Limiting For-Profit Provision in Nursing Home Markets

Hyein Cho* and Hans Zhu (Job Market Paper)†

November 18, 2025

[Click here for the latest draft]

Abstract

We examine whether policies that ban for-profit providers and allow for subsequent takeovers by not-for-profits can be effective at addressing quality shortfalls. We consider the US nursing home industry, where quality provision has been a concern for many decades. Our motivating evidence suggests that not-for-profit providers choose higher-quality inputs than their for-profit counterparts but are more prevalent in higher socioeconomic markets and serve wealthier residents. Thus, for-profit providers play an important role in providing access. To explain these facts and explore counterfactual policies, we estimate a structural model of nursing home demand and supply that allows firms to have nonpecuniary motives and costs that differ across provider types. The structural model reveals that for-profit providers have a strong cost advantage for serving needier residents. This results in them choosing a lower quality and lower priced product to maximise their margins. Not-for-profit providers choose higher quality, and therefore higher prices, not because of their nonpecuniary motive, but because they prefer to avoid directly competing with for-profit providers by serving residents with stronger preferences for quality. Therefore, banning for-profit providers while allowing for takeovers tends to reduce consumer surplus because not-for-profits that take over for-profits significantly raise prices to cover their higher costs. These results underscore the role that for-profit providers play in expanding access to nursing home care.

*Cornerstone Research; hyein.cho@cornerstone.com

†National Association of Insurance Commissioners; hanszhu2024@u.northwestern.edu

Many thanks to our advisors Rob Porter, David Dranove, Gaston Illanes and Vivek Bhattacharya for their generous guidance and advice. We thank Molly Schnell for her sponsorship of our project with NBER and feedback. We thank Alex Boche, José D. Salas, Jin Yang and Jason Zhao and participants in Northwestern IO lunch for helpful discussions and comments. We thank Elizabeth Adams, Mohan Ramanujan and Sara Schwartz at NBER for assistance with access to data.

1 Introduction

In health and education settings, policymakers and consumers frequently complain that some firms provide low-quality services. Two common features in these markets are the ability of policymakers to decide who is allowed to compete through certification or entry requirements and competition between for-profit (FP) and not-for-profit (NFP) providers. Policymakers and other commentators often blame FP providers for quality shortfalls, which leads these individuals to question whether FP providers should be allowed to compete. For example, policymakers in California sought to limit the operations of for-profit colleges due to systemic quality issues (Mello, 2019).[1] Changing the composition of firm types may not be the most obvious policy solution to quality shortfalls, but in practice, many other reforms have had limited success.[2] Thus, in this paper, we ask whether policymakers should increase NFP provision and decrease FP provision in these kinds of markets.

We study this question in the context of the US nursing homes industry, where low quality provision is a severe problem that policymakers have long struggled to solve.[3] In recent years, New York policymakers considered banning all new FP providers (Hogan, 2021). Ultimately, this did not pass, but several states including Massachusetts, New Jersey, and New York imposed strict profit caps of 5% of expenses on for-profit nursing homes (Jaffe and Kaiser, 2021).

In this paper, we study the effects of these types of policies by studying the effects of bans on FP nursing homes, allowing for subsequent takeovers by NFP nursing homes. If NFP providers have nonpecuniary motives, then their incentives will be more in line with a social planner's. Increased NFP provision could therefore lead to increased quality. In addition, Weisbrod (1988) suggests that NFP firms can solve information asymmetries. When quality is difficult to observe, consumers may have an explicit preference for NFP providers, reflecting trust in their nonprofit objectives.

On the other hand, if the business models of FP and NFP providers systematically differ, then so could their costs. If FP providers are more cost-efficient, then they could play an important role

[1] Similar concerns have arisen in for-profit medical schools and nursing homes (Knight, 2021; Campbell and Harrington, 2024; Penzenstadler, 2022).

[2] One example is pay-for-performance where the overall results are mixed in both health and education settings (Cohodes et al., 2023; Fryer, 2013; Gupta, 2021; Alexander, 2020; Finkelstein et al., 2018). Another is the increased provision of information about quality – 'report cards' – that also presents mixed results in health and education settings (Dranove, 2011; Dranove and Jin, 2010). The key issue is that firms can game payment schemes and report cards to avoid improving quality.

[3] A study report by the National Academies of Sciences, Engineering, and Medicine (2022) provides a summary of the evolution of policy and reforms to improve nursing home quality going back several decades. In their introduction, they reflect on their predecessor report from 1986, which raised serious concerns regarding quality provision. They also highlight how COVID-19 laid bare the continued quality failings in nursing homes. Approximately 40% of all US COVID-19 deaths were among nursing home residents (SteelFisher et al., 2021).

in expanding access to nursing home care, serving at lower price and serving residents who may not otherwise have received access to nursing home care. In addition, FP providers serve roughly two-thirds of the market. A ban on all FP providers would dramatically reduce the supply of services and increase the distance between a residents' prior residence and nursing home, which may be undesirable if residents value proximity to service.[4] Summarising, the effects of these policies are ambiguous and we estimate a structural model of nursing home demand and supply, encompassing these forces, to examine their effects on quality, access and welfare.

We begin by using a nationwide sample of nursing homes to document patterns of quality and access across FP and NFP providers. In this paper, the main characterisation of socioeconomic background will be whether the resident is a private payer, who pays the private price set by the nursing home out of pocket, or is covered by Medicaid, which typically requires exhaustion of wealth and assets for eligibility.[5] We use cross-sectional variation as FP and NFP providers operate distinct business models and rarely change their for-profit status from year-to-year.

We find that NFP providers choose higher quality – measured in terms of higher nursing intensity – than their FP counterparts. On the other hand, FP providers are more prevalent in poorer markets and serve more Medicaid residents than NFP providers. This holds even within markets where NFP and FP nursing homes compete. The result on quality is consistent with the literature, but our result regarding NFP provision across and within markets is new and may be surprising given the supposed nonpecuniary motives of a NFP provider.

The key to understanding these results is to conceptualise NFP providers as offering a higher-quality, and thus higher-priced product, which is preferred by residents who value quality more, especially private-payers. FP providers provide a lower-priced, and thus lower-quality product that is suited to residents who value quality less, including Medicaid payers who may pay the private price for some part of their stay.[6] These results underscore that the welfare effects of decreasing FP provision and increasing NFP provision are ambiguous. More NFP provision might increase quality on average, but access to nursing home care could be reduced, especially for Medicaid residents.

The reduced-form facts alone are not sufficient to justify our interpretation of the observed quality access patterns. In particular, we do not know why NFP providers choose higher quality than their FP counterparts. For instance, is it driven by differing preferences for quality across residents, the nonpecuniary motives of NFP firms, or different cost functions? In addition, our

[4]Most papers estimating resident demand in health economics include distance in utility and find that it is a significant determinant of resident choice (Hackmann, 2019; Ho, 2006; Town and Vistnes, 2001). A similar treatment of distance can also be found in education settings (Dinerstein et al., 2020).

[5]We introduce payer types in greater detail, including Medicare payers, when we discuss the setting in Section 2.

[6]Since private prices come from state cost reports, this result is based on California data (where our structural estimation takes place).

reduced-form facts do not indicate whether FP providers prefer serving Medicaid residents and whether NFP providers prefer serving private-payers. This depends on the relative margins across firm and payer-types, which in turn depend on demand- and supply-side factors. Marginal costs are not directly observed in the data. Therefore, to complete these explanations, we need a structural model of nursing home demand and supply that generates estimates of all the parameters of interest. In addition, for the counterfactuals of interest, there are no natural experiments that provide exogenous variation in the number of FP versus NFP providers. Thus, a structural model of nursing home demand and supply is needed to understand the welfare effects of novel regulations.

We estimate a structural model of nursing home demand and supply on markets in California following Hackmann (2019). Nursing home demand is modelled as a standard discrete choice problem. We observe many individual characteristics which allows us to model price and quality elasticities that vary significantly at the individual level. This gives rise to the potential for market-segmentation from demand-side factors. On the supply side, nursing homes compete in an oligopoly game by choosing qualities and private prices to maximise an objective that includes profits and nonpecuniary motives towards quantity of care. Following our motivating evidence, we consider a supply side that is significantly richer than other papers in this literature. We allow cost functions and the quantity-of-care motive to vary systematically across NFP and FP providers. Cost functions also vary systematically with the payer-type quantities served and do so nonlinearly, reflecting that the cost of serving patients of different payer-types varies due to their differing care needs. This allows us to capture payer-type margins that vary at the firm level and will be the key to explaining the patterns of access and provision.

Our model estimates reveal that NFP providers have a nonpecuniary value for providing an additional bed–day of care of approximately $33 – 18% of their private price. The corresponding value for FP providers is not significantly different from zero. On the cost side, we find that overall, NFP providers have higher quality costs. Our quality measure – nursing intensity – aggregates across two different types of nurses. NFPs use a mix of nurses which includes more of the higher qualification and higher cost nurses, which explains quality cost differences. Regarding payer-type quantities, we find that FP providers have significantly lower payer-type cost parameters than NFP providers. We find that a large proportion of these cost differences are likely attributable to differences in unobserved quality. These include dimensions of quality related to accommodation quality and other aspects of nursing care not captured by the nursing hours we include such as differences in medical and care equipment and supplies. For example, for Medicaid payers where the cost difference is around $40 on average, around 75% of the cost difference is attributable to differences in unobserved quality. The remainder we interpret as differences in the efficiency of providing nursing home care.

We then use the model to explain the in-sample patterns of quality, access and provision. We find that NFP providers choose higher quality not because of their nonpecuniary motive but due to a market segmentation strategy that serves residents who value quality more, including private-payers. The effect of the nonpecuniary motive, then, is for NFP providers to discount their prices and quality to serve more residents than they would if their nonpecuniary value were zero. Next, turning to patterns related to access and provision, we find that FP providers make significantly larger margins on Medicaid payers than do NFP providers. This explains why FP providers are more prevalent in markets with lower socioeconomic status, which as we showed have more Medicaid residents. NFP providers cannot compete as well with the lower costs of FP providers and ultimately serve markets with higher socioeconomic status and fewer Medicaid residents.

Finally, we turn to our policy counterfactuals. We consider two types of counterfactuals. In the first, we ban FP nursing homes with no further extensive margin changes. In the second, we ban FP nursing homes and have them be taken over by a local NFP nursing home. Since government providers are included in our pool of NFP providers, this could also be thought of as a government takeover.[7] The new NFP nursing home then follows a NFP business model with the associated increase in unobserved quality, although nursing hours are still endogenous. That is, we replace all the FP cost parameters with their NFP counterparts and set the unobserved cost shocks to the mean of the NFP unobserved cost shocks.[8] On the demand side, since we estimate a preference for NFP providers, we also add that to a resident's evaluation of the nursing home. In these counterfactuals, we ignore any transition costs and compare the competitive Nash-Bertrand equilibrium observed in the data prior to the change with that after a change made by a social planner who maximises consumer surplus subject to nursing home capacity constraints and a profit constraint. The latter requires that the nursing home makes at least as much profit as in the observed equilibrium.[9] We do this to conduct a 'generous' assessment that can be interpreted as an 'upper bound' of the value of these types of policies.

Bans without takeovers yield mixed results. Across the range of scenarios we consider, there is a median gain in consumer surplus of approximately \$1.3 million per year arising from large increases in quality. However, there is significant heterogeneity, including losses in consumer surplus in approximately 45% of the scenarios we consider. Moreover, in all scenarios, there are large losses in the number of Medicaid residents being served because of the large decrease in supply and the banning of FP providers that serve relatively more Medicaid residents. Bans with takeovers fare no better. In this case, the median loss in consumer surplus is approximately \$2.7 million per year, arising from relatively large increases in price required to cover the higher costs that NFP

[7] Around 20% of NFP providers in our pool are government providers.

[8] While it is natural for a NFP to extend their existing business model, we conduct a sensitivity test where we keep some of the costs fixed at the FP level to examine robustness to the NFP deciding not to increase unobserved quality.

[9] The profit constraint ensures that the social planner has to set prices and quality while accounting for firm revenues and costs.

providers incur. On the other hand, there are small decreases in the number of Medicaid residents being served, so bans with takeovers preserve equitable access relative to bans without takeovers. Again, note that our assessment was already generous towards these policies, and thus, overall, our results suggest that reducing FP provision and increasing NFP provision are unlikely to be successful policies. The counterfactuals underscore the interpretation that FP providers expand access to nursing home care by providing the market with a product that is better suited to serving residents in markets with lower socioeconomic status.

Related literature

While we combine and draw on tools from several papers and bodies of literature for our model, we view our contribution as primarily empirical. Our paper contributes to two bodies of literature. First, this project adds to the extensive literature on NFP providers by estimating a structural model of NFP and FP providers. One focus of the literature has been on understanding the differences between FP and NFP providers in various regulated markets, such as the hospital industry (Newhouse, 1970; Norton and Staiger, 1994; Sloan, 2000; Ballou and Weisbrod, 2003; Horwitz and Nichols, 2009; Tom and Jacobson, 2010; Bayandir, 2012; Dranove et al., 2017; Garthwaite et al., 2018), nursing home industry (Chou, 2002; Grabowski and Hirth, 2003; Ballou, 2005, 2008; Grabowski et al., 2013; Lu and Lu, 2021), and postsecondary education industry (Deming et al., 2012). However, these papers usually approach these differences from a reduced-form perspective, focusing on identifying differences in observable outcomes. For the nursing home industry, earlier works typically find that NFP providers exhibit some form of altruistic motive, typically through better-quality care in some form. However, as Weisbrod (1988) discusses, in general, NFP providers are not well understood.

Reduced-form findings of better-quality care alone are not informative about what is different about NFP providers, especially in an equilibrium with competing FP providers. A structural model allows us to consider a broad range of factors in a coherent way. Our findings reveal that while not-for-profits do have nonprofit motives, they provide higher quality not because of their altruistic motive but because of a market segmentation strategy. Next, we also document novel patterns of access and market segmentation and provide a complete explanation through the lens of the spatial distribution of payer-types and suitability of firm types for particular payer-types. We believe that these results on FP and NFP have some generalisability. For example, similar patterns of quality and access are seen in the postsecondary education industry (Deming et al., 2012).

Second, this paper contributes to the literature on long-term care in the US (Cheng, 2023; Ching et al., 2015; Einav et al., 2022; Gandhi, 2023; Gandhi and Olenski, 2024; Hackmann et al., 2024; Harrington et al., 2017; Lin, 2015; Olenski, 2022). A number of papers study determinants of quality and find that Medicaid reimbursement rates (Nyman, 1985; Grabowski, 2001; Hackmann, 2019) and nurse staffing ratios (Harrington et al., 2000) are important. While we borrow many aspects of Hackmann's (2019) framework, his paper focuses on studying the effect of Medicaid reimbursement rates on quality. FP versus NFP provision does not play a substantial role in his paper. Other sets of papers find that FP ownership (Chou, 2002; Grabowski and Hirth, 2003) and private equity ownership (Gupta et al., 2021) result in lower quality. These results suggest that if FP providers' inferior quality comes from investing less in quality determinants, limiting FP provision and increasing NFP provision may be welfare-enhancing. However, if FP facilities provide access to care to lower socioeconomic status populations who would not have received care otherwise, reducing FP provision may leave a void in these communities. Li et al. (2015) document that racial and ethnic minorities are more likely to obtain care from facilities with FP ownership. Our project is the first to document and explain the quality access trade-off of NFP and FP provision in a unified framework.

