Consumer Responsiveness to Quality and its Consequences: Evidence from the Nursing Home Market

By Alden Cheng*

This paper studies nursing home residents' responsiveness to quality and its mortality consequences. Using administrative data on the universe of residents, I estimate substantial variation in quality of nursing homes in California. Yet, structural estimates reveal that average responsiveness quality is very low, with residents who were younger, highly educated, free from dementia, and who made their choices after the introduction of the star rating system being more responsive. Counterfactual simulations suggest that despite potentially large reductions in mortality from increased responsiveness or capacity at higher-quality nursing homes, star ratings had modest effects through these channels. Instead, much of the mortality reduction came from quality investments by nursing homes in areas where consumers' responsiveness increased the most, and where quality was low to begin with.

Health expenditures in the US add up to roughly 20 percent of GDP. Yet, healthcare quality in certain sectors leaves much to be desired, with nursing homes being a prime example. A potentially important factor contributing to this underinvestment in quality is consumers' low responsiveness to quality (Arrow 1963; Gaynor 2006; Salop and Stiglitz 1977): when responsiveness to quality is low, firms are incentivized to supply suboptimal amounts of quality (Dranove and Satterthwaite 1992).

Despite the potential importance of the consumer responsiveness to provider quality, there is limited empirical work on this due to several reasons. First, publicly available quality measures may be gamed by providers, and quality estimation based on outcomes is complicated by issues such as selection bias and misreporting. Second, demand estimation is challenging because of capacity constraints and the possibility that healthcare providers may reject certain types of patients (rejections that are rarely directly observed in the data). Finally, it is difficult to interpret demand estimates: the "correct" level of demand is not clear-cut, and demand estimates may reflect a mixture of consumer preferences and other factors such as information frictions. Therefore, this paper takes a step in filling this gap in the

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literature by measuring information frictions about quality of care in nursing homes and quantifying the consequences.

I choose the nursing home setting to study this issue for three reasons. First, this is a setting wherein quality significantly impacts consumer wellbeing. Indeed, understaffing, abuse, and negligence has been well documented, especially at for-profit nursing homes (Comondore et al. 2009), and this has often resulted in severe health consequences, even death, for residents (Cenziper, Jacobs, Crites, and Englund 2020). Second, poor nursing home quality is an issue of great interest to policymakers; for example, President Biden proposed a slew of reforms aimed at improving nursing home quality in his 2022 State of the Union speech. Third, nursing homes are an important part of the healthcare sector: 1.3 million Americans live in nursing homes (National Center for Health Statistics 2017), and more than half of those aged 57–61 today will spend some time in a nursing home (Hurd, Michaud, and Rohwedder, 2017).

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

In the second step, I use these quality estimates to study residents' responsiveness to quality, taking into account unobserved supply-side constraints arising from selective admissions practices by nursing homes (Gandhi 2023). I use distance and temporary occupancy fluctuations as demand and supply instruments respectively in my structural demand model, and I estimate the model using Gibbs sampling with data augmentation to avoid the curse of dimensionality (Agarwal and Somaini 2022).[1]

In the final step, I combine these structural estimates with counterfactual simulations to study the effects of the introduction of star ratings by the Centers for Medicare and Medicaid Services (CMS) at the end of 2008, which can be viewed as an information intervention. Specifically, I decompose the effects of star ratings on mortality into components due to changes in consumers' responsiveness to quality, nursing homes' admissions policies, and nursing homes' quality choice. In addition, I compare these effects to counterfactuals where residents are more responsive to quality, nursing homes do not face capacity constraints, as well as the potential effects of a policy which financially incentivized nursing homes in Illinois to increase their staffing levels (Gandhi, Olenski, Ruffini, and Shen 2024).

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 2–2.5 percentage points less likely to die within 90 days of admission (all else equal), a 27–33 percent reduction relative to the baseline mortality rate. Moreover, the correlations between my quality measure and publicly available nursing home characteristics have the expected signs, but my quality measure is a

[1] The number of possible distinct sets of nursing homes willing to admit each resident increases exponentially with the number of nursing homes in her vicinity, exceeding 10^{60} for some residents. This makes methods such as maximum likelihood that require directly integrating over each distinct possibility computationally infeasible.

far stronger predictor of resident outcomes than these other variables.

Despite the high stakes for residents, I estimate that average responsiveness to quality is an order of magnitude smaller than existing estimates in the literature.[2] Patterns of heterogeneity in responsiveness to quality are consistent with information frictions playing a role: older and cognitively impaired residents are less responsive, whereas residents who have at least a Bachelor's degree, and who made their choices after the introduction of the star ratings are more responsive.

Finally, counterfactual simulations suggest that the effect of star ratings on mortality is moderates mainly through its effects on nursing homes' quality choice, rather than changes in responsiveness to quality and nursing homes' admissions policies. However, this does not imply that these two channels are unimportant: simulations indicate even larger reductions in mortality if all consumers were as responsive to quality as the most responsive consumer, and/or if capacity constraints were eliminated. These reductions in these latter simulations are similar in magnitude to a generous interpretation of the simulated effects of the financial incentive scheme targeted at increasing nursing home staffing levels studied in Gandhi, Olenski, Ruffini, and Shen (2024).

This paper is connected to several strands of literature. It adds to the literature on consumer decision-making in healthcare (Abaluck and Gruber 2011, 2016, 2020; Handel 2013; Handel and Kolstad 2015; Handel, Kolstad, Minten, and Spinnewijn 2021; Kolstad 2013; Chan, Gentzkow, and Yu 2022; Mullainathan, and Obermeyer 2022) in a choice environment that is very different qualitatively from previous work in this area, which typically focuses on insurance demand. Quality estimation is often unnecessary in insurance settings, and capacity constraints and unobserved rejections are less of an issue for demand estimation. Moreover, estimates of demand for insurance are easier to interpret given than benefits and costs to the consumer are both measured in dollar terms.

Relatedly, this paper also adds to a previous body of work on determinants of choice quality more generally. In particular, my finding that disadvantaged residents tend to make worse nursing home choices echoes results in other settings, such as Handel, Kolstad, Minten, and Spinnewijn (2021) in the context of insurance choice in the Netherlands, and Walters (2012) in the context of school choice.

Methodologically, the present paper is one of the first to estimate demand while accounting for unobserved choice set constraints due to dynamic supply side incentives. The two main papers that previously estimate such a model are Gandhi (2023) and Agarwal and Somaini (2022), and my structural demand model contains elements from both.[3] Separately, my estimation of nursing home quality is related to a vast literature on value-added models, most of which is in education (Chetty, Friedman, and Rockoff 2014; Abaluck, Bravo, Hull, and Starc 2021; Angrist, Hull, Pathak, and Walters 2021), and also provides one of the first applications of double machine learning in this area (Belloni, Chernozhukov, and Hansen, 2014; Chernozhukov et al. 2018).

Finally, this paper contributes to a growing literature on nursing homes in economics. Much of the prior literature has focused on the supply-side (e.g., the effect of private equity ownership on nursing home behavior (Gandhi, Song, and Upadrashta 2020; Gupta, Howell, Yannelis, and Gupta 2021)),

[2]The estimate implies that residents are willing to tolerate a 3.5–21.7 percentage point higher probability of death within 90 days in exchange for a one-mile reduction in travel distance.

[3]This is related more broadly to a literature on demand estimation with unobserved choice set constraints arising from various sources. The source of these choice set constraints typically motivates the model and identification strategy, which may be based on consideration set formation (Abaluck and Adams-Prassl 2021), consumer search (Abaluck and Compiani 2020), or two-sided matching (Agarwal and Somaini 2022). Since the choice set constraints in this paper are due to nursing home behavior, I use a two-sided matching model for my demand estimation.

admission and discharge decisions by nursing homes (Gandhi 2023; Hackmann, Pohl, and Ziebarth 2020), and the effect of reimbursement rates and competition (Hackmann 2019; Gandhi, Olenski, Ruffini, and Shen 2024), although there is also a smaller number of studies on consumer choice (Gandhi 2023) and quality estimation (Einav, Finkelstein, and Mahoney 2022; Hackman, Rojas, and Ziebarth 2024). The present paper contains elements of all three, but the main focus is on consumer choice.

This paper proceeds as follows. In section 1, I provide background on the nursing home industry and its residents, and describe the data I use for my analysis. I then estimate nursing home quality and validate these estimates in section 2, before using them to study residents' responsiveness to quality and information frictions in section 3. In section 4, I study the effects of the star ratings through different channels and compare it to various demand- and supply-side counterfactuals via simulations. Section 5 concludes.

1 Background

1.1 Nursing Home Industry

There are roughly 15,000 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).[4] Nursing home residents vary widely in their medical conditions and needs, but as a crude approximation, they fall into two broad categories: short-stay and long-stay. Short-stay residents typically require rehabilitative care following an acute care hospital stay — for example, to recover from knee or hip replacement surgery. These patients are expected to recover sufficiently during their nursing home stay to be discharged and are typically covered by Medicare.[5] By contrast, long-stay residents often suffer from chronic conditions (e.g., cognitive decline), and are unlikely be discharged in the short term. Many of these residents are covered by Medicaid, which has substantially lower reimbursement rates than Medicare.[6] Finally, short-stay residents account for the majority of nursing home admissions, but at any given point in time, roughly half of residents residing in nursing homes are long-stay.

Despite substantial health expenditures in nursing homes, which totaled approximately $170 billion in 2016 (or roughly 5 percent of all healthcare spending in the US), both CMS data and anecdotal evidence show that poor quality remains endemic. These issues are especially prevalent at for-profit nursing homes (Comondore et al. 2009), which account for the majority of nursing homes in the US.[7] This paper focuses on one potential reason that the profit incentive has not resulted in greater quality investments: information frictions faced by residents about nursing home quality.

[4] More precisely, throughout this paper I colloquially refer to skilled nursing facilities (SNFs) that are certified by the CMS as nursing homes.

[5] Medicare reimburses up to 100 days following a hospital stay that lasts at least three days (with full coverage for the first 20 days and partial coverage for days 21–100). Reimbursement rates are also a function of resident care requirements and cost of inputs.

[6] Specifically, because long-term care insurance is uncommon in the US (Brown and Finkelstein, 2007, 2008, 2011), long-stay residents typically pay out-of-pocket until they become eligible for Medicaid (if they do not already qualify at the time of admission).

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

1.2 Choice of Quality Measure

Measuring information frictions about nursing home quality requires a definition of quality. In reality, nursing home quality is multidimensional, and reflecting this notion, a variety of quality measures have been used in the past, including skilled staffing levels, deficiency citations during inspections by regulators,[8] resident outcomes, and the CMS five-star rating system introduced towards the end of my sample (which aggregates many of these components into a single index). 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.[9] Hence, I use 90-day risk-adjusted survival rate as my primary quality measure, which is easier to measure and 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. For example, gaming of staffing levels,[10] resident outcomes,[11] deficiency citations,[12] and the five-star ratings by nursing homes has been well documented over the years.[13] Moreover, even unintentional errors in misreporting can be problematic: for instance, if understaffing at low-quality nursing homes results in fewer adverse outcomes being discovered, then quality measures based on these outcomes will be biased upwards for low-quality nursing homes.

Second, death is less likely than other outcome-based measures to be affected by truncation bias. This refers to the scenario wherein a resident suffers an adverse outcome (other than death) but dies before having another assessment, in which case the adverse outcome may not be recorded in the data.[14,15]

Third, death shortly after admission is an undesirable outcome for most types of residents.[16] This is important given that I am studying residents from all payer sources, and goals of care vary substantially across different types of residents.[17]

Finally, mortality is a commonly used health outcome in the prior economics literature (Doyle, Graves, Gruber, and Kleiner 2015; Deryugina and Molitor 2020; Finkelstein, Gentzkow, and Williams

[8] Inspections are conducted annually, but complaints may also trigger additional inspections.

[9] Evidence of this is shown in section 2.3.1.

[10] Staffing levels were self-reported by nursing homes during the period of this study, and were often unaudited. A comparison with staffing numbers since payroll-based reporting was introduced in 2016 reveals that these earlier self-reported numbers are likely to be substantially inflated (Geng, Stevenson, and Grabowski 2019).

[11] Schizophrenia diagnoses rose sharply in the years following 2012 when the government began publicly releasing information about inappropriate antipsychotic use (Thomas, Gebeloff, and Silver-Greenberg 2021).

[12] Some nursing homes temporarily increase inputs during the period wherein the annual inspections are expected to occur.

[13] Because the five-star ratings are a function of deficiency citations, staffing levels, and resident outcomes, gaming of these former measures will affect the star ratings as well (Silver-Greenberg and Gebeloff 2021).

[14] In theory, one could attempt to address this by estimating a hazard model to account for the censoring. However, even setting aside the difficulty of estimating many fixed effects in a hazard model, the assumption of uninformative censoring that many hazard models rely on is violated in this setting. This is because censoring induced by mortality is likely correlated with a host of other adverse outcomes in the time window shortly before death.

[15] I do not observe deaths occurring in other settings after a resident has been discharged, so in this sense, 90-day mortality may also suffer from truncation bias. However, even if I did observe deaths after discharge from nursing homes, it is unclear whether nursing homes are at fault for these deaths. Moreover, in section 3, I show that my quality estimates remain stable when I use mortality over shorter or longer durations than 90 days as the outcome, suggesting that truncation bias is unlikely to play a major role.

[16] I drop a relatively small number of residents who were either comatose or already on hospice upon admission, given that short-term mortality may not be an appropriate quality measure for these residents.

[17] For example, the quality measure based on discharge readiness recently developed by Einav, Finkelstein, and Mahoney (2022) is an excellent quality measure for short-stay residents, which is the population they study. However, it is a less appropriate quality measure for long-stay residents, who are by definition unlikely to be discharged in the short term.

2021; Abaluck, Bravo, Hull, and Starc 2021), which makes it easier to interpret the magnitude of effect sizes found in my study.[18]

1.3 Data

The primary data source for this paper is the Minimum Data Set 2.0 (MDS), and all nursing homes that receive federal funding are required to fill out MDS assessment forms at regular intervals (42 CFR §483.20).[19,20] Data collected from the MDS assessments includes information on residents' 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,[21] and several studies on the accuracy of MDS data have found it to be fairly reliable (Shin and Scherer 2009).[22] The richness of this data will play an important role in the risk adjustment for quality estimation in the next section.

I supplement the MDS with data on nursing homes from other sources. This includes the Online Survey Certification and Reporting (OSCAR) surveys (which contain information such as nursing homes' ownership status and staffing levels), data on deficiency citations, five-star ratings for nursing homes, and Medicare cost reports.[23]

These data sets also contain the information needed to compute distances between residents' prior addresses and nursing homes as well as nursing home occupancy levels over time, which are key components for my empirical strategies in sections 2 and 3. In particular, I compute distances by combining the five-digit zip code of residents' prior addresses from the MDS with nursing homes' street addresses from the OSCAR data, which I convert to GPS coordinates using the Google Maps API.[24] To calculate nursing homes' occupancy levels over time, I use admission and discharge dates from the MDS.

I focus on the first stays of residents between the years 2000 and 2010, given that the MDS 2.0 and

[18] In contrast, it is more difficult to interpret the magnitudes of demand based on various other quality measures. For example, while development of pressure sores is a commonly used quality measure in the health services literature on nursing homes, the economic cost of a pressure sore is not well-established, which makes it difficult to determine whether a given level of demand for this quality measure is "too large" or "too small."

[19] The set of nursing homes receiving federal funding account for roughly 96 percent of all nursing homes (Grabowski, Gruber, and Angelelli 2008).

[20] Assessment forms must completed upon admission, at discharge (or death), quarterly in between, and whenever there is a significant change in status.

[21] Appendix Tables A.1 and A.2 contain a finer breakdown of the different types of data collected on each resident. The full MDS 2 assessment form is available on the CMS website.

[22] 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. 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.

[23] 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. Data on deficiencies, Medicare cost reports, and five-star ratings are available from the CMS website.

[24] I also convert the five-digit zip codes for residents' prior addresses into GPS coordinates using the U.S. Department of Housing and Urban Development's ZIP Code Crosswalk Files for Quarter 1 of 2010, and I compute the distances between residents' and nursing homes' addresses using the "geodist" module in Stata.

OSCAR data overlap over this period. In addition, I restrict the sample to nursing homes in California with at least 100 new stays over this period so that quality can be estimated relatively precisely.[25,26] Because of the computational expense of the structural demand model, I further restrict my sample period to 2008–2010 for the demand estimation in section 3.[27] Finally, I consider the single year of 2009 for my counterfactual simulations in section 4, given that various assumptions that the simulations depend on (e.g., counterfactual nursing home entries and exits) are more suspect over longer time horizons. Additional details about the data can be found in Appendix B.

1.4 Summary Statistics

Panel A of Table 1 presents summary statistics for the residents (at admission) in my sample. We observe that the average resident age is 77 years old, the majority of residents are white, and only a minority have a Bachelor's or graduate degree. Most residents are admitted from an acute care hospital, and reflecting their poor state of health in general, almost a quarter of residents have dementia at admission, and 7.5 percent die within 90 days of admission.[28] Appendix Table A.3a contains more detailed summary statistics for nursing home residents.

Panel B summarizes nursing home statistics,[29] showing that nursing homes have 120 beds on average, occupancy rates tend to be quite high (86 percent on average)[30], and most are owned by chains or are for profit. In addition, I have data on the number of deficiencies that nursing homes are cited for as well as self-reported staffing levels. Reflecting the prevailing wisdom that many nursing homes are understaffed, registered nurses (RNs) provide less than 25 minutes of care for each resident per day on average.

[25] I choose to study nursing homes in a single state mainly for computational reasons, but also because nursing home regulations differ across states. I choose California due to its large population, and because most of its population live relatively far away from state borders (and thus nursing homes in other states are relatively unlikely to be in nursing home residents' choice sets).

[26] Additional sample restrictions include the exclusion of nursing homes that do not file cost reports because these tend to be specialized facilities (e.g., specializing in subacute care or mental disease), and the exclusion of a relatively small number of residents who were either comatose or on hospice upon admission. A more detailed account of sample restrictions can be found in Appendix B.

[27] I choose this particular time window because it allows me to study the effect of the introduction of CMS five-star ratings at the end of 2008.

[28] 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.

[29] These summary statistics are based on OSCAR surveys, which are conducted annually. In addition, these statistics are weighted by number of admissions, although the general patterns for statistics that are not weighted by number of admissions are qualitatively similar (see Appendix Table A.4).

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

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

Panel A: Residents (N=653,946)		*Panel B: Nursing Homes (J=840)*	
Age	77.541	Number of Beds	123.989
	(12.991)		(51.812)
Race: White	0.735	Occupancy Rate	86.198
	(0.441)		(10.171)
Bachelor's/Graduate Degree	0.131	Chain	0.641
	(0.338)		(0.480)
Admitted from Acute Care Hospital	0.889	For-Profit	0.913
	(0.314)		(0.282)
Has Dementia	0.233	Deficiencies	6.573
	(0.423)		(8.156)
Death Within 90 days of Admission	0.075	RN hours per resident day	0.387
	(0.264)		(0.354)

Notes: This table contains summary statistics for residents and nursing homes in California between 2000 and 2010. The unit of observation for nursing homes' summary statistics is a nursing home-year, and each observation is weighted by the number of residents admitted to the nursing home for their first stay during that year.

2 Estimation of Nursing Home Quality

In this section, I estimate quality of nursing homes in California, and validate these estimates using a distance-based IV strategy. I then explore the relationship between my quality estimates and other potential quality measures, as well as the degree of geographical concentration in nursing home quality.

2.1 Framework for Quality Estimation and Validation

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

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

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

The literature on value-added estimation in education has often found that controlling for lagged values of the outcome variable is important (Chetty, Friedman, and Rockoff 2014).[31] 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.

[31] Alternatively, value-added estimation in education sometimes also uses test score gains as the dependent variable.

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.[32] Hence, I use a modification of the post-double-selection method in Belloni, Chernozhukov, and Hansen (2014) to select an appropriate set of controls for my quality estimation (see Appendix I for details).[33,34,35]

We can use either empirical Bayes or fixed effects quality estimates of the causal effects β_j. The advantage of the empirical Bayes is that it accounts for statistical noise (by shrinking the OLS estimates towards zero according to the signal-to-noise ratio), which results in a distribution of quality estimates that better approximates the true quality distribution (in the sense of minimizing the unconditional mean-squared error sense). On the other hand, fixed effects quality estimates are also useful if we are interested in the quality of specific nursing homes, which is the case when we model residents' choice of nursing homes. In practice, I show that the main results of the paper are unchanged whether we use empirical Bayes or fixed effects quality estimates $\{\alpha_j\}$.

Issues of overfitting and statistical noise aside, and 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 exogenous variation in the quality of residents' chosen nursing homes, I leverage residents' preferences for nursing homes that are closer to their address.

To elaborate, I derive the following structural equation from equation (1):

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

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

For this IV validation exercise, I use leave-year-out quality estimates $\alpha_i^{\sim t(i)}$ to avoid a mechanical relationship between resident outcomes and the quality estimate of residents' chosen nursing homes.

[32] An extreme example of this would be if some of the controls (that one does not need to control for to obtain consistent estimates of quality) end up being perfectly collinear with some of the nursing home choice dummies, in which case we would be unable to estimate quality for these nursing homes.

[33] At a high level, the post-double-selection method uses lasso to choose the appropriate subset of controls for the estimation of treatment effects in settings with many controls. Because omitted variables bias depends on the relationship between the omitted variable and the dependent and treatment variables, one runs two lasso regressions of the dependent variable and the treatment variable on the controls. To account for the possibility of modest variable selection errors in this first step, one takes the union of the two sets of controls selected by lasso in the two lasso regressions, and estimates the treatment effect controlling for these variables.

[34] A modification of the standard post-double-selection method is required for my setting, given that the standard method applies to the case with a single (or at most a few) treatment variable(s), whereas treatment in my setting corresponds to $J - 1 > 800$ nursing home choice dummies. To address this, I use a model reduction strategy motivated by a correlated effects approach, which then allows me to apply the standard post-double-selection method.

[35] 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.

Specifically, the outcome Y_i is used in the estimation of nursing home quality α_j, so 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 not 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.[36] For Z_i to be a valid instrument, several assumptions must be satisfied.

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

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

IV Assumption 2 (Exclusion Restriction). *The instrument 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 Z_i residualized of resident characteristics X_i.

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

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

The first stage assumption can be easily tested by estimating equation (3) using OLS. As for the exclusion restriction, one way to interpret this condition is that the quality of nearby nursing homes can only affect a resident's outcome through the quality of the nursing home she ultimately chooses (after controlling for her characteristics). This may be violated, for instance, if residents choose where they live based on nursing home quality and preferences varied by unobserved health status u_i, or if high-quality nursing homes choose to locate where unobservably healthier residents tend to live.

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

I do not focus much on the fallback condition (Abaluck, Bravo, Hull, and Starc 2021), since it is difficult to interpret,[37] and the case wherein quality estimates are unbiased on average but the

[36] 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.

