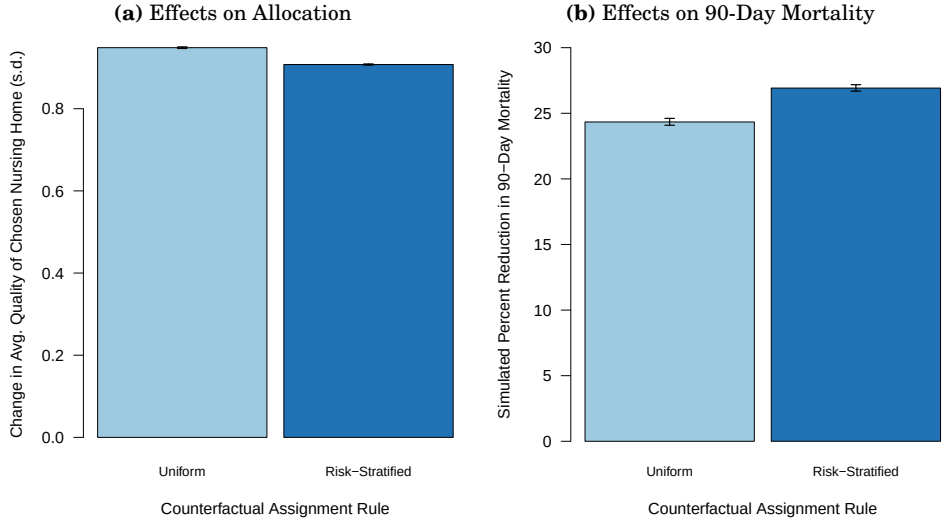
Notes: This figure shows predicted 90-day mortality from a regression of 90-day mortality on a rich set of baseline demographic and health characteristics, a linear time trend, and a post-star ratings indicator. The discontinuity illustrated in the figure is the estimated effect of star ratings on 90-day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

Figure A.21. Scatterplot of Quality Against Cost Parameter



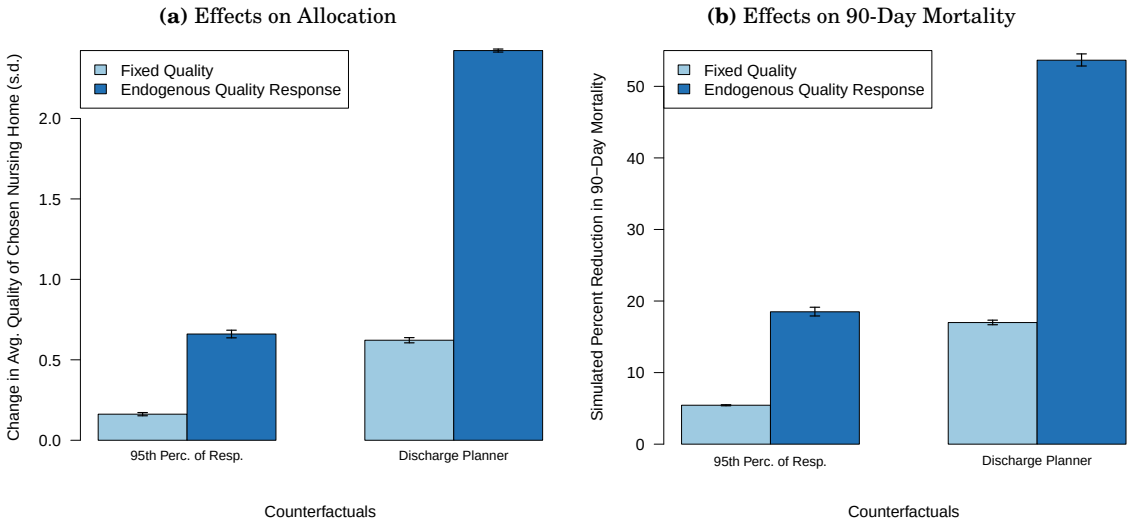
Notes: This figure shows a scatterplot of quality q_j against the calibrated cost parameter c_j for the model of endogenous quality choice.