2 Setting

2.1 Nursing Homes

We examine Medicare-certified Skilled Nursing Facilities to study the US nursing homes industry. Skilled nursing facilities primarily provide skilled nursing care and related services for residents who require medical or nursing care and are not primarily for the care and treatment of mental diseases or personal non-nursing care (42 U.S. Code § 1395i–3). Specifically, nursing homes provide two services. First, they provide medical care to individuals who require short-term rehabilitative stays after hospitalization. Second, they provide long-term care services to individuals who require daily nursing care and additional therapy care.

The two distinct functions of the nursing home give rise to significant variation in resident characteristics, some of which we summarise in table 13 in appendix A.1. Here, we highlight the large variation in the distance between a resident's prior residence and their nursing home. Figure 1 plots a histogram of the distance between a Californian resident's prior residence and their nursing home using our individual level data from 2000-2010. Much of the mass is concentrated towards the left, with approximately 10% of stays being in the same zip and the median distance being 12.8 miles. This suggests that nursing home residents have a preference for being close to their prior residence. On the other hand, there is also a long tail leading to the average distance being 36.3 miles.

Nursing homes are primarily reimbursed on a prospective price-per-day basis. Prospective means that the prices are set by the relevant authority ahead of time. Residents can be distinguished

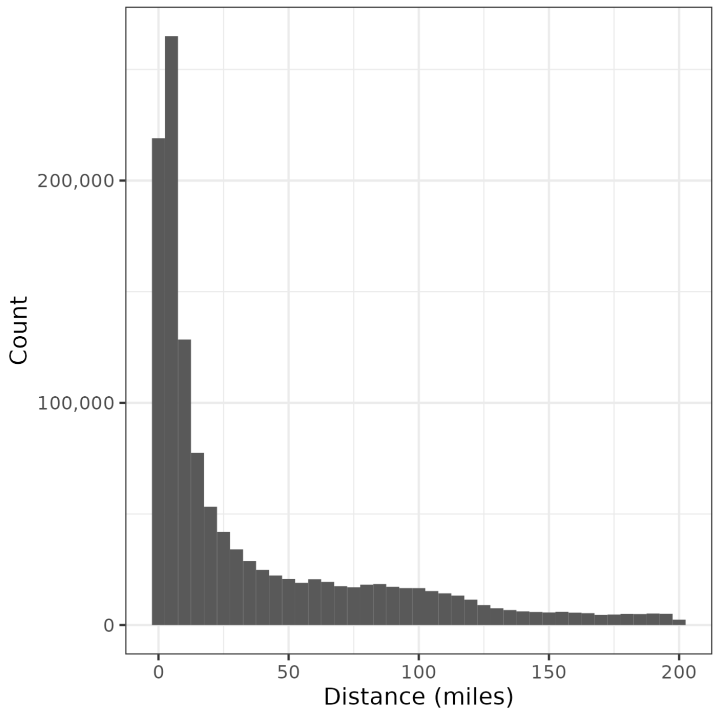


Figure 1: Histogram of distance between a residents' prior residence and nursing home

by the funding source for their stay, or their 'payer-type'. In this paper, we focus on three payer-types: Medicare, private-pay and Medicaid. These are not exhaustive, but make up 87% of stays. Medicare covers post-acute care after hospitalisation for up to 100 days. The first 20 days are fully covered, while there is a copayment for 20-100 days.[10] After residents exhaust those 100 days, they pay the private price set by the nursing home, unless they qualify for Medicaid. As long-term care insurance take-up is relatively low (Brown and Finkelstein, 2007), much of the payment comes from out-of-pocket. Finally, if residents exhaust their financial resources and become unable to pay prices out-of-pocket, Medicaid covers their nursing home expenses.

Medicare rates are set by the Centers for Medicare & Medicaid Services and take into account factors such as geographic adjustments and expected facility population care needs. Because of the latter, Medicare tends to pay the most.[11] Medicaid prices are set at the State level and are relatively low. Advocates and experts have recognised the low rate as a longstanding problem.[12]

[10]Since the copayment is facility invariant, we ignore the role of the copayment in our analysis.

[11]For example, in California in 2018, the average Medicare, private-pay and Medicaid prices were $307.0, $306.1 and $294.2 per bed-day respectively. Average prices are calculated as total revenues divided by resident-days for each payer-type. We use California data here as data about private-pay residents is only available from state cost report data and our structural estimation will be based on California.

[12]For instance, the Committee on Improving Quality in Long-Term Care explored these concerns in its 2001 report citing policy discussion going as far back as the 1980s (Wunderluch and Kohler, 2001). One of Hackmann's (2019) key contributions is to suggest that increasing Medicaid reimbursement rates from their relatively low rates is an effective

The issue is particularly acute as Medicaid rates are not set with explicit adjustments for expected facility population care needs as with Medicare rates. Given the prospective nature of Medicaid and Medicare prices, we think of nursing homes as taking them as given.

2.2 Not-for-Profit Organisations

NFP organisations are organized and operated exclusively for specific purposes and must not inure any of the earnings to any private shareholder or individual (Internal Revenue Service, 2023).[13] Under section 501(c)(3) of the Internal Revenue Code, these organisations are tax-exempt from sales and property taxes and can receive tax-deductible donations. [14]

NFP organisations must file annual reports (Form 990 or its variant) which include information about revenue, expenditure, and income. Also, NFP organisations may be subject to audits by the IRS or have to submit an audited financial statement depending on specific state laws.[15] We take the effectiveness of this regulation as given and consider NFP and FP as firms of different types throughout our analysis.

policy for improving quality.

[13]Specific purposes include charitable, religious, educational, scientific, literary, testing for public safety, fostering national or international amateur sports competition, and preventing cruelty to children or animals.

[14]See https://www.irs.gov/charities-non-profits/exempt-organizations-what-are-employment-taxes

[15]See https://www.councilofnonprofits.org/running-nonprofit/nonprofit-audit-guidec/state-law-nonprofit-audit-requirements

2.3 NFP and FP Nursing Homes

Table 1: Summary Statistics from facility-level data

	NFP	FP
Provider count in 2000	5,889	11,075
	(33.3%)	(66.7%)
Provider count in 2018	4,463	10,437
	(30.0%)	(70.0%)
Average entries per year	34.1	60.6
Average exits per year	86.5	114.0
Average conversions to other type per year	146.6	124.0
Bed size	98.3	109.1
Average Prop. Medicare in 2018	13.4	13.2
Average Prop. Medicaid in 2018	51.2	63.9

Note: Data in this table are sourced from our facility-level data covering 2000-2018 and includes all states.

Table 1 presents summary statistics about the facility-level data by FP status. Approximately 30% of the Medicare-certified nursing homes are not-for-profits, while this share has decreased over time. On average, facility sizes are fairly similar, with FP facilities being slightly larger. Regarding facility observables, a diverse set of organisations own NFP nursing homes. Of the 4,463 NFP providers in 2018, 953 providers are government-owned, 502 are operated by religious organisations and the remainder by private, NFP organisations. It is generally understood that for-profit nursing homes tend to operate as part of larger chains (Harrington et al., 2012), but the exact extent of this has been difficult to quantify because ownership of for-profit nursing homes is notoriously opaque.[16]

Table 1 also provides summary statistics about the Medicaid and private payer shares (weighted by length of stay) at FP and NFP facilities in 2010. It's notable that across all the summary statistics, FP providers serve more Medicaid residents and less private-pay residents than their NFP counterparts. We interpret these statistics as supporting the idea that FP providers play an important role in providing access to care in needier communities. Differences in ownership and payer-types served are also suggestive of the different business models adopted by FP versus NFP nursing

[16] To improve transparency the Biden Administration recently introduced reforms to increase reporting and monitoring of nursing home ownership (Centers for Medicare and Medicaid Services, 2023). We commenced an exercise to identify chain ownership of nursing homes in California by hand-coding. Most FP providers appeared to be part of a within-state or cross-country chain, whereas NFP providers typically appear to be independent or operate a handful of facilities at most.

homes.

There is little entry and exit, with more in the for-profit sector. This may be explained by NFP providers having limited financing options: they are legally banned from accruing earnings to any private shareholder or individuals, and thus limited from equity financing. Conversions between FP and NFP nursing homes are relatively rare.

2.4 Cross-subsidisation in nursing homes

To contextualise some of our results later, it is important to understand that the US nursing homes industry is also a story of cross-subsidisation. Not only is the extent of cross-subsidisation significant, but the form also differs dramatically across NFP and FP providers. First, we consider the usage of related parties. Related parties are somewhere in between vertically integrated firms and not. An owner of a nursing home may own or have financial interests in several other businesses which are not directly vertically integrated and operate independently. For instance, in addition to the nursing home, they could have financial interests in businesses operating in catering, cleaning, medical goods, real estate and so on.[17] The nursing home could contract with these related party businesses at inflated prices and through Medicaid and Medicare reimbursements which partially scale with past reported costs, extract rents from Government.

Gandhi and Olenski (2024) study this practice in the state of Illinois and find that in 2019, 68% of profits were 'hidden' using this practice, primarily through property costs and to a lesser extent management costs. While Gandhi and Olenski are the first to formally study this problem, nursing home consumer advocates and some thinktanks have thought this to be a big problem throughout the entire US nursing homes industry for some time now (The National Consumer Voice for Quality Long Term Care, 2023; Hammond, 2022). CMS cost report data allows us to have a look at the extent of usage of related parties. In 2018, about 49% and 83% of NFP providers and FP providers respectively used related party transactions. The mean and median dollar spend on related party transactions in 2018 for NFP providers is $2.72 million and $1.76 million, and for FP providers is $2.79 million and $2.03 million respectively. These figures suggest that the usage of related parties is greater by FP providers, consistent with Gandhi and Olenski's analysis. We do not believe that this issue poses a first-order problem for our analysis. As Gandhi and Olenski (2024) show, the hidden profits arise mostly from property and management costs which can be thought of as fixed costs from the perspective of the delivery of nursing home services. In that case, pricing and quality choices are unaffected. Where there are related party transactions about nursing home services, then we may overstate costs by being unable to address this issue.

[17] See Rau (2017) (https://kffhealthnews.org/news/care-suffers-as-more-nursing-homes-feed-money-into-corporate-webs/) for an interesting investigative piece that provides examples of related party usage.

A different type of cross-subsidisation is primarily used by NFP providers and is based on other related upstream facilities which they may operate. Since nursing homes are downstream of these facilities this kind of cross-subsidisation does not pose a significant challenge to our analysis. This context is still important for understanding the business model of NFP providers, how different it is from FP providers and why NFP providers might offer a higher quality and higher priced product. These facilities are independent living facilities and assisted living facilities.[18] They allow residents to live in a community with some level of supervision. Unlike nursing homes, they do not provide much in the way of medical care. Where medical care is provided, the costs may be partially or fully covered by Medicaid or Medicare. However, the majority of the cost – accommodation costs – are not. This also means that this sector is much less regulated, with little comprehensive data.

Many NFP organisations operate independent living facilities, assisted living facilities and nursing homes, often in close proximity. In these cases, the provider can offer a continuity of care contract or proposition to residents. The resident can enter the provider's care at an independent living facility or assisted living facility, and have the comfort of knowing that their or their partner's nursing home care is sorted if they need it. Data on providers that offer continuity-of-care arrangements are relatively limited, but Zarem (2010) cites that 82% of such providers are NFP and 18% are FP. More recently, Nelson (2018) cites that 78% of such providers are NFP and 22% are FP.

The cross-subsidisation became clear when a CEO of a NFP nursing home told us in an interview that they believed that NFP providers are unlikely to acquire or construct new nursing home facilities, unless they can also acquire or construct an independent living or assisted living facility. Assisted living and independent living facilities are unregulated so we do not have any data about these, but this kind of cross-subsidisation makes sense. Independent living and assisted living facilities mostly take residents who pay the private price out-of-pocket. Also, their costs are likely to be easier to manage than for nursing homes because they don't have to provide as much medical care. Further, cross-subsidisation can also be enabled by residents who place a premium on valuing the security of being able to go to a nursing home in the same community and under the same provider as the independent living or assisted living facility.

This does not mean that the nursing home facility in these arrangements are exclusive to residents of the upstream facilities however. We hand-collected data on whether each nursing home in California in 2018 was likely to be associated with an independent living or assisted living facility. We found that the average and third quartile share of Medicaid payers at nursing homes associated with such facilities is 39% and 66% respectively. By regulation a nursing home which accepts Medicaid residents at all, is not allowed to discriminate in their admission decisions.

[18] Independent living facilities are often referred to as retirement villages.

3 Data

We use three sets of data. Most of the descriptive analysis uses data covering all US states between 2010 and 2018. Structural estimation will focus on resident stays in California from 2000 to 2010.

Resident Data The basis of our resident data is the nursing home Minimum Data Set (MDS). As per federal law (42 CFR §483.20), all nursing homes that are eligible to provide care and be reimbursed by CMS either through Medicare or Medicaid are required to complete assessments about their residents. Assessments are essentially an extensive survey that results in a dataset that provides a comprehensive 'assessment' of the resident's health, mental condition and cognitive abilities. Assessments are conducted upon admission, discharge and throughout the resident's stay on an at least a quarterly basis. This data allows us to construct a panel of resident stays which is the basis of our structural estimation. It also provides zip-codes of where residents previously lived which allows us to construct zip-centroid distances.

Although the MDS also contains information about resident payer-types, it has been noted in the nursing homes literature that the payer-type fields in this data have inaccuracies (Grabowski et al., 2008; Hackmann, 2019; Cheng, 2023).[19] Following the literature, we use Medicare claims data from the Medicare Provider and Analysis Review (MedPAR) files to identify when residents are covered by Medicare. To identify when residents are covered by Medicaid, we draw upon the Medicaid Analytic Extract (MAX) files. For 2001-2005 we have access to the MAX Long Term Care file and for 2006-2013, the MAX Personal Summary file. We also supplement this with data from the Medicare Beneficiary Summary file which we have from 2000-2019.

Facility Data We obtain facility characteristics and location data from LTCFocus who derive their data from the Centres for Medicare and Medicaid Services (CMS) Online Survey, Certification and Reporting database.[20] Since data on private prices are not collected by any regulators we follow the literature and infer private prices by dividing total revenues with total quantity from California nursing homes cost report data (Huang and Hirth, 2016; Gandhi, 2023). We also source facility financial data (costs) from California cost report data.

[19]There does not appear to be a comprehensive understanding about the source of inaccuracies, but there appear to be two types of issues. As described in Cheng (2023) (section B.2) one issue may arise from nursing home uncertainty about the payer-type. A second issue may arise from payer-types not being updated in the data from the admission assessment, even when the payer-type may have changed in a subsequent assessment (Grabowski et al., 2008).

[20]LTCFocus is a Gerontology and Healthcare Research center at Brown University. LTCFocus Public Use Data is sponsored by the National Institute on Aging (P01 AG027296) through a cooperative agreement with the Brown University School of Public Health.

Geographic and Demographics Data We source our demographic and geographic data from various datasets from the census bureau. It is worth noting that demographic data, including populations by age at the zipcode level only exist in the 2000 and 2010 decennial census and from the American Community Survey from 2010 onwards.[21] These data exist at the county level for our whole sample period.

4 Motivating Evidence

4.1 Quality Provision

We take total nursing hours per resident-day as the quality choice of interest, following the previous literature (Hackmann, 2019; Lin, 2015, 2014; Friedrich and Hackmann, 2021). We interpret nursing hours per resident-day as a product attribute rather than an input. This reflects nursing hours being the most important determinant of resident quality outcomes and that in nursing homes, nurses play a broader role than just the delivery of medical care - they help residents with their daily lives.