[37] In particular, η_i is not a structural parameter but rather arises from a complicated statistical relationship between

fallback condition fails is a knife-edge one (Chetty, Friedman, and Rockoff 2014). Moreover, because my instrument varies only at the geographical level, the inclusion of county fixed effects makes it less likely that the fallback condition is violated (similar to the exclusion restriction).

Finally, there is a positive correlation between the measurement error in the quality estimates and the instrument (which 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 K, I derive a correction factor for the IV estimates when using the fixed effects quality estimates, and show the shrinkage underlying the empirical Bayes quality estimates cancels out the attenuation bias to a first order so that no correction factor is needed for the IV results based on empirical Bayes quality estimates.

2.2 Quality Estimation Results

The standard deviation of my quality estimates is between 0.02 and 0.025 (for the empirical Bayes and fixed effects estimates respectively), which implies that a resident who goes to a nursing home with one standard deviation higher quality is 2–2.5 percentage points less likely to die within 90 days (all else equal). This is a 27–33 percent reduction in 90-day mortality compared to the baseline mortality rate of 7.5 percent, suggesting that nursing home choice can have a quantitatively meaningful impact on mortality even in the short run. Appendix Figure A.2 shows that the distribution of my quality estimates is roughly bell-shaped, with a notable left tail of low-quality nursing homes.

Next, I validate these quality estimates by estimating the forecast coefficient in equation (2) using IV. Figure 1 provides support for 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. By contrast, the lack of a clear relationship between the instrument and survival probability based on resident characteristics net of nursing home effects (which I use as a proxy for baseline health) lends confidence to the exclusion restriction.[38,39]

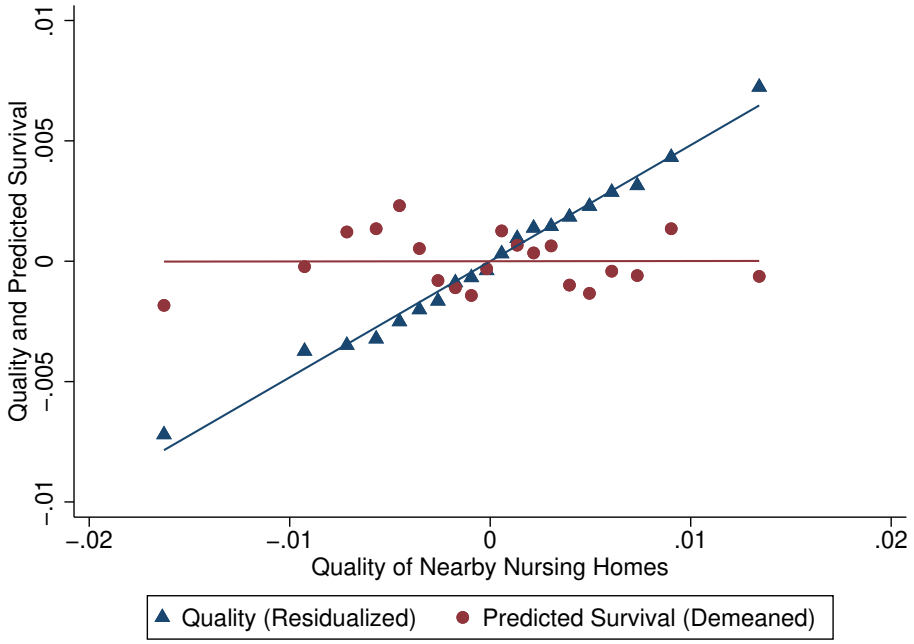
the causal parameters β_j and the quality estimates α_j.

[38] I compute the probability of surviving at least 90 days based on the quality estimation procedure, where I use the predicted values based on resident characteristics but not the nursing home effects.

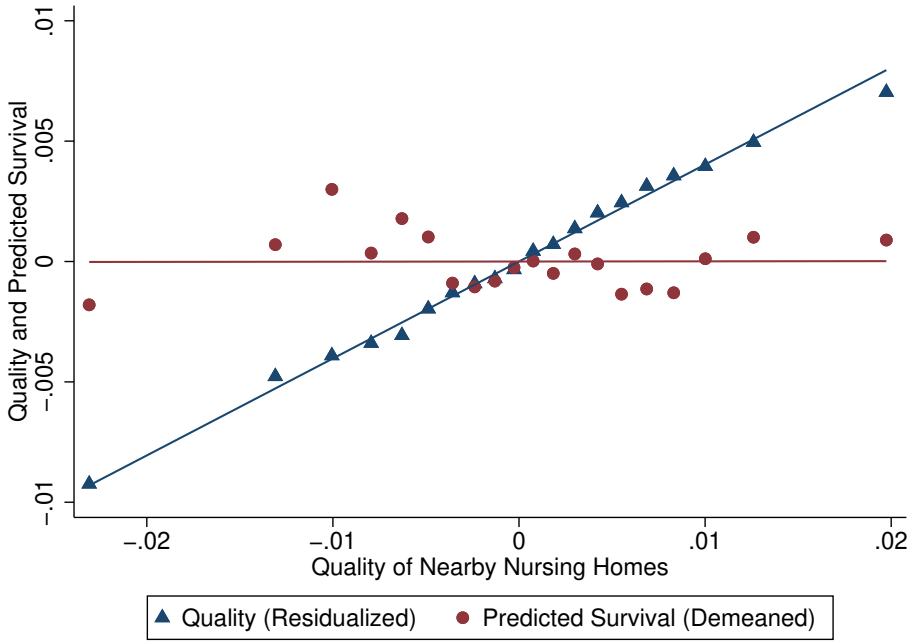
[39] The balance test in Figure 1 checks whether the residualized instrument is correlated with survival probability. A stronger version of this test that checks whether the *unresidualized* instrument is correlated with survival probability is shown in Appendix Figure A.3. These results reveal that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

Figure 1: First Stage Assumption and Exclusion Restriction

(a) Empirical Bayes Quality Estimates



(b) Fixed Effects Quality Estimates



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

Table 2 shows IV estimates of the forecast coefficient from different specifications, for the empirical Bayes quality estimates in columns 1 and 2, and the fixed effects quality estimates in columns 3 and 4 (corrected for attenuation bias). In all the specifications, the first stage F-statistics are over 100, and estimates of the forecast coefficient are not statistically different from one at the 5 percent significance level, supporting the validity of my quality estimates.

Table 2: IV Estimates of the Forecast Coefficient

	Dependent Variable: 90-Day Survival			
Quality Measure:	Empirical Bayes		Fixed Effects	
	(1)	(2)	(3)	(4)
TSLS				
Quality of Nursing Home Chosen by Resident	0.971	0.946	0.955	0.907
	(0.086)	(0.089)	(0.084)	(0.090)
Reduced Form				
Avg. Quality of Nursing Homes Close to Resident	.479	.456	.417	.365
	(.067)	(.066)	(.058)	(.056)
First Stage				
Avg. Quality of Nursing Homes Close to Resident	.494	.482	.436	.403
	(.043)	(.041)	(.038)	(.036)
Definition of Nursing Homes Close to Resident	Within 5 Miles	5 Nearest	Within 5 Miles	5 Nearest
Adjusted for Attenuation Bias			X	X
Demographic and Health Controls	X	X	X	X
County Fixed Effects	X	X	X	X
Kleibergen-Paap rk Wald F statistic	134	137	129	127
Number of Observations	577,087	632,207	577,087	632,207

Notes: This table presents IV estimates of the forecast coefficient (e.g., the effect of nursing home quality estimate on resident outcomes), instrumenting quality of chosen nursing home with quality of nursing homes close to each resident. Nursing home quality estimates are based on the regression of one-year survival on nursing home fixed effects and the full set of controls for resident demographics and health. Standard errors clustered at the nursing home level are displayed 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.4 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.

A disadvantage of including residents from all payer sources in my sample is that there may be truncation bias due to the fact that I do not observe deaths after discharge for residents who are not covered by Medicare. On the other hand, even if I did observe deaths after discharge for all residents, it is unclear whether nursing homes are responsible for these deaths. Nonetheless, to gauge whether such truncation bias 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.[40] Appendix Figures

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

A.5 and A.6 shows that quality estimates based on mortality over different time horizons are all highly correlated, suggesting that truncation bias is unlikely to meaningfully affect my results.

Finally, in Appendix Section D, I consider several alternative identification strategies for estimating the forecast coefficient, such as using different instruments or conducting an event study based on entry by high-quality nursing homes. To summarize the results from these exercises briefly, I do not find any evidence that my quality estimates are biased; the identifying assumptions for these alternative specifications are not always met, but in the cases where they are, the results support the validity of my quality estimates. 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).

2.3 Discussion of Nursing Home Quality Estimates

2.3.1 Relationship Between Different Dimensions of Quality

Table 3 shows that the correlations between my quality estimates and observable nursing home characteristics have the expected signs — skilled staffing levels and CMS star ratings are positively correlated with my quality measure, whereas for-profit status and number of cited deficiencies are negatively correlated with quality (Grabowski et al. 2016; You et al. 2016).[41] Appendix Table A.7 shows that the same patterns hold as well for the fixed effects quality estimates.

However, only a small fraction of the variation in my quality measure can be explained by these quality indicators,[42] and I demonstrate in Appendix Table A.8 that my quality measure is a stronger (out-of-sample) predictor of resident outcomes than these quality indicators, suggesting that it contains information about nursing home quality beyond that which can be gleaned through publicly available metrics.[43]

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.

[41] 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.

[42] The regression of my quality estimates on all these quality indicators has an R-squared of only 0.04.

[43] Specifically, Appendix Table A.8 shows results from regressions of survival on leave-year-out quality estimates and nursing home characteristics, wherein I standardize all right-hand-side variables to facilitate comparisons and multiply coefficients and standard errors by 100 for better legibility. 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). Moreover, both the coefficient on my quality measure and the R-squared remain essentially unchanged when I include other quality indicators in the regression.

Table 3: Relationship Between Empirical Bayes Quality Estimates and Nursing Home Characteristics

	Quality Estimates (s.d.)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2009 Star Ratings (s.d.)	0.0783**							0.0483
	(0.0310)							(0.0315)
RN hours per resident day (s.d.)		0.0942***						0.218***
		(0.0352)						(0.0490)
LPN hours per resident day (s.d.)			0.100***					0.116***
			(0.0209)					(0.0324)
CNA hours per resident day (s.d.)				0.0908***				-0.0398
				(0.0158)				(0.0259)
Deficiencies (s.d.)					-0.0467***			-0.0206
					(0.0157)			(0.0132)
For-Profit (s.d.)						-0.0881***		-0.0693***
						(0.0297)		(0.0261)
Chain (s.d.)							-0.0346	-0.0158
							(0.0279)	(0.0263)
N	(0.0340)	(0.0329)	(0.0331)	(0.0335)	(0.0340)	(0.0333)	(0.0341)	(0.0322)
R-squared	0	0	0	0	0	0	0	0

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 long-stay residents it has over the sample period. Standard errors are clustered by nursing home.

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 and truncation bias for these other outcomes aside, Appendix Figures A.7 and A.8 shows that my survival-based quality estimates tend to be positively correlated with quality estimates based on these other outcomes.

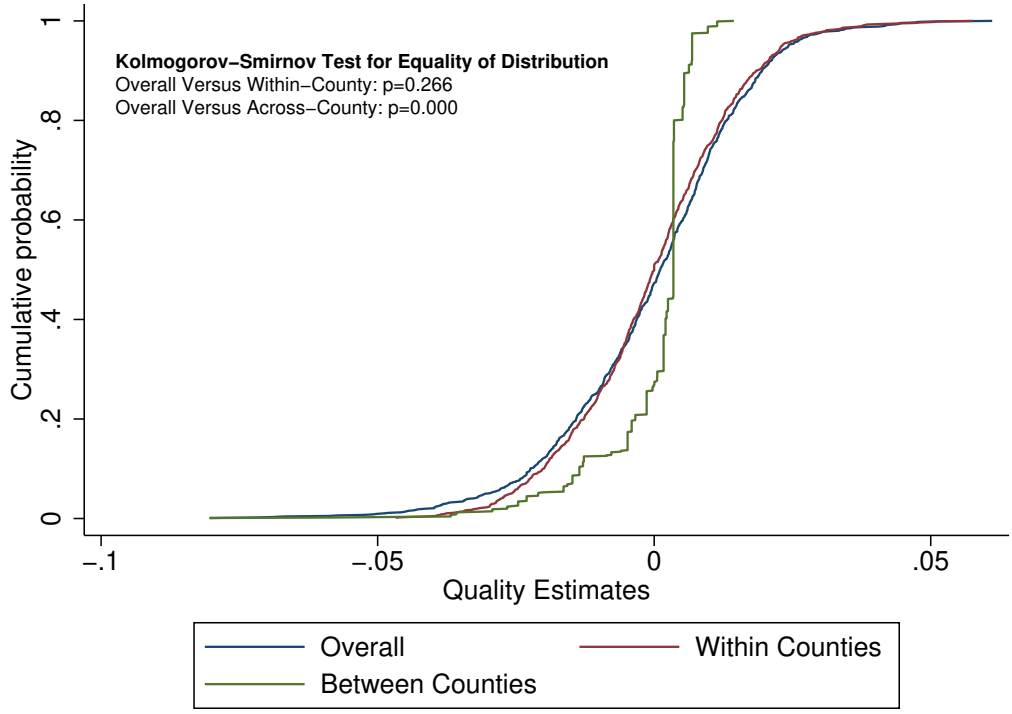
2.3.2 Geographical Variation in Nursing Home Quality

Finally, while the quality estimates indicate substantial variation in nursing home quality across California, the degree of local variation is also important for consumer choice; in particular, if quality is highly geographically concentrated, then residents living in certain areas may not have access to high-quality nursing homes. To shed light on whether this is the case, Figure 2 plots empirical cumulative distribution functions (ECDFs) showing the overall variation in the empirical Bayes nursing home quality estimates as well as the within- and across-county variations in quality.[44] The figure shows that there is almost as much variation in nursing home quality within counties as there is overall,[45] implying that there tends to be both high-quality and low-quality nursing homes close to each resident. Appendix Figure A.9shows that the same holds true for fixed effects quality estimates. Whether residents are able to take advantage of this variation is the main topic of the next section.

[44] To plot the within-county quality variation, I use the residuals from a regression of my quality estimates on county fixed effects. To plot across-county quality variation, I use average quality within each county.

[45] Moreover, within-county variation in quality accounts for far more of the overall variation than across-county variation in quality: while the Kolmogorov-Smirnov test for equality of distributions clearly rejects the null that the overall and across-county distributions of quality are equal, but not the null that the overall and within-county distributions of quality.

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



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

3 Residents' Responsiveness Nursing Home Quality

In this section, I use my survival-based quality estimates as inputs into a structural model to study residents' responsiveness to quality. I start in section 3.1 by showing evidence that there are unobserved constraints on residents' choice sets due to selective admissions practices by nursing homes (Gandhi 2023), and that naive demand estimates that ignore these constraints may be misleading. In section 3.2, I describe how I address these unobserved choice set constraints by outlining a structural demand model and estimation procedure based on recent advancements in the empirical matching literature (Agarwal and Somaini 2022). Finally, in section 3.3, I present results from the structural demand estimation, and explore the plausibility of various explanations for the findings.

3.1 Selective Admissions by Nursing Homes

Residents vary widely in their profitability to nursing homes, which gives nursing homes a financial incentive to reject certain residents, thus imposing unobserved constraints on residents' choice sets.

Naïve demand estimates that ignore these constraints 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 that these problems may be relevant in this setting, I show how naïve conditional logit estimates of residents' responsiveness to nursing home quality which do not take into account nursing homes' capacity constraints and selective admissions policies 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, she may be "forced" to choose a lower-quality nursing home than she would like. Hence, naïve demand estimates for these types of residents would be lower, and vice versa for residents where higher-quality nursing homes nearby face relatively lower capacity strain.

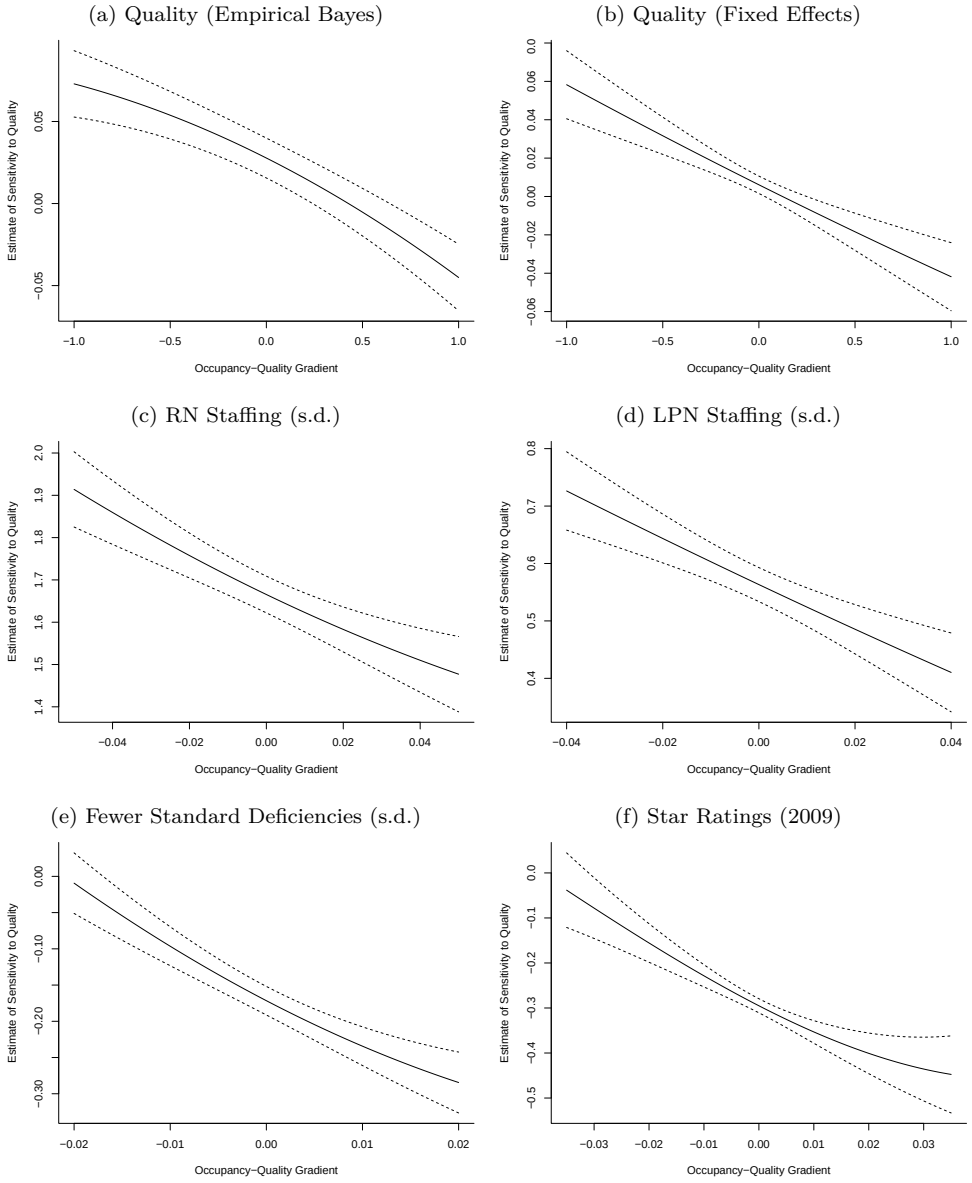
To operationalize this, for nursing homes close to each resident i, I regress a measure of capacity strains faced by these nursing homes on their quality, denoting the estimated coefficient by $\hat{\Delta}_i$. I then estimate conditional logit models where I allow responsiveness to quality to vary as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

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

Figure 3 shows that conditional logit estimates of responsiveness to quality is 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 conditional logit estimates of average responsiveness to quality may be biased by capacity constraints and unobserved rejections by nursing homes. 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 we know that this is unlikely since occupancy of different nursing homes are orthogonal to resident characteristics.[46]

[46] 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 3: Conditional Logit Estimates of Residents' Responsiveness to Quality as a Function of $\hat{\Delta}_i$



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

Having shown that capacity constraints are likely relevant for demand estimation, I outline a model of selective admissions to help provide some intuition for the structural estimation in the next subsection. This model is a modest extension of the one in Gandhi (2023) in that it incorporates nursing home quality in order to derive some additional comparative statics, hence I focus mostly on intuition in a simplified version of the model in the main text, leaving the general model and technical details to Appendix Section E.

Suppose that new residents arrive at some Poisson rate λ_A, and residents in nursing homes are discharged at some Poisson rate λ_D. Residents vary in their "profitability" Π_i to nursing homes, while nursing homes vary in their total number of beds b_j and quality q_j. Nursing homes receive a flow payoff $\Psi_j(N_{jt})$ that depends on their current census N_j (i.e., the number of residents currently in the nursing home), as well as an instantaneous payoff Π_i whenever it admits a new resident. Assuming that nursing homes do not know their rivals' censuses, each nursing home chooses an admissions policy $\{a_{jt}(N_{jt})\}$ whereby it admits a resident at time t if and only if $\Pi_i \in a_{jt}(N_{jt})$, and we require that $a_{jt}(b_j) = \{\}$.

Hence, profit-maximizing nursing homes' optimal admissions policy is the solution to an optimal control problem in which they maximize the expected present discounted value of profits at each point in time t:

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

where ρ is a discount rate, τ_i^A is resident i's arrival time, $v_{ij}(q_j)$ is her indirect utility for nursing home j, $\mathcal{O}_i$ denotes the set of nursing homes that are willing to admit her, and $\mathcal{F}_j^j$ is a filtration representing the nursing home's information.

The more general version of this model in Appendix Section E allows nursing homes to choose their quality in the first period. In addition, nursing homes observe more characteristics about residents who apply, the profitability of the same resident may vary across nursing homes, different types of residents have different discharge rates, and the flow profits $\Psi_j(\cdot)$ depend not only on the number of residents in the nursing home, but also on the number of each type of resident. Assumptions underlying the model are also spelled out clearly, and admissions thresholds and equilibrium conditions are given explicitly.

Given the memorylessness property of arrivals and discharges, the optimal admissions policy is time invariant: $a_{jt}^*(N_{jt}) = a_j^*(N_{jt})$ for all t. Moreover, since nursing homes prefer more profitable residents, the admissions policy takes a threshold form, whereby $a_j^*(N_{jt}) = [\bar{\Pi}_j(N_{jt}), \infty)$. Importantly, it can be shown that admissions threshold $\bar{\Pi}_j(N_{jt})$ is increasing in N_{jt}. This is intuitive since the option value of spare beds is greater when nursing homes are closer to capacity, so they will be more selective in these times by setting a higher profitability threshold. This 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.*

To measure capacity strain faced by nursing homes at each point in time, I use temporary occupancy fluctuations, defined as the seven-day average of some occupancy measure residualized of nursing home-month fixed effects.[47] 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 also implies

[47] 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 a seven days is a reasonable approximation of the time window during which they are making these choices.