Figure A.22. Simulated Effect of Uniform and Risk-Stratified Assignment Rules



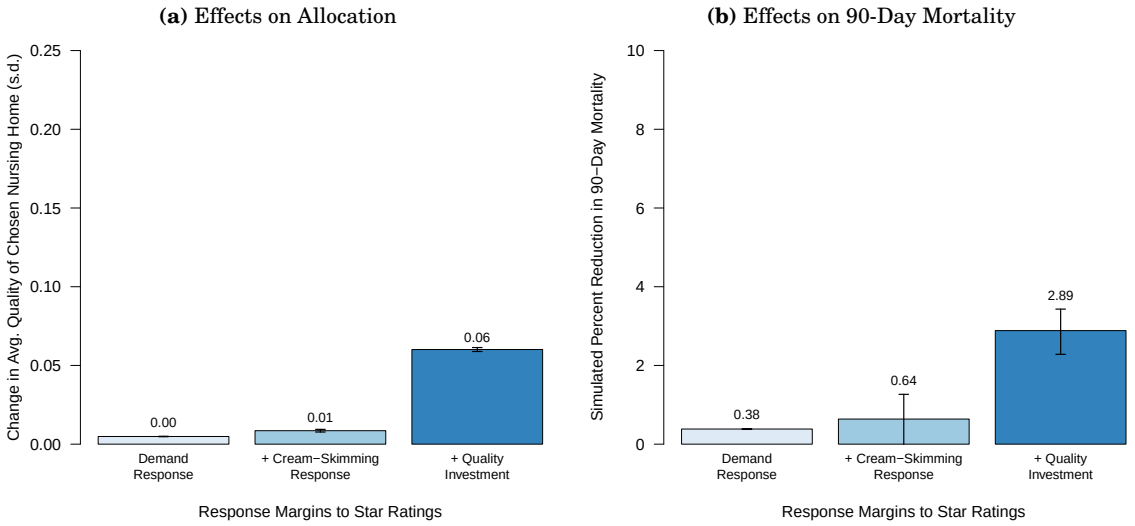
Notes: This figure shows the simulated effects of uniform and risk-stratified assignment rules. Panel (a) plots the simulated average change in quality of nursing homes chosen by residents (in standard deviations), and panel (b) plots the percent reduction in simulated 90-day mortality relative to the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

Figure A.23. Simulated Effect of Demand-Side Counterfactuals on Allocation and Mortality Accounting for Endogenous Quality Responses



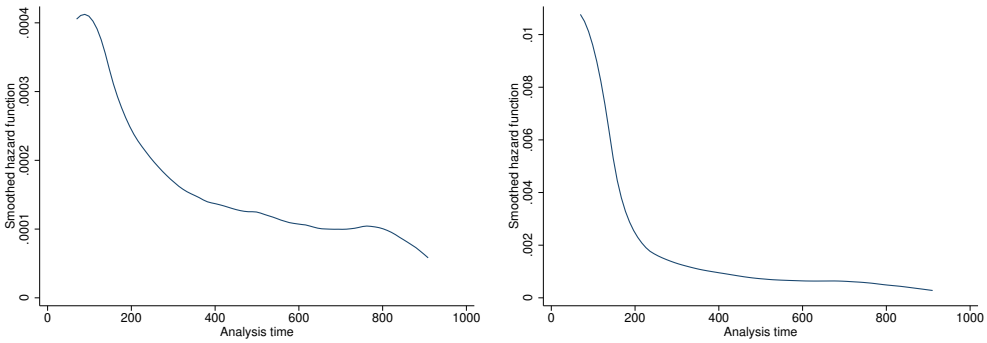
Notes: This figure shows the simulated effects of increasing residents' responsiveness to quality the 95th percentile and the provision of quality-ranked shortlists of available nursing homes by discharge planners, holding quality fixed in the light-blue bars or allowing for endogenous quality responses 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 the status quo.