Table 2, shows that FP providers are associated with lower nursing hours across all nursing types. The first row of Table 2 presents differences in unconditional means of nursing hours per resident day for each nurse type. Reading the columns from left to right, the nursing types go from higher skill, higher qualification to lower skill, lower qualification. FP providers use fewer nursing hours across both registered nurses and licensed practical nurses. They also use fewer certified nursing assistants, thus the scope for substitution away from higher skilled labour to lower skilled labour is limited. The second row presents coefficient estimates of the FP indicator when nursing intensities are regressed on a FP indicator along with facility controls and time and zip fixed effects.[22] We see the same pattern even allowing for time-invariant differences across zipcodes. In appendix A.2, we use the same specification to explore the private prices set by nursing homes and find that NFP nursing homes in California also set higher private prices.[23]

These results are consistent with our interpretation that NFP providers offer a higher quality, higher priced product, while FP providers offer a lower quality, lower priced product. To disen-

[21]Strictly speaking, these are termed as zip-code tabulation areas by the U.S. Census Bureau, since data are not directly collected at the zipcode level.

[22]We use zip fixed effects instead of facility fixed effects because we think it's reasonable to treat the FP status of nursing homes as exogenous and compare across FP and NFP providers in the same market. As described in section 2, the business models of NFP and FP providers are different and it seems unlikely that these would be changed from year-to-year to attain different benefits. This is also reflected in our data as it is uncommon for the FP status to change - see table 1).

[23]Private prices are sourced from California cost reports, thus the sample used is different to the all states data used here.

tangle whether these choices are driven by preferences for quality, differing costs and, or differing nonpecuniary motives we will turn to a structural model of nursing home demand and supply.

Table 2: Differences in Nursing Inputs

Hours/ resident-day	Registered Nurse	Licensed Practical Nurse	Certified Nursing Assistant
FP (Diff. in Means)	-0.322	-0.083	-0.380
FP (Regression)	-0.200	-0.055	-0.308
	(0.009)	(0.009)	(0.012)
Mean of dep. var	0.492	0.853	2.26

Note: These results use yearly facility-level data across 2010-2018 and all states. Controls include facility size (in beds), aggregate assisted daily living score, which measures how dependent the population is on carer support for daily needs, aggregate case mix index, which measures how much medical care the population requires and proportion of Medicaid and Medicare residents in the facility. Year and zip fixed effects are included with standard errors clustered at the facility-level.

Throughout this paper we focus on a nursing home's choice of nursing hours rather than quality outcomes. There are two reasons for this. First, comprehensively and accurately measuring quality outputs is difficult. Recent literature has made progress on this issue (Cheng, 2023; Einav et al., 2022); however, the quality measurement in these works are ultimately based on short-term mortality relating to a nursing home's role as a rehabilitation center rather than as a long-term care provider. Second, the role of costs will be important in the structural model and counterfactuals. There is a clear relationship between inputs and costs, less so for outputs and costs. Still, Grabowski et al. (2013) find that NFP nursing homes provide better-quality outcomes than their FP counterparts.

4.2 Access to Providers and Patterns of Provision

From Table 1, we already know that FP providers serve a large proportion of the market and supply many beds. Here, we focus on the fact that FP providers systematically serve different markets and different residents compared to their NFP counterparts. Table 3 column 2 presents the results of regressing the number of NFP providers minus the number of FP providers in the same zip-code regressed on zip-level demographics. NFP providers are more prevalent in richer zipcodes and less prevalent where there are larger populations of older people.

Our story for this result is that NFP providers serve a product better suited to private payers, while FP providers serve a product better suited to Medicaid payers. To build support for this interpretation we turn to columns 3-6 of table 3. Here, we compute the proportion of residents of a given payer-type amongst the population of all residents at all nursing homes of a given firm type in a zip-code and regress that on zip-level demographics. We find that both FP and NFP nursing homes serve more private-pay residents in markets with higher socioeconomic status and more Medicaid residents in markets with lower socioeconomic status.[24] A 1% increase in median income is associated with approximately 10 percentage points more private payers and a decrease in Medicaid payers of a similar magnitude. These facts suggest that the spatial distribution of payer-types is correlated with socioeconomic characteristics.

To complete the story, we also need to show that FP providers prefer serving Medicaid residents and that NFP providers prefer serving private-payers.[25] In other words, that Medicaid residents are more profitable for FP providers and private-payers are more profitable for NFP providers. This requires estimation of a structural model of nursing home demand and supply, since marginal costs are not directly observed. To be clear, we do not have in mind a model where providers choose where to locate. As shown in table 1, entry is relatively rare compared to exits. Rather, the average facility is relatively old,[26] and location determines which facilities are more likely to stand the 'test of time'.[27]

[24]The positive sign on the log 65 plus coefficient for private payers likely reflects a mechanical effect, that private payers are older. We observe that 80% of the private payers in our California sample are 65 or older. Younger residents at nursing homes are much more likely to be covered by Medicaid or Medicare. The former can include young people who are disabled, while the latter would include people who are receiving additional rehabilitation at a nursing home.

[25]In theory, nursing homes could selectively admit residents to serve more of their preferred payer-type. However this is prohibited by regulation. Gandhi (2023) studies selection admissions by nursing homes. Our interpretation of his work is that the regulations are effective. He does find evidence that nursing homes undertake selective admissions and in particular discriminate against Medicaid-eligible residents. However, as we discuss in appendix B.3, the magnitude of selective admissions which Gandhi finds is quite small. Moreover, selective admissions do not affect the arrival rate of preferred payer-types. For these reasons, we regard location patterns as more important and do not deal with selective admissions in this paper.

[26]To the extent that most facilities were constructed many years, or even decades before our sample, we are unable to think about endogenous location decisions.

[27]Another potential reason for the observed NFP location patterns is that NFP providers may find it easier to secure donations and funding in wealthier locations. In interviews with industry members we heard that the role of donations and funding is relatively limited. In appendix A.3, we verify this claim and show that most NFP nursing homes do not receive any donations, including those in higher income markets.

Table 3: Location patterns

Dep. Var	#NFP - #FP	Prop. Private Payers Served by NFP	Prop. Private Payers Served by FP	Prop. Mcaid Payers Served by NFP	Prop. Mcaid Payers Served by FP
log(Median Income)	0.167	0.108	0.080	-0.121	-0.141
	(0.016)	(0.013)	(0.007)	(0.018)	(0.011)
log(50-64)	-0.060	-0.107	-0.032	0.094	0.052
	(0.005)	(0.010)	(0.005)	(0.013)	(0.009)
log(65 plus)	-0.069	0.126	0.033	-0.150	-0.072
	(0.005)	(0.010)	(0.005)	(0.014)	(0.008)
Share Black	-0.030	-0.046	-0.043	0.108	0.077
	(0.037)	(0.035)	(0.011)	(0.046)	(0.018)

Note: These results use facility-level data across 2010-2018 and all states. All specifications include year and county fixed effects as well as controls for the log of the zip area and proportion of the zip which is urban. Standard errors clustered at the county level.

Whereas table 3 studies patterns relating to access from an across-market point of view, we show in table 4 that similar patterns exist within-markets. Table 4 presents the results of regressing the proportion of a given payer-type in a nursing home's population on a FP indicator, facility controls and year and zip fixed effects. Crucially, the inclusion of zip fixed effects means that we are using within-market variation to identify the FP coefficient. Even in markets where both providers of both types are operating, we see that FP providers serve larger proportions of Medicaid payers and lower proportions of Medicare and private-payers compared to their NFP counterparts. To the extent that Medicaid residents cannot afford to pay out-of-pocket, we interpret these results to suggest that even when NFP providers are located in markets with lower socioeconomic status, they still tend to serve more well-off residents. These results are again consistent with the market segmentation story where the NFP providers' product of higher quality is more suited to private payers and FP providers' product of lower quality is more suited to Medicaid payers.

Table 4: Proportion of payer-types served

	Prop. Medicaid Payers	Prop. Medicare Payers	Prop. Private Payers
FP	0.140	-0.060	-0.080
	(0.004)	(0.003)	(0.003)
Mean dep. var	0.60	0.15	0.25

Note: These results use facility-level data across 2010-2018 and all states. Controls include facility size (in beds), aggregate assisted daily living score, which measures how dependent the population is on carer support for daily needs, aggregate case mix index, which measures how much medical care the population requires. All specifications include year and zip fixed effects. Standard errors clustered at the zip level.

4.3 Entries, Exits and Takeovers in California

Bans on some or all FP providers will reduce the number of nursing homes and by itself reduce welfare. But we should also be interested in further extensive margin changes. In response to fewer providers in the market from a ban, new NFP providers could enter. A fair evaluation of a ban should capture these effects. However, as we saw in table 1, entry activity is limited. This suggests that the fixed costs of constructing and certifying a new facility are likely to be large. Since the limited entries happen even with a larger rate of exits, this is likely to hold even in a counterfactual where some nursing homes are banned. Motivated by recent concerns about takeovers and acquisitions,[28] we consider the prevalence of takeovers. Lack of transparency in ownership is notorious in the nursing homes industry.[29] Our facility-level data assigns facility IDs based on location rather than facility-owner, thus to address this gap we undertook a hand-coding exercise to identify likely changes in ownership. This was done on the basis of changes in facility name, administrator, profit-status and googling facility histories. We summarise the results below:

[28]Gupta et al. (2021) find that the wave of private equity takeovers increased mortality in nursing homes. Harrington et al. (2017) notes that these patterns of FP takeovers are common in many countries and are often associated with quality deficiencies.

[29]This has led to recent improvements in regulation of ownership, with the Centers for Medicare and Medicaid services requiring more data and disclosures about nursing home ownership (Centers for Medicare and Medicaid Services, 2023)

Table 5: Entries, exits and takeovers in California, 2000-2018

	New facility	Facility closure	Own type takeover
FP	36	130	523
NFP	13	117	4

Note: There are very few across firm type takeovers. 21 NFP becoming FP and 2 FP to NFP.

The relative magnitude of takeover versus entry activity amongst FP providers is striking. In appendix A.4, we check that our hand-coded takeovers do reflect true takeovers by looking for evidence of changes in management. We find that there is a significant shift in the payer-type population of FP facilities which undergo takeovers, suggestive of a change from management. Gupta et al. (2021) explicitly study takeovers by private equity. While they do not look at changes in payer-type populations, we do find similar results on nursing hours and costs. To be clear, we do not regard the effect of the takeover as important (except that there is one) as our counterfactual focuses on FP facilites being taken-over by NFP providers. In-sample takeovers are of little relevance except that they highlight that the relevant margin of extensive margin activity for the counterfactual should be from takeovers rather than the construction of new facilities.

5 Structural Model

There are two reasons why we develop and estimate a structural model. First, we are interested in studying counterfactual outcomes when we vary the number of NFP and FP providers. To the best of our knowledge, there are no satisfactory policy changes with exogenous variation in the number of NFP versus FP providers which would allow us to explore such counterfactuals. Second, our motivating evidence illustrates some interesting patterns with regards to quality, access and provision across FP and NFP providers but cannot explain why. A sufficiently flexible structural model is required to coherently examine a range of potential causes. In addition, we showed that NFP providers are more prevalent in markets with higher socioeconomic status and FP providers are more prevalent in markets with lower socioeconomic status. We also showed that providers serve more Medicaid and less private payers in markets with lower socioeconomic status and vice-versa for markets with higher socioeconomic status. To complete the argument that the location patterns are explained by NFP and FP providers preferring particular payer-types, we need to examine the margins that providers make on each payer-type. We estimate these with a structural model.

The core of our model is a static oligopoly game where providers compete by choosing their private price p_{jt} and quality (total nursing hours per resident-day) TN_{jt}[30]. Markets will be defined by metropolitan statistical area-year pairs in California from 2000-2010. Providers draw their cost and demand shocks before setting prices and quality, and these are all observed by providers, thus the equilibrium concept is a Nash equilibrium. Following this, residents choose the nursing home which maximises their utility.

Before spelling out the details, we provide a quick preview to highlight the important features. Providers have standard motivations from profit, but they may also have nonpecuniary motives. Specifically, we allow for providers to explicitly place value on the quantity-of-care they serve, and this will be a parameter to be estimated. If residents value quality for example, then a nonpecuniary motive for quantity-of-care served could lead to the provider choosing higher quality as well. This necessitates the estimation of demand. Provider costs are also relevant. Different payer-types may have different costs (and margins) and these costs may also differ by firm-type. Whether a firm would prefer to choose a higher quality depends on in addition to their objective, whether higher quality attracts more desirable, higher-margin residents. This justifies the estimation of a rich supply model and can also explain the market segmentation we document. Modelling payer-type margins not only allows us to explain quality choices, but also the patterns of access we document. In addition to choosing prices and quality to target particular payer-types, firms in markets with more of the desirable payer-types will be relatively profitable and more likely to operate there.

6 Demand

We adopt a similar model of demand as Hackmann (2019). We model a resident i's decision of which nursing home j to choose to maximise their daily utility.[31] Since some residents never pay the private-price, while some do, we distinguish resident utility by $y \in \{\text{non-priv}, \text{pays priv}\}$. For brevity we will call y a payer-type as well when there should be no ambiguity. Then an individual's utility is:

$$u_{ijt}^{y} = \beta_{1i}^{d} D_{ij} + \beta_{2i}^{d} D_{ij}^{2} + \beta^{I} \mathbf{1}(j = j(t-1)) + \beta^{NFP} NFP_j + \beta_i^{TN} TN_{jt} + \beta_i^{p,y} p_{jt}^{priv} + \xi_{jt}^{y} + \varepsilon_{ijt}$$

[30] We model providers who choose their quality by choosing their total nursing hours per resident-day. This follows previous structural work such as Hackmann (2019) and Lin (2015) and a broader literature on the effects of nursing inputs on quality outcomes (Lin, 2014; Friedrich and Hackmann, 2021). We also follow the literature and restrict nursing hours to focus exclusively on higher-skilled nurses - registered nurses and licensed practical nurses but not certified nursing assistants.

[31] Residents implicitly choose the nursing home which maximises the utility of their entire stay which is the product of their daily utility and length of stay. Implicit in this, we assume that length of stay is exogenous. On the demand side this means that residents do not evaluate how their length of stay might change if they chose a different nursing home. On the supply side, this means providers' choices cannot affect the length of stay through their quality choices.

Coefficients which vary by individual are of the form:

$$\beta_i^k = \beta^k + \sum_r z_{ir}^k \beta_r^k$$

With $\beta_i^{p,\text{non-priv}} = 0$.

Residents have preferences for distance D_{ij} which are allowed to be nonlinear. We allow preferences for distance to vary by age of the resident on entry, realised length of stay and whether the resident has a legal guardian who is not themselves - this could be a family member or a lawyer.[32]

We allow for inertia in demand through $\mathbf{1}(j = j(t-1))$, reflecting high switching costs once a resident has moved into a nursing home. Since our data span a long period (2000-2010), many residents undergo multiple stays. Inertia could introduce dynamic considerations however, we assume that residents are myopic so that they do not take into account how inertia could affect their future decisions. The presence of inertia could also introduce invest-harvest incentives for nursing homes to price and choose quality dynamically. We are not aware of any papers or reports with these concerns, thus we abstract from these possibilities in modelling.

We allow residents to have preferences for NFP providers. This preference captures the idea of NFPs as solving information asymmetry problems. If quality is unobserved or hard to verify, residents may prefer NFP providers as their incentives may be more closely aligned with their own residents' (Weisbrod, 1988). Although residents in our model observe a nursing home's total nursing hours per resident day, there may be other aspects of quality that a resident has imperfect information about. For example, this could include how well-trained nurses are for the nursing home. Differences in quality that are unobserved to the econometrician and systematic across NFP versus FP may also be captured in this preference. For example, our data on nursing homes does not include information about the quality of the accommodation. If NFP provide better-quality accommodation on average than FP providers, and residents value this, it would be picked up in this preference for NFP providers.