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

Table 4 shows results supporting prediction 1 based on regressions at the nursing home-day level: conditional on nursing home-month fixed effects, nursing homes admit fewer new residents on days when occupancy is higher than usual, and this finding is not sensitive to the functional form used for occupancy.[48] Moreover, as Appendix Table A.9 shows, this result is robust to alternative measures of new admissions, such as a dummy for any new admissions, and the flow of residents (i.e., admissions minus discharges).

Table 5 shows support for prediction 2: when nursing homes are closer to capacity, they are less likely to admit residents suffering from Alzheimer's or dementia even conditional on other resident characteristics such as post-acute care status, race, education, age, gender and marital status, with Appendix Table A.10 showing that these results also hold unconditionally. This is consistent nursing homes' complaints that they are not reimbursed adequately for residents with dementia (Kosar et al. 2023).[49] Appendix Section L describes these tests of selective admissions in more detail, and also presents results of these tests for additional specifications and resident characteristics.

Table 4: Effect of Occupancy on Admissions

	Number of New Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.273***		
	(0.0142)		
Lagged 7-Day Avg. Occupancy		-0.00807***	
		(0.000376)	
Lagged 7-Day Avg. Occ. Percentile			-0.00229***
			(6.98e-05)
Nursing Home-Month Fixed Effects	X	X	X
N	3,503,121	3,503,121	3,503,121

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

[48] Strictly speaking, prediction 1 only tests whether capacity constraints are relevant and does not directly test for selective admissions (unlike prediction 2). Nonetheless, prediction 1 serves as a sanity check for the model of selective admissions.

[49] 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.

Table 5: Reduced Form Evidence of Selective Admissions

	Dummy for Whether Resident Has Dementia		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.0549***		
	(0.0139)		
Lagged 7-Day Avg. Occupancy		-0.000848***	
		(0.000210)	
Lagged 7-Day Avg. Occ. Percentile			-0.000217***
			(7.21e-05)
Nursing Home-Month Fixed Effects	X	X	X
Controls	X	X	X
N	645,864	645,864	645,864

Notes: This table shows regression results at the resident level wherein the dependent variable is a dummy for whether the resident has Alzheimer's or dementia, and the independent variables are various measures of nursing home occupancy, as well as controls for other resident characteristics (specifically, post-acute care status, race, education, age, gender, and marital status of the resident). Standard errors are clustered at the nursing home level.

3.2 Structural Model for Demand Estimation

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

3.2.1 Identification of Two-Sided Matching Model

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

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

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

Agarwal and Somaini (2022) establish a sharp set of conditions under which these preferences are non-parametrically identified. The key substantive requirement for identification is the existence of demand and supply instruments,[50] which in my case are $dist_{ij}$ and occ_{ij}, respectively. Intuitively, we need the supply side instrument for the reasons described above: without fluctuations in nursing home occupancy, we cannot tell whether certain types of residents tend to choose higher-quality nursing

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

homes because they are more responsive to nursing home 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.[51]

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

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

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

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

The assumption that merits most discussion is the exclusion restriction for temporary occupancy fluctuations as the supply instrument. Let us first consider why simply using occupancy (rather than fluctuations in it) as the supply instrument is likely to violate the exclusion restriction, and how this will affect our demand estimate. Suppose that high-quality nursing homes tend to have higher occupancy rates on average but that all else equal, residents prefer nursing homes with lower occupancy rates (which violates the exclusion restriction for this instrument). 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.10 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).

3.2.2 Estimation Framework

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

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

of residents' and nursing homes' preferences:

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

where x_i contains resident i's characteristics, w_j denotes nursing home j's characteristics (including quality β_j), and ϵ_{ij} and ω_{ij} follow independent Gaussian distributions. I impose the location normalization for residents' utility by setting the utility of a nursing home and the intercept to zero,[52] 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.

County fixed effects were shown to be important in the distance IV estimates in the previous section, but suffers from the downside that counties vary significantly in terms of size, and does not exploit the variation in residents' locations within each county. So, for the structural analysis, I define each resident i's choice set as the set of all nursing homes within 15 miles of her prior address, $\mathcal{J}_i$.[53] Some of these nursing homes may be unwilling to admit her but the identities of these nursing homes (if any) 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 is actually *able* to choose from is $2^{J_i} - 1$, where $J_i \equiv |\mathcal{J}_i|$.[54] 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,[55] or restrict the number of nursing homes in each resident's choice set.[56]

To address the curse of dimensionality, I estimate the model using a Gibbs sampler with data augmentation on the latent variables v_{ij} and π_{ij}, a method that provides a convenient dimension reduction without requiring further substantive assumptions (Agarwal and Somaini 2022). At a high level, the Gibbs sampling method involves iteratively drawing the structural error terms (ϵ', ω') and the parameters $\theta \equiv (\kappa', \psi')'$,[57] in a way that respects the matching outcomes.[58] Under standard conditions, the draws of θ will eventually converge to the stationary distribution,[59] and I conduct inference using

[52] 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.

[53] Using fixed effects based on a radius around each resident for the distance IV is infeasible, since this will be equivalent to zip code fixed effects, conditional on which there will no remaining variation in the instruments (i.e., quality of nursing homes nearby).

[54] The average value of 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, J_i can be larger than 200, in which case there are $2^{200} - 1 > 10^{60}$ possibilities.

[55] 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). This restriction drastically reduces the possibilities for the set of nursing homes that are willing to admit the resident from 2^{J_i} to J_i.

[56] 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, and may thus result in an unrepresentative sample. The ECDF of residents' distances to their chosen nursing homes, shown in Appendix Figure A.11, indicates that more than 80 percent of residents choose a nursing home within 15 miles, but only less than 60 percent of residents choose a nursing home within 5 miles.

[57] This procedure follows a Bayesian approach, so the parameters $\theta \equiv (\kappa', \psi')'$ are treated as random, with some prior distribution. The posterior distribution of θ is updated in each iteration.

[58] Thus, denoting the nursing home that resident i is admitted to by $\mu(i)$, in each iteration, we must ensure that $\pi_{i,\mu(i)} \geq 0$, and that the resident prefers $\mu(i)$ to all other nursing homes that she is eligible for (i.e., $v_{i,\mu(i)} \geq v_{ij}$ for all j such that $\pi_{ij} \geq 0$). Similarly, for a nursing home j that is not chosen by resident i, we must ensure that either it is less desirable than her chosen nursing home ($v_{ij} \leq v_{i,\mu(i)}$) or that she is not eligible for it ($\pi_{ij} < 0$).

[59] Specifically, the transition kernel for the Gibbs sampler has to be irreducible and aperiodic. More primitive conditions

the draws of θ after an initial burn-in period.[60,61] Appendix G describes the full algorithm for the Gibbs sampler in detail.

3.3 Demand Estimation Results

3.3.1 Estimates of Responsiveness to Nursing Home Quality

Table 6 presents estimates of the structural demand model described in the previous subsection, using either the empirical Bayes quality estimates, or fixed effects quality estimates, with the full supply side estimates shown in Appendix Table A.11. Across all specifications, the coefficients on the demand and supply side instruments (distance to nursing home and occupancy fluctuations) are highly statistically significant, so the low demand estimate is unlikely to be due to weak identification. In addition, the coefficient on quality on the supply side equation is negative and statistically significant, consistent with a model of profit-maximizing nursing homes given that the option value of spare beds is higher for nursing homes that expect greater future demand.

Table 6: Structural Demand Estimates

Quality Measure:	Empirical Bayes	Fixed Effects	Empirical Bayes	Fixed Effects
	(1)	(2)	(3)	(4)
Resident Preferences				
Distance to Nursing Home (in miles)	-0.168***	-0.168***	-0.168***	-0.172***
	(0.001)	(0.001)	(0.001)	(0.001)
Quality	0.752*	4.59***	21.826***	16.381***
	(0.507)	(0.159)	(1.125)	(0.507)
Quality x Dementia			-1.489***	-1.412***
			(0.358)	(0.186)
Quality x Age			-0.232***	-0.149***
			(0.014)	(0.005)
Quality x At Least Bachelor's Degree			3.791***	0.604***
			(0.526)	(0.181)
Quality x Post-Star Ratings			0.622**	0.679***
			(0.274)	(0.147)
Supply Side				
Temporary Fluctuations in log(occupancy)	-3.305***	-2.585***	-2.534***	-2.218***
	(0.209)	(0.182)	(0.14)	(0.124)
Quality	-4.035*	-27.128***	2.186*	-6.901***
	(2.592)	(0.771)	(2.007)	(0.924)
Resident Chars. in Supply Side	X	X	X	X
Quality Interacted with Resident Chars. in Supply Side			X	X

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

have also been derived that ensure the transition kernel for the Gibbs sampler has these properties (Robert and Smith 1994).

[60] In particular, 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).

[61] Although the Gibbs sampler is derived following a Bayesian approach, the Bernstein-von Mises theorem implies that the distribution of θ will converge to the distribution of the maximum likelihood estimator under correct specification. Therefore, our Bayesian inferences based on the results of the Gibbs sampler are also (asymptotically) correct from the frequentist point of view.

The positive coefficient estimate for the two different quality measures in columns 1 and 2 indicates that residents are responsive to nursing home quality on average. However, in terms of magnitude, average responsiveness to quality is quite low: the demand coefficients on quality β_j and distance $dist_{ij}$ imply that the marginal rate of substitution (MRS) between quality (in percentage points) and distance is:

$$MRS = \frac{d(dist_{ij})}{d\beta_j} = -\frac{\partial v_{ij}/\partial \beta_j \cdot 0.01}{\partial v_{ij}/\partial dist_{ij}} = \begin{cases} -\dfrac{0.00752}{-0.162} \approx 0.046 & \text{Empirical Bayes} \\ -\dfrac{0.0459}{-0.162} \approx 0.283 & \text{Fixed Effects} \end{cases}$$

Assuming full information on the part of residents, this MRS estimate implies that in exchange for a one-mile reduction in travel distance, residents are willing to tolerate between a $1/0.283 \approx 3.53$ and $1/0.0459 \approx 21.7$ percentage point higher probability of dying within 90 days (more than 1–10 times the standard deviation in quality, which is 2–2.5 percentage points). These estimates are also an order of magnitude lower than estimates in hospital settings, which range from 1.8 at the low end (Chandra, Finkelstein, Sacarny, and Syverson 2016) to 8 at the high end (Tay 2003).

One explanation for why estimated responsiveness to quality is so low is that there are other dimensions of quality that residents care more about, some of which may be negatively correlated with my quality measure. For example, perhaps high-quality nursing homes according to my mortality-based measure provide an overly medicalized regime at the expense of residents' comfort. To test the plausibility of this explanation, in column 1 of Appendix Table A.12, I show estimates of residents' responsiveness to various nursing home characteristics, including staffing levels and deficiency citations. While estimates indicate that residents are responsive to RN and LPN staffing, the estimated sign on deficiency citations is the wrong sign (suggesting that residents prefer nursing homes with more deficiency citations).

A second related concern with these estimates of low responsiveness to quality is omitted variables bias in the demand equation. However, this seems unlikely since in order for omitted variables bias to bias the demand estimate downwards it has to be valued by residents but negatively correlated with quality, and we saw that my quality measure is positively correlated with nursing home characteristics in intuitive ways, in Table 3. Indeed, when we include these other nursing home characteristics in the demand equation, we observe in column 3 and 5 of Appendix Table A.12 that the coefficient estimate on quality on the demand side becomes smaller than when they are not included in columns 2 and 4 (which replicate columns 1 and 2 of Table 6).

While the result that estimated responsiveness becomes smaller after adding controls is reassuring, it does not rule out the existence of an unobserved omitted variable that is valued by residents but negatively correlated with quality. Hence, I perform a sensitivity analysis in the spirit of Altonji, Elder, and Taber (2005) and Oster (2019), to get a sense of "how bad" the omitted variables must be in order to completely explain the result of low responsiveness to quality. In particular, using methods from Cheng (2023) on selection on unobservables for discrete choice models, Appendix Figure A.12 shows that in order for omitted variables bias to completely explain the discrepancy between my demand estimate and previous estimates from the hospital setting, residents need to value the omitted variable more than 100 times more than they do observable quality measures, based on the type of assumption

on the proportional selection relationship adopted by Oster (2019).

A third possible explanation for the low demand estimate is that residents may not directly observe nursing home quality β_j. A natural way to model this is to assume residents only receive a noisy signal of quality, which they combine with publicly available information about nursing homes to make an optimal forecast about β_j.[62] I illustrate with a simple model in Appendix Section M that if this is the case, residents should value nursing home characteristics that are positively correlated with β_j. Yet, this is at odds with the negative demand coefficient on fewer deficiencies in columns 3 and 5 of Appendix Table A.12.

Finally, a fourth explanation for the low demand estimate is that it may the result of functional form misspecification, or attenuation bias due to the fact that quality was estimated. To test this possibility, I replace quality with nursing home fixed effects in residents' utility equation, and plot these mean utilities against nursing home quality in Appendix Figure A.14. This scatterplot shows that there is hardly any relationship between residents' preferences and nursing home quality (linear or otherwise), suggesting that functional form misspecification is unlikely to be the main explanation for the low demand estimate. Moreover, Abaluck et al. (2021) shows that even if there is estimation noise in quality, the slope of the best fit line in this figure provides an upper bound for demand, and we observe that the implied upper bound for the MRS remains substantially smaller than MRS estimates from the literature.

While average responsiveness to nursing home quality may be low, previous research has shown that "choice quality" may vary with consumer characteristics (Handel, Kolstad, Minten, Spinnewijn 2021). Indeed, columns 3 and 4 show that there is systematic heterogeneity in responsiveness to quality: for instance, residents who are free from Alzheimer's/dementia, younger, more educated, White, and who made their choices after the introduction of star ratings tended to be more responsive to nursing home quality. There are several possible explanations for these patterns of heterogeneity. One possibility is that some residents face greater information frictions which explains their low responsiveness to quality. Another is that residents with longer life expectancy (conditional on surviving their nursing home stay) are likely to place a greater value on (mortality-based) nursing home quality.

Finally, Appendix Table A.13 shows that my estimates are robust to the possibility that some residents are able to delay their nursing home choice until capacity strain at their preferred nursing home eases. In particular, these estimates are based on the subsample of post-acute care residents, who are likely to face greater time pressure when choosing a nursing home given that they are about to be discharged from a hospital. We observe that estimates of residents' responsiveness to quality and heterogeneity in responsiveness remain qualitatively similar to the main estimates in Table 6.

While it may be difficult to nail down information frictions as the reason for my estimates of low responsiveness to quality and heterogeneity in responsiveness, an information intervention by the CMS — its introduction of the star ratings system at the end of 2008 — allows us to gain more insight into this issue. Moreover, by combining the structural estimates with event study estimates and counterfactual simulations in the next section, I study the effects of the intervention on mortality through the channels of residents' responsiveness to quality, nursing homes' admissions policies, nursing homes' quality choice.

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

4 Counterfactual Simulations

The CMS introduced the star ratings system at the end of 2008 in an attempt to reduce potential information frictions residents and their families face when choosing nursing homes. Indeed, according to the CMS, "the goal of the rating system is to help consumers make meaningful distinctions among high- and low-performing nursing homes"[63]. While the star ratings' effect on choice patterns and nursing home quality has previously been studied in Perraillon, Konetzka, He and Warner (2015), this is a partial equilibrium analysis since nursing homes are likely to respond to changes in demand. Hence, in this section, I will study the effect of star ratings not only on residents' responsiveness to quality, but also nursing homes' admissions policies and quality choice, as well the effects of each of these channels on mortality.

4.1 Changes in Responsiveness to Quality and Admissions Policies

I start by estimating a more flexible version of the structural model described in the previous section, but allowing changes in the responsiveness to quality and changes in nursing homes' admissions policies post-star ratings to vary by resident characteristics and nursing home quality. The results from this structural model is summarized in Figure 4.

Panel (a) shows the estimated distributions of responsiveness to quality pre/post-star ratings. First, we observe that there is substantial heterogeneity in responsiveness both before and after the star ratings, with the point estimates ranging from slightly negative to more than ten times the average MRS estimate. In addition, the post-star ratings distribution is shifted slightly to the right, consistent with the estimates from column 4 of Table 6, but the magnitude of this increase is small relative to overall heterogeneity.

Nursing homes' optimal admissions policies are likely a function of residents' responsiveness to quality. As a summary of changes in admissions policies, in panel (b), I plot the distributions of $-\pi_{ij}$ excluding the component attributable to occupancy pre- and post-star ratings. I call this value the admissions threshold since larger values imply that nursing homes set a higher bar for who they are willing to admit. We observe that the post-ratings distribution is shifted slightly to the left, suggesting that nursing homes' admissions policies are slightly more lenient after the introduction of star ratings.

To better understand the impact of these changes on different types of residents, in panel (c) I show a bin scatter of the change in responsiveness against pre-ratings responsiveness to quality. We observe that responsiveness to quality increased the most among the types of residents who were already relatively responsive to quality before the star ratings were introduced, suggesting that the demand-side effects star ratings may have been regressive. Similarly, panel (d) shows a binscatter of the change in admissions threshold against the pre-ratings thresholds. We observe that the admissions threshold is lowered by a greater amount for the types of residents who were already unlikely to be rejected by nursing homes pre-reform, suggesting that supply-side effects of the star ratings may also have been regressive.

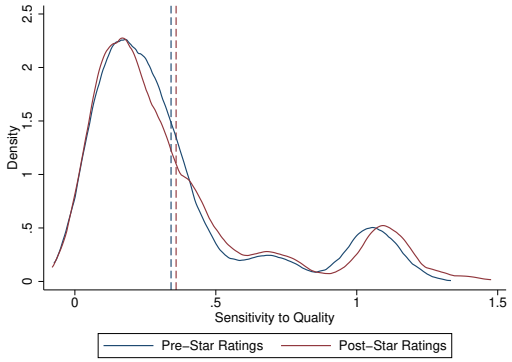
Finally, panels (e) and (f) show how the demand and supply sides interact. In panel (e), we observe that the change in admissions threshold is increasing in quality. This is intuitive, since higher-quality nursing homes expect to face greater demand after an overall increase in responsiveness to quality, and

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

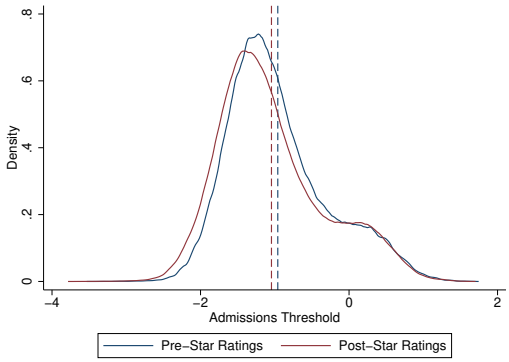
would thus be more selective about which residents to admit. Further supporting this interpretation, panel (f) shows that the change in threshold is positively associated with the change in responsiveness of nearby residents.

Figure 4: Responsiveness to Quality and Admissions Policies Pre- and Post-Star Ratings

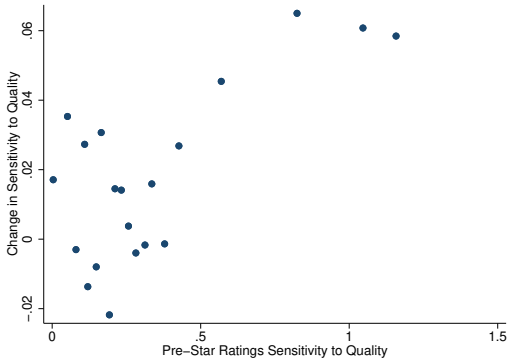
(a) Distribution of Responsiveness to Quality



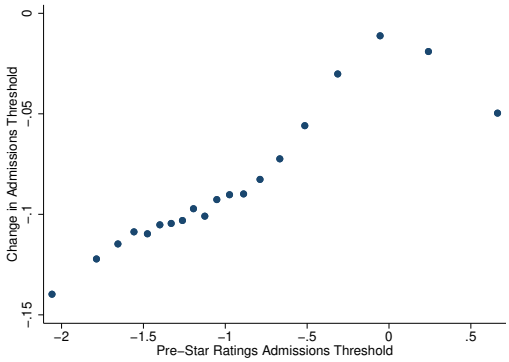
(b) Distribution of Admissions Threshold



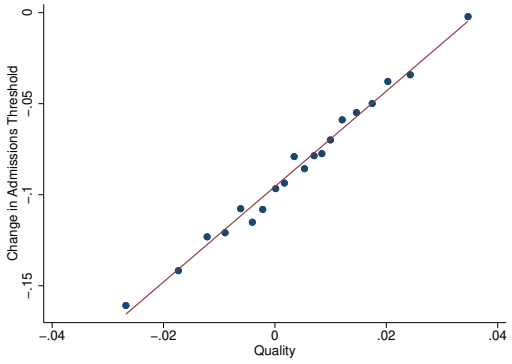
(c) Change in Responsiveness vs Pre-Ratings Responsiveness



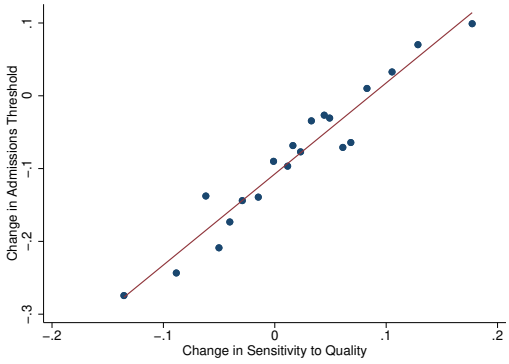
(d) Change in Adm. Thres. vs Pre-Ratings Thres.



(e) Change in Adm. Threshold vs Quality



(f) Change in Adm. Thres. vs Change in Responsiveness



Notes: Panels (a) and (b) present kernel density plots of the estimated pre- and post-star ratings distributions of responsiveness to quality and admissions thresholds respectively. Panel (c) shows a binscatter of the change in responsiveness to quality against the pre-ratings responsiveness. Panel (d) shows a binscatter of the change in admissions threshold against the pre-ratings admissions threshold. Panel (e) shows a binscatter of the change in admissions threshold against nursing home quality. Panel (f) shows a binscatter of the change in admissions threshold against change in responsiveness to quality. 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.

4.2 Quality Responses by Nursing Homes

Another margin of response by nursing homes to the star ratings is their choice of quality. To study this, I estimate nursing home quality using the same methodology as in section 2, but at a yearly level. While nursing home quality estimates at the year-level are quite noisy, we can study which *types* of nursing home tended to increase quality the most after the star ratings were introduced.