Figure A.24. 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.

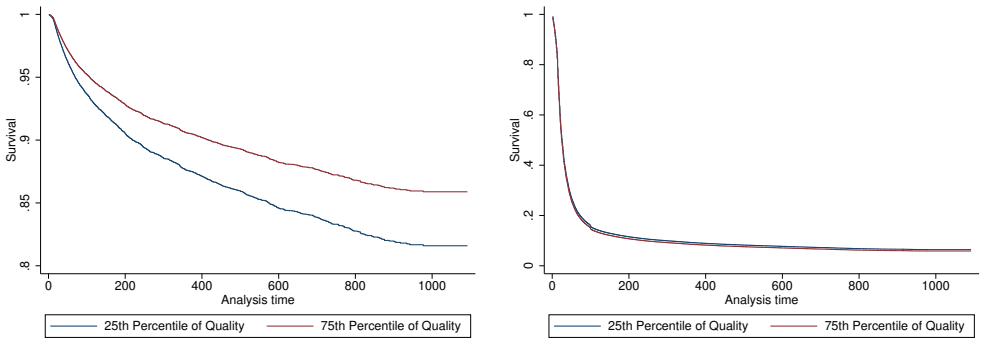
Figure A.25. Cause-Specific Baseline Hazard Functions, $h_{c,0}(t)$



(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.

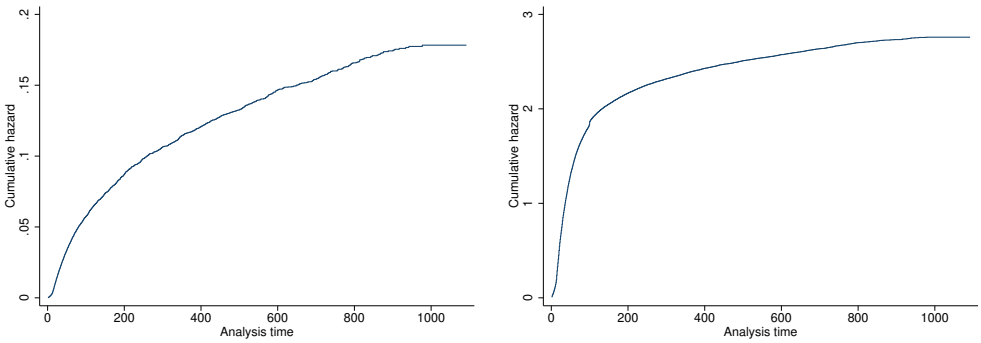
Figure A.26. Survival Curves for Cause-Specific Hazard Model (Split by Nursing Home Quality)



(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).

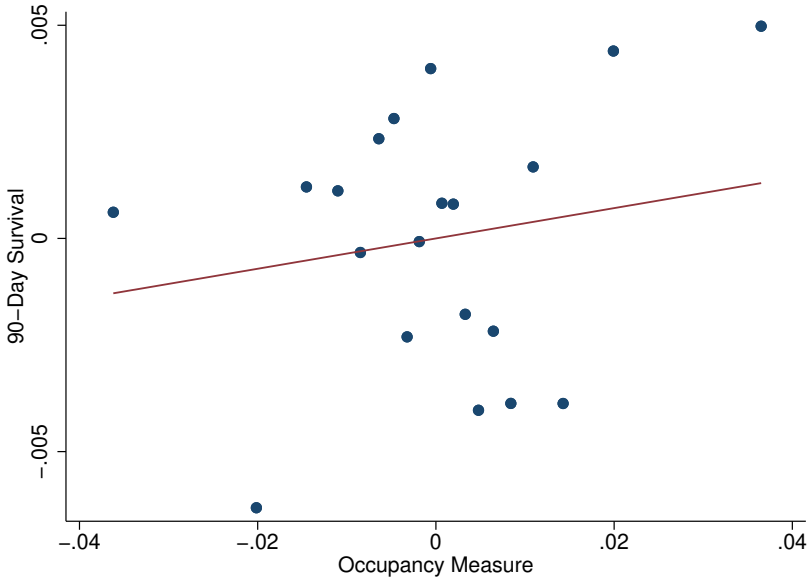
Figure A.27. Cause-Specific Cumulative Baseline Hazard Functions, $H_{c,0}(t)$