We allow preferences for quality to vary by whether the resident is a private, Medicare or Medicaid payer, length of stay and a large range of other demographics.[33] Preferences for price vary with whether a resident pays the private price on entry, their age, their length of stay, whether they

[32]For length of stay, it would be ideal to use an anticipated length of stay instead of actual length of stay to correspond more closely with a resident's decision making. While the MDS2.0 contains an anticipated stay variable, we find that there are too many missing cases for this to be usable. We incorporate realised length of stay by bucketing stays into 3 groups. Stays within 30 days, stays from 30-100 days and stays of 100 days or over. The 30 day choice coincides with bucketing used for the anticipated length of stay in the MDS data, while the 100 day choice corresponds to the Medicare limit.

[33]This includes age, a resident's depression rating scale score - a measure of mental health, cognitive performance scale score, assisted daily living score, clinically complex scale score, whether they have alzheimer's, are female, are nonwhite, have at least a bachelor's education and whether they have a legal guardian who is not themselves.

have at least a bachelor's degree and whether they have a legal guardian who is not themselves. ξ_{jt} are the unobserved demand shocks and ε_{ijt} are the standard type 1 EV idiosyncratic demand shocks. For estimation we can define nursing home mean utilities:

$$\delta_{jt}^{\text{priv}} = \alpha^{TN} TN_{jt} + \alpha^{p,priv} p_{jt}^{\text{priv}} + \alpha^{NFP} NFP_{jt} + \xi_{jt}^{\text{priv}}$$
$$\delta_{jt}^{\text{non-priv}} = \alpha^{TN} TN_{jt} + \alpha^{NFP} NFP_{jt} + \xi_{jt}^{\text{non-priv}}$$

Although markets are defined by metropolitan statistical areas, for tractability, we restrict a resident's choice set to all nursing homes within 50 miles of their prior residence. As we saw in figure 1 this allows us to capture a majority of residents, approximately 75%. However, there is a tail of residents which are omitted from estimation. We also make two types of exclusions for facility-years, where excluded facility-years are pooled into an outside option with utility normalised to 0.[34] First we exclude facility-years if there is a missing observable (assuming they are missing at random). Second, we drop a facility-year if there are less than 10 stays.

Our rich supply model necessitates some choices on the demand side. We defer the bulk of this discussion to when we introduce supply. For now, the goal of these choices is to enable us to retain as many resident-stays across as many facility-years for the estimation of supply. First, while we model nursing homes as choosing and committing to their quality and private price choices each year, individual nursing home stays need not adhere to a calendar year and 22% of stays in our data overlap with at least 1 year. We assume that the nursing home commits to the same price and quality throughout a resident's stay. That is, in subsequent years the nursing home's pricing and quality choices apply only to residents entering in that year. Since residents only decide at the start of their stay, allowing for prices and quality to change for the resident in subsequent years would result in having to treat the resident as locked in for subsequent years.[35]

Secondly, although Private-pay, Medicare and Medicaid make up the vast majority of residents, some residents are of a different payer-type altogether. Two examples of such payer-types are those who access nursing home care through Veteran Affairs or a Medicare/Medicaid managed care program. The facility data reports that approximately 8% of resident-days are from such payer-type days. In both these cases, residents face restrictions on their choice set which we do not observe. We also don't know the prices that nursing homes get from these residents. For these reasons, we do not model demand from these residents and treat them as exogenous on the supply side.

We estimate demand using a two-step procedure following Hackmann (2019) and Olenski (2022). In the first step, we recover $(\delta_{jt}^{y}, \beta_i^k, \beta_{1i}^d, \beta_{2i}^d, \beta^I)$ by Maximum likelihood. As is standard

[34]Note that the universe of residents are those who choose a nursing home (but not necessarily one we observe). That is, the outside option does not include choices made by old people who choose not to go to a nursing home.

[35]Since private price setting is largely unregulated, and nursing homes do not typically advertise their private price rates, to the best of our knowledge it is not clear what happens in practice.

in demand estimation, conditional on δ^y_{jt}, the remaining variation in price and quality is exogenous. In the second step, we recover the remaining mean preference parameters with a generalised method of moments estimator. Private prices and quality are correlated with ξ^y_{jt} thus we need to instrument for them.

We include in our instruments a number of excluded cost-shifters: zip-level house price indices, zip-level active nurses and the distance weighted average proportion of Medicaid and Medicare residents across facilities. House price indices are a stand-in for property input costs. Active nurses is constructed from Californian nursing license board data and is the number of active nurses who have a home address in the corresponding zip. This captures the supply of nurses in a location which should in turn affect input prices. The distance weighted average proportion of Medicaid and Medicare residents are also regarded as cost-shifters. Different groups of residents have different care needs and thus have different costs.[36] Since they are market level shifters they should not be correlated with ξ^y_{jt}. Finally, we also add three instruments based on rival characteristics. The distance-weighted total number of NFP and FP providers and the distance-weighed sum of total capacity. To address the concern that these cost shifters and rival characteristic instruments could be spatially correlated with demand shifters we partial out zip and year fixed effects from the instruments.[37]

Table 6 presents key parameters in our demand estimates. A full list of parameter estimates with demographic interactions can be found in table 15 in the appendix. We summarise the variation in distance, price and quality elasticities in figure 2.

[36]This is indeed the case in our structural estimates.

[37]One concern could be for example that we documented in the motivating evidence that the proportion of private-payers is higher in higher-income areas.

Table 6: Main demand estimates

Coefficient	Estimate
Distance (miles)	-0.1650
	(0.00004)
Distance squared	0.0016
	(0.00002)
Inertia	5.4225
	(0.00125)
Total Nursing	1.3341
	(0.01940)
Total Nursing x Medicaid Payer	-0.2100
	(0.00003)
Total Nursing x Medicare Payer	-0.0020
	(0.00000)
Private Price	-0.0395
	(0.00032)
NFP	1.2705
	(0.01293)

Note: These results use individual-level data from 2000-2010 in California. Standard errors bootstrapped with 250 iterations.

The signs and magnitudes of our demand parameter estimates make sense. Our distance parameter estimates suggest that residents dislike being at a nursing home far away from their prior residence, although the dislike diminishes with distance. Figure 2 shows the distribution of distance elasticities.[38] The average is -0.75. The spike in the bin at 0 arises because our distances are based on zip-centroids and a substantial fraction are at a nursing home which shares the same zip as their prior residence. Our distance elasticities are considerably smaller than those found in Gandhi (2023) and Olenski (2022). This is likely because our data contain residents who often travel quite far, as figure 1 suggests.[39]

The inertia parameter indicates that residents have a strong preference for staying at the same nursing home if they have multiple nursing home stays. Residents value quality. Figure 2 also

[38]The distribution is truncated on the right at 3, approximately 1% of distance elasticities exceed 3.

[39]Although Gandhi (2023) studies the Californian market like we do, he limits resident choice sets to 20km from their prior residence and focuses on the years 2004-2006. Olenski (2022) estimates a structural model on nursing homes in Illinois.

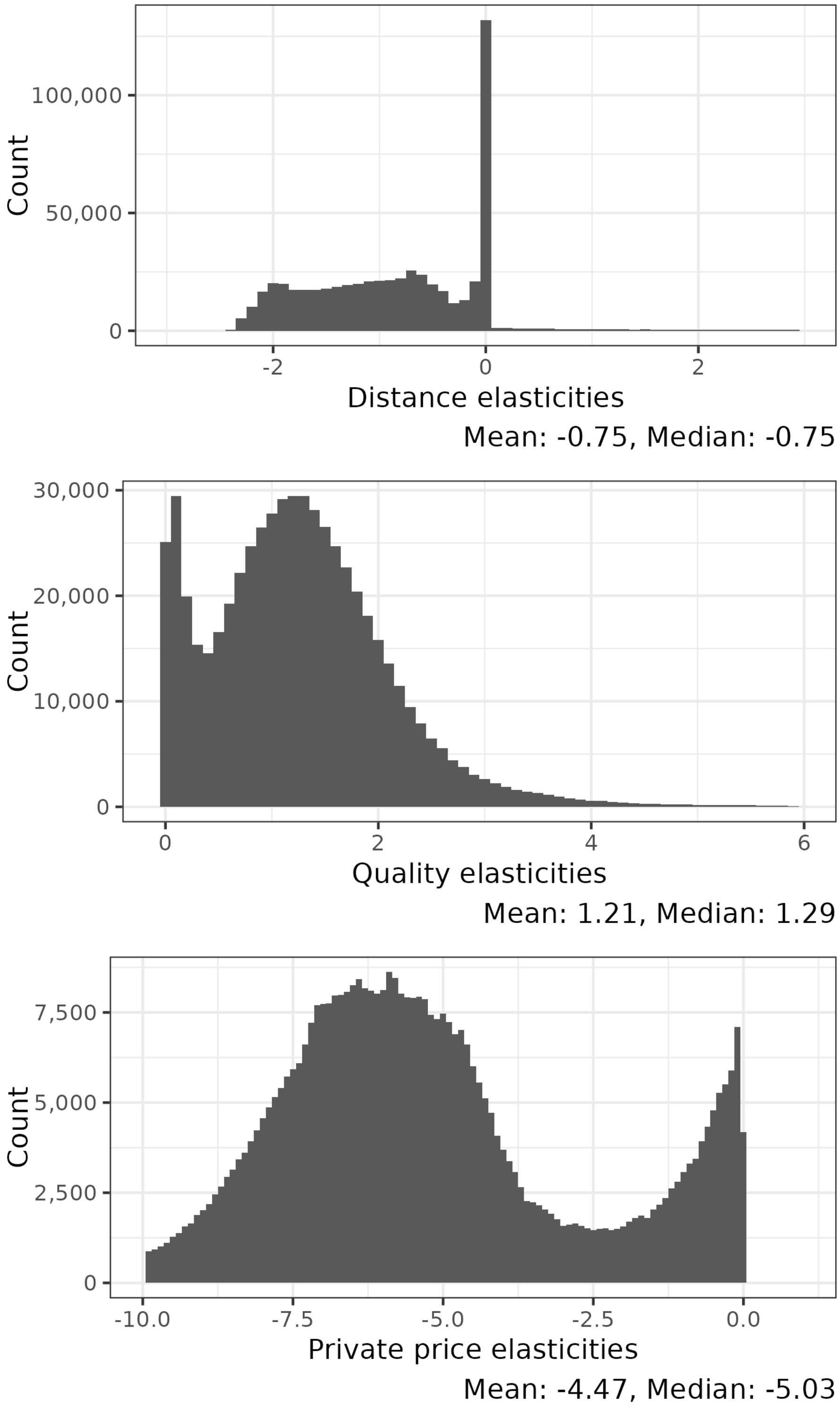


Figure 2: Individual demand elasticities

shows there is significant variation in quality elasticities.[40] From the parameter estimates in table 6, one systematic pattern worth noting is that residents who are a Medicaid payer at the time of entering a nursing home have a lower preference for quality compared to their Medicare and private payer counterparts. This is consistent with NFP providers choosing higher quality to provide a product more suited to private payers. FP providers who serve a product for Medicaid payers, do not have to choose as high of a quality. Our average quality elasticity is roughly comparable to those in Gandhi (2023). Residents dislike the private price if they have to pay. Figure 2 shows that there is significant variation in price elasticities.[41] We find consumers are significantly more price elastic than in Gandhi (2023). Some sources of difference include the inclusion of an inertia parameter and that we use a longer sample which captures more longer stays. Comparing price and quality elasticities we see that residents generally respond more to prices than quality. This is consistent with Cheng (2023) who generally finds that residents undervalue quality provision. Finally, the preference for NFP providers is significant. This indicates that consumers value NFP providers for their motive and/or that there are dimensions about quality not captured in our demand specification which differ systematically across FP and NFP providers which residents value. We return to this point when we examine our supply estimates.

7 Supply

In each market, providers first observe their unobserved demand and cost shocks and then compete by choosing their private (per-day) price and total nursing hours in a static oligopoly. To setup the nursing home's problem we first need to aggregate individual choice probabilities using our estimated demand system into firm quantities. Ignoring the m subscript for brevity, let $q^{\tau}_{jt} := \sum_i s^{\tau}_{ijt} Days^{\tau}_i$ be the quantity of resident-days for each payer-type served, $Q_{jt} = \sum_{\tau} q^{\tau}_{jt}$ be the total quantity of resident-days served across all payer-types and $f \in \{FP, NFP\}$.

In addition, nursing homes also face components of 'fixed' demand. As discussed previously, these arise from stays that overlap multiple calendar years, residents who we dropped as they chose a nursing home more than 50 miles away from their prior residence, and residents who we do not have the data or model to construct choice probabilities for. Let $\bar{q}^{\tau}_{jt}$ and $\bar{Q}_{jt}$ represent fixed demand from such stays. In counterfactuals, these components will remain fixed. $\bar{q}^{\tau}_{jt}$ and $\bar{Q}_{jt}$ are derived from the difference of facility reported payer-day stays and q^{τ}_{jt}, Q_{jt}. With these definitions

[40]The distribution is truncated on the right at 6 (and not on the left), approximately 0.05% of quality elasticities are larger than 6.

[41]The distribution is truncated on the left at -10 (and not on the right), approximately 4% of price elasticities are larger in absolute value than 10.

in hand, the nursing home's problem is:

$$\max_{TN_{jt}, p_{jt}^{priv}} \underbrace{\sum_{\tau=\text{mcaid, mcare, priv,ins}} q_{jt}^{\tau} p_{jt}^{\tau} + \bar{q}_{jt}^{priv} \bar{p}_{jt}^{priv} + \sum_{\tau=\text{mcaid,mcare,ins,oth}} \bar{q}_{jt}^{\tau} p_{jt}^{\tau}}_{\text{Total Revenue}}$$
$$- \underbrace{C^f(q_{jt}^{\tau}, \bar{q}_{jt}^{\tau}, TN_{jt})}_{\text{Total Costs}} + \underbrace{\alpha_Q^f Q_{jt}}_{\text{nonpecuniary motives}}$$

Providers choose their total nursing hours and private prices to maximise profits and the quantity-of-care they provide. Total revenues consist of the revenues from demand which nursing homes can affect and revenues from demand which is fixed. In the first term, the payer-types 'priv' and 'ins' refer separately to payer-days where the resident pays the private price and 'ins' when the resident's stay is covered by long-term insurance. As long-term insurance makes up a small proportion of stays - 6% - we do not model these distinctly and will think of such stays as being funded by a program like Medicare or Medicaid where the resident does not pay the private price.[42]

We separate fixed private quantities from other payer-types to highlight that we treat the price for these quantities as fixed at the observed price in the data. That is, we do not allow the nursing home to internalise the infra-marginal gains or losses from adjusting the private price on the fixed quantities. If we did, then in counterfactuals the firm would always set $p_{jt}^{priv} = \infty$ as the fixed quantities are locked in. In the third term 'oth' refers to other payer-types such as those in Veterans's Affairs, none of which we model in demand.

The parameter α_Q^f governs how much providers of a particular organisation type value providing (non-fixed) quantity in equivalent profits and are parameters to be identified and estimated.[43] They vary by f meaning that a separate parameter for each organisation type will be estimated. For this draft, $f \in \{NFP, FP\}$ meaning that we will only estimate a parameter for all NFP and FP providers in California. Nothing about this method precludes us from a finer partition which we will consider in future drafts.

Given the importance of nonpecuniary motives, we briefly discuss our modelling choices. Papers often capture other motives by assuming that firms care about consumer surplus in addition to profits. We decided against using consumer surplus for two reasons. First, using consumer surplus also implies that firms consider willingness to pay in their nonpecuniary motive. We think it is more plausible that nursing homes, particularly NFP nursing homes, would simply weight residents equally in their nonpecuniary motive. Secondly, interpretation of consumer surplus for both the econometrician and nursing home is not as straightforward as not all residents face the

[42] Analogously, in demand estimation we treat a resident who is covered by long-term insurance as not paying the private price.