To do so, I estimate event studies of the form:

$$q_{jt} = \alpha_0^{did} + \sum_{m=-5}^{2} \beta_k^{did} \mathbb{I}[t - 2008 = m] \times treat_j + \delta_t^{did} + \gamma_j^{did} + \epsilon_{jt}^{did}, \tag{7}$$

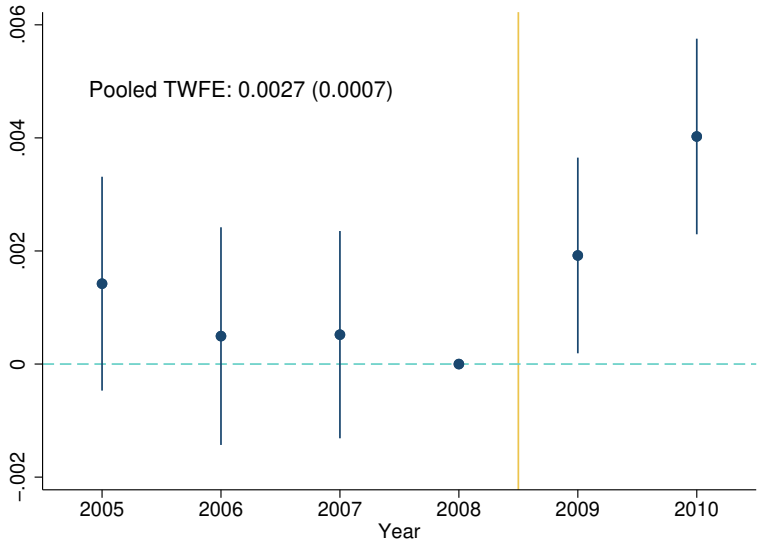
defining the treated and control groups in two ways: first comparing nursing homes facing lower or higher competition, and second comparing nursing homes for which responsiveness to quality of residents living nearby increased by more or less.[64]

In the first comparison, the effect of star ratings on the quality choice of nursing homes facing lower competition (relative to those facing higher competition) is ambiguous. On the one hand, nursing homes facing lower competition have less incentive to increase quality if residents nearby do not have much choice. On the other hand, nursing homes facing higher competition may already have higher quality pre-star ratings, so it may be difficult for them to increase quality much further. The theoretical prediction for the second comparison is less ambiguous: if the responsiveness to quality of residents living nearby increases by more, nursing homes should also increase their quality by a greater amount.

[64] For the first comparison, I compute the average size of the choice set (i.e., number of nursing homes within a 15-mile radius) of residents living within a 15-mile radius of each nursing home, and define nursing homes as facing higher (or respectively, lower) competition if the average size of the choice set of residents living nearby is above (below) the median. For the second comparison, I compute the average change in demand for residents living within 15 miles of a nursing home, and define a nursing home as facing greater (lower) changes in demand if this average change is above (below) median.

Figure 5: Event Study Estimates of Star Ratings on Quality of Different Nursing Homes (Empirical Bayes)

(a) Treated: Low Competition



(b) Treated: Low ΔResponsiveness

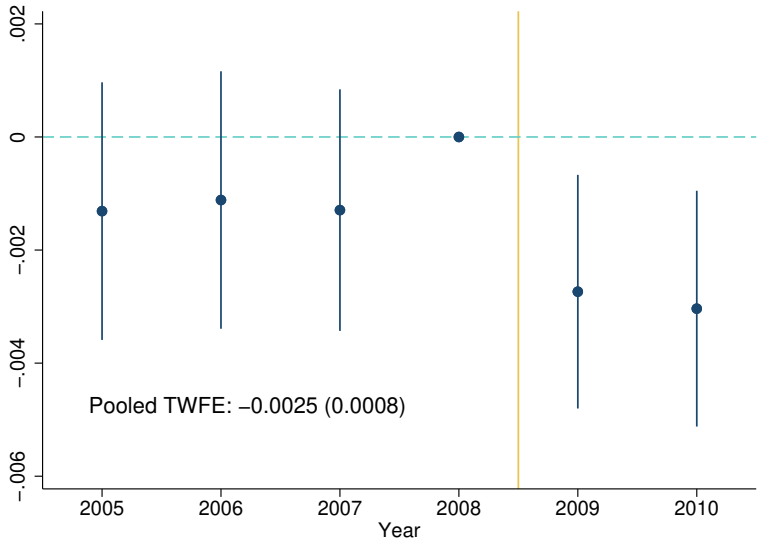
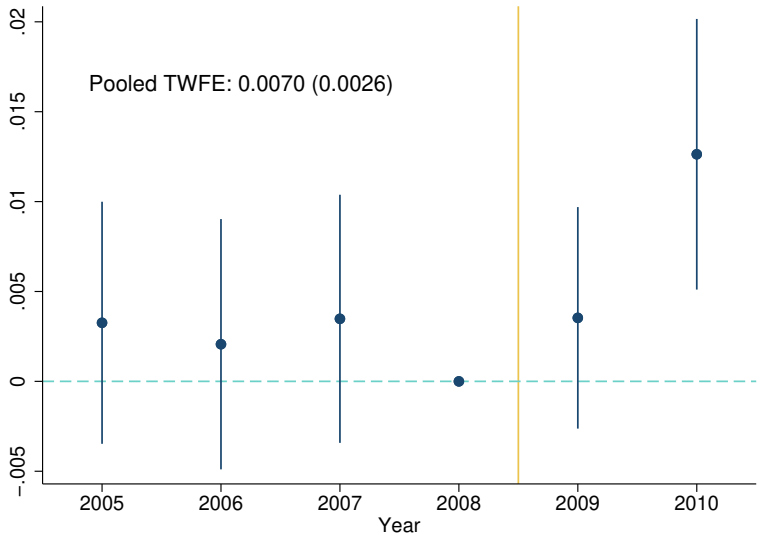
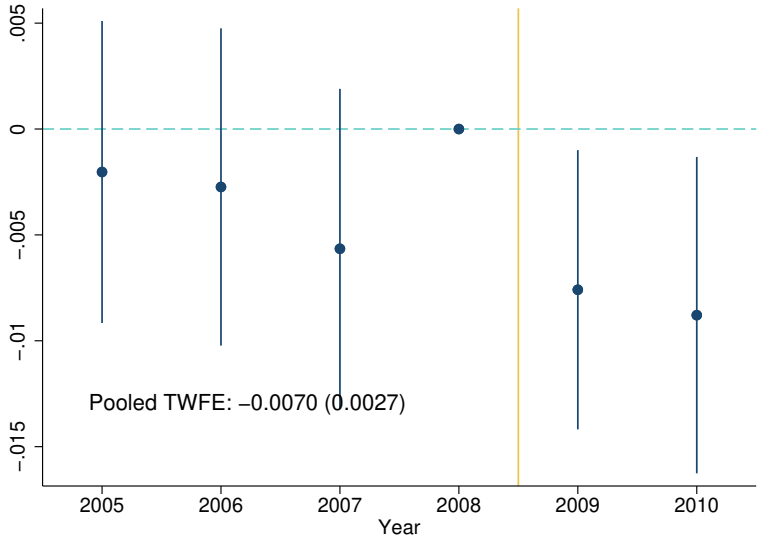


Figure 6: Event Study Estimates of Star Ratings on Quality of Different Nursing Homes (Fixed Effects)

(a) Treated: Low Competition



(b) Treated: Low ΔResponsiveness



Figures 5 and 6 show the event study estimates for these two specifications. In panel (a), we observe that nursing homes facing low competition increased their quality by relatively more following the introduction of star ratings. This is consistent with the fact that these nursing homes had lower-quality pre-star ratings. In panel (b), we see that if responsiveness to quality of nearby residents increased by less, nursing homes also increased quality by a lesser amount.

4.3 Simulation Procedure

In this subsection, I describe how I combine estimates of the star ratings' effects on residents' responsiveness to quality, nursing homes' admissions policies, and nursing homes' quality choice to study the effects of these channels on mortality. To do so, I combine these estimates with the structural model and a competing risks model for deaths and discharges to conduct counterfactual simulations.

4.3.1 Counterfactuals

I start with counterfactuals that simulate the effects of star ratings through changes in residents' responsiveness to quality, nursing homes' admissions polices, and nursing homes' quality choice on resident mortality. In the simulations, I consider the set of residents admitted to a nursing home in 2009, and set the estimated responsiveness and admissions policies to either their pre- or post-star ratings levels to turn off or on the first two channels. To simulate the effects of quality adjustments by nursing homes, I adjust the quality of nursing homes by nursing home characteristics, based on the difference-in-difference estimates in the previous section.

It is possible that the star ratings was not the most effective information intervention possible, so I also consider counterfactuals where I set the responsiveness to quality of residents to the highest estimated responsiveness among residents in the data. In addition, I consider counterfactuals where there are no capacity constraints, which rules out selective admissions.

Finally, I compare these counterfactuals with one based on a supply-side policy, namely the financial incentives aimed at increasing staffing levels of nursing homes in Illinois, studied in Gandhi, Olenski, Ruffini, and Shen (2024). I use the difference-in-difference estimates in their paper to impute counterfactual staffing levels for nursing homes in my sample, and adjust nursing home quality accordingly based on the correlation between my quality measure and staffing levels. Appendix Section H.4 describes the implementation of these counterfactuals in more detail.

4.3.2 Competing Risks Model of Deaths and Discharges

While the structural model in section 3 provides a way to simulate nursing home admissions that accounts for selective admissions practices, we also need a way to simulate resident exits from nursing homes. This is because nursing homes' admission decisions depend on occupancy, which is a state variable that is a function of both resident admissions and exits. In addition, because the outcome of interest is mortality, we must decompose resident exits into deaths and discharges. Given that deaths and discharges are competing risks,[65] standard hazard methods that do not account for competing risks will typically produce misleading estimates.[66] Hence, I account for this codependency using a model of competing risks (specifically, using cause-specific hazards that depend on resident and nursing home characteristics), which I estimate semiparametrically by maximizing a modified partial likelihood. Appendix Section H describes the competing risks model and its estimates in more detail.

[65] 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.

[66] 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.

4.3.3 Outline of Simulation Algorithm

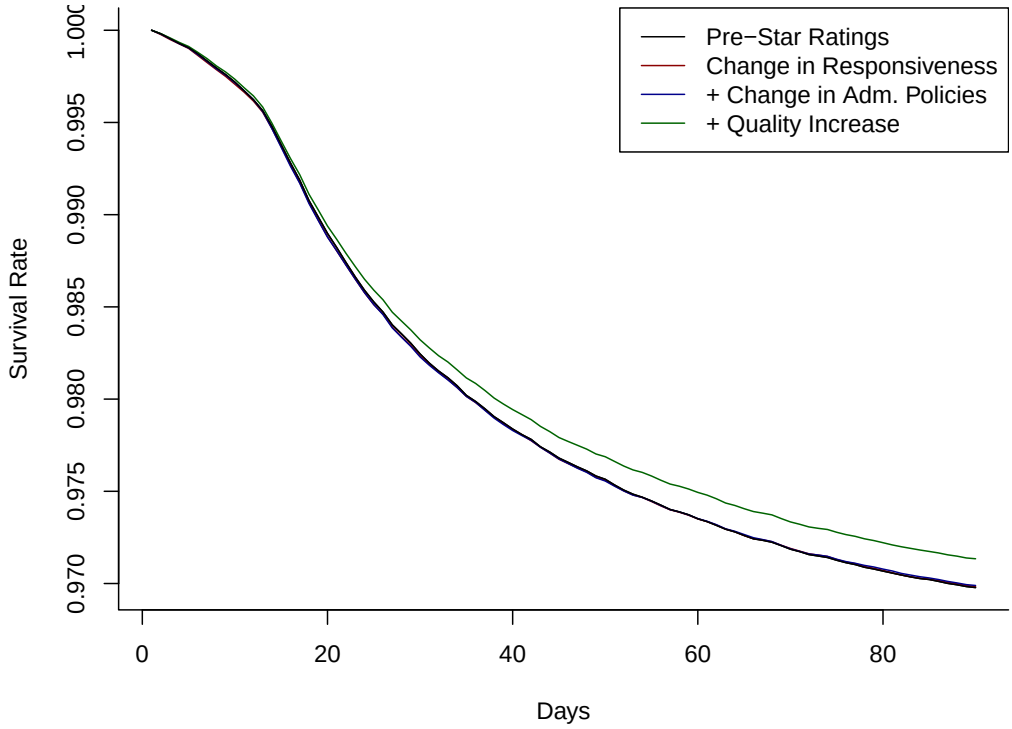
For each day of the simulation, I draw $\bar{n}$ residents from the data, and first simulate admissions using the structural model in section 3. In particular, residents are admitted to the nursing home they value the most (based on their counterfactual preferences) among the set of nursing homes willing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

4.4 Simulation Results

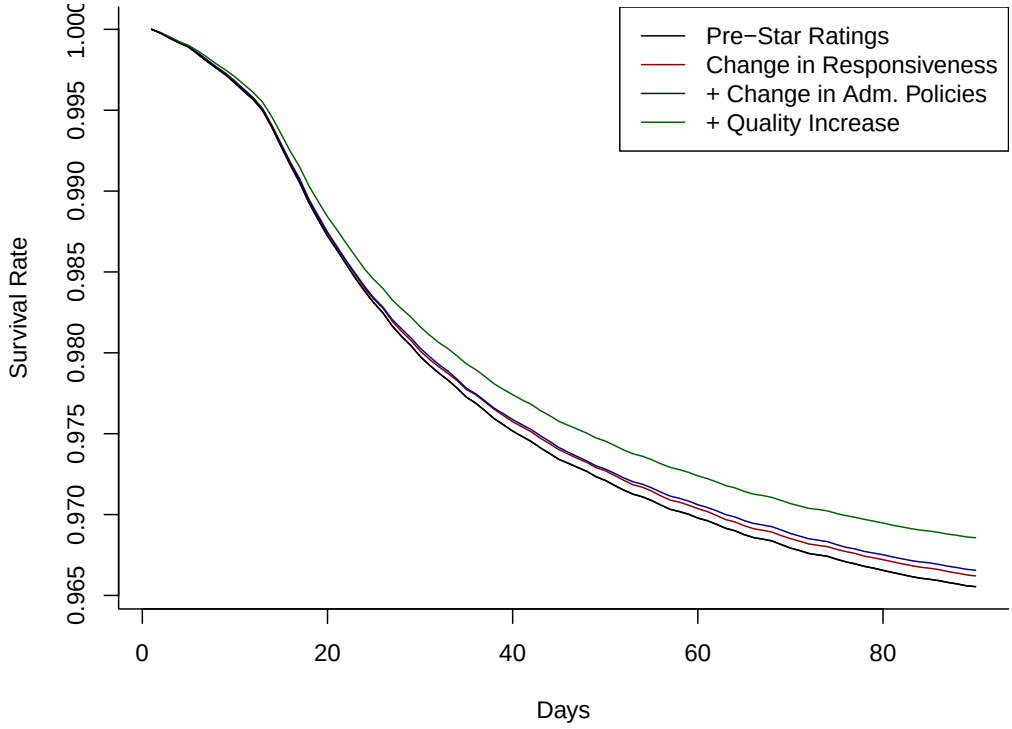
Figure 7 shows the simulated effects of star ratings through different channels, plotting the simulated survival rate of residents from the day they are admitted to 90 days after admission under different counterfactuals. We observe that the simulated effect of changes in responsiveness to quality and admissions policies are between zero and half of the overall effects of the star ratings, which is somewhat unsurprising given the modest changes we saw in panels (a) and (b) of Figure 4. The simulated effect of star ratings through quality adjustments by nursing homes accounts for between one-half and most of the star ratings' effect, amounting to roughly a 5–9 percent reduction in mortality.

Figure 7: Simulated Effect of Star Ratings Through Different Channels

(a) Empirical Bayes Quality Estimates



(b) Fixed Effects Quality Estimates

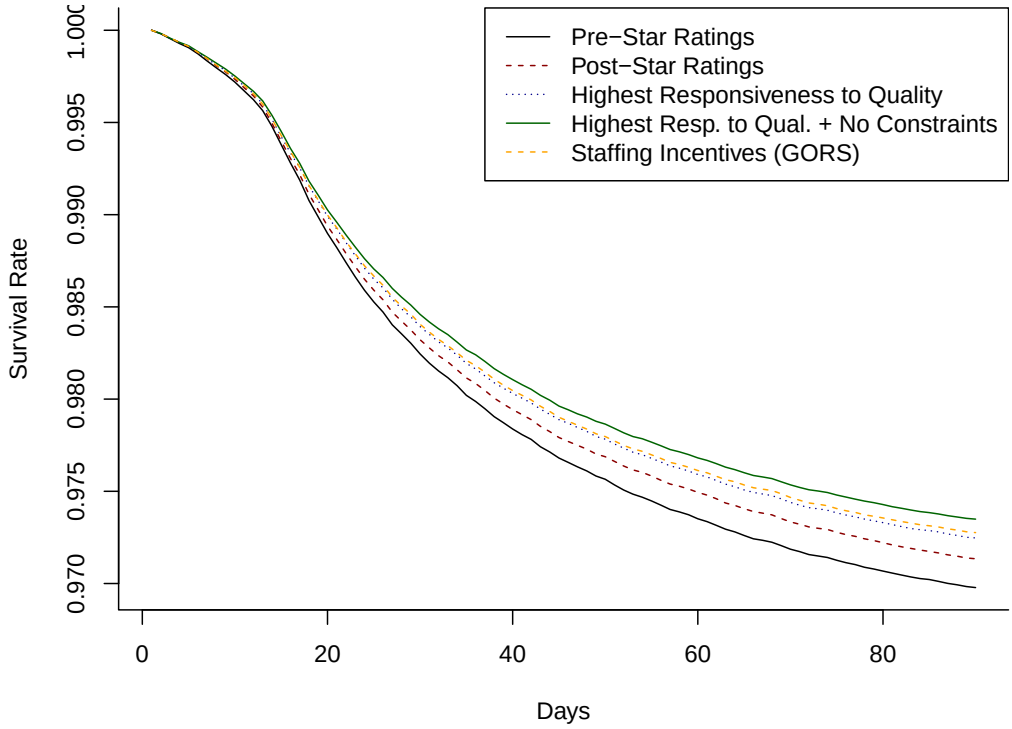


This figure plots the simulated survival rate of residents over time, from the day they are admitted to 90 days after admission.

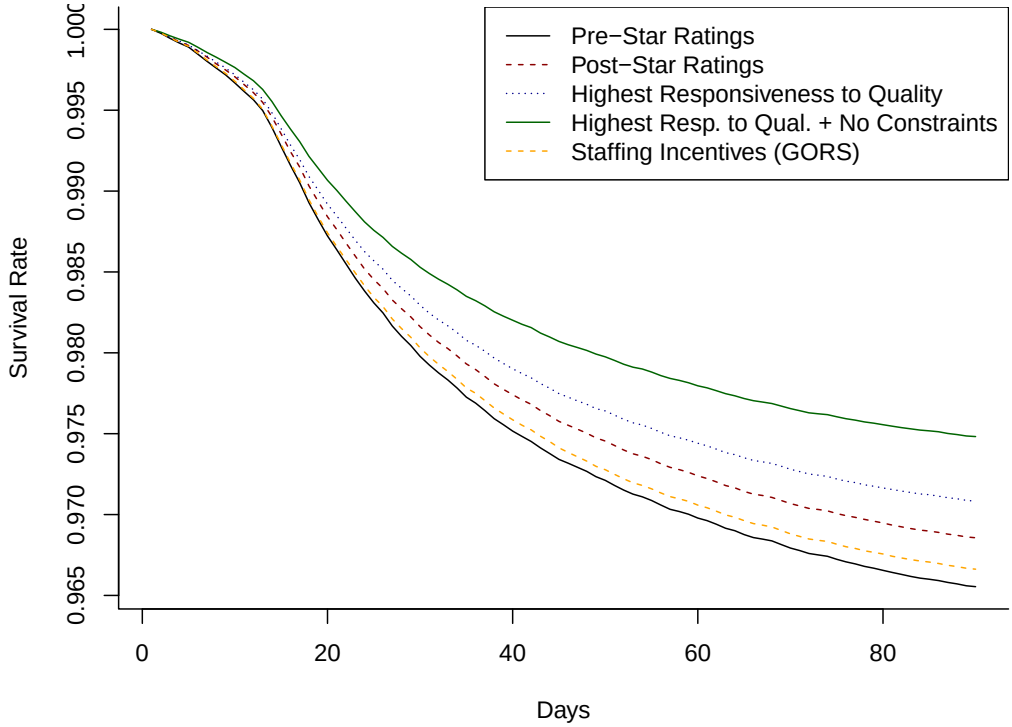
While the effect of star ratings on mortality through changes in responsiveness to quality and admissions policies are relatively small, this does not imply that these channels are unimportant. Indeed, Figure 8 shows that holding nursing home quality constant, if we set all residents' responsiveness to quality to be equal to the value for the most responsive resident, the simulated reduction in mortality is about 1.7 overall effects of the star ratings. If in addition we remove capacity constraints from nursing homes, reductions in mortality are even larger, about 2.4–3 times the effects of star ratings. By comparison, the simulated effect of a supply-side policy similar to the financial incentives for adequate staffing studied in Gandhi, Olenski, Ruffini, and Shen (2024) is a reduction in mortality that is 0.4–1.9 times the effect of star ratings.

Figure 8: Simulated Effect of Star Ratings Versus Other Counterfactuals

(a) Empirical Bayes Quality Estimates



(b) Fixed Effects Quality Estimates



This figure plots the simulated survival rate of residents over time, from the day they are admitted to 90 days after admission.

4.5 Discussion

While the effects of star ratings on consumers' responsiveness to quality are relatively small, information interventions in this setting may still be effective for a few reasons. First, we observed that some nursing homes increased their quality in response to changes in consumer responsiveness, which had a larger effect on mortality than the direct effect on consumer responsiveness.

Second, even if we hold nursing homes' quality and admissions policies constant, the simulated effects of increasing all residents' responsiveness to quality to that of the most responsive residents' exceeds that of the star ratings. While modeling nursing homes' capacity choices is beyond the scope of this paper, it seems plausible that high-quality nursing homes may expand in response to higher demand, and mortality reductions in simulations that additionally remove capacity constraints are more than double that of star ratings (even while holding quality fixed).

Finally, the star ratings were a relatively "light touch" information intervention. Most residents are admitted to nursing home for post-acute care rehabilitation and face time pressures when making their choice, so they may not have adequate time to thoroughly research their nursing home options. It seems plausible that an intervention targeted at hospital discharge planners may be more effective, given their influence over post-acute care residents' nursing home choice.

5 Conclusion

In this paper, I study demand for quality in the Californian nursing home market. I demonstrate that despite substantial variation in nursing home quality and the consequential impact quality can have on resident health, many residents, especially those with greater information frictions, are not responsive to quality differences. The introduction of the star ratings had some effect on consumers' responsiveness to quality, and some nursing homes responded by adjusting their admissions policies and/or quality. Nonetheless, the effects of these changes on mortality pale in comparison to counterfactuals where responsiveness to quality for all residents are equal to the most responsive resident's, and/or capacity constraints are removed, even holding quality fixed.