(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.28. 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:
- Age, race, gender, and marital status
- Insurance status

Cognitive patterns:
- Whether resident is comatose
- Short-term and long-term memory
- Memory/recall ability:
  - Current season, location of own room, staff names/faces, etc.
- Cognitive skills for daily decision-making
- Disordered thinking/awareness
- Change in cognitive patterns

Communication/hearing patterns:
- Hearing
- Communication devices/techniques
- Modes of expression
- Ability to make self understood
- Speech clarity
- Ability to understand others
- Change in communication/hearing

Vision patterns:
- Vision adequacy
- Visual limitations/difficulties
- Use of visual appliances

Mood and behavioral Patterns:
- Indicators of depression, anxiety, and sad mood;
- Mood persistence
- Change in mood
- Behavioral symptoms:
  - Wandering, verbally/physically abusive, etc.
- Recent change in behavioral symptoms

Psychosocial well-being:
- Sense of initiative/involvement
- Unsettled relationships
- Feelings about past roles

Physical functioning and structural problems:
- ADL self-performance and support provided: walking, dressing, eating, etc.
  - Walking
  - Dressing
  - Eating, etc.
- Independence in bathing
- Test for balance
- Functional limitation in range of motion
- Modes of locomotion
- Modes of transfer
- Task segmentation
- ADL functional rehabilitation potential
- Change in ADL function

Continence:
- Continence self-control
- Bowel elimination pattern
- Appliances and programs
- Change in urinary continence

Disease diagnoses:
- Indicators for various diseases
- Indicators for various infections
- ICD-9 codes for other diagnoses

Table A.1. 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:
  - Parenteral/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.2. Additional Summary Statistics for Residents

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.3. 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 admissions over the sample period.

Table A.4. Instrumental Variables Estimates of the Forecast Coefficient Based on Fixed Effects Quality Estimates

	(1)	(2)	(3)	(4)
Panel A. First stage: leave-year-out quality estimates				
Leave-year-out quality in five closest nursing homes	0.466	0.403	0.440	0.429
	(0.040)	(0.036)	(0.043)	(0.046)
F-statistic	133.7	126.5	105.6	86.8
Panel B. Reduced form: 90-day survival				
Leave-year-out quality in five closest nursing homes	0.466	0.366	0.422	0.385
	(0.056)	(0.056)	(0.059)	(0.065)
Panel C. 2SLS: 90-day survival				
Leave-year-out quality estimates	0.999	0.909	0.961	0.897
	(0.062)	(0.090)	(0.072)	(0.083)
Demographic and health controls	X	X	X	X
Region fixed effects	HSA	County	ZIP3	ZIP3 $\times$ Urban
Observations	632,122	632,122	632,122	632,122

Notes: This table presents first-stage, reduced-form, and two-stage least squares estimates of the forecast coefficient. The outcome in Panels B and C is 90-day survival. The endogenous variable is the leave-year-out fixed effects quality estimate for nursing homes, and the instrument is the average quality of the five nursing homes closest to each resident. All regressions include a correction for attenuation bias, controls for residents' demographics and health, and region fixed effects of increasing granularity: Hospital Service Area, county, three-digit ZIP code, and the interaction between three-digit ZIP code and urban classification. A ZIP code is classified as urban if it is less than 50 miles from one of eight major urban centers. Standard errors, clustered at the nursing home level, are reported in parentheses.