[43] Since fixed demand does not respond to prices or quality, it makes no difference whether the quantity includes fixed demand or not.

private price.

Since Newhouse (1970) conceptualised modelling NFP objectives with both quality and quantity-of-care motives, another choice is the lack of a nonpecuniary motive for quality. The challenge is that we cannot separately identify a nonpecuniary motive for quality. To identify the quantity nonpecuniary motive we match simulated variable costs with actual variable costs in the data as we explain shortly. We have not been able to find a suitable set of moments to allow us to identify a nonpecuniary motive for quality as well.[44] A nonpecuniary motive for quantity is still sufficient for our research questions however. Since consumers value quality, we capture the possibility that firms may have a nonpecuniary reason for choosing a higher quality - to serve more residents.

Firm cost functions are as follows:

$$C^f(q_{jt}^{\tau}, \bar{q}_{jt}^{\tau}, TN_{jt}) = \underbrace{(Q_{jt} + \bar{Q}_{jt})(\gamma_0^f TN_{jt} + \gamma_1^f TN_{jt}^2 + \gamma_2^f K_{jt} + \gamma_3^f K_{jt}^2 + \gamma_4^f o_{jt} + \delta^f W_{jt} + \eta_{jt})}_{\text{Costs common across payer-types}} + \underbrace{\sum_{\tau=\text{mcaid,mcare,allpriv}} \phi_0^{\tau,f}(q_{jt} + \bar{q}_{jt}^{\tau}) + \phi_1^{\tau,f}(q_{jt} + \bar{q}_{jt}^{\tau})^2}_{\text{Costs arising from payer-types}} + \underbrace{\gamma_5^f TN_{jt} + U_{jt} TN_{jt}}_{\text{Observed and unobserved quality fixed costs}}$$

Cost functions differ systematically across firm types which allows us to explore differences in firm efficiencies. Some costs are common across all residents, while others are specific to a payer-type. Total nursing is treated as common across payer-types. This assumption is primarily made out of necessity. Specifically, the data do not breakdown nursing hours across payer-types. Thus we will be unable to model variation in quality costs due to variation in payer-type quantities.

We include a nonlinear quality cost term ($\gamma_1^f TN_{jt}^2$) so that there are diminishing returns to quality from cost. Other aspects of common costs include size of the facility, measured by number of beds K_{jt}. We allow for there to be economies of scale in size. We allow for common costs to vary in resident population characteristics W_{jt} (beyond those not captured by differences in payer-type populations). Specifically W_{jt} includes facility population ADL and case-mix index (CMI) averages.[45] o_{jt} represents the proportion of 'other' payer-type days being served at the nursing home.

For identification of supply parameters, we will be matching variable costs as we describe in

[44]One candidate could be the matching of model implied nursing wages and simulated wages. The main problem with this moment however, is that since total nursing hours includes both registered nurses and licensed practical nurses, matching wages in this way would require that all nursing homes of a given firm type use the same mix of registered and licensed practical nurses. If not, then the matching of the actual wage rate is biased by also matching towards the average mix of nurses. In practice, we find this matching to deliver less credible supply parameter estimates. We intend to work on this for future drafts as allowing for a nonpecuniary motive for quality seems important

[45]Case-mix indexes are another way of measuring a resident's medical needs and are directly used for the purposes of calculating facility Medicaid and Medicare reimbursements.

more detail shortly. Matching variable costs means that we need to match quantities perfectly, since otherwise variable costs may differ from differences in quantities rather than differences in true to estimated parameters. As noted previously, there are some residents who receive their funding from government under a program other than Medicaid or Medicare. These residents are 'fixed' – in the way we described previously –, but still contribute to nursing home costs. Finally η_{jt} captures unobserved facility marginal cost shocks.

The second component of costs varies by the quantities of residents across each payer-type.[46] On average different types of payers have different care needs leading to differences in costs. This also accords with our interviews with industry where it was common to see them discuss the 'margin' on each payer-type. We allow for economies of scale in serving each payer-type. This also means that payer-type margins vary at the facility-level. Finally the last term captures observed and unobserved costs only associated with quality. The latter is needed to rationalise a firm's quality choices with the data through the quality first-order condition.

Having described the supply model, we can discuss estimation and identification. It is useful to consider the first-order conditions abstracting away from the cost function:

$$[p_{jt}^{priv}]: \ \frac{\partial}{\partial p_{jt}^{priv}} \left(\sum_{\tau} q_{jt}^{\tau} p_{jt}^{\tau} \right) = -\alpha_Q^f \frac{\partial Q_{jt}}{\partial p_{jt}^{priv}} + \frac{\partial C^f \left((q_{jt}^{\tau} + \bar{q}_{jt}^{\tau})_{\tau}, \eta_{jt} \right)}{\partial p_{jt}^{priv}}$$
$$[TN_{jt}]: \ \frac{\partial}{\partial TN_{jt}} \left(\sum_{\tau} q_{jt}^{\tau} p_{jt}^{\tau} \right) = -\alpha_Q^f \frac{\partial Q_{jt}}{\partial TN_{jt}} + \frac{\partial C^f \left((q_{jt}^{\tau} + \bar{q}_{jt}^{\tau})_{\tau}, \eta_{jt}, U_{jt} \right)}{\partial TN_{jt}}$$

The left-hand side of these first-order conditions are the marginal revenues from adjusting price or quality and are known given our demand system.[47] As usual, we can invert these equations, project them onto the observables and recover parameters with assumptions on the unobserved cost shocks η_{jt}, U_{jt}.

This representation also highlights that α_Q^f can be viewed as rotating marginal revenues outwards. When $\alpha_Q^f > 0$, firms have nonpecuniary incentives for serving a higher quantity and are willing to incur a higher level of marginal cost. Therefore, the identification challenge with α_Q^f is to distinguish between higher levels of marginal cost arising from firms with more inefficient marginal cost function parameters, or firms which care more about providing quantity-of-care. We follow a similar idea as in Hackmann (2019) and Kim (2024) and match the mean of simulated variable costs with the mean of actual variable costs.[48] We match variable costs because unlike those two papers, our cost function exhibits many nonlinearities. Thus, we cannot compute

[46] There is a small abuse of notation here. In the payer-types we do not have 'ins' and 'priv'. Instead we have 'allpriv', this reflects that for cost, we pool the privately insured and out-of-pocket payers into one group of payers

[47] Note that in general, $\frac{\partial q_{jt}^{\tau}}{\partial p_{jt}^{priv}}, \tau = \{mcaid, mcare\}$ need not be 0 due to residents who transition to and from paying the private price.

[48] Constructing variable costs from the data requires taking a stance on what is 'variable'. We use the categories of

marginal costs from data (as say, average variable cost) and directly match marginal costs. Since α_Q^f does not affect variable costs it rationalises the difference between simulated and observed variable costs.[49]

The remaining identification challenges are standard. Since the firm chooses TN_{jt} and p_{jt}^{priv} knowing η_{jt} and U_{jt}, they are likely correlated. Thus we need instruments Z_{jt} which shift TN_{jt} and p_{jt}^{priv} but are not correlated with cost otherwise.[50] With instruments Z_{jt} in hand we can construct the moment conditions $E[Z\eta] = 0$ and $E[ZU] = 0$ for a GMM estimator.[51] We construct the moment conditions separately for each firm type and estimate the supply model for each firm type. This means we do not impose any further parametric structure on how costs between NFP and FP providers can differ.

Our rich cost function specification has many endogenous variables for each moment condition. Accordingly, many instruments are required. We use county-level log median income, log 50-64 population and log 65+ population which we view as excluded demand shifters. The next set of instruments are those relating to competitors. The number of distance-weighted FP and NFP nursing homes, the distance-weighted sum of total beds and distance to nearest nursing home. All of these relate to exogenous characteristics about competitors which are not correlated with the nursing home's own η_{jt}, U_{jt}. These should shift the quantities that the nursing home faces and the quality they choose in response to those exogenous factors.

The final set of instruments relates to discharges to nursing homes from other medical facilities. Discharges to nursing homes from other types of medical facilities are unlikely to be correlated with the nursing home's own η_{jt}, U_{jt}, but shift the quantities they are likely to serve. We use the distance of a nursing home to the nearest hospital, as hospitals can discharge residents directly to nursing homes.

We also look at home-health discharges. Home-health services provide nursing care to residents in their own home instead of at a nursing facility. Since nurses cannot typically be at someone's house 24/7, people who find themselves needing more intensive supervision can be discharged to a nursing facility. We have home health data that provides the total number of dis-

operating expenses by cost center in the cost report data adding the following categories: Skilled Nursing Care, all Ancillary services except Home Health Services and all support services except Administration. We do not include property expenses, interest expenses and provisions for bad debts which are likely to be fixed costs and subject to the tunnelling concerns discussed in Gandhi and Olenski (2024).

[49]Since quality fixed costs are fixed from the perspective of quantity they are also not included in the matching of variable costs.

[50]We treat K_{jt} as exogenous. In the data we observe very few changes in capacity over time. Across all providers and years we only see expansions of capacity in 3.4% of cases and contractions of capacity in 4.4% of cases.

[51]In constructing these moment conditions, it is worth noting that U_{jt} does not show up in the pricing first order condition. Thus for a given guess of parameters, we can compute η_{jt} and then use the quality first order condition to back out the implied U_{jt}

charges to intermediate care facilities or skilled nursing facilities at a facility-year level. This enables us to construct distance-weighted discharges for a particular nursing home. The data we use also breaks down home health quantities by payer-type (private-payer, Medicare, Medicaid), but not specifically the number of discharges to particular nursing homes. Since this directly speaks to our payer-type quantities we also include these distance weighted home-health quantities. All else equal a higher quantity served at a home health facility also results in more discharges.

Table 7: quantity-of-care motive and quality cost parameters

	FP	NFP
Quantity Motive	9.32	32.94
	(5.91)	(9.26)
Quality Cost	1.09	0.59
	(0.45)	(0.42)
Convex	0.09	0.38
Quality Cost	(0.20)	(0.16)
Normalised Quality	0.09	0.75
Fixed Cost	(0.28)	(0.53)
N	7460	886

Note: Parameters can be interpreted in $/bed-day. These results use facility-level data from 2000-2010 in California. Standard errors do not take into account demand parameter uncertainty.

A full table of supply parameter estimates is presented in appendix B.2, we begin here with table 7 which presents estimates of the quantity-of-care motive and quality cost parameters. All of these can be interpreted in terms of dollars per bed-day. The objective parameter estimates indicate that NFP and FP providers value providing an additional bed-day of care at approximately $33 and $9 respectively, although in the latter case the estimate is noisy and not significantly different from 0. These results are consistent with regulations requiring NFP providers to provide public benefits in return for their generous tax treatment.

The result for NFP providers appears to be of a similar magnitude as in Hackmann (2019). Hackmann (2019) considers government and private NFP nursing homes separately and estimates that they act as if they have a marginal cost advantage of $36 and $23 respectively. To gauge the relevance of the $33 estimate, note that the average NFP private price is approximately $188 per bed-day so this represents about 18% of the price. In addition, we can think of this parameter in