The finding that responsiveness to quality plays an important role naturally leads to a number of follow-up questions. For example, in order for policymakers to design effective information interventions, it is critical for us to gain a better understanding of the underlying sources of these information frictions. Moreover, information frictions are also relevant for critical social issues such as racial disparities. For instance, in ongoing work, I find that other than in-group preferences, discrimination, and location, heterogeneity in responsiveness to quality is another contributory factor to the disproportionate concentration of black residents in low-quality nursing homes.

References

Abaluck, Jason, Mauricio M. Caceres Bravo, Peter Hull, and Amanda Starc. 2021. "Mortality effects and choice across private health insurance plans." *The Quarterly Journal of Economics* 136 (3): 1557–1610.

Abaluck, Jason, and Giovanni Compiani. 2020. "A Method to Estimate Discrete Choice Models that is Robust to Consumer Search." Working paper.

Abaluck, Jason, and Jonathan Gruber. 2011. "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program." *American Economic Review* 101 (4): 1180–1210.

Abaluck, Jason, and Jonathan Gruber. 2016. "Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance." *American Economic Review* 106 (8): 2145–2184.

Agarwal, Nikhil, and Paulo Somaini. 2022. "Demand Analysis under Latent Choice Constraints." Working Paper.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2005. "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." *Journal of Political Economy* 113 (1): 151–184.

Angrist, Joshua D., Peter D. Hull, Parag A. Pathak, and Christopher R. Walters. 2017. "Leveraging Lotteries for School Value-Added: Testing and Estimation." *The Quarterly Journal of Economics* 132 (2): 871–919.

Angrist, Joshua D., Peter D. Hull, Parag A. Pathak, and Christopher R. Walters. 2021. "Race and the Mismeasure of School Quality." National Bureau of Economic Research Working Paper 29608.

Angrist, Joshua D., Guido W. Imbens, and Donald B. Rubin. 1996. "Identification of Causal Effects Using Instrumental Variables." *Journal of the American Statistical Association* 91 (434): 444–455.

Armour, Philip. 2018. "The Role of Information in Disability Insurance Application: An Analysis of the Social Security Statement Phase-In." *American Economic Journal: Economic Policy* 10 (3): 1–41.

Aron-Dine, Liran Einav, Amy Finkelstein, and Mark Cullen. 2015. "Moral Hazard in Health Insurance: Do Dynamic Incentives Matter?" *The Review of Economics and Statistics* 97 (4): 725–741.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2014. "Inference on Treatment Effects after Selection among High-Dimensional Controls." *Review of Economic Studies* 81 (2): 608–650.

Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. "The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment." *The Quarterly Journal of Economics* 127 (3): 1205–1242.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2022. "Revisiting Event Study Designs: Robust and Efficient Estimation." Working paper.

Breslow, Norman E. 1972. "Contribution to the discussion on the paper by DR Cox. Regression and life tables." *JR Statist. Soc. B* 34: 216–217.

Brooks, Stephen P., and Andrew Gelman. 1998. "General methods for monitoring convergence of iterative simulations." *Journal of computational and graphical statistics* 7 (4): 434–455.

Brot-Goldberg, Zarek C., Amitabh Chandra, Benjamin R. Handel, and Jonathan T. Kolstad. 2017. "What does a deductible do? The impact of cost-sharing on health care prices, quantities, and spending dynamics." *The Quarterly Journal of Economics* 132 (3): 1261–1318.

Brown, Jeffrey R., and Amy Finkelstein. 2007. "Why is the market for long-term care insurance so small?" *Journal of Public Economics* 91 (10): 1967–1991.

Brown, Jeffrey R., and Amy Finkelstein. 2008. "The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market." *American Economic Review* 98 (3): 1083–1102.

Brown, Jeffrey R., and Amy Finkelstein. 2011. "Insuring Long-Term Care in the United States." *Journal of Economic Perspectives* 25 (4): 119–142.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics* 225 (2): 200–230.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs". *Econometrica* 82 (6): 2295–2326.

Card, David. 1993. "Using Geographic Variation in College Proximity to Estimate the Return to Schooling." National Bureau of Economic Research Working Paper 4483.

Card, David, and Stefano DellaVigna. 2020. "What do Editors Maximize? Evidence from Four Economics Journals." *The Review of Economics and Statistics* 102 (1): 195–217.

Card, David, Alessandra Fenizia, and David Silver. 2019. "The Health Impacts of Hospital Delivery Practices." National Bureau of Economic Research Working Paper 25986.

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

Centers for Medicare & Medicaid Services. 2000–2010. "Cost Reports." Department of Health and Human Services. https://data.cms.gov/provider-compliance/cost-report/skilled-nursing-facility-cost-report.

Centers for Medicare & Medicaid Services. 2000–2010. "Health Deficiencies." Department of Health and Human Services. https://data.cms.gov/provider-data/dataset/r5ix-sfxw.

Centers for Medicare & Medicaid Services. 2000–2010. "Provider Information." Department of Health and Human Services. https://data.cms.gov/provider-data/dataset/4pq5-n9py.

Cenziper, Debbie, Joel Jacobs, Alice Crites, and Will Englund. 2020. "Profit and pain: How California's largest nursing home chain amassed millions as scrutiny mounted." *The Washington Post*, December 31. https://www.washingtonpost.com/business/2020/12/31/brius-nursing-home/ (accessed January 1, 2021).

▶**Chan, David C., Matthew Gentzkow, and Chuan Yu.** 2022. "Selection with variation in diagnostic skill: Evidence from radiologists." *The Quarterly Journal of Economics* 137 (2): 729–783

Chen, Yiwei. 2018. "User-Generated Physician Ratings — Evidence from Yelp." Working paper.

Cheng, Alden. 2023. "Selection on Unobservables in Discrete Choice Models." Working paper.

▶**Comondore, Vikram R, P J Devereaux, Qi Zhou, Samuel B Stone, Jason W Busse, Nikila C Ravindran, Karen E Burns, Ted Haines, Bernadette Stringer, Deborah J Cook, Stephen D Walter, Terrence Sullivan, Otavio Berwanger, Mohit Bhandari, Sarfaraz Banglawala, John N Lavis, Brad Petrisor, Holger Schünemann, Katie Walsh, Neera Bhatnagar, Gordon H Guyatt.** 2009. "Quality of care in for-profit and not-for-profit nursing homes: systematic review and meta-analysis." *Bmj* 339.

Cooper, Zack, Joseph J. Doyle Jr., John A. Graves, and Jonathan Gruber. 2022. "Do Higher-Priced Hospitals Deliver Higher-Quality Care?" National Bureau of Economic Research Working Paper 29809.

▶**De Chaisemartin, Clément, and Xavier d'Haultfoeuille.** 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110 (9): 2964–96.

▶**Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins.** 2018. "Double/Debiased Machine Learning for Treatment and Structural Parameters." *The Econometrics Journal* 21 (1): C1–C68.

▶**Chetty, Raj, John N. Friedman, and Jonah E. Rockoff.** 2014. "Measuring the Impacts of Teachers I: Evaluating bias in Teacher Value-Added Estimates." *American Economic Review* 104 (9): 2593–2632.

▶**Deryugina, Tatyana, and David Molitor.** 2020. "Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina. *American Economic Review* 110 (11): 3602–3633.

▶**Donabedian, Avedis.** 1985. "Twenty years of research on the quality of medical care: 1964-1984." *Evaluation and the Health Professions* 8: 243–265.

▶**Doyle, Joseph, John Graves, Jonathan Gruber, and Samuel Kleiner.** 2015. "Measuring Returns to Hospital Care: Evidence from Ambulance Referral Patterns." *Journal of Political Economy* 123 (1): 170–214.

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

▶**Einav, Liran, Amy Finkelstein, and Neale Mahoney.** 2018. "Provider incentives and healthcare costs: Evidence from long-term care hospitals." *Econometrica* 86 (6): 2161–2219.

Einav, Liran, Amy Finkelstein, and Neale Mahoney. 2022. "Producing Health: Measuring Value Added of Nursing Homes." Working Paper.

▶**Einav, Liran, Amy Finkelstein, Sendhil Mullainathan, and Ziad Obermeyer.** 2018. "Predictive modeling of US health care spending in late life." *Science* 360 (6396): 1462–1465.

▶**Eliason, Paul J., Paul L.E. Grieco, Ryan C. McDevitt, and James W. Roberts.** 2018. "Strategic patient discharge: The case of long-term care hospitals." *American Economic Review* 108 (11): 3232–65.

▶**Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams.** 2021. "Place-Based Drivers of Mortality: Evidence from Migration." *American Economic Review* 111 (8): 2697–2735.

Fletcher, Jason M., Leora I. Horwitz, and Elizabeth Bradley. 2014. "Estimating the Value Added of Attending Physicians on Patient Outcomes." National Bureau of Economic Research Working Paper 20534.

Gandhi, Ashvin. 2024. "Picking your patients: Selective admissions in the nursing home industry." Working Paper.

Gandhi, Ashvin, Andrew Olenski, Krista Ruffini, and Karen Shen. 2024. "Alleviating Worker Shortages Through Targeted Subsidies: Evidence from Incentive Payments in Healthcare." Working Paper.

Gandhi, Ashvin, YoungJun Song, and Prabhava Updrashta. 2022. "Private equity, consumers, and competition: Evidence from the nursing home industry." Working Paper.

▶**Geng, Fangli, David G. Stevenson, and David C. Grabowksi.** 2019. "Daily Nursing Home Staffing Levels Highly Variable, Often Below CMS Expectations." *Health Affairs* 38 (7): 1095–1100.

▶**Gold, Marthe R., David Stevenson, and Dennis G. Fryback.** 2002. "HALYS AND QALYS AND DALYS, OH MY: Similarities and Differences in Summary Measures of Population Health." *Annual Review of Public Health* 23: 115–34.

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

▶**Guo, Audrey, and Jonathan Zhang.** 2019. "What to expect when you are expecting: Are health care consumers forward-looking?" *Journal of Health Economics* 67: 1–16.

Gupta, Atul, Sabrina T. Howell, Constantine Yannelis, and Abhinav Gupta. 2021. "Does Private Equity Investment in Healthcare Benefit Patients? Evidence from Nursing Homes." National Bureau of Economic Research Working Paper 28474.

▶**Hackmann, Martin B.** 2019. "Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the

Nursing Home Industry." *American Economic Review* 109 (5): 1684–1716.

Hackmann, Martin B., Juan S. Rojas, and Nicolas R. Ziebarth. 2020. "Patient Versus Provider Incentives in Long-Term Care." Working Paper.

Hackmann, Martin B., R. Vincent Pohl, and Nicolas R. Ziebarth. 2024. "Creative Financing and Public Moral Hazard: Evidence from Medicaid and the Nursing Home." Working Paper.

▶**Han, Xu, Niam Yaraghi, and Ram Gopal.** 2016. "Five-star ratings for sub-par service: Evidence of inflation in nursing home ratings." *Governance Studies at Brookings*: 1–22.

▶**Han, Xu, Niam Yaraghi, and Ram Gopal.** 2018. "Winning at all costs: Analysis of inflation in nursing homes' rating system." *Production and Operations Management* 27 (2): 215–233.

▶**Handel, Benjamin R.** 2013. "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts." *American Economic Review* 103 (7): 2643–2682.

▶**Handel, Benjamin R., and Jonathan T. Kolstad.** 2015. "Health Insurance for "Humans": Information Frictions, Plan Choice, and Consumer Welfare" *American Economic Review* 105 (8): 2449–2500.

Handel, Benjamin R., Jonathan Kolstad, Thomas Minten, and Johannes Spinnewijn. 2021. "The Social Determinants of Choice Quality: Evidence from Health Insurance in the Netherlands." Working Paper.

▶**Handel, Benjamin R., and Joshua Schwartzstein.** 2018. "Frictions or Mental Gaps: What's Behind the Information We (Don't) Use and When Do We Care?" *Journal of Economic Perspectives* 32 (1): 155–178.

▶**Hastings, Justine S., and Jeffrey M. Weinstein.** 2008. "Information, school choice, and academic achievement: Evidence from two experiments." *The Quarterly Journal of Economics* 123 (4): 1373–1414.

▶**Hull, Peter.** 2018. "Estimating Hospital Quality with Quasi-experimental Data." Working Paper.

▶**Hurd, Michael D., Pierre-Carl Michaud, and Susann Rohwedder.** 2017. "Distribution of lifetime nursing home use and of out-of-pocket spending." *PNAS* 104 (37): 9838–9842.

▶**Imbens, Guido, and Karthik Kalyanaraman.** 2012. "Optimal Bandwidth Choice for the Regression Discontinuity Estimator." *The Review of Economic Studies* 79 (3): 933–959.

LTCFocus. 2000–2010. "LTCFocus Public Use Data." Sponsored by the National Institute on Aging (P01 AG027296) through a cooperative agreement with the Brown University School of Public Health. https://doi.org/10.26300/h9a2-2c26

Jaffe, Susan. 2021. "3 States to Limit Nursing Home Profits in Bid to Improve Care." *Kaiser Health News*, October 25. https://susanjaffe.org/2021/10/25/https-khn-org-news-article-3-states-limit-nursing-home-profits-in-bid-to-improve-care/ (accessed July 6, 2022).

▶**Kahneman, Daniel, and Amos Tversky.** 1979. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47 (2): 263–292.

▶**Kolesár, Michael, and Christophe Rothe.** 2018. "Inference in Regression Discontinuity Designs with a Discrete Running Variable." *American Economic Review* 108 (8): 2277–2304.

▶**Kolstad, Jonathan T.** 2013. "Information and Quality when Motivation is Intrinsic: Evidence from Surgeon Report Cards." *American Economic Review* 103 (7): 2875–2910.

▶**Konetzka, R. Tamara, David C. Grabowski, Marcelo Coca Perraillon, and Rachel M. Werner.** 2015. "Nursing Home 5-Star Rating System Exacerbates Disparities In Quality, By Payer Source." *Health Affairs* 34 (5): 819–827.

▶**Konetzka, R. Tamara, and Marcelo Coca Perraillon.** 2016. "Use Of Nursing Home Compare Website Appears Limited By Lack Of Awareness And Initial Mistrust Of The Data". *Health Affairs* 35 (4): 706–713.

▶**Konetzka, Tamara R., Daniel Polsky, and Rachel M. Werner.** 2013. "Shipping out instead of shaping up: Rehospitalization from nursing homes as an unintended effect of public reporting." *Journal of Health Economics* 32 (2): 341–352.

▶**Kosar, Cyrus M., Vincent Mor, Rachel M. Werner, Momotazur Rahman.** 2023. "Risk of Discharge to Lower-Quality Nursing Homes Among Hospitalized Older Adults With Alzheimer Disease and Related Dementias." *JAMA Network Open* 6 (2): e2255134–e2255134.

▶**Lee, David S., and David Card.** 2008. "Regression discontinuity inference with specification error." *Journal of Econometrics* 142 : 655–674.

▶**Liu, Enwu, Maggie Killington, Ian D. Cameron, Raymond Li, Susan Kurrle, and Maria Crotty.** 2021. "Life expectancy of older people living in aged care facilities after a hip fracture." *Scientific Reports* 11 (1): 1–9.

▶**Mullainathan, Sendhil, and Ziad Obermeyer.** 2022. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." *The Quarterly Journal of Economics* 137 (2): 679–727.

National Center for Health Statistics. 2017. "Nursing Home Care." Centers for Disease Control and Prevention. https://www.cdc.gov/nchs/fastats/nursing-home-care.htm (accessed: July 16, 2023).

Novotney, Amy. 2020. "More than 6 in 10 Americans now say they would rather die than live in nursing home: survey." *McKnight's Business Daily*, December 9. https://www.mcknightsseniorliving.com/home/news/business-daily-news/more-than-6-in-10-americans-now-say-they-would-rather-die-than-live-in-nursing-home-survey/ (accessed July 13, 2023).

▶**Oster, Emily.** 2019. "Unobservables Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics* 37 (2): 187–204.

Rafiei, Yasmin. 2022. "When Private Equity Takes Over a Nursing Home." *The New Yorker*, August 25. https://www.newyorker.com/news/dispatch/when-private-equity-takes-over-a-nursing-home (accessed August 26, 2022).

▶**Romley, John A., and Dana P. Goldman.** 2011. "How Costly Is Hospital Quality? A Revealed-Preference Approach." *Journal of Industrial Economics* 59 (4): 578–608.

▶**Ryskina, Kira L., R. Tamara Konetzka, and Rachel M. Werner.** 2018. "Association between 5-star nursing home report card ratings and potentially preventable hospitalizations." *INQUIRY: The Journal of Health Care Organization, Provision, and Financing* 55: 1–14.

▶**Schelling, Thomas C.** 1971. "Dynamic models of segregation." *Journal of Mathematical Sociology* 1 (2): 143–186.

▶**Shin, Juh Hyun, and Yvonne Scherer.** 2009. "Advantages and Disadvantages of Using MDS Data in Nursing Research." *Journal of Gerontological Nursing* 35 (1): 7–17.

Silver-Greenberg, and Robert Gebeloff. 2021. "Maggots, Rape and Yet Five Stars: How U.S. Ratings of Nursing Homes Mislead the Public." *The New York Times*, March 13. https://www.nytimes.com/2021/03/13/business/nursing-homes-ratings-medicare-covid.html (accessed March 13, 2021).

▶**Sun, Liyang, and Sarah Abraham.** 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* 225 (2): 175–199.

Thomas, Katie, Robert Gebeloff, and Jessica Silver-Greenberg. 2021. "Phony Diagnoses Hide High Rates of Drugging at Nursing Homes." *The New York Times*, September 11. https://www.nytimes.com/2021/09/11/health/nursing-homes-schizophrenia-antipsychotics.html (accessed June 22, 2022).

▶**Tyler, Denise A., Emily A. Gadbois, John P. McHugh, Renée R. Shield, Ulrika Winblad, and Vincent Mor.** 2017. "Patients Are Not Given Quality-Of-Care Data About Skilled Nursing Facilities When Discharged From Hospitals." *Health Affairs* 36 (8): 1385–1391.

▶**Vats, Dootika, James M. Flegal, and Galin L. Jones.** 2019. "Multivariate output analysis for Markov chain Monte Carlo." *Biometrika* 106 (2): 321–337.

Walters, Christopher. 2012. "A Structural Model of Charter School Choice and Academic Achievement." Working Paper.

▶**Werner, Rachel M., R. Tamara Konetzka, and Daniel Polsky.** 2013. "Nursing Homes: Evidence from State Medicaid Programs." *Health Services Research* 48 (4): 1393–1414.

▶**World Health Organization.** 2013. "WHO methods and data sources for global burden of disease estimates 2000–2011." *Geneva: Department of Health Statistics and Information Systems.*

For Online Publication

Appendix

A Additional Background on Nursing Homes

A.1 Brief History of the Nursing Home Industry

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

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

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

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

Recently, the COVID-19 pandemic has shaken up the nursing home industry. First, the significant number of COVID-related nursing home deaths has increased public scrutiny over nursing home quality.[67] 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, and because Medicare reimbursement rates are substantially higher than Medicaid rates, this trend threatens the financial viability of nursing homes that were already operating on thin profit margins before the pandemic.

A.2 More Details on Various Nursing Home Quality Measures

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

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

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

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

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

A persistent issue with many of these quality measures is gaming by nursing homes. Staffing levels during the period of my sample were self-reported, rarely audited, and likely to be inflated (Geng, Stevenson, and Grabowski 2019). Outcome-based measures also show signs of manipulation; for example, after the government began publicly releasing information about inappropriate antipsychotic use in 2012, schizophrenia diagnoses rose sharply, the implication being that some were made not on a clinical basis but simply so that nursing homes could continue administering antipsychotics to residents as a form of chemical restraint without having it counted as inappropriate antipsychotic use (Thomas, Gebeloff, and Silver-Greenberg 2021). Deficiency citations may not always provide an accurate picture of nursing home quality either, given that nursing homes may behave differently around the time of inspections. For instance, Geng, Stevenson, and Grabowski (2019) find that staffing levels at nursing homes spike during the week of inspections, and there are anecdotal accounts of other strategic behaviors by nursing homes.[68]

B Data Appendix

B.1 Sample Construction

For the quality estimation sample, 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. I include all possible 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). Finally, the provider number for some residents cannot be matched with nursing homes in the OSCAR dataset. I examine each of these unmatched provider numbers, correcting obvious typos (e.g. the digit 0 being replaced with a letter *O*) and dropping observations when it cannot be determined which nursing home the provider number corresponds to.

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

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

[68] 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).

heterogeneity in information frictions faced by consumers, we may also expect corresponding variation in their degree of foresight.

B.2 Payer Source Data

The data on payer source at admission recorded in the MDS is less reliable than claims data. This is in part because nursing homes are sometimes unsure at the time of admission (which is when they complete the initial MDS assessment form) how they are ultimately going to be reimbursed for the resident, and in fact, claims they submit 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.[69] 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).[70]

B.3 Variable Definitions

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

[69] 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.

[70] 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.

C Model for Quality Estimation

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

$$Y_{ij} = \mu_j + a_i, \tag{8}$$

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 (8) to obtain:

$$\begin{aligned} Y_i &= Y_{i1} + \sum_{j=2}^{J} (Y_{ij} - Y_{i1}) D_{ij} \\ &= \mu_1 + \sum_{j=2}^{J} \beta_j D_{ij} + a_i, \end{aligned} \tag{9}$$

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:

$$a_i = X_i'\gamma + u_i,\ \mathbb{E}[X_i u_i] = 0, \tag{10}$$

and substitute this into equation (9) 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:

$$\beta_j = \lambda \alpha_j + \eta_j,\ \mathbb{E}[\alpha_j \eta_j] = 0. \tag{11}$$

Substituting equation (11) into equation (1), I obtain equation (2) as desired.

D Alternative Identification Strategies for Estimation of the Forecast Coefficient

In this section, I describe three alternative identification strategies for estimating the forecast coefficient.

In addition to distance between residents and nursing homes, temporary occupancy fluctuations provide an additional source of exogenous variation that may be used to estimate the forecast coefficient λ. To take advantage of this, I estimate an IV model using variation in quality of residents' chosen nursing homes induced by distance and temporary occupancy fluctuations. Specifically, I use $\{\alpha^{\sim t(i),k}, occ^{t(i),k}, \alpha_i^{\sim t(i),k} \times occ^{t(i),k}\}_{k=1}^{K}$ as my instruments, where the superscript k denotes the kth

closest nursing home to the resident.[71] The idea behind the interaction terms is that if high-quality nursing homes close to a resident are close to capacity at the time the resident is looking for one, she is more likely to be admitted to a low-quality nursing home. Estimates of this IV specification, shown in Appendix Table A.6, reveal that adding occupancy instruments hardly changes estimates of the forecast coefficient (which are still not statistically different from one).[72]

An alternative distance IV strategy is to use the quality of nearby nursing homes *excluding the nursing home actually chosen by the resident* as instruments. The idea underlying the first stage of this strategy is akin to Bayesian updating: if a resident values quality and is well-informed about it, then the fact that there are high-quality nursing homes close to her but that she did not choose suggests that her chosen nursing home is likely to be high quality as well. It turns out that the first stage for this IV specification is violated, which is unsurprising given our finding in section 3 that average demand for quality is low and that substantial information frictions are likely to be present.