Table A.5. 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.6. 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.7. Predictivity of Quality and Nursing Home Characteristics for Resident Outcomes

Quality Measure:	Indicator for Resident Surviving At Least 90 Days After Admission x 100			
	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 legibility. The unit of observation is a resident, and standard errors are clustered at the nursing home level.

Table A.8. Reduced Form Evidence of Selective Admissions with Nursing Home x Month Fixed Effects

	Medicaid		Post-Acute Care		Alzheimer's/Dementia	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged 7-Day Avg. Log Occupancy						
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						
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						
Lagged 7-Day Avg. 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.9. 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	0.039^{***}	0.038^{***}	0.041^{***}	0.041^{***}	0.034^{***}	0.034^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-Acute Care	-0.051^{***}	-0.051^{***}	-0.052^{***}	-0.052^{***}	-0.050^{***}	-0.050^{***}
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Alzheimer's/Dementia	0.027^{***}	0.026^{***}	0.030^{***}	0.029^{***}	0.024^{***}	0.024^{***}
	(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	0.213	0.213	0.258	0.258	0.169	0.169
Number of Observations	1,923,155	1,923,155	960,942	960,942	962,213	962,213
R-squared	0.131	0.149	0.138	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.10. Structural Estimates: Instrumenting for Nursing Home Quality

	Full Sample		Post-Acute Care	
	Baseline (1)	Control Function (2)	Baseline (3)	Control Function (4)
Resident Preferences				
Distance to Nursing Homes (in Miles)	−0.171***	−0.171***	−0.172***	−0.172***
	(0.001)	(0.001)	(0.001)	(0.001)
Quality	18.213***	18.672***	17.184***	16.492***
	(1.050)	(1.456)	(1.616)	(1.706)
Quality Residual		−0.540		0.728
		(1.187)		(1.004)
Quality × Alzheimer's/Dementia	−1.014***	−0.899***	−0.851***	−1.064***
	(0.278)	(0.299)	(0.309)	(0.299)
Quality × Age	−0.218***	−0.217***	−0.203***	−0.202***
	(0.010)	(0.010)	(0.019)	(0.013)
Quality × At Least Bachelor's Degree	2.685***	2.825***	3.060***	2.914***
	(0.342)	(0.314)	(0.373)	(0.383)
Quality × English as Primary Language	2.141***	2.171***	2.338***	2.381***
	(0.335)	(0.345)	(0.330)	(0.297)
Quality × Black	−0.025	−0.037	−0.219	−0.047
	(0.500)	(0.473)	(0.407)	(0.426)
Quality × Hispanic	−0.412	−0.328	−0.298	−0.467
	(0.384)	(0.419)	(0.357)	(0.413)
Quality × Post-Star Ratings	0.239	0.199	0.284	0.260
	(0.249)	(0.248)	(0.262)	(0.250)
Nursing Homes' Admissions Policies				
Capacity Strain	−10.129***	−10.209***	−9.829***	−9.785***
	(0.192)	(0.226)	(0.158)	(0.266)
Quality	−14.776***	−14.955***	−17.507***	−17.822***
	(0.605)	(0.389)	(1.684)	(0.832)
Medicaid	−0.126***	−0.197***	−0.113***	−0.143***
	(0.022)	(0.047)	(0.019)	(0.018)
Post-Acute Care	0.075	0.053**		
	(0.049)	(0.024)		
Alzheimer's/Dementia	−0.113***	−0.146***	−0.137***	−0.094***
	(0.033)	(0.027)	(0.024)	(0.022)
Age	0.032***	0.032***	0.034***	0.033***
	(0.001)	(0.001)	(0.001)	(0.001)
At Least Bachelor's Degree	−0.029	−0.061*	−0.092**	−0.059
	(0.019)	(0.032)	(0.039)	(0.041)
English as Primary Language	−0.030	−0.052**	−0.090***	−0.107***
	(0.024)	(0.022)	(0.018)	(0.024)
Black	−0.401***	−0.393***	−0.372***	−0.377***
	(0.031)	(0.019)	(0.029)	(0.036)
Hispanic	0.012	−0.037	−0.091***	−0.069*
	(0.024)	(0.025)	(0.014)	(0.040)
Average Demand for Quality	0.198 (0.015)	0.231 (0.071)	0.219 (0.013)	0.182 (0.061)
10th Percentile of Demand for Quality	-0.025 (0.014)	0.010 (0.072)	0.010 (0.012)	-0.029 (0.058)
90th Percentile of Demand for Quality	0.465 (0.021)	0.495 (0.072)	0.467 (0.030)	0.432 (0.068)
First-Stage F-Statistic	–	88	–	88
Year fixed effects in supply equation	X	X	X	X
Observations	5,492,614	5,492,614	5,124,314	5,124,314