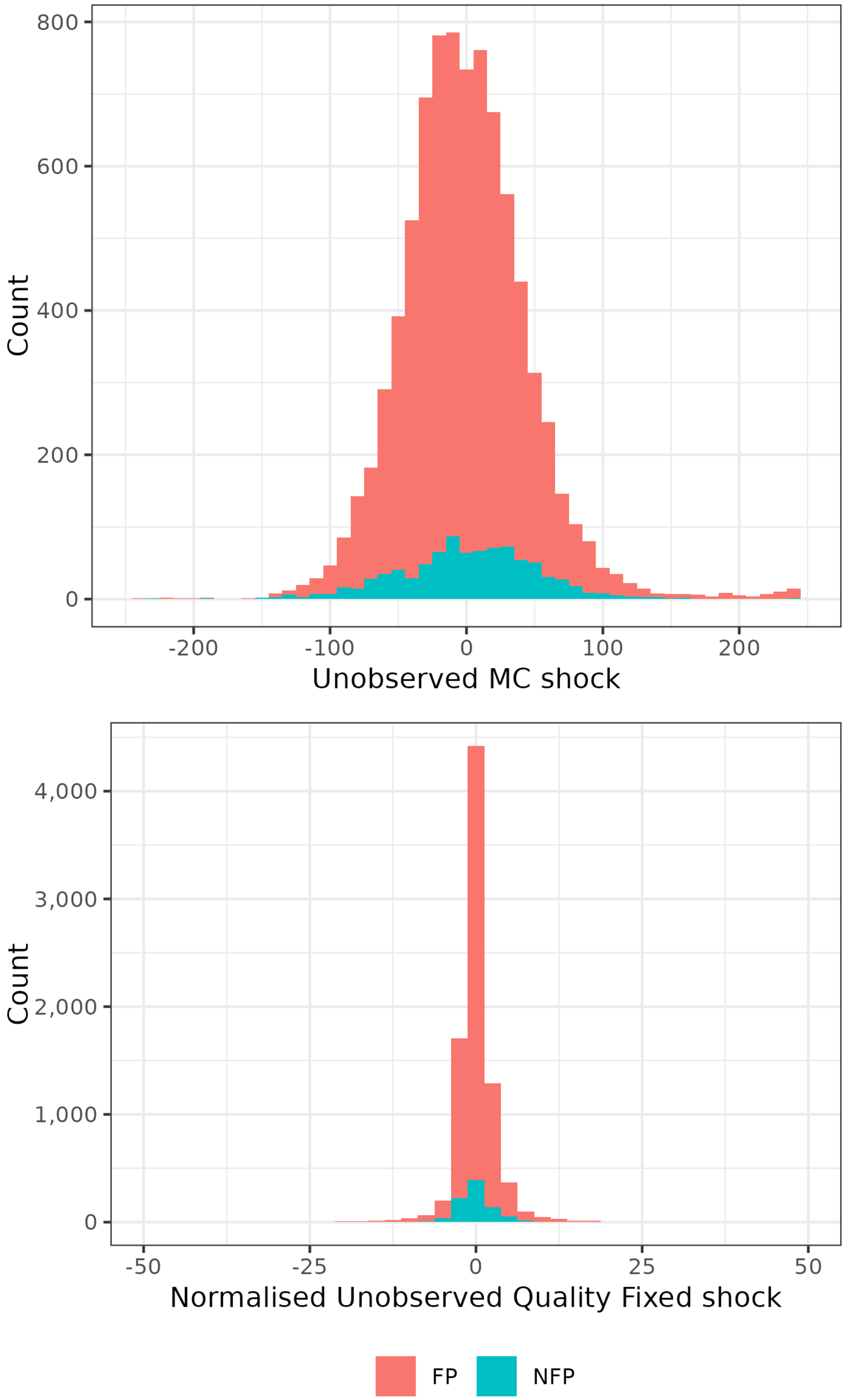


Figure 3: Realised unobserved cost shocks

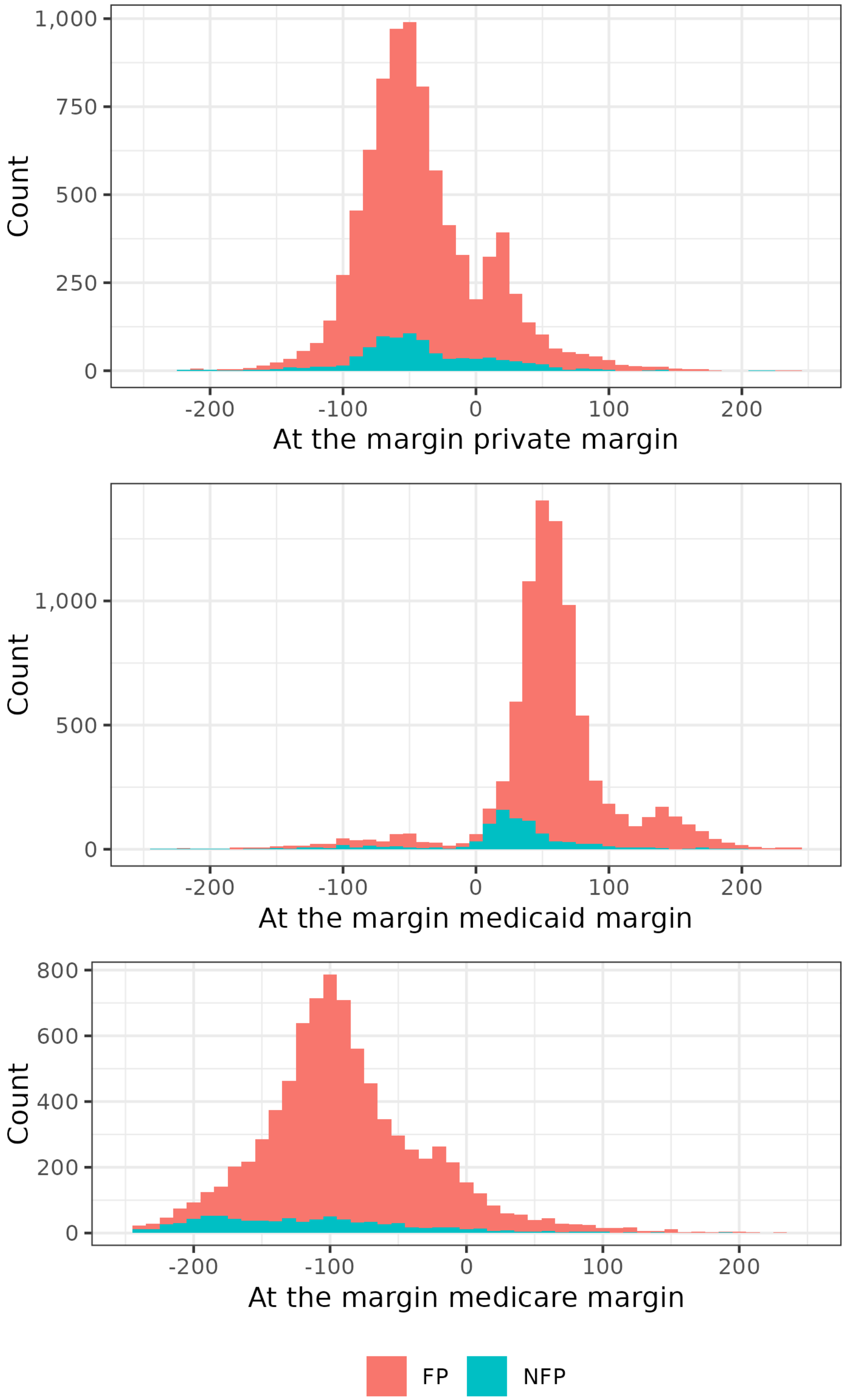


Figure 4: Payer-type margins, at observed quantities

light of the distribution of firm-year level realisations of margins (price minus marginal cost) at the observed quantities in figure 4.[52] Given the relatively small margins NFP providers make, $33 is fairly substantial. We can also think of the parameter as shifting each of the margin distributions for NFP to the right by $33. Since the bins are of width $10, this is roughly 3 bins to the right.

Table 8: Firm-level quality costs

	Mean	25 Pct	Median	75 Pct
Quality Variable Cost				
FP	1.32	0.98	1.18	1.43
NFP	1.66	0.79	1.01	1.34
Average Total Quality Costs				
FP	1.43	1.06	1.28	1.56
NFP	2.71	1.37	1.78	2.44

Note: All costs in $/bed-day. Average total quality costs refer to adding the variable and fixed quality costs and averaging by the firm's quantity served.

Turning to quality costs, since we allow for variable, fixed and nonlinear quality cost components, table 8 summarises the firm-level quality costs. From table 7, we see that while NFP providers have a lower linear quality cost parameter (0.59) compared to FP providers (1.09), the convex component is larger (0.38 versus 0.09). Over relevant ranges of quality however, table 8 shows that generally, NFP providers have lower variable quality costs.

For quality fixed costs, we have normalised the parameter estimates by median total quantities so that they can be interpreted in dollars per bed-day. For FP providers they are not significantly different from zero, while for NFP providers they are positive and relatively large. By computing the average total quality variable cost (averaging over the total quantity served), table 8 shows that overall, NFP providers have larger quality costs.

We think these patterns are consistent with the mix of nurses which NFP providers use which features considerably more registered nurses than FP providers as demonstrated in table 2. Registered nurses can be thought of as something like a 'manager'. They supervise other nurses and have a broader view of residents, while licensed practical nurses are responsible for the execution

[52]The presence of negative margins is reasonable in this setting for two reasons. First, firms are allowed to make negative margins because of the quantity-of-care motive. Second, firms only have one quality and one pricing choice to make, thus there is the potential for across payer-type cross-subsidisation. On average, Medicaid residents account for 62% of bed-days. To this extent, it makes sense that Medicaid margins are generally larger than for other payer-types.

of providing care (Lin, 2014). Higher quality fixed costs are consistent with the usage of more registered nurses. In addition, registered nurses are more costly than licensed practical nurses, which matches with the higher overall quality cost of NFP providers.

A potential direct interpretation of the quality costs are that they should be the average wage paid to licensed practical nurses and registered nurses. In this light, quality costs may be too low given that the average wage in the data is approximately $25 per hour. On the other hand, since we only allow quality costs to enter as a common cost across all payer-types, some of the quality cost could be picked up either in the unobserved quality fixed cost which figure 3 shows some variation for, or the specific payer-type costs.

Table 9: Firm-level payer-type marginal costs

	Mean	25 Pct	Median	75 Pct
Private-payer MC				
FP	209.9	171.8	203.0	242.5
NFP	229.1	196.1	232.9	266.5
Medicaid payer MC				
FP	100.0	64.9	93.7	126.3
NFP	139.1	104.4	141.2	174.4
Medicare payer MC				
FP	273.5	229.7	264.6	306.9
NFP	318.3	279.0	327.2	364.7

Note: All costs in $/bed-day. These firm-level marginal costs include the common cost component.

Next we turn to the payer-type costs. Given that costs are nonlinear with each payer-type quantity, we summarise the firm-level payer-type marginal costs in table 9. The underlying supply parameter estimates can be found in appendix B.2. First, we observe that across FP and NFP providers, Medicaid payers are the least costly, with private payers next and Medicare payers being the most costly. Qualitatively this is in line with the price hierarchy that Medicaid pays the least, followed by private prices and then Medicare prices. When looking at the payer-type margins in figure 4 we see that the hierarchy differs with Medicaid payers being relatively more profitable compared to Private payers and Medicare payers.

To understand these costs and why the relative sizes might be disproportionate compared to prices, we turn to table 10. Here we look at the 'actual' variable costs used in cost matching. The two main categories of cost in that data (making up on average 80% of the variable cost) are the skilled nursing cost center - encapsulating all costs directly attributable to physician and nursing care provided to residents and, what we call the non-nursing cost center which includes costs due to general sanitation and laundry of the facility, dietary fulfilment and resident non-medical activities. We regress those costs on a NFP indicator and each of the payer-type quantities and include a specification where we use county and year fixed effects. We do not attach a causal intepretation to this table, but it does illustrate the variation in the cost matching moments.

One fact that we can see is that the cost of a nursing home associated with more Medicare residents is dramatically higher than for other types of residents. For example, for the skilled nursing cost center, with county and year fixed effects, an increase of one Medicare bed-day is associated with an increase of \$123.26 in additional variable costs for a FP nursing home and \$123.26 + \$61.60 = \$184.86 for a NFP nursing home. A similar pattern is observed for non-nursing costs. This likely reflects the heightened medical and care needs associated with Medicare residents and explains why we find Medicare residents to be particularly costly as well.

Turning to Medicaid margins versus private-pay margins, table 10 suggests that it's unlikely that cost matching moments alone can explain why our model finds that Medicaid payers are much less costly than private payers. We think that these results may arise because without nursing home fixed effects, our estimation uses across-nursing home variation to identify parameters. Nursing homes with many private payer residents compared to those with few may have significantly higher costs arising from differences in quality other than the nursing hours we consider. The use of nursing home fixed effects would restrict the amount of instruments available for use as we would need instruments that have sufficient variation at the facility-level, of which there are not many.

Next, turning to comparisons across FP and NFP providers, we find that FP providers generally have lower marginal costs across payer-types. For private payers the difference seems to be approximately \$20-30, for Medicaid payers the difference seems to be approximately \$40-50 and for Medicare payers the difference seems to be approximately \$50-60. To the best of our knowledge, there are no other papers which study whether FP providers have more efficient cost functions than their NFP counterparts. Lu and Lu (2021) study conversions from NFP to FP nursing homes and find that converted FP nursing homes are able to reduce costs by reducing nursing administration costs which is consistent with some FP providers having more efficient cost functions.[53]. In the absence of other empirical evidence, we can apply the framework of Hart et al. (1997) who argue that government employee incentives to reduce costs are weaker than for a private firm as they do not appropriate all the gains of their efforts. Around 20% of our NFP providers are publicly owned. For the remainining 80% a similar argument applies. NFP providers are required to

[53] The generalisability of Lu and Lu (2021)'s finding is unclear. This is because their identifying variation is based on nursing homes which convert from NFP to FP, which they suggest are often 'failing' NFP nursing homes.

reinvest any profits back into the organisation, and regulation works to limit the ability of firms to distribute profits through higher wages. Thus, NFP employees will also be unable to appropriate additional profits from cost reduction.

Still these cost differences are large, thus it's worth exploring if there are any other systematic factors contributing to them. Returning to table 10, we see cost differences in the variable cost data as well. NFP on average incur approximately \$500,000 to \$665,000 per year more than FP in the skilled nursing cost center and approximately \$200,000 more in non-nursing expenses. Adding these up (\$700,000 to 865,000) and dividing by the average total bed-days a NFP serves, these differences amount to approximately \$25-30 per bed-day which explains a significant portion of the differences in payer-type costs between FP and NFP providers. While some of these cost differences are likely attributable to differences in efficiencies between FP and NFP providers, this analysis suggests that a large proportion of the cost differences arise from unobserved and/or unmodelled differences in quality, consistent again with NFP providers serving a higher priced, higher quality product more suited to private payers and residents with stronger quality elasticities.

In terms of the difference from the skilled nursing cost center, recall that the quality measure we use includes only nursing hours from registered nurses and licensed practical nurses. As table 2 shows, certified nursing assistants (CNA) play a significant role, and that NFP providers choose more CNA nursing hours per bed-day of 2.26 versus 1.88 for FP providers. CNAs do not show up in our cost function explicitly but are a part of variable costs in the data through the skilled nursing cost center, so this is likely to influence the difference in costs between NFP and FP providers.

Secondly, the fact that NFP providers incur higher non-nursing costs might suggest that NFP also provide higher non-medical quality than their FP counterparts. For example cleaner facilities, better food and more social activities for residents. These are not explicitly accounted for in the cost function but are a part of the variable costs we match with. Overall, we interpret differences in costs between FP and NFP as attributable to differences in different dimensions of quality. Another reason we find this plausible is that it is consistent with the NFP business model of operating upstream facilities (independent living and assisted living facilities) whose residents mostly pay a private price. Quality should be especially important for those facilities for attracting residents who have more outside options, for example staying at home. It seems reasonable to think of similar quality choices applying to the nursing home facility.

While these data suggest that CNAs and non-medical quality might be important we do not model them explicitly. In the case of CNAs, we did not want to introduce further endogenous variables and we found that pooling CNAs with registered nurses and licensed practical nurses led to implausible quality preference estimates. For non-medical quality, the issue is that we do not observe the underlying inputs at all. Still, these factors are accounted for in costs indirectly through cost matching as we just described. On the demand side, they are captured by the preference for

NFP providers which we found to be significant materially and statistically.

Table 10: Factors driving cost differences

Coef	Skilled Nursing Cost Center			Non-Nursing Cost Center		
Intercept	26.01	4.59		9.10	2.18	
($000,000)	(0.15)	(0.25)		(0.05)	(0.09)	
NFP	0.31	6.64	5.01	1.47	2.32	2.00
($000,000)	(0.46)	(0.67)	(2.82)	(0.16)	(0.24)	(0.84)
Q Private		35.33	82.09		11.67	29.56
		(2.25)	(3.08)		(0.80)	(1.12)
Q Mcare		178.37	123.26		48.16	27.73
		(3.30)	(7.68)		(1.17)	(2.97)
Q Mcaid		51.99	62.05		18.34	21.89
		(0.77)	(4.68)		(0.27)	(0.74)
NFP x Q Private		-18.68	-27.44		1.07	-4.17
		(5.13)	(10.53)		(1.83)	(4.18)
NFP x Q Mcare		110.14	61.60		59.59	44.19
		(16.64)	(33.17)		(5.93)	(11.98)
NFP x Q Mcaid		-4.45	2.45		-1.89	0.11
		(2.34)	(8.70)		(0.83)	(3.89)
County + Year FE			X			X

Note: All costs in $/bed-day unless otherwise specified. These results use facility-level data from 2000-2010 in California.

According to our supply estimates many nursing homes make a loss. Specifically, approximately 71% and 38% of NFP-year and FP-year cases respectively, record a loss. Taking into account, the quantity-of-care motive 65% and 34% of NFP-year and FP-year cases still have a total-objective less than 0. We think this is a problem and will work on this for future drafts, however, it's important to also note that going by the cost report data alone, 77% of all firm-years make losses which is significantly more than what we estimate. There is good reason to think that a significant proportion of these are true losses given the cross-subsidisation involved in the market.

Model Discussion

Identification of supply parameters relies on the inversion of first-order conditions being correct. Or, in other words, that the supply model is correct. This is especially so for the quantity-of-care motive parameter since it rationalises the difference between observed and model simulated variable costs. Here, we discuss two threats to our supply model.

The first threat relates to incentives for nursing homes to price dynamically because of capacity constraints.[54] Nursing homes may take into account the option-value of empty beds (for serving a more profitable resident) in their pricing and quality choices. We consider specifications of supply in appendix B.3 which allow for these forces. We find no evidence to suggest that nursing homes set prices and quality to take into account potential opportunity costs or option-values of empty beds.

The second threat is that, FP providers are typically part of a large chain. FP nursing homes in the same chain that are close enough may have smaller incentives to compete which could also cause issues for our inversion. Unfortunately, as chain ownership is opaque in the data, we have not been able to account for chain effects. In future drafts, we may complete the hand-coding of chains to enable us to do so, however, there are also reasons to suggest that chain effects are limited.

First, our in-sample takeovers presented in appendix A.4 provide some tangential evidence about this. Most of the FP to FP acquisitions that we observe are likely to be from larger chains acquiring other FP nursing homes. New owners appear to improve profits by changing the composition of the nursing home population towards Medicare payers while being able to maintain costs.[55] There do not seem to be otherwise any significant changes in price and quality. These results accord to some extent with Gupta et al. (2021) who explicitly study takeovers by private equity. While they do not look at changes in payer-type populations, they find similar results on nursing hours and costs.

In part, we expect that the limited pricing and quality effect is because nursing homes which are part of chains often still operate independently to a significant extent. For example, the largest nursing home chain in the US,[56] - the Ensign group - describes on their website a business model where each nursing home is run independently by its own management team and employees.[57] In

[54]The fact that we have inertia in demand could also lead to harvest-invest type dynamic pricing and quality incentives. We do not not think this type of dynamic pricing and quality incentive matters in this setting. Multiple stays are not that common and prices and quality are not personalised.