Finally, one might consider estimating λ using an event study analysis based on nursing home entry (or exit). To this end, I use entry by high-quality nursing homes close to a resident as the event, and study the effect this has on the quality of nursing homes chosen by residents (which we can think of as the first stage) as well as on resident outcomes (which can be thought of as the reduced form). I implement the event study using methods from Borusyak, Jaravel, and Spiess (2022), considering that recent work has highlighted the shortcomings of conventional estimation methods such as two-way fixed effects when treatment effects are heterogeneous and treatment is staggered (de Chaisemartin and D'Haultfœuille 2020; Sun and Abraham 2021; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2022). Unfortunately, this event study is underpowered, and there is suggestive evidence that the parallel trends assumption is violated.

E 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

[71] The definition of the occupancy measure *occ* corresponds to the definition used for the structural demand estimation in section 3: lagged 7-day average of log occupancy, residualized of nursing home-month fixed effects.

[72] I do not include results with $K > 3$ instruments in Appendix Table A.6 because the F-statistics suggest that these specifications may suffer from many weak instruments bias.

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 the 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:

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

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

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

Nursing homes' optimal admissions policy is affected by its quality choice q_j through $\hat{p}_j(c_i)$. In particular, holding other nursing homes' quality constant, the higher q_j is the greater the probability that future residents will choose it if offered a spot, and the higher $\hat{p}(c_i)$ will be. 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. On the other hand, in reality nursing homes may not be profit-maximizers, and may also place weight on its residents' welfare. Nursing homes placing greater weight on its residents' welfare will choose a higher level of quality, and their admissions policy may also be less sensitive to its census and the profitability of potential residents. Motivated by these observations, in my structural estimation I include quality and its interaction with temporary occupancy fluctuations in the supply-side equation.

F Identification of the Matching Model

This section discusses how the model of demand and selective admissions maps into the framework in Agarwal and Somaini (2022), and the formal assumptions required for identification. I also briefly comment on how these assumptions relate to the setting in this paper.[73]

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Theorem 1 *(Agarwal and Somaini 2022). If Assumptions I1–I4 hold and $|\mathcal{J}| > 1$, then for every w, (i)*

the function $v_j^2(x,\cdot)$ is identified for every $j \in \mathcal{J}$ and $dist_j \in supp(dist_j)$, and (ii) the joint distribution of (u_i, π_i^{cutoff}) is identified for every value (u,π) in the interior of $v^2(x, supp(dist)) \times supp(occ) = \Pi_{j=1}^J v_j^2(x, supp(dist_j)) \times supp(occ)$, where $\pi_i^{cutoff}(x_i,\zeta_i) \equiv sup\{occ : \pi(x_i,\zeta_i,occ) \geq 0\}$.

G 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,[74] and refer to the nursing home that resident i ends up in by $\mu(i)$.

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

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

[74] 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.

(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:

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

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

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

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

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

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

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

with posterior mean and covariance matrices given by:

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

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

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

H Simulation Details

H.1 Assumptions for Counterfactual Simulations

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

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

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

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

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

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

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

The main threat to Assumption C3 is that nursing homes that are experiencing a temporary spike in occupancy may provide poorer care during this period (e.g., because they are short-staffed). To test this hypothesis, in Appendix Figure A.18 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.18

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.[75] 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.[76] 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,[77] and nursing homes face legal liabilities if they try to forcefully evict residents who are not ready to be discharged (§483.10, §483.21).[78] 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.2 Background on the Cause-Specific Hazard Model

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

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

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

where t_i is the event time for individual i, d_i is the number of individuals experiencing the event at

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

[76] 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).

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

[78] 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.

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

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

However, this has the undesirable property that the sum of these separate survivor function estimates will generally exceed the survivor function estimate for the composite outcome:

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

which is the case even if the competing risks are independent.[79]

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:

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

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:

$$h_c(t|\mathbf{X}) \equiv \lim_{\Delta t \to 0} \frac{Pr(t \leq T < t + \Delta t, C = c | T \geq t, \mathbf{X})}{\Delta t}, \tag{12}$$

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

$$h_c(t|\mathbf{X}) = h_{c,0}(t) exp(\mathbf{X}' \beta_{c,haz}), \tag{13}$$

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

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

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

$$CIF_c(t|\mathbf{X}) = \int_0^t S(u|\mathbf{X}) h_c(t|\mathbf{X}) du, \tag{14}$$

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

[79] 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 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 (14) 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.3 Simulating Exit Times from the Cause-Specific Hazard Model

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

$$T^c_{ij} = H^{-1}_{c,0}\left(-log(U^c_{ij}) exp(-\mathbf{X}_{ij}' \beta_{c,haz})\right), \tag{15}$$

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.4 Counterfactual Details

The structural model which the counterfactuals are based on includes interactions between resident characteristics and quality, as well as as triple interactions between resident characteristics, quality, and a dummy for the post-star ratings time period (2009–2010) in the demand side equation. In the supply side equation, I include nursing home quality, resident characteristics, as well as interactions between resident characteristics and a post-star ratings dummy.

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. To simulate the effect of star ratings through the channels of changes in residents' responsiveness (or respectively, nursing homes' admissions policies), I set the coefficients on the interactions terms with the post-star ratings dummy to zero on the supply (demand) side.

To simulate the effect of star ratings through the channel of quality adjustments by nursing homes, I use the pooled difference-in-difference estimates, increasing quality for nursing homes with below-median values of average choice set size of (potential) residents nearby, and nursing homes for which average responsiveness to quality of residents nearby increased by above the median change. I check that quality (estimated at the yearly level) did indeed stay roughly constant on average for the other nursing homes.

The counterfactuals where all consumers were as responsive to quality as the most responsive consumer and where there are no capacity constraints are straightforward. For the former, I compute the estimated responsiveness to quality for each resident based on their characteristics, find the maximum value, and set all residents' responsiveness to this value in the counterfactual. For the latter, I ignore the supply side, so that residents are always admitted to the nursing home they most prefer.

To simulate the potential effect of a financial incentive scheme targetting staffing levels, I use estimates from Gandhi, Olenski, Ruffini, and Shen (2024) who study such a scheme in Illinois. They find that the scheme increased staffing levels primarily at nursing homes with above-median Medicaid share, using difference-in-difference estimates. So, I take convert their estimates to percent increases in RN and LPN staffing, and impute counterfactual RN and LPN staffing at nursing homes with above-median Medicaid share in my data based on these percent increases. I then use the correlation between RN and LPN staffing levels with my quality measure to impute counterfactual quality for these nursing homes.

H.5 Simulation Algorithm

As described in the previous subsection, various counterfactuals may change the structural demand and supply parameters (κ and ψ), nursing home quality (q_j) to counterfactual values (which differ from their estimated values). Hence, in this subsection, I use tildes (e.g., $\tilde{\kappa}$) 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 days 30 days before the start of the sample in 2009, where $\tilde{o}_{jt}$ is the occupancy of nursing home j at time t, and:
$$o\tilde{c}c_{j,t} = \left(\frac{1}{7}\sum_{s=t-7}^{t-1} log(\tilde{o}_{js})\right) - \left(\frac{1}{30}\sum_{s=t-30}^{t-1} log(\tilde{o}_{js})\right),$$
approximates the occupancy measure used in the structural estimates (i.e., average log occupancy in the week leading up to a resident making her nursing home choice, demeaned of month fixed effects).

2. For $t = 1, ..., T^{sim}$:

   (a) For resident $i_t = 1, ..., I_t$:

      i. Draw $\bar{n} = 200$ residents from the sample of residents admitted to a nursing home in 2009.

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

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

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

iii. Find the nursing home the resident is assigned to given these counterfactual values of the latent variables, which I denote by $\tilde{\mu}(i_t)$.[80] This is given by:

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

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

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

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

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

i. First, set:

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

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:

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

where $\bar{\tilde{occ}}_{j,m(t)}$ is the average value of $log(\tilde{o}_{j,t})$ in the month of t.

I 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.[81] 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

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

[81] An extreme example of overfitting 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.

variables selected in these two Lasso regressions for the final estimation of the treatment effect.[82] 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.

J 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

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

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

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

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

$$\hat{\alpha}_j = \frac{\hat{\sigma}_\beta^2}{\hat{\sigma}_\beta^2 + \hat{\sigma}_\epsilon^2/N_j}\left[\frac{1}{N_j}\sum_{i'=1}^{N_j}(Y_{ji'} - \hat{\mu}_1 - X'_{ji'}\hat{\gamma})\right] + \frac{\hat{\sigma}_\epsilon^2/N_j}{\hat{\sigma}_\beta^2 + \hat{\sigma}_\epsilon^2/N_j}\left[\frac{1}{N}\sum_{j=1}^{J}\sum_{i'=1}^{N_j}(Y_{ji'} - \hat{\mu}_1 - X'_{ji'}\hat{\gamma})\right], \quad (16)$$

where N is the total number of observations.[83]

K 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.[84] Define the fixed effects quality estimate by $\hat{\alpha}_j$, and its empirical Bayes counterpart by $\hat{\alpha}_j^{EB}$ (and similarly for the instruments, which are average estimated quality of nursing homes close to each resident). Given that we use a finite-sample estimate $\hat{\alpha}_j = \alpha_j + e_{\alpha,j}$ (or its empirical Bayes counterpart) in place of the estimate $\alpha_i \equiv \lim_{N_{j(i)}\to\infty}\hat{\alpha}_i$ that we will obtain in large samples, it suffers from measurement error, and similarly for $\hat{Z}_i = Z_i + e_{Z,\mathcal{N}_i}$ (or its empirical Bayes counterpart) since it is defined using the $\hat{\alpha}_j$'s, where $\mathcal{N}_i$ is the set of nursing home close to the resident and $Z_i \equiv \lim_{N_{j(i)}\to\infty}\hat{Z}_i$.

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

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

[83] 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".

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

denote the population reduced form and first stage as:

$$Y_i = a_0 + \delta_r Z_i + e_i^r,$$

$$\alpha_i = b_0 + \delta_f Z_i + e_i^f,$$

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

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

K.1 IV Using the Fixed Effects Quality Estimates

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

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

and:

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

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

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

where λ is the population IV estimate.

Since:

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

we also have:

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

In addition, we have:

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

Hence, we find that:

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

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

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

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

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

K.2 IV Using the Empirical Bayes Quality Estimates

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

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

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

First, assuming $\alpha_j \perp N_j$ (which is a reasonable approximation given that occupancy rates at all 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:

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

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

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

Next, 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:

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

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 given by:

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

L Reduced Form Evidence of Selective Admissions

In this section, I describe my tests of selective admissions in more detail (Gandhi 2023), and also present additional test results. I test prediction 1 in section 3.1 by running the following regression at the nursing home-day level:

$$admit_{jdmt} = \gamma_0^a + \gamma_1^a o\check{c}c_{jdmt} + \delta_{jmt}^a + \xi_{jdmt}^a,$$

where $admit_{jdmt}$ is a measure of nursing home j's admissions on day d of month m in year t, $o\check{c}c_{jdmt}$ is the average log occupancy over the seven days preceding this date,[85] and δ_{jmt}^a are nursing home-month fixed effects.[86] A negative estimate for γ_1^a would be in line with prediction 1.

To test prediction 2, I run the following resident-level regressions:

$$x_i = \gamma_0^x + \gamma_1^x occ_{\mu(i),d(i),m(i),t(i)} + \tilde{x}_i'\gamma_{\tilde{x}}^x + \delta_{\mu(i)}^x + \xi_i^x,$$

for different resident characteristics x_i, controlling for other resident characteristics $\tilde{x}_i$ and nursing home fixed effects $\delta_{\mu(i)}^x$, where $\mu(i)$ is the nursing home that resident i is admitted to, and similarly $d(i)$, $m(i)$, and $t(i)$ indicate the day, month, and year that resident i was admitted respectively. Evidence that $\gamma_1^x \neq 0$ would be in line with prediction 2, and we would expect γ_1^x to be positive for characteristics considered desirable by nursing homes (e.g., those associated with higher profitability).

Table 4 and Appendix Table A.9 show regression estimates testing prediction 1. I consider different measures for admissions behavior $admit_{jdmt}$ (number of new residents, a dummy for any new residents, and flow of residents) and the occupancy measure (lagged seven-day average occupancy/log occupancy/occupancy percentile). Regardless of the specification, the estimate of γ_1^a remains negative and statistically significant (at the five percent significance level), consistent with prediction 1.

Table 5 and Appendix Table A.10 shows results from tests of prediction 2. In particular, we see that when nursing homes are closer to capacity, they are less likely to admit residents with dementia, regardless of the precise measure of occupancy used, and whether one controls for other resident characteristics. This is in line with prediction 2, considering that dementia residents are more costly for nursing homes to take care of, and nursing home administrators often complain that increased reimbursements from risk adjustments do not adequately compensate for the increased cost (Kosar et al. 2023).

[85] Although I observe the date each resident's stay begins, this often does not correspond to the actual day the nursing home makes the admission decision, which often precedes the start of each stay by several days. Therefore, I use the average over the seven days leading up to the day of admission for the occupancy measure. I also consider occupancy measures other than log occupancy, such as occupancy in levels and occupancy percentile.

[86] A practical challenge with testing these model predictions is that nursing homes may expand or contract over time (due to reasons outside of the model), and thus we must control for time-varying nursing home capacity. While nursing homes report their total number of beds, this figure is only updated annually, and there is substantial measurement error. Hence, in my analysis I only use variation from short-term fluctuations in nursing home occupancy. Related to this point, for my main sample I drop the relatively small number of nursing homes with occupancies that changed by a factor of more than two over the period of 2008–2010, in case there are underlying issues connected to these large expansions or contractions that are not accounted for by the nursing home-month fixed effects. Nonetheless, I also estimate demand for quality without dropping these nursing homes as a robustness check in panel B of Appendix Table A.12, and I still obtain a very low demand estimate.

M Simple Model of Imperfect Information About Quality

Suppose that residents do not directly observe nursing home quality β_j, but only a noisy signal of it, $\check{\beta}_j = \beta_j + e_j^{\beta}$, as well as publicly available information about the nursing home $w_{\sim\beta,j}$, which includes reported staffing levels, ownership status, and number of cited deficiencies.[87] Assume also that $e_j^{\beta} \sim^{i.i.d.} N(0, \sigma^2_{e^\beta})$, and is independent of everything else.

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

$$\tilde{\beta}_j \equiv \mathbb{E}[\beta_j|\check{\beta}_j] = \frac{\sigma^2_{e^\beta}}{\sigma^2_{e^\beta}+\sigma^2_{\beta}} w'_{\sim\beta,j}\beta_{\beta}^{w_{\sim\beta}} + \frac{\sigma^2_{\beta}}{\sigma^2_{e^\beta}+\sigma^2_{\beta}}\check{\beta}. \tag{17}$$

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

$$v_{ij} = w'_{\sim\beta,j}\overbrace{\left[\left(\frac{\kappa^{\tilde{\beta}}\sigma^2_{e^\beta}}{\sigma^2_{e^\beta}+\sigma^2_{\beta}}\right)\cdot\beta_{\beta}^{w_{\sim\beta}}\right]}^{\equiv\kappa^{\tilde{\beta}}_{w_{\sim\beta}}} + \overbrace{\left[\frac{\sigma^2_{\beta}}{\sigma^2_{e^\beta}+\sigma^2_{\beta}}\cdot\kappa^{\tilde{\beta}}\right]}^{\equiv\kappa^{\tilde{\beta}}_{\beta}}\beta_j + \kappa^{dist} dist_{ij} + \tilde{\epsilon}_{ij}, \tag{18}$$

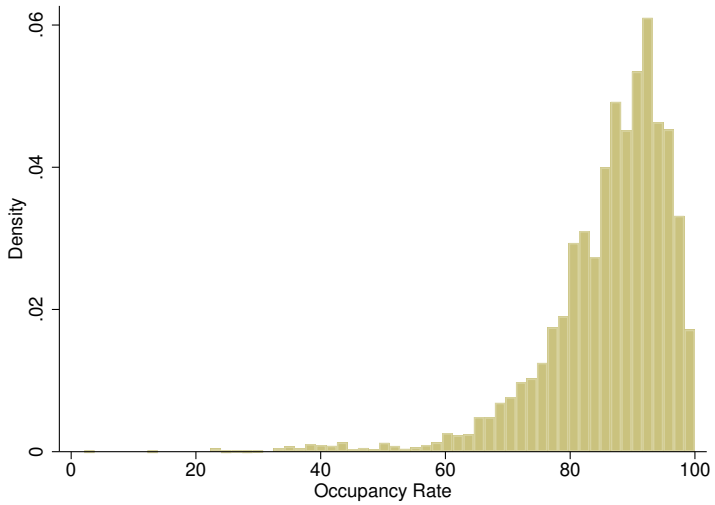
where $\tilde{\epsilon}_{ij} \equiv \kappa^{\tilde{\beta}}_{\beta} e_j^{\beta} + \epsilon_{ij}$ is a composite error term that is conditionally independent of the instruments given the covariates. Then, it is clear from the expression for $\kappa^{\tilde{\beta}}_{w_{\sim\beta}}$ that if residents have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

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

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

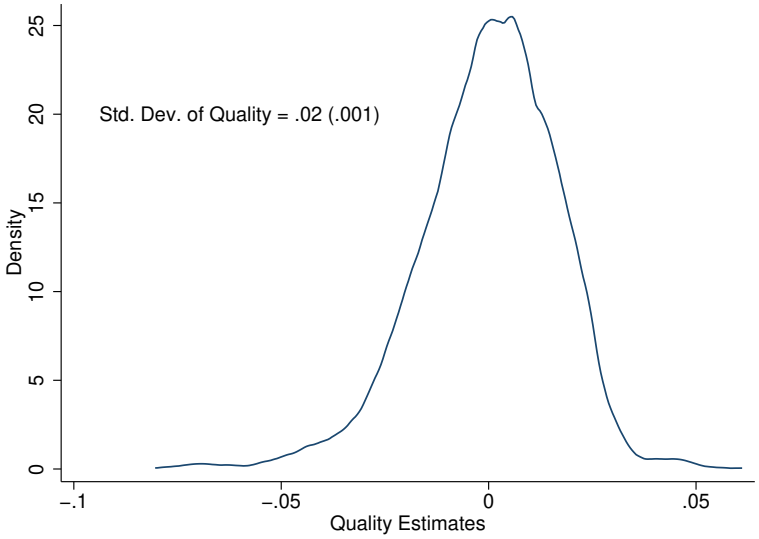
A Appendix Figures and Tables

Figure A.1: Nursing Home Occupancy Rates



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

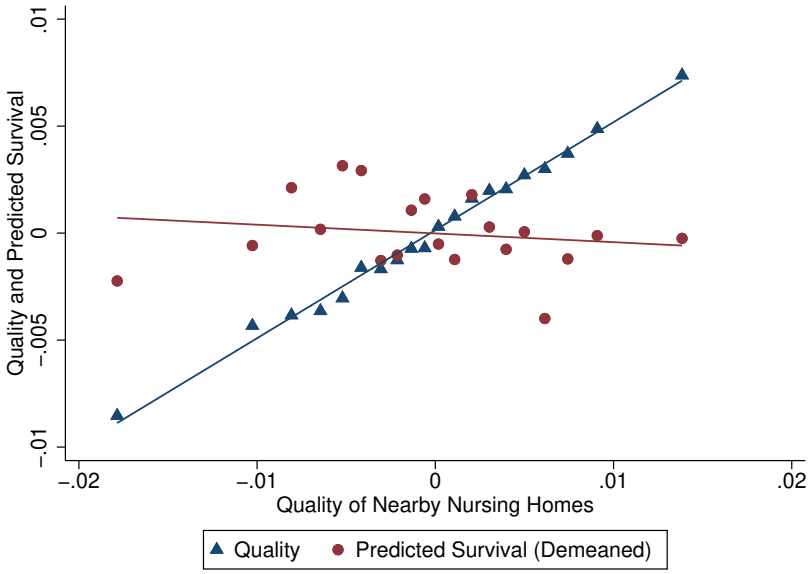
Figure A.2: Kernel Density Plot of Nursing Home Quality Estimates



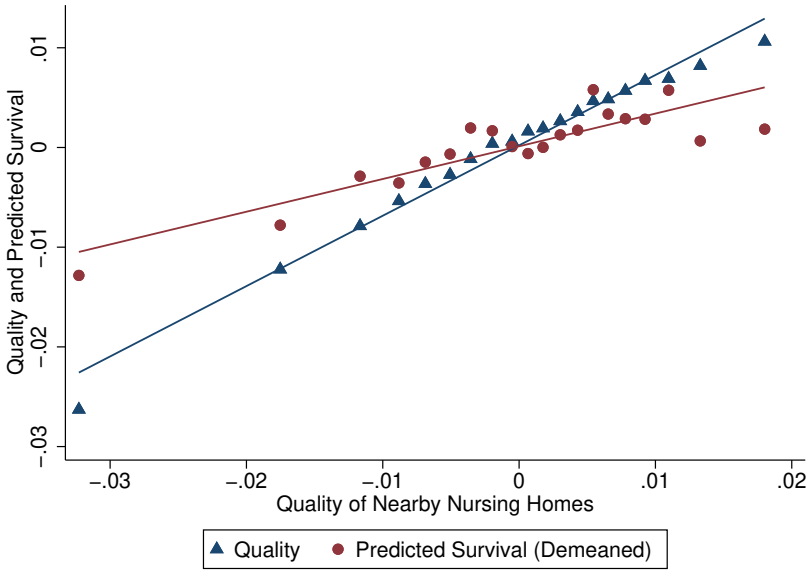
Notes: This figure contains a kernel density plot of the main quality estimates, using an Epanechnikov kernel. The standard error for the standard deviation of nursing home quality displayed in the figure is calculated based on the square root of the variance from the inverse of the Fisher information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

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

(a) County Fixed Effects



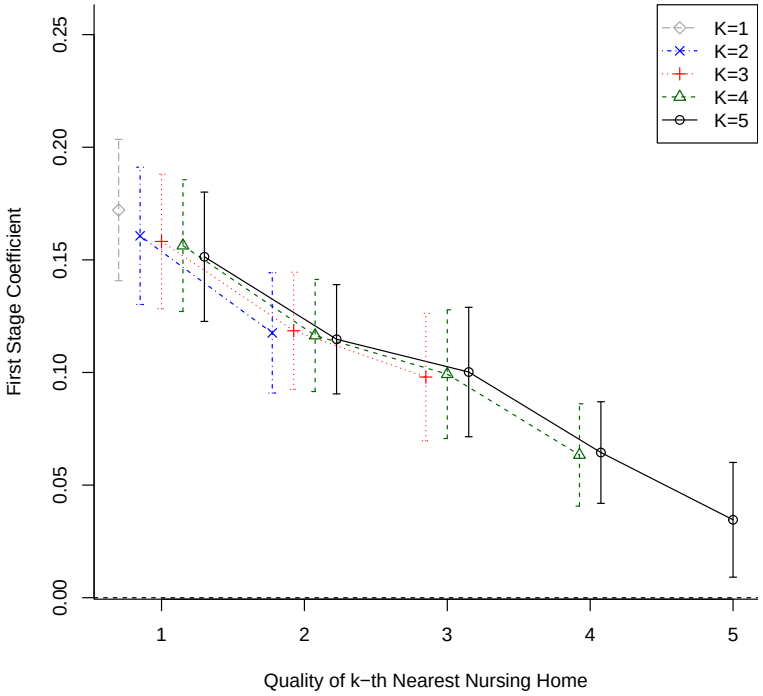
(b) No County Fixed Effects



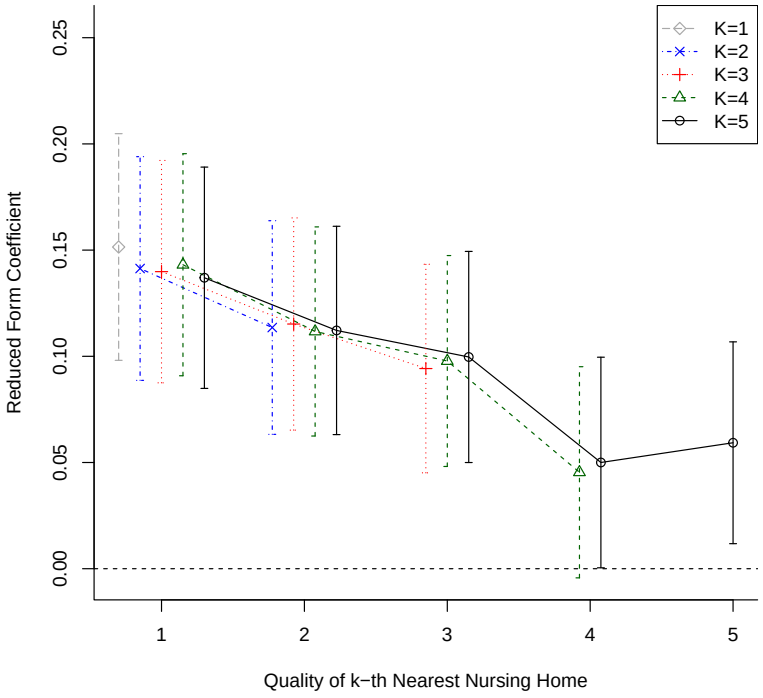
Notes: The x-axis in these figures correspond to the average quality of the five nearest nursing homes to each resident. Variables in panel A are residualized of county fixed effects, whereas variables in panel B are not residualized of county fixed effects.