Notes: This table reports estimates from the structural model. Coefficient estimates and their standard errors are based on the posterior mean and standard deviation of the Gibbs chain respectively, with standard errors reported in parentheses. Demand for quality is defined as the marginal rate of substitution between quality (in percentage points) and distance (in miles). To compute the average, 10th percentile, and 90th percentile of demand for quality over the sample and their standard errors, I take 1,000 draws of the coefficient estimates from the posterior distribution, computing individual-specific demand for each draw as well as the mean, 10th percentile, and 90th percentile across individuals in each draw, and then take the mean and standard deviations of these statistics across draws. The full-sample specifications include all residents, while the post-acute care specifications restrict the sample to residents admitted from acute care hospitals. A burn-in period corresponding to the first half of the chain was used.

Table A.11. Structural Estimates: Controlling for Preferences for Correlates of Quality

	Full Model		Demand Only	
	Full Sample (1)	Post-Acute Care (2)	Full Sample (3)	Post-Acute Care (4)
Resident Preferences				
Distance to Nursing Homes (in Miles)	−0.170***	−0.172***	−0.158***	−0.159***
	(0.001)	(0.001)	(0.0005)	(0.0005)
Quality	15.490***	9.677***	2.948***	−0.360
	(1.627)	(1.136)	(0.732)	(0.789)
Quality × Alzheimer's/Dementia	−1.107***	−1.279***	−1.455***	−1.431***
	(0.285)	(0.287)	(0.269)	(0.284)
Quality × Age	−0.193***	−0.122***	−0.060***	−0.016*
	(0.017)	(0.012)	(0.008)	(0.009)
Quality × At Least Bachelor's Degree	3.072***	3.112***	2.486***	2.609***
	(0.332)	(0.357)	(0.310)	(0.315)
Quality × English as Primary Language	2.610***	2.325***	1.992***	1.880***
	(0.334)	(0.356)	(0.310)	(0.308)
Quality × Black	−0.552	−0.974**	−1.401***	−1.582***
	(0.412)	(0.447)	(0.380)	(0.382)
Quality × Hispanic	−0.446	−0.825**	−0.512	−0.850**
	(0.383)	(0.410)	(0.351)	(0.381)
Quality × Post-Star Ratings	0.417	0.402	0.567***	0.616***
	(0.263)	(0.251)	(0.199)	(0.213)
For-Profit	0.185***	0.209***	0.181***	0.200***
	(0.005)	(0.006)	(0.005)	(0.005)
Chain	0.118***	0.113***	0.107***	0.122***
	(0.004)	(0.004)	(0.003)	(0.004)
Nursing Homes' Admissions Policies				
Capacity Strain	−10.243***	−10.380***		
	(0.240)	(0.319)		
Quality	−13.194***	−10.505***		
	(1.217)	(0.770)		
Medicaid	−0.118***	−0.196***		
	(0.032)	(0.017)		
Post-Acute Care	0.108***			
	(0.041)			
Alzheimer's/Dementia	−0.121***	−0.066**		
	(0.019)	(0.028)		
Age	0.032***	0.031***		
	(0.001)	(0.001)		
At Least Bachelor's Degree	−0.085***	−0.134***		
	(0.020)	(0.038)		
English as Primary Language	−0.090***	−0.110**		
	(0.027)	(0.046)		
Black	−0.390***	−0.430***		
	(0.030)	(0.020)		
Hispanic	−0.048**	−0.116***		
	(0.024)	(0.038)		
Average Demand for Quality	0.175 (0.022)	0.132 (0.016)	0.003 (0.007)	-0.001 (0.006)
10th Percentile of Demand for Quality	-0.042 (0.019)	-0.038 (0.018)	-0.136 (0.012)	-0.130 (0.014)
90th Percentile of Demand for Quality	0.427 (0.035)	0.317 (0.021)	0.152 (0.012)	0.121 (0.019)
Year fixed effects in supply equation	X	X	X	X
Observations	5,492,614	5,124,314	5,492,614	5,124,314