[55]Since our model estimates suggest that Medicare payers are the most costly, in the lens of our model, the maintenance of cost would have to be due to systematic changes to the cost function outside of the scope of the model.

[56]According to Definitive Healthcare, see `https://www.definitivehc.com/blog/top-10-largest-skilled-nursing-facilities`

[57]See for example `https://ensigngroup.net/about/`

addition, in our hand-coding exercise, it was often the case that nursing home webpages showed little about their owner or even a consistent branding for nursing homes we suspected to be of the same chain.

8 Explaining Quality and Access Patterns

With our estimated model of nursing home demand and supply, we can now revisit and explain our motivating evidence through the lens of the model. We begin by conducting a series of counterfactuals to explain quality choices and market segmentation. In these counterfactuals, we change the relevant supply or demand parameters and then solve for the new pricing and quality equilibrium. As our markets are defined by MSA-year pairs and our data span 2000-2010 we have many markets to work with. We pick a small, representative market. Specifically, we pick the Santa Barbara MSA in 2005 - halfway through our sample. The Santa Barbara MSA has 3 NFP nursing homes and 4 FP nursing homes. It has the most NFP providers out of small markets (markets with less than 10 nursing homes) and sits in the middle in terms of total nursing home residents.

In table 11, we present a series of 3 counterfactuals to explore which forces can explain why NFP providers choose higher quality than their FP counterparts. We consider three possibilities. First, since we found that NFP providers have a nonpecuniary motive for quantity-of-care, it could be the case that this causes them to choose higher quality to serve more residents. Figure 4 suggests that NFP providers would also like to serve Medicaid bed-days, but our cost estimates also suggest that FP providers have a significant cost advantage which allows them to set lower private prices to attract Medicaid residents who are private payers for some portion of their stay. Given the strong competition for Medicaid payers, NFP providers might substitute away by choosing higher quality to compete for more private-payers. Therefore if we took away the FP Medicaid cost advantage, then NFP providers might be able to better compete for Medicaid residents and choose lower quality instead. Finally, on the demand side, we estimated weaker quality preferences from Medicaid residents compared to private-pay residents. This could also lead NFP providers to choose higher quality to compete for private-pay residents.

In the first row, we present the average prices and quality of providers from the observed Nash-Bertrand equilibrium as a baseline. In the second row, we consider the role of the NFP's quantity-of-care motive, by setting the NFP quantity-of-care weight parameter from the estimated \$33 per bed-day to zero. In the resulting equilibrium, prices and quality increase on average. Interpreted oppositely, all else equal, NFP nursing homes find that to increase the quantity-of-care served, it is best to cut quality and prices instead of raising prices and quality. This is consistent with Cheng (2023), who finds that residents tend to undervalue quality. This means that the quantity-of-care motive is not the reason why NFP providers choose higher quality.

Next, we consider the role of the FP's Medicaid cost advantage. We take away the FP's Medicaid cost advantage by setting their Medicaid payer-type cost parameters to be the same as the NFP's. In the resulting equilibrium, we find significant decreases in quality, while FP providers raise their price slightly, given their now higher cost. Although FP and NFP providers both decrease quality, the gap in quality narrows. Given that FP providers have become less competitive for Medicaid residents, we interpret this result as NFP providers switching from a market segmentation approach where they compete for private-payers to competing for Medicaid residents, where they only need to choose a quality that is a bit better than the FP providers' choice. In other words, the higher NFP quality choice is likely to be explained by the market segmentation strategy given that FP providers are particularly competitive for Medicaid residents.

In the last row, we equalise preferences for quality to be the same across private payers and Medicaid payers. In the resulting equilibrium we find that both types of providers choose higher quality, which makes sense given that quality elasticities for the average resident are now larger. The gap in quality choices between NFP versus FP providers also becomes larger under this counterfactual, which may reflect that the gains from increasing quality for NFP providers increase by more than for FP providers. Under either the observed equilibrium or in this counterfactual, NFP providers choose considerably larger quality, thus it seems unlikely that differing preferences in quality are the main driver for higher quality choices by NFP providers. Summarising the results from this exercise, market segmentation driven by the strength of FP providers at serving Medicaid payers appears to be the main reason for why NFP providers choose higher quality.

Table 11: Explaining quality choices

	FP		NFP	
	Average Price	Average Quality	Average Price	Average Quality
Observed	190.6	0.88	209.3	1.19
Null NFP objective	195.3	0.96	247.7	2.83
Set FP mcaid cost to NFP mcaid cost	193.6	0.73	209.6	0.86
Equalise mcaid quality pref to priv. pay pref	190.6	1.28	208.9	1.71

Note: These counterfactuals use the Santa Barbara MSA in 2005, which has 3 NFP and 4 FP nursing homes.

Now we turn to explaining patterns of access. Our motivating evidence established that NFP providers are more prevalent in higher income markets and serve less Medicaid and more private-pay residents than their FP counterparts. Since nursing homes are able to serve more private payers in higher income markets and more Medicaid residents in lower income markets, we hypothesised that the patterns of access can be explained by FP providers finding Medicaid residents more profitable and NFP providers finding private-pay residents more profitable. Since payer-type margins are not directly observed, this was one of the motivations for the structural model.

Focusing on figure 4, the rightwards shift in the distribution of Medicaid margins for FP relative to NFP providers (and more so compared to other payer-types) is a clear indication that FP providers find Medicaid residents particularly profitable. On the NFP side, while Medicaid residents appear to also be the most profitable, our counterfactuals in table 11 just showed NFP providers prefer to avoid directly competing with FP providers for Medicaid residents. Since private payer margins seem considerably better than Medicare margins, we can interpret the NFP pricing and quality choices as taking what they can get from the Medicaid residents that they are able to serve and private-payers.

9 Banning for-profit providers

Finally, we use the estimated structural model to simulate the effects of counterfactual bans, allowing for subsequent takeovers by NFP providers. In each of the small markets (less than 10 nursing homes in 2005), we consider a range of scenarios, beginning with the lowest quality FP nursing home and cumulatively adding higher quality FP nursing homes.

In the ban counterfactual, FP nursing homes leave the market. In the takeover counterfactual, the targeted FP nursing home is taken over by a local 'NFP' nursing home. Since our pool of NFP nursing homes includes government providers (around 20% of NFP providers), we could also think of this as government directly taking over the nursing home. The takeover version of the counterfactual allows us to account for the concern that consumer surplus will reduce simply because a product is being removed from the market. While in most papers, new entry is considered instead of takeovers, as we discussed in the motivating evidence, new nursing home entry seems relatively unlikely and takeover seems like a more reasonable proposition.

In terms of implementation, for the ban counterfactual, we simply remove the targeted FP providers and solve for the new solution. In the takeover counterfactual, we change parameters on the demand and supply side for the targeted nursing homes and then solve for the new solution. On the demand side, we add the NFP 'product attribute' to targeted nursing homes, so that residents take into account their preference for NFP providers when evaluating the nursing homes which are taken over. On the supply side, we change all of the FP parameters with their NFP counterparts. We replace the unobserved cost shocks with the mean of the corresponding

NFP cost shocks.

These changes represent a counterfactual where a local NFP nursing home replaces the FP 'product' with their own. While total nursing hours remains endogenous, the NFP taking over the FP introduces higher unobserved quality in line with its existing product offering and incurs the associated higher level of cost. This is a reasonable counterfactual to consider to the extent that it seems natural that the NFP would partially extend its existing business model given the 'local' nature of the takeover. We do not explicitly model a takeover process and any transition costs incurred. To that extent, we regard our evaluation as generous to the policy. Given the static nature of our model and counterfactual, we also interpret the results from a long-run point of view.

We evaluate the changes relative to the observed Nash-Bertrand equilibrium. After the change, we solve a social planner's problem. We interpret the social planner's solution as representing the upper bound on the effectiveness of the policy. If consumer surplus (CS) decreases or increases by only small amounts, then the policy is unlikely to be beneficial under any form of conduct which could change given substantive changes in market structure. In the social planner's problem we solve the following problem:

$$max_{(p_j^{priv}, TN_j)_{j=1,...,J}} CS$$

Subject to capacity constraints $Q_j \leq \bar{Q}_j, j = 1, ..., J$ and profit constraints $\pi_j \geq \tilde{\pi}_j$

Here $CS = \sum_i Days_i CS_i$, where CS_i is the usual logit logsum formula for consumer surplus. When expressing consumer surplus in dollars, we assume that residents who never pay the private price otherwise have the same price preferences as with someone who does. The capacity constraint is needed since with large changes to total capacity, demand could exceed supply for a given nursing home. As we discussed earlier, our model did not find evidence for changes to firm pricing and quality as they approach capacity, thus we think it's reasonable to model this as a hard constraint. Note that since total capacity is calculated as the number of beds multiplied by days in a year, a 100% capacity constraint is likely generous. In practice, stays are 'continuous' and cannot be split across different periods.

While the capacity constraint is enough to stop the social planner from choosing zero prices and infinite quality, the social planner could still effectively set zero market share for a given provider - effectively banning them. This arises because there are two types of 'excess entry' forces. First, as there are quality fixed costs there is the classic Mankiw and Whinston (1986) excess fixed costs force. Two nursing homes which choose the same level of quality incurs double the quality fixed costs in the market. Second, firms are heterogeneous in costs and some nursing homes may be particularly inefficient. Under the competitive Nash-Bertrand equilibrium, the firm may be able to make positive profits, however, the social planner may prefer to simply allocate zero market share to such a firm so that other firms serve more quantity at lower cost.

To ensure that we can exogenously vary market structure in the way we intend, we impose a profit constraint - that the firm has to make at least as much profit as they make in the observed equilibrium $\tilde{\pi}_j$. This means that the social planner has to respect that the firm should receive market share in order to earn at least as much profit in the social planner's solution as under the observed Nash-Bertrand equilibrium.

In the takeover counterfactual, the profit constraint implies that the NFP which takes over a FP has to earn as much profit as the FP did in the observed equilibrium which may be inconsistent with a NFP's nonpecuniary motive. Accordingly, we also consider versions of counterfactuals where we replace the profit constraint with an objective constraint - that the firm should reach at least the same objective they do in the social planner's solution as under the competitive Nash-Bertrand equilibrium. The main effect of this change is to allow the social planner to substitute profit with the firm's nonpecuniary value for quantity-of-care. This especially applies for a social planner considering a NFP (which have a larger quantity-of-care motive) which takes over a FP.

Table 18 presents the results of these counterfactuals. The top half presents the results of the counterfactuals with the profit constraint, while the bottom half presents the results with the objective constraint. The change in CS due to losses in nursing homes holds fixed prices and quality at the levels of the observed Nash-Bertand equilibrium and focuses on the change arising from the loss of nursing homes.

Results on bans without takeovers might at first seem favourable. Across scenarios, the median change in CS is around \$1.3 million. However, around 45% of scenarios have reductions in CS. In addition, under most scenarios, there are large losses in access to nursing home care. Many Medicaid residents previously served by FP nursing homes, no longer have access to nursing home care. For these reasons we regard the results of these counterfactuals as unfavourable. The reason why CS might improve is because we compare a social planner's solution with a competitive Nash-Bertrand equilibrium. This can be seen by the social planner's choice of significantly higher quality. But even under this generous benchmark, there are too many markets with losses in CS.

When allowing for an objective constraint instead, we find the the increase in consumer surplus becomes smaller and in the median market there is now a small decrease. The social planner chooses a smaller increase in price and quality in line with the nursing home's preference of discounting prices and quality to serve more residents. This result likely arises because the NFP's quantity of care motive forces the social planner to choose a solution which has lower CS to satisfy the firm's objective constraint.

When allowing for takeovers we find a clearer negative result. Consumer surplus declines in the average and median scenario. Under the takeover, the nursing home adopts the higher unobserved quality and cost structure of the local NFP nursing home. In doing so however, the social planner has to raise prices significantly to ensure that profits are maintained. On the other hand since the nursing home is still in operation, the losses in Medicaid residents being served is relatively small. The losses are non-zero as with the increase in prices some residents may prefer to pick the outside option - nursing homes not captured in our analysis.

When allowing for an objective constraint instead the results are more favourable, but still overall negative. The average scenario has a positive effect. This is because prices do not increase by as much, as the social planner is able to substitute some of the profits for firm objective value which increases with more residents being served. In summary, even under an exceptionally generous benchmark we find that banning FP nursing homes, and allowing for takeovers is unlikely to be successful policy. The policymaker either has to accept large losses in access to nursing home care, or higher prices especially for residents who did not seek a higher priced, higher quality nursing home to begin with.

Finally, we conduct one sensitivity test. In the takeover counterfactual we interpret the local NFP as taking over the FP nursing home and extending its business model with the corresponding increase in unobserved quality. Since FP nursing homes serve more medicaid patients, a NFP taking over the FP could instead opt to not increase quality, including dimensions of unobserved quality, to avoid raising prices by as much. Since total nursing hours is endogenous we allow the NFP taking over the FP to choose lower quality through less total nursing hours in the counterfactuals considered thus far. On the other hand as we do not observe other dimensions of quality we have to treat the costs as fixed at either the NFP level or FP level. One sensitivity test we can do for the takeover counterfactual is to consider the same counterfactual, but only replace the FP quantity-of-care motive with the NFP quantity-of-care motive, change the quality cost parameters from FP to their NFP counterparts and replace unobserved cost shocks. In this counterfactual, residents know that the NFP taking over the FP is not planning on conferring improvements in unobserved quality and evaluates the nursing home as if it were a FP. On the supply side, the NFP still has its quantity-of-care motive which matters when we use the objective constraint, however since it does not provide the higher unobserved quality, its quantity cost parameters are the same as the FP. [58] We report the results of this exercise in appendix B.4. Overall our assessment remains the same. While the results are more favourable to the policy change, the median scenario still records a negative consumer surplus change with both the profit constraint and objective constraint.

[58]Since we do not have structural estimates about how much of the differences in costs are due to differences in efficiencies versus unobserved quality, we focus on the case where we assume all of the cost differences arise from differences in unobserved quality. This will again be a relatively favorable assessment of the policies as this assumes a NFP cost function which is more similar to a FP cost function, than the true NFP cost function.

Table 12: Bans under the social planner's problem

	No takeover with profit cons.		Takeover with profit cons.	
	Mean	Median	Mean	Median
Change in CS ($m)	1.1	1.3	-0.6	-2.7
Change in CS due to losses in nursing homes ($m)	-2.2	-1.6		
Change in average price	117.6	97.0	252.5	266.5
Change in average quality	4.0	4.5	0.8	0.9
Change in Medicaid quantity ('000 bed-days)	-67.1	-58.7	-4.9	-1.7
	No takeover with objective cons.		Takeover with objective cons.	
Change in CS ($m)	0.3	-0.1	1.0	-1.9
Change in CS due to losses in nursing homes ($m)	-2.2	-1.6		
Change in average price	103.2	89.6	146.0	161.3
Change in average quality	3.6	3.4	0.4	0.3
Change in Medicaid quantity ('000 bed-days)	-67.0	-59.4	-2.5	-0.5

Note: All markets with at most 10 nursing homes and at least one NFP in 2005. Each scenario corresponds to one market with one set of targeted FP providers. The sets of targeted FP providers for a given market consist of a set with the lowest quality FP provider, a set with the lowest quality and second lowest quality FP provider, and so on, with the largest set being all FP providers. Changes are computed relative to the Nash-Bertrand equilibrium with all firms in the market. Since costs are heterogeneous, the changes need not be monotonic in the number of targeted FP providers.