Figure A.4: First Stage and Reduced Form for Different IV Specifications

(a) First Stage



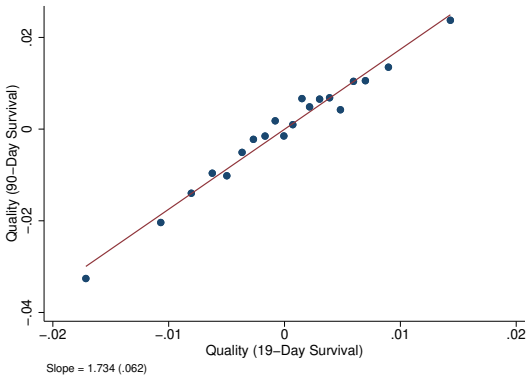
(b) Reduced Form



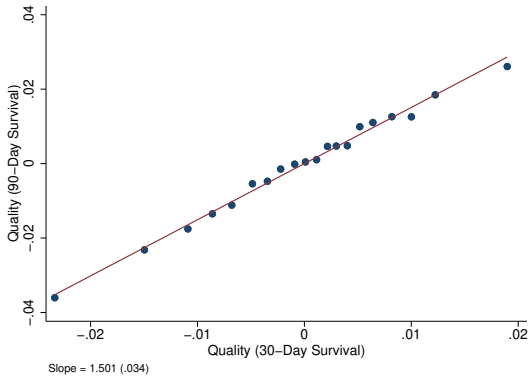
Notes: These figures plot the first-stage and reduced-form coefficients and the associated 95 percent confidence intervals for IV specifications that use the quality of the K nearest nursing homes to each resident as the instrument(s), for K ranging from one to five.

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

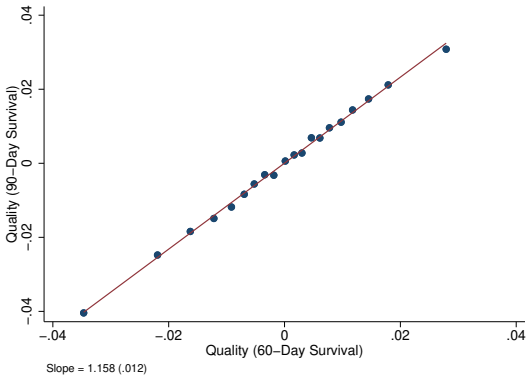
(a) 19-Day Versus 90-Day Mortality



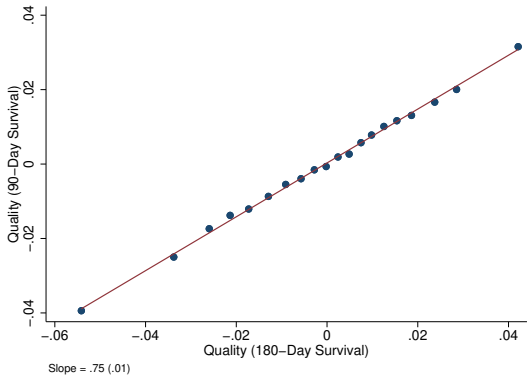
(b) 30-Day Versus 90-Day Mortality



(c) 60-Day Versus 90-Day Mortality



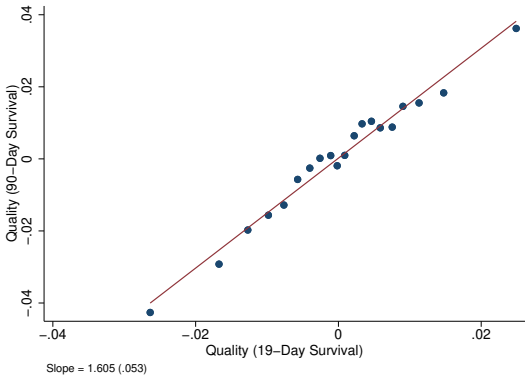
(d) 180-Day Versus 90-Day Mortality



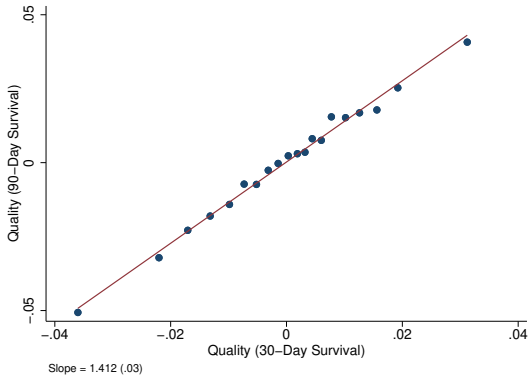
Notes: The x-axis of these figures correspond to empirical Bayes quality estimates using survival for at least 19, 30, 60, or 180 days as the outcome. The bin scatters are weighted by the number of observations for each nursing home, and the standard errors are clustered by nursing home.

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

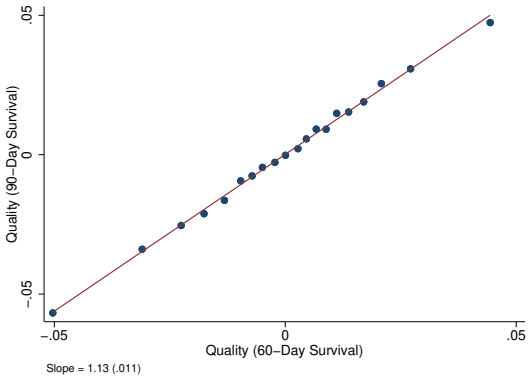
(a) 19-Day Versus 90-Day Mortality



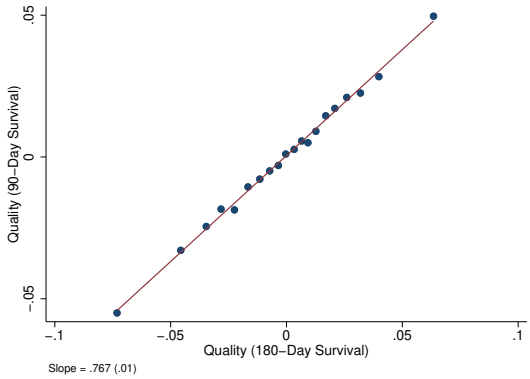
(b) 30-Day Versus 90-Day Mortality



(c) 60-Day Versus 90-Day Mortality

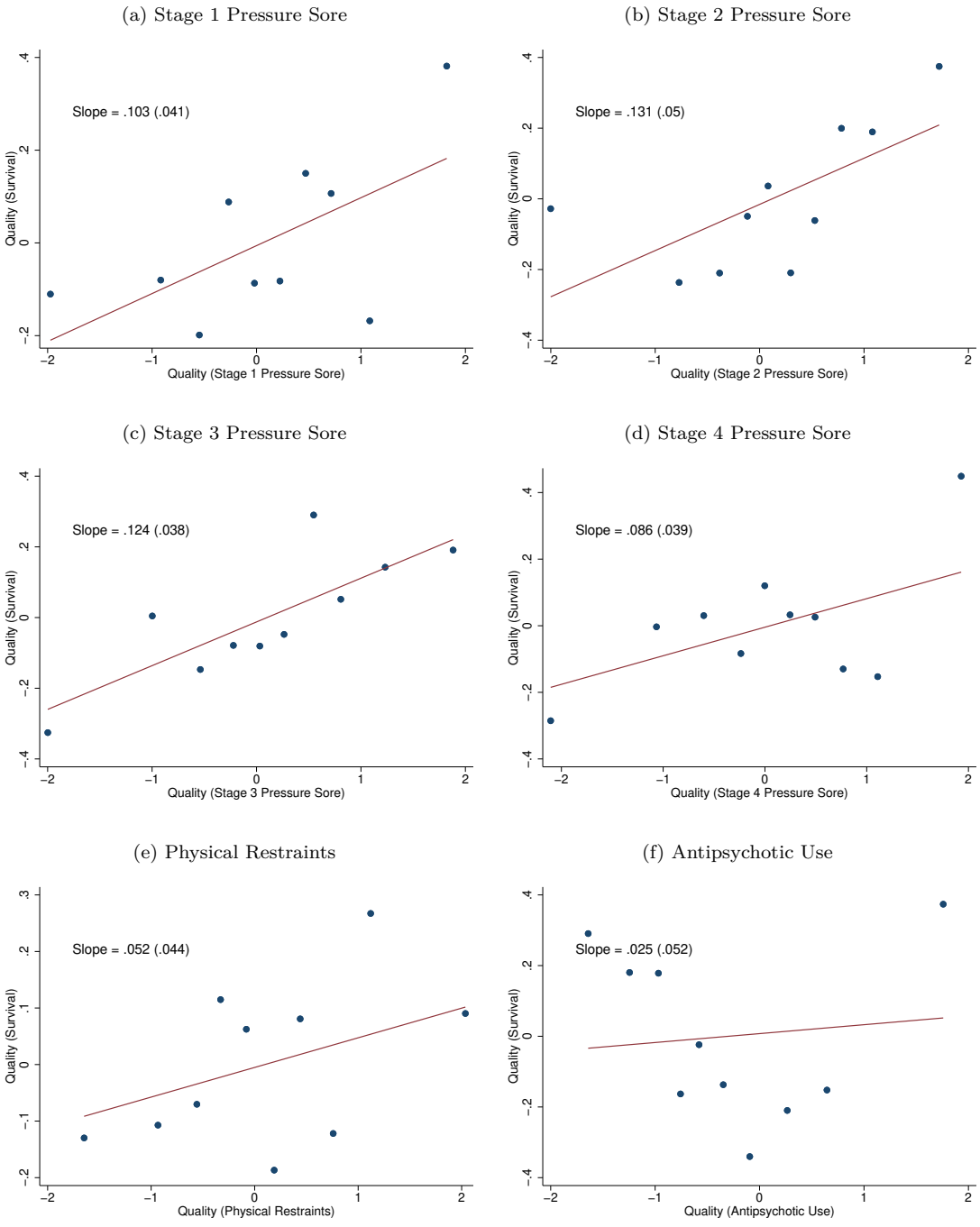


(d) 180-Day Versus 90-Day Mortality



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

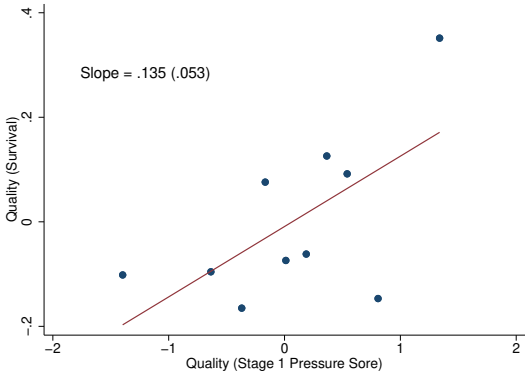
Figure A.7: Relationship Between Empirical Bayes Quality Estimates and Quality Estimates Based on Other Outcomes



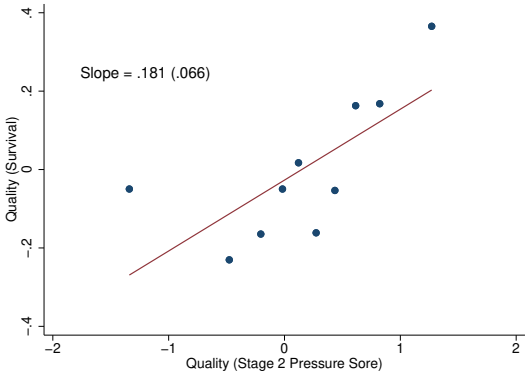
Notes: The x-axis of these figures correspond to quality estimates using other resident outcomes (instead of 90-day survival rate) as the dependent variable. The estimation procedure is the same as for my main quality estimates, except that I use a different outcome variable, and I do not use double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

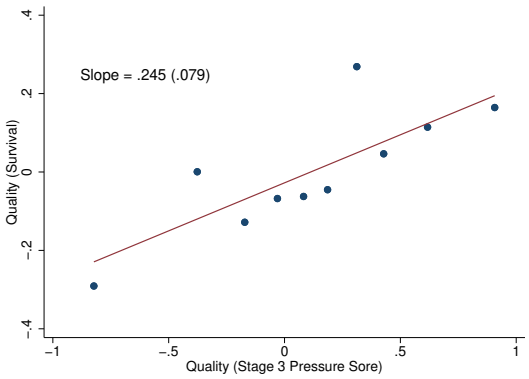
(a) Stage 1 Pressure Sore



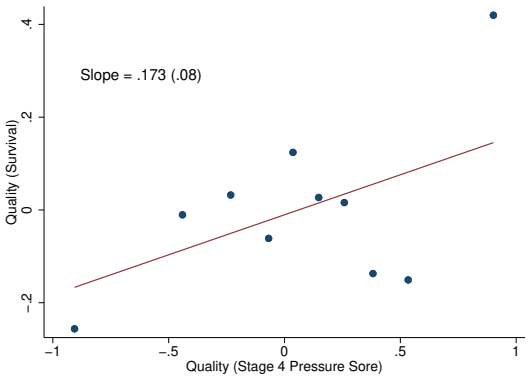
(b) Stage 2 Pressure Sore



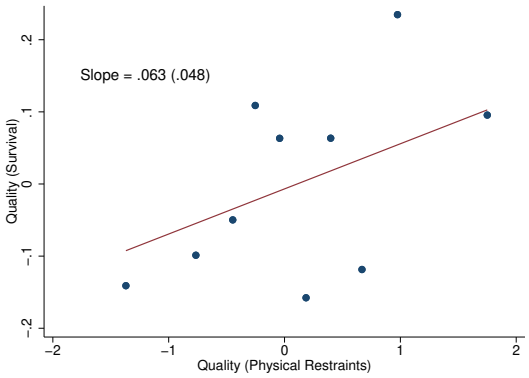
(c) Stage 3 Pressure Sore



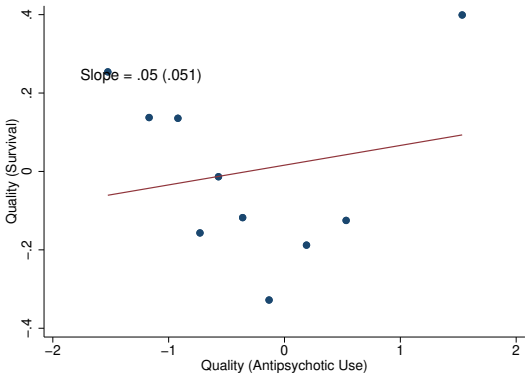
(d) Stage 4 Pressure Sore



(e) Physical Restraints

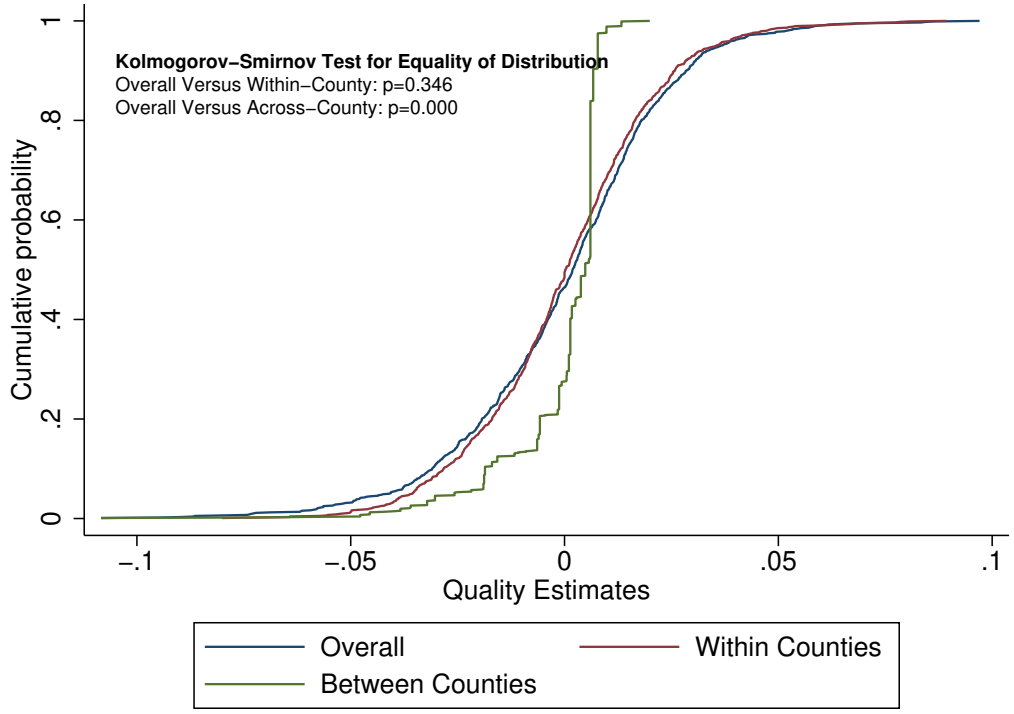


(f) Antipsychotic Use



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.