Notes: This table reports estimates from the structural model. Coefficient estimates and their standard errors are based on the posterior mean and standard deviation of the Gibbs chain respectively, with standard errors reported in parentheses. Demand for quality is defined as the marginal rate of substitution between quality (in percentage points) and distance (in miles). To compute the average, 10th percentile, and 90th percentile of demand for quality over the sample and their standard errors, I take 1,000 draws of the coefficient estimates from the posterior distribution, computing individual-specific demand for each draw as well as the mean, 10th percentile, and 90th percentile across individuals in each draw, and then take the mean and standard deviations of these statistics across draws. The full-sample specifications include all residents, while the post-acute care specifications restrict the sample to residents admitted from acute care hospitals. A burn-in period corresponding to the first half of the chain was used.

Table A.12. Structural Estimates: Different Supply-Side Specifications

	Full Sample			Post-Acute Sample		
	Baseline (1)	Occupancy Rate (2)	Quality Interactions (3)	Baseline (4)	Occupancy Rate (5)	Quality Interactions (6)
Resident Preferences						
Distance to Nursing Homes (in Miles)	-0.171^{***}	-0.171^{***}	-0.171^{***}	-0.172^{***}	-0.172^{***}	-0.172^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quality	18.213^{***}	15.661^{***}	16.405^{***}	17.184^{***}	11.260^{***}	14.984^{***}
	(1.050)	(1.210)	(1.071)	(1.616)	(1.055)	(1.200)
Quality × Alzheimer's/Dementia	-1.014^{***}	-1.125^{***}	-1.330^{***}	-0.851^{***}	-1.260^{***}	-1.496^{***}
	(0.278)	(0.301)	(0.358)	(0.309)	(0.299)	(0.515)
Quality × Age	-0.218^{***}	-0.192^{***}	-0.202^{***}	-0.203^{***}	-0.140^{***}	-0.197^{***}
	(0.010)	(0.012)	(0.012)	(0.019)	(0.012)	(0.013)
Quality × At Least Bachelor's Degree	2.685^{***}	2.992^{***}	3.890^{***}	3.060^{***}	3.079^{***}	3.643^{***}
	(0.342)	(0.324)	(0.399)	(0.373)	(0.381)	(0.717)
Quality × English as Primary Language	2.141^{***}	2.230^{***}	3.703^{***}	2.338^{***}	2.331^{***}	4.584^{***}
	(0.335)	(0.329)	(0.788)	(0.330)	(0.316)	(0.434)
Quality × Black	-0.025	-0.411	-5.304^{***}	-0.219	-0.806^{*}	-7.282^{***}
	(0.500)	(0.482)	(0.563)	(0.407)	(0.425)	(0.830)
Quality × Hispanic	-0.412	-0.291	0.684	-0.298	-0.482	0.733
	(0.384)	(0.409)	(0.709)	(0.357)	(0.376)	(0.620)
Quality × Post-Star Ratings	0.239	0.276	0.599^{*}	0.284	0.395	0.567
	(0.249)	(0.249)	(0.349)	(0.262)	(0.252)	(0.398)

Table A.12. Structural Estimates: Different Supply-Side Specifications (continued)

	Full Sample			Post-Acute Sample		
	Baseline (1)	Occupancy Rate (2)	Quality Interactions (3)	Baseline (4)	Occupancy Rate (5)	Quality Interactions (6)
Nursing Homes' Admissions Policies						
Capacity Strain	-10.129^{***}	-10.609^{***}	-9.844^{***}	-9.829^{***}	-10.200^{***}	-9.858^{***}
	(0.192)	(0.260)	(0.242)	(0.158)	(0.281)	(0.220)
Quality	-14.776^{***}	-12.708^{***}	3.858^{*}	-17.507^{***}	-11.973^{***}	-9.818^{***}
	(0.605)	(0.761)	(2.213)	(1.684)	(0.424)	(2.820)
Occupancy Rate		-0.00742^{***}			-0.0117^{***}	
		(0.0005)			(0.0010)	
Medicaid	-0.126^{***}	-0.231^{***}	-0.149^{***}	-0.113^{***}	-0.180^{***}	-0.186^{***}
	(0.022)	(0.047)	(0.019)	(0.019)	(0.018)	(0.034)
Post-Acute Care	0.075	0.006	0.084^{***}			
	(0.049)	(0.021)	(0.028)			
Alzheimer's/Dementia	-0.113^{***}	-0.110^{***}	-0.245^{***}	-0.137^{***}	-0.045^{**}	-0.157^{***}
	(0.033)	(0.025)	(0.023)	(0.024)	(0.022)	(0.024)
Age	0.032^{***}	0.030^{***}	0.035^{***}	0.034^{***}	0.030^{***}	0.032^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
At Least Bachelor's Degree	-0.029	-0.135^{***}	0.018	-0.092^{**}	-0.169^{***}	-0.023
	(0.019)	(0.033)	(0.027)	(0.039)	(0.034)	(0.037)
English as Primary Language	-0.030	-0.108^{***}	0.046^{**}	-0.090^{***}	-0.153^{***}	0.004
	(0.024)	(0.022)	(0.021)	(0.018)	(0.022)	(0.029)
Black	-0.401^{***}	-0.361^{***}	-0.568^{***}	-0.372^{***}	-0.325^{***}	-0.509^{***}
	(0.031)	(0.019)	(0.023)	(0.029)	(0.035)	(0.031)
Hispanic	0.012	-0.038	0.018	-0.091^{***}	-0.040	0.004
	(0.024)	(0.028)	(0.035)	(0.014)	(0.037)	(0.039)
Quality × Alzheimer's/Dementia			4.883^{***}			3.707^{*}
			(1.183)			(2.107)
Quality × Age			-0.226^{***}			0.034
			(0.032)			(0.031)
Quality × At Least Bachelor's Degree			-5.821^{***}			-3.819
			(1.655)			(2.516)
Quality × English as Primary Language			-9.089^{***}			-12.548^{***}
			(2.741)			(1.420)
Quality × Black			17.884^{***}			21.976^{***}
			(1.308)			(1.766)
Quality × Hispanic			-4.676^{**}			-6.094^{***}
			(2.067)			(1.581)
Quality × Post-Star Ratings			-2.116^{*}			-1.140
			(1.222)			(1.491)
Average Demand for Quality	0.198 (0.015)	0.170 (0.017)	0.230 (0.008)	0.219 (0.013)	0.149 (0.012)	0.189 (0.013)
10th Percentile of Demand for Quality	-0.025 (0.014)	-0.037 (0.016)	-0.040 (0.018)	0.010 (0.012)	-0.024 (0.014)	-0.114 (0.018)
90th Percentile of Demand for Quality	0.465 (0.021)	0.413 (0.024)	0.518 (0.015)	0.467 (0.030)	0.343 (0.018)	0.487 (0.020)
Year fixed effects in supply equation	X	X	X	X	X	X
Observations	5,492,614	5,492,614	5,492,614	5,124,314	5,124,314	5,124,314

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