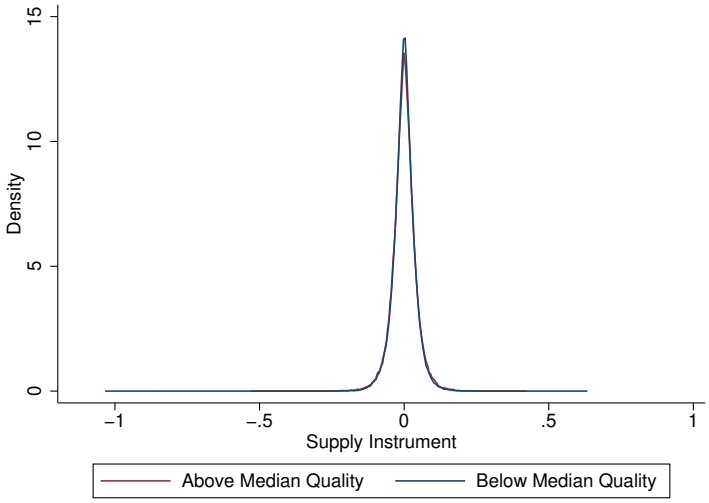
Figure A.9: ECDF of Fixed Effects Quality Estimates (Overall, Within Counties, and Between Counties)



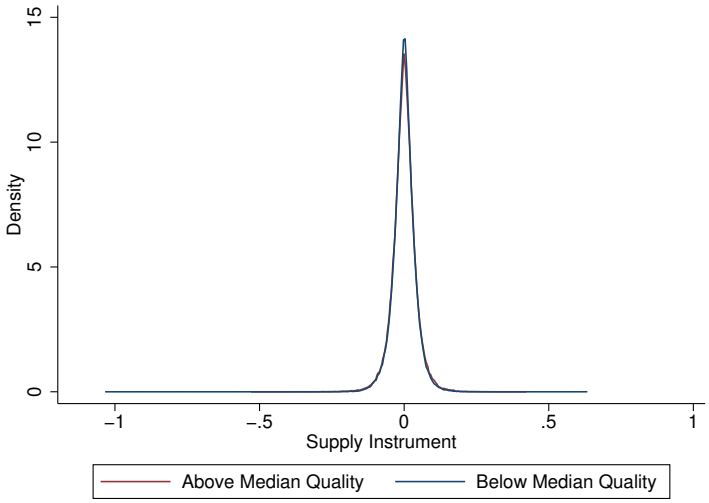
Notes: This figure plots the empirical CDFs showing the overall variation in nursing home quality, as well as the within-county and across-county variations in quality in blue, red, and green respectively. Within-county variation is plotted using the residuals from a regression of the quality estimates 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.10: Kernel Density Plot of occ_{ij} for Nursing Homes with Above-Median and Below-Median Quality

(a) Empirical Bayes Quality Estimates

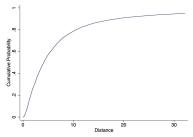


(b) Fixed Effects Quality Estimates



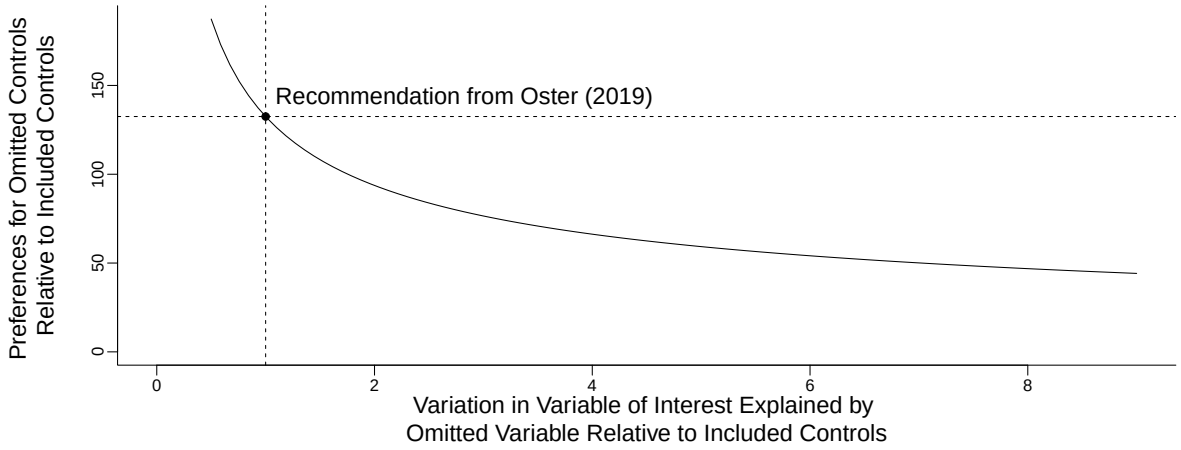
Notes: This figure contains the kernel density plot for the distributions of the supply side instrument occ_{ij} at above-median and below-median quality nursing homes, based on the Epanechnikov kernel. The unit of observation is a resident-nursing home pair (for nursing homes within 15 miles of each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

Figure A.11: Empirical CDF of Distance Between Residents and Their Chosen Nursing Homes



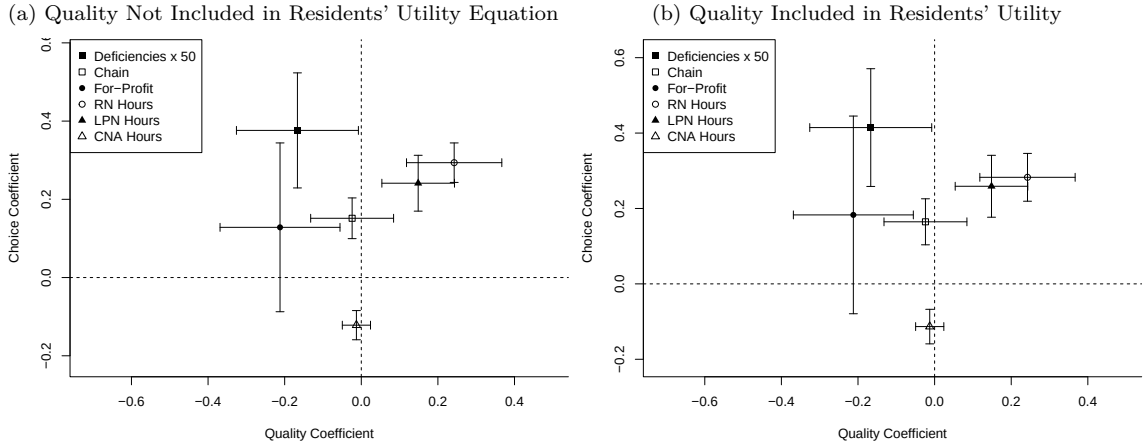
Notes: This figure shows the empirical CDF of distances between residents and their chosen nursing homes. The unit of observation is a resident.

Figure A.12: Conditions Under Which Selection on Unobservables Can Explain the Low Demand Estimate



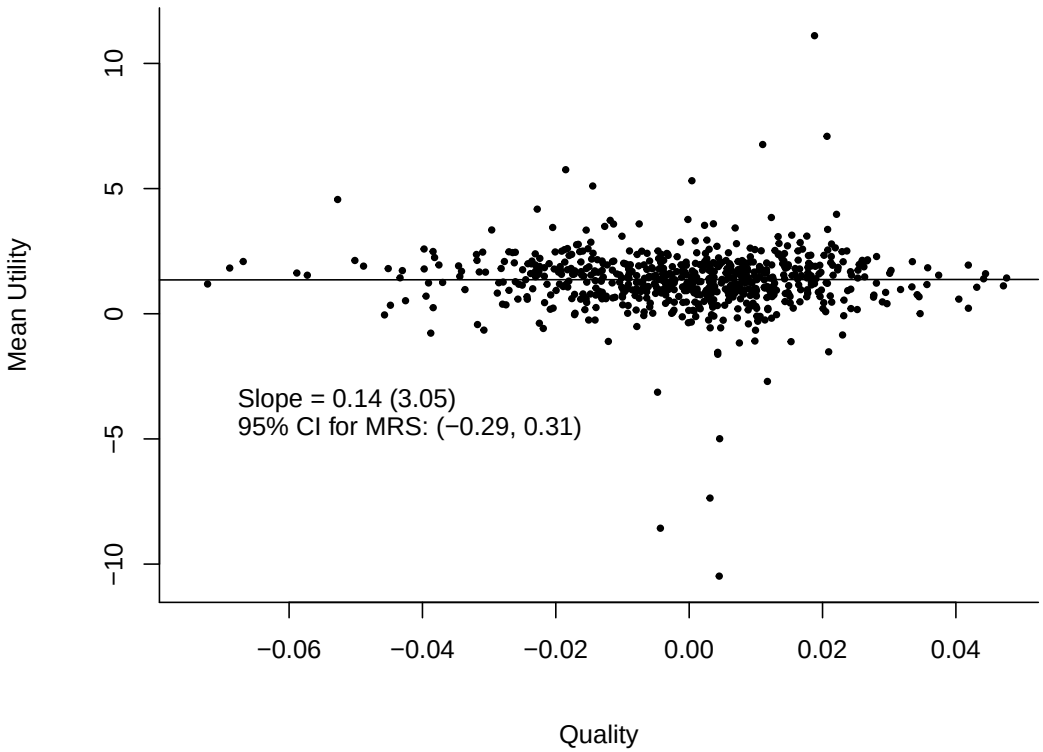
Notes: This figure shows conditions under which omitted variables bias can completely account for the low demand estimate in this paper, using methods from Cheng (2023). The x-axis represents hypothetical values of the proportional selection relationship (Oster 2019), i.e., the omitted variable's importance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

Figure A.13: Plots of Choice Coefficients Against Quality Coefficients on Nursing Home Characteristics



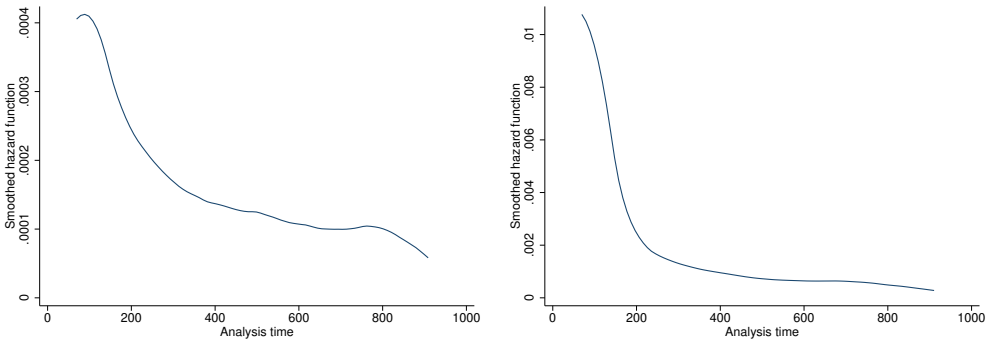
Notes: The y-axis corresponds to estimates of the choice coefficients from the structural demand model where utility is a function of nursing home characteristics (as well as nursing home quality β_j in panel B, but not in panel A). The x-axis corresponds to coefficient estimates from a regression of quality on the same nursing home characteristics. Error bars correspond to 95 percent confidence intervals.

Figure A.14: Scatterplot of Mean Utility Against Quality



Notes: This figure plots mean utilities (net of distance preferences) from the structural demand estimation (i.e. the estimated nursing home fixed effects in residents' preferences) against the quality estimates on the x-axis. The unit of observation is a nursing home, and the regression for the best fit line is weighted by the number of observations corresponding to the nursing home in the entire sample.

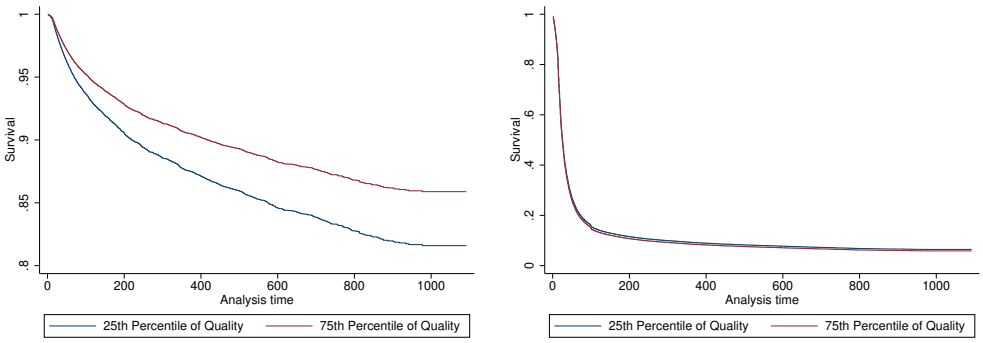
Figure A.15: Cause-Specific Baseline Hazard Functions, $h_{c,0}(t)$



(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.

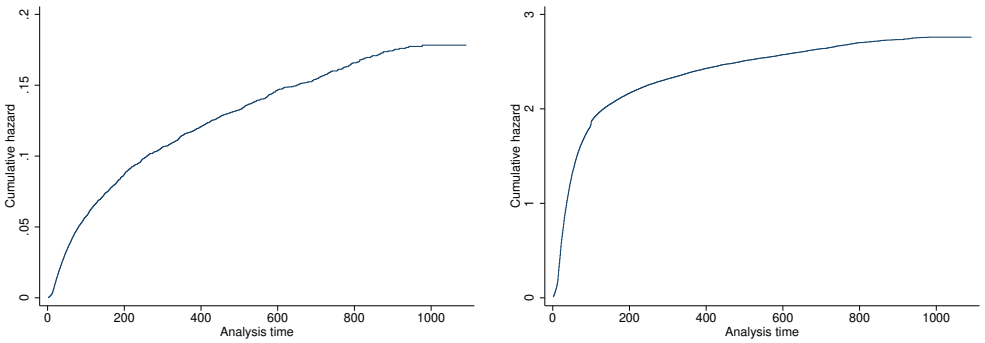
Figure A.16: Survival Curves for Cause-Specific Hazard Model (Split by Nursing Home Quality)



(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).

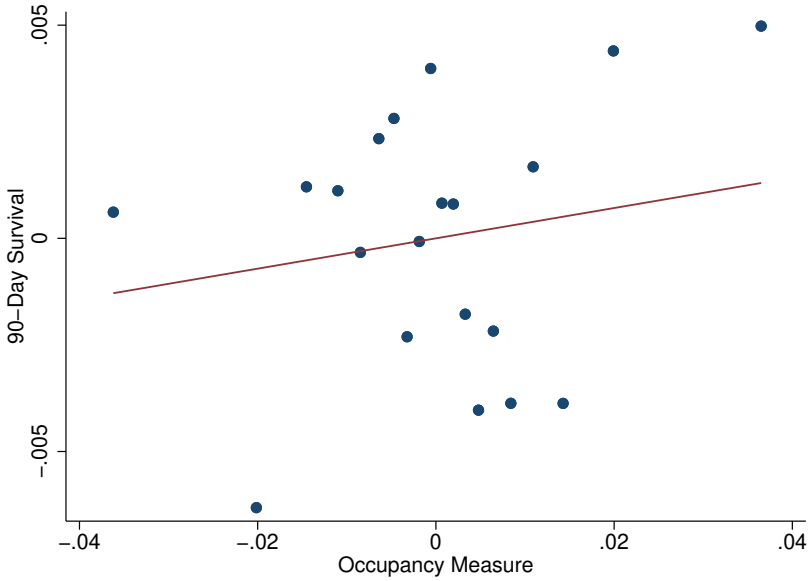
Figure A.17: Cause-Specific Cumulative Baseline Hazard Functions, $H_{c,0}(t)$



(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.18: Relationship Between Occupancy Fluctuations and Resident Outcomes



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

Table A.1: Controls for Resident Characteristics at Admission

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

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

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

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

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

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

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

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

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

Table A.3: Additional Summary Statistics

(a) 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.4: Summary Statistics for Nursing Homes (Not Weighted by Admissions)

Nursing Homes (J=840)	
Number of Beds	105.065
	(48.194)
Occupancy Rate	86.958
	(7.493)
Chain	0.600
	(0.411)
For-Profit	0.877
	(0.309)
Deficiencies	6.259
	(3.541)
RN hours per resident day	0.331
	(0.281)

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

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	110	68	49	38	31	26	22	19	17	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	68	49	37	30	26	22	19	17	14
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 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: IV Specification Using Both Variation in Distance and Temporary Occupancy Fluctuations as Instruments

	Dependent Variable: 90-Day Survival		
	(1)	(2)	(3)
TSLS			
Forecast Coefficient, λ	0.909	0.909	0.857
	(0.119)	(0.104)	(0.0986)
Demographic Controls	X	X	X
Health Controls	X	X	X
County Fixed Effects	X	X	X
Number of Nearest Nursing Homes	1	2	3
Kleibergen-Paap rk Wald F statistic	39	24	16
Number of Observations	586,483	536,936	490,154

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 quality of the *K* nearest nursing homes to the resident's prior address, and occupancy measure for the *K* nearest nursing homes and its interaction with quality, for *K* ranging from 1 to 3. Standard errors clusted at the nursing home level are shown in parentheses.

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

	Quality Estimates (s.d.)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2009 Star Ratings (s.d.)	0.0783**							0.0483
	(0.0310)							(0.0315)
RN hours per resident day (s.d.)		0.0942***						0.218***
		(0.0352)						(0.0490)
LPN hours per resident day (s.d.)			0.100***					0.116***
			(0.0209)					(0.0324)
CNA hours per resident day (s.d.)				0.0908***				-0.0398
				(0.0158)				(0.0259)
Deficiencies (s.d.)					-0.0467***			-0.0206
					(0.0157)			(0.0132)
For-Profit (s.d.)						-0.0881***		-0.0693***
						(0.0297)		(0.0261)
Chain (s.d.)							-0.0346	-0.0158
							(0.0279)	(0.0263)
N	(0.0340)	(0.0329)	(0.0331)	(0.0335)	(0.0340)	(0.0333)	(0.0341)	(0.0322)
R-squared	0	0	0	0	0	0	0	0

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 long-stay residents it has over the sample period. Standard errors are clustered by nursing home.

(a) Fixed Effects Quality Estimates

	Quality Estimates (s.d.)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2009 Star Ratings (s.d.)	0.0816							0.0494
	(0.0347)							(0.0356)
RN hours per resident day (s.d.)		0.097						0.211
		(0.0353)						(0.0502)
LPN hours per resident day (s.d.)			0.107					0.117
			(0.0226)					(0.0344)
CNA hours per resident day (s.d.)				0.0962				-0.0386
				(0.0181)				(0.0284)
Deficiencies (s.d.)					-0.0527			-0.0252
					(0.0175)			(0.0148)
For-Profit (s.d.)						-0.0825		-0.061
						(0.0314)		(0.0286)
Chain (s.d.)							-0.0555	-0.0377
							(0.0308)	(0.0296)
N	10,103	10,118	10,119	10,112	10,121	10,121	10,121	10,089
R-squared	0.007	0.010	0.012	0.009	0.003	0.007	0.003	0.032

Notes: This table shows correlations between the nursing home quality estimates (based on the nursing home fixed effects from an OLS regression) 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 admitted to the nursing home for their first stay over the sample period. Standard errors are clustered by nursing home.

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

	Indicator for Resident Surviving At Least 90 Days After Admission x 100			
Quality Measure:	Empirical Bayes		Fixed Effects	
	(1)	(2)	(3)	(4)
Leave-Year-Out Quality Estimate (s.d.)	1.324***	1.309***	1.339***	1.322***
	(0.0383)	(0.0394)	(0.0397)	(0.0406)
2009 Star Ratings (s.d.)		0.0186		0.0351
		(0.0296)		(0.0311)
RN hours per resident day (s.d.)		0.0378		0.0522
		(0.0502)		(0.0494)
LPN hours per resident day (s.d.)		0.0662		0.0797*
		(0.0443)		(0.0448)
CNA hours per resident day (s.d.)		-0.00987		-0.0155
		(0.0507)		(0.0511)
Deficiencies (s.d.)		-0.00571		-0.00702
		(0.0405)		(0.0404)
Chain (s.d.)		-0.0171		-0.0251
		(0.0304)		(0.0310)
For-Profit (s.d.)		0.0389		0.0516
		(0.0333)		(0.0338)
N	632,207	631,807	632,207	631,807
R-squared	0.140	0.140	0.140	0.140

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

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

(a) Dependent Variable: Any New Residents

	Any New Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.195***		
	(0.00970)		
Lagged 7-Day Avg. Occupancy		-0.00540***	
		(0.000238)	
Lagged 7-Day Avg. Occ. Percentile			-0.00158***
			(4.30e-05)
Nursing Home-Month Fixed Effects	X	X	X
N	3,503,121	3,503,121	3,503,121

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

(b) Dependent Variable: Flow of Residents

	Flow of Residents		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-3.108***		
	(0.114)		
Lagged 7-Day Avg. Occupancy		-0.0885***	
		(0.00314)	
Lagged 7-Day Avg. Occ. Percentile			-0.0227***
			(0.000408)
Nursing Home-Month Fixed Effects	X	X	X
N	3,503,121	3,503,121	3,503,121

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

Table A.10: Reduced Form Evidence of Selective Admissions (Without Controlling for Other Resident Characteristics)

	Dummy for Whether Resident Has Dementia		
	(1)	(2)	(3)
Lagged 7-Day Avg. Log Occupancy	-0.0358**		
	(0.0145)		
Lagged 7-Day Avg. Occupancy		-0.000564***	
		(0.000218)	
Lagged 7-Day Avg. Occ. Percentile			-9.80e-05
			(7.60e-05)
Nursing Home-Month Fixed Effects	X	X	X
N	646,065	646,065	646,065

Notes: This table shows regression results at the resident level wherein the dependent variable is a dummy for whether the resident has Alzheimer's or dementia, and the independent variables are various measures of nursing home occupancy. Standard errors are clustered at the nursing home level.

Table A.11: Supply Side Estimates for Table 6

Quality Measure:	Empirical Bayes	Fixed Effects	Empirical Bayes	Fixed Effects
	(1)	(2)	(3)	(4)
Supply Side				
Temporary Fluctuations in log(occupancy)	-3.305***	-2.585***	-2.534***	-2.218***
	(0.209)	(0.182)	(0.14)	(0.124)
Quality	-4.035*	-27.128***	2.186*	-6.901***
	(2.592)	(0.771)	(2.007)	(0.924)
Dementia	-0.211***	-0.005	-0.216***	-0.273***
	(0.047)	(0.034)	(0.02)	(0.032)
Age	0.062	0.072**	0.089***	0.099***
	(0.067)	(0.029)	(0.034)	(0.028)
At Least Bachelor's Degree	0.038***	0.012***	0.041***	0.039***
	(0.002)	(0)	(0.002)	(0.001)
Year (2009)	0.003	-0.045***	0.049***	0.122***
	(0.026)	(0.013)	(0.019)	(0.018)
Year (2010)	0.133***	0.1***	0.107***	0.249***
	(0.022)	(0.019)	(0.038)	(0.029)
Quality x Dementia			5.532***	8.116***
			(1.154)	(0.658)
Quality x Age			-0.374***	-0.244***
			(0.038)	(0.017)
Quality x At Least Bachelor's Degree			-6.429*	-1.97***
			(3.333)	(0.758)
Quality x Post-Star Ratings			-2.383***	-3.904***
			(0.887)	(0.258)
Intercept	-1.821***	0.565***	-2.031***	-1.698***
	(0.093)	(0.089)	(0.056)	(0.058)

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

Table A.12: Residents' Responsiveness to Other Nursing Home Characteristics

Quality Measure:	None	Empirical Bayes		Fixed Effects	
	(1)	(2)	(3)	(4)	(5)
Resident Preferences					
Distance to Nursing Home (in miles)	-0.172***	-0.168***	-0.17***	-0.168***	-0.17***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quality		0.752*	-0.802***	4.59***	3.97***
		(0.507)	(0.287)	(0.159)	(0.118)
Fewer Deficiencies (Z-Score)	-0.03***		-0.032***		-0.04***
	(0.003)		(0.004)		(0.002)
RN Hours Per Resident-Day	0.793***		0.757***		0.633***
	(0.016)		(0.017)		(0.018)
LPN Hours Per Resident-Day	0.353***		0.325***		0.231***
	(0.01)		(0.016)		(0.017)
Supply Side					
Temporary Fluctuations in log(occupancy)	-2.605***	-3.305***	-2.664***	-2.585***	-2.354***
	(0.176)	(0.209)	(0.169)	(0.182)	(0.129)
Quality		-4.035*	-1.432*	-27.128***	-23.691***
		(2.592)	(1.276)	(0.771)	(1.11)
Controls for Resident Characteristics in Supply Side	X	X	X	X	X
Controls for Nursing Home Characteristics in Supply Side	X		X		X

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

Table A.13: Structural Estimates for the Post-Acute Care Sample

Quality Measure:	Empirical Bayes	Fixed Effects	Empirical Bayes	Fixed Effects
	(1)	(2)	(3)	(4)
Resident Preferences				
Distance to Nursing Home (in miles)	-0.169***	-0.17***	-0.17***	-0.173***
	(0.001)	(0.001)	(0.001)	(0.001)
Quality	1.387***	4.85***	22.151***	15.532***
	(0.352)	(0.154)	(0.954)	(0.514)
Quality x Dementia			-1.555***	-1.332***
			(0.298)	(0.146)
Quality x Age			-0.236***	-0.137***
			(0.011)	(0.007)
Quality x At Least Bachelor's Degree			4.177***	0.707***
			(0.333)	(0.172)
Quality x Post-Star Ratings			0.786**	0.844***
			(0.396)	(0.118)
Supply Side				
Temporary Fluctuations in log(occupancy)	-3.019***	-2.292***	-2.655***	-2.26***
	(0.167)	(0.126)	(0.129)	(0.111)
Quality	-8.151***	-27.846***	-12.375***	-7.064***
	(1.42)	(0.842)	(2.276)	(0.899)
Controls for Resident Characteristics in Supply Side	X	X	X	X
Quality Interacted with Resident Chars. in Supply Side			X	X

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