10 Conclusion

Should policymakers reduce FP provision and increase NFP provision in regulated markets such as health and education? Overall, we argue that the balance of the model and empirical evidence suggests that it does not. In some other settings such as hospitals, papers have argued that NFP providers may simply be FP providers in disguise (Dranove et al., 2017). We find significant differences between NFP and FP providers. Consistent with past work, NFP providers have non-pecuniary motives for providing quantity of care. However, unlike in previous papers, we argue that this motive plays a relatively small role in determining market structure. NFP providers also choose higher quality and likely do so on more dimensions than that which we explicitly model. However, higher quality comes at a 'cost'. Furthermore, as Medicaid payers – who account for the majority of bed–days – value quality less, differential costs ultimately become a first-order consideration in determining market structure and nursing home choices. Viewing FP providers as offering a product better suited and providing access to Medicaid payers, it is clear that they play an important role in nursing home care and that banning FP nursing homes is unlikely to be a fruitful policy solution.

A broader takeaway is that given the limited policy success in this industry, one might have hoped that NFP provision could be a silver bullet. This is especially the case because it does not necessarily involve the government spending substantially more money, which history demonstrates is a difficult ask. Ultimately, these results suggest that increased NFP provision is unlikely to be a substitute for increased government funding through measures such as paying nursing homes more as in Hackmann (2019) or a stronger regulator, which was a key recommendation in National Academies of Sciences, Engineering, and Medicine (2022). Finally, we began this paper with general health and education settings in mind. We leveraged the US nursing homes industry to study this question, which necessitates addressing unique institutional features. However, similar patterns can be found in other markets such as post-secondary education (Deming et al., 2012). Accordingly, we contend that this framework and the lessons learned may have broader applicability beyond the US nursing homes industry.

References

Alexander, Diane, "How do Doctors Respond to Incentives? Unintended Consequences of Paying Doctors to Reduce Costs," *Journal of Political Economy*, 2020, *128* (11), 4046–4096.

Ballou, Jeffrey P., "An Examination of the Presence of Ownership Effects in Mixed Markets," *Journal of Law, Economics and Organization*, 2005, *21* (1), 228–255.

—, "Do Nonprofit and Government Nursing Homes Enter Unprofitable Markets?," *Economic Inquiry*, 2008, *46* (2), 241–260.

— **and Burton A Weisbrod**, "Mangerial rewards and the behavior of for-profit, governmental, and nonprofit organizations: evidence from the hospital industry," *Journal of Public Economics*, 2003, *87*, 1895–1920.

Bayandir, Esra Eren, "Hospital ownership type and treatment choices," *Journal of Health Economics*, 2012, *31*, 359–370.

Brown, Jeffrey R. and Amy Finkelstein, "Why is the Market for Long-Term Care Insurance So Small?," 2007.

Campbell, Sean and Charlene Harrington, "For-profit nursing homes are cutting corners on safety and draining resources with financial shenanigans - especially at midsize chains that dodge public scrutiny," *The Conversation*, 2024.

Centers for Medicare and Medicaid Services, "Biden-Harris Administration Continues Unprecedented Efforts to Increase Transparency of Nursing Home Ownership," 2023.

Cheng, Alden, "Demand for Quality in the Presence of Information Frictions: Evidence from the Nursing Home Market," *Working Paper*, 2023.

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

Cho, Sungjin, Gong Lee, John Rust, and Mengkai Yu, "Optimal Dynamic Hotel Pricing," *Working paper*, 2018.

Chou, Shin Yi, "Asymmetric information, ownership and quality of care: An empirical analysis of nursing homes," *Journal of Health Economics*, 2002, *21* (2), 293–311.

Cohodes, Sarah, Ozkan Eren, and Orgul Ozturk, "The Long Run Effects of A Comprehensive Teacher Performance Pay Program on Student Outcomes," *Working Paper*, 2023.

Deming, David J., Claudia Goldin, and Lawrence F. Katz, "The For-Profit Postsecondary School Sector: Nimble Critters or Agile Predators?," *Journal of Economic Perspectives*, dec 2012, *26* (1), 139–164.

Dinerstein, Michael, Christopher Neilson, and Sebastián Otero, "The Equilibrium Effects of Public Provision in Education Markets: Evidence from a Public School Expansion Policy," *Working Paper*, 2020.

Dranove, David, "Health Care Market, Regulators and Certifiers," *Handbook of Health Economics*, 2011, *2*, 639–690.

— **and Ginger Zhe Jin**, "Quality Disclosure and Certification: Theory and Practice," *Journal of Economic Literature*, 2010, *48* (4), 935–963.

—**, Craig Garthwaite, and Christopher Ody**, "How do nonprofits respond to negative wealth shocks? The impact of the 2008 stock market collapse on hospitals," *RAND Journal of Economics*, 2017, *48* (2), 485–525.

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

Farronato, Chiara and Andrey Fradkin, "The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry," *American Economic Review*, 2022, *112* (6), 1782–1817.

Finkelstein, Amy, Yunan Ji, Neale Mahoney, and Jonathan Skinner, "Mandatory Medicare Bundled Payment Program for Lower Extremity Joint Replacement and Discharge to Institutional Postacute Care Interim Analysis of the First Year of a 5-Year Randomized Trial," *Journal of the American Medical Association*, 2018.

Friedrich, Benjamin U. and Martin B. Hackmann, "The Returns to Nursing: Evidence from a Parental-Leave Program," *Review of Economic Studies*, 2021.

Fryer, Roland G., "Teacher Incentives and Student Achievement: Evidence from New York City Public Schools," *Journal of Labor Economics*, 2013, *31* (2), 373–407.

Gandhi, Ashvin, "Picking Your Patients: Selective Admissions in the Nursing Home Industry," *Working Paper*, 2023.

— **and Andrew Olenski**, "Tunneling and Hidden Profits in Health Care," *Working Paper*, 2024.

Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo, "Hospitals as Insurers of Last Resort," *American Economic Journal: Applied Economics*, 2018, *10* (1), 1–39.

Grabowski, David C., "Medicaid reimbursement and the quality of nursing home care," *Journal of Health Economics*, 2001, *20* (4), 549–569.

— **and Richard A. Hirth**, "Competitive spillovers across non-profit and for-profit nursing homes," *Journal of Health Economics*, 2003, *22* (1), 1–22.

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

__ , **Zhanlian Feng, Richard Hirth, Momotazur Rahman, and Vincent Mor**, "Effect of nursing home ownership on the quality of post-acute care: An instrumental variables approach," *Journal of Health Economics*, jan 2013, *32* (1), 12–21.

Gupta, Atul, "Impacts of Performance Pay for Hospitals: The Readmissions Reduction Program," *American Economic Review*, 2021, *111* (4), 1241–1283.

__ , **Sabrina Howell, Constantine Yannelis, and Abhinav Gupta**, "Does Private Equity Investment in Healthcare Benefit Patients? Evidence from Nursing Homes," *NBER Working Paper*, 2021.

Hackmann, Martin B., "Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home Industry," *American Economic Review*, 2019, *109* (5), 1684–1716.

__ , **Vincent Pohl, and Nicolas R. Ziebarth**, "Patient versus Provider Incentives in Long-Term Care," *American Economic Journal: Applied Economics*, 2024, *16* (3), 178–218.

Hammond, Bill, "Following the Money: An Analysis of 'related company' transactions in New York's nursing home industry," *Empire Center Reports*, 2022.

Harrington, C., D. Zimmerman, S. L. Karon, J. Robinson, and P. Beutel, "Nursing Home Staffing and Its Relationship to Deficiencies," *Journals of Gerontology - Series B Psychological Sciences and Social Sciences*, 2000, *55* (5), S278–S287.

Harrington, Charlene, Brian Olney, Helen Carrillo, and Taewoon Kang, "Nurse Staffing and Deficiencies in the Largest For-Profit Nursing Home Chains and Chains Owned by Private Equity Comapnies," *Health Services Research*, 2012, pp. 106–128.

__ , **Frode F. Jacobsen, Justin Panos, Allyson Pollock, Shailen Sutaria, and Marta Szebehely**, "Marktization in Long-Term Care: A Cross-Country Comparison of Large For-profit Nursing Home Chains," *Health Services Insights*, 2017, *10*, 1–23.

Hart, Oliver, Andrei Shleifer, and Robert W. Vishny, "The Proper Scope of Government: Theory and an Application to Prisons," *Quarterly Journal of Economics*, 1997, *112* (4), 1127–1161.

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

Hogan, Bernadette, "New York Assembly releases package of nursing home reform bills," *New York Post*, 2021.

Horwitz, Jill and Austin Nichols, "Hospital ownership and medical services: Market mix, spillover effects, and nonprofit objectives," *Journal of Health Economics*, 2009, *28*, 924–937.

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

Internal Revenue Service, "Exemption Requirements - 501(c)(3) Organizations," 2023.

Jaffe, Susan and Health News Kaiser, "3 states limit nursing home profits in bid to improve care," 2021.

Kim, Paul HS, "Risk Corridors in Medicare Part D: Financial Risk Sharing or Profit Limiting Mechanism?," *Working paper*, 2024.

Knight, Victoria, "Once Banned, For-Profit Medical Schools Are On the Rise Again In The U.S.," *KFF Health News*, 2021.

Li, Yue, Charlene Harrington, Helena Temkin-Greener, Kai You, Xueya Cai, Xi Cen, and Dana B. Mukamel, "Deficiencies in Care at Nursing Homes and Racial/ Ethnic Disparities across Homes Fell, 2006-11," *Health Affairs*, 2015, *34* (7), 1139–1146.

Lin, Haizhen, "Revisiting the relationship between nurse staffing and quality of care in nursing homes: An instrumental variables approach," *Journal of Health Economics*, 2014, *37*, 13–24.

__, "Quality choice and market structure: A dynamic analysis of nursing home oligopolies," *International Economic Review*, 2015, *56* (4), 1261–1290.

Lu, Lauren Xiaoyuan and Susan Feng Lu, "Does Nonprofit Ownership Matter for Firm Performance? Financial Distress and Ownership Conversion of Nursing Homes," *Management Science*, 2021, *68* (7), 5127–5145.

Mankiw, Gregory D. and Michael D. Whinston, "Free Entry and Social Inefficiency," *The RAND Journal of Economics*, 1986, (1), 48–58.

McClure, Jonathon, "Markups and Costs under Capacity Constraints: the Welfare Effects of Hotel Mergers," *Working paper*, 2023.

Mello, Felicia, "What happened to California's crackdown on for-profit colleges," *Cal Matters*, 2019.

National Academies of Sciences, Engineering, and Medicine, *The National Imperative to Improve Nursing Home Quality: Honoring Our Commitment to Residents, Families, and Staff*, Washington DC: The National Academies Press, 2022.

Nelson, Mary K., "Only 22% of CCRCs in the U.S. are For-Profit," *Senior Housing News*, 2018.

Newhouse, Joseph P, "Toward a Theory of Nonprofit Institutions: An Economic Model of a Hospital," *American Economic Review*, 1970, (1), 64–74.

Norton, Edward C. and Douglas O. Staiger, "How hospital ownership affects access to care for the uninsured," *RAND Journal of Economics*, 1994, *25* (1), 171–185.

Nyman, John A., "Prospective and 'cost-plus' medicaid reimbursement, excess medicaid demand, and the quality of nursing home care," *Journal of Health Economics*, 1985, *4* (3), 237–259.

Olenski, Andrew, "Reallocation and the (In)efficiency of Exit in the US Nursing Homes Industry," *Working paper*, 2022.

Penzenstadler, Nick, "Congess examines 'horrors' at for-profit nursing homes, blames poor staffing," *USA Today*, 2022.

Rau, Jordan, "Care Suffers as More Nursing Homes Feed Money into Corporate Webs," *KFF Health News and New York Times*, 2017.

Sloan, Frank A., "Not-For-Profit Ownership and Hospital Behavior," in "Handbook of Health Economics," Vol. 1 2000, chapter 21, pp. 1141–1174.

SteelFisher, Gillian K., Arnold M. Epstein, David C. Grabowski, Karen E. Joynt Maddox, E. John Orav, and Michael L. Barnett, "Persistent challenges of COVID-19 in skilled nursing facilities: The administrator perspective," *Journal of the American Geriatrics Society*, 2021, *69* (4), 875–878.

The National Consumer Voice for Quality Long Term Care, "Where do the Billions of Dollars go? A look at Nursing Home Related Party Transactions," 2023.

Tom, Chang and Mireille Jacobson, "What do Nonprofit Hospitals Maximise? Evidence from California's Seismic Retrofit Mandate," *Working Paper*, 2010.

Town, R. and G. Vistnes, "Hospital Competition in HMO Networks," *Journal of Health Economics*, 2001, *20*, 733–753.

Weisbrod, Burton A., *The Nonprofit Economy*, Harvard University Press, 1988.

Wunderluch, Gooloo S. II. and Peter O. Kohler, "Improving the Quality of Long-term Care," *Committee on Improving Quality in Long-Term Care*, 2001.

Zarem, Jane E., "Today's Continuing Care Retirement Community (CCRC)," *Leading Age Report*, 2010.

Appendix

A Supplemental facts

A.1 Resident individual characteristics

Table 13: Summary statistics from resident-level data

	Average	10th pct	50th pct	90th pct
ADL score	12.5	7	13	17
Age (cond. $>= 65$)	82	71	82	92
CLN score	1.3	0	1	2
Length of Stay (days)	148	7	30	410

This data is from the resident-level panel which informs our structural estimation and covers 2000-2010 in CA.

According to table 13, residents vary significantly in their length of stay, entering age of residents,[59] care needs and medical needs. Care needs can be measured by a resident's assisted daily living (ADL) score which measures how dependent residents are on nursing care for their daily living. Scores can range from 4 to 18, with higher scores indicating more dependency. 4 can be thought of as normal functioning, while 18 would be someone who is completely dependent on nursing care. Medical needs can be summarised by a resident's clinically complex scale (CLN) score which takes values of 0,1,2 or 3, with 0 representing no additional medical needs and 3 representing a high level of medical needs.

[59] We restrict the age of residents to those at least 65 to exclude residents who are likely to be very different from the population of primary interest. The long-term care function means that nursing homes may also serve young people with significant disabilities, for example.

A.2 NFP nursing homes charge higher private prices than FP nursing homes in California

Table 14: Differences in Private Prices

	Difference in Means	Regression
FP	-17.8	-15.7
		(4.92)

Note: These results use yearly facility-level data from 2000-2010 in California. Controls include facility size (in beds), aggregate assisted daily living score which measures how dependent the population is on carer support for daily needs, aggregate case mix index which measures how much medical care the population requires and proportion of Medicaid and Medicare payers in the facility. Year and zip fixed effects are included with standard errors clustered at the facility-level.

A.3 Donations are unlikely to play a role in explaining location patterns

We argue that one reason why NFP providers are relatively more prevalent in higher income markets is because they serve a larger proportion of relatively profitable private-pay residents. Another reason could be that it is easier to source donations when the local population is wealthier on average. In interviews with industry, we heard that donations do not play much of a role as the cause of nursing home care is relatively unappealing. We check this claim empirically by drawing on supplemental data from the National Center for Charitable Statistics (NCCS) who compile and clean data from NFP annual form 990 filings. This data reports the contributions which nursing homes receive each year along with usual financial data. Contributions includes boths donations and government funding, but are not separately split in the NCCS data. Figure 5 is a histogram of nursing home contribution rates as a proportion of total revenues separated by the income quartile of the nursing home's zip. A few nursing homes receive all of their revenue in the form of contributions. These are likely to be government-run nursing homes. On the other hand, the vast majority receive none, and zip income quartile has very little affect on this distribution. We interpret this as clear evidence that donations do not matter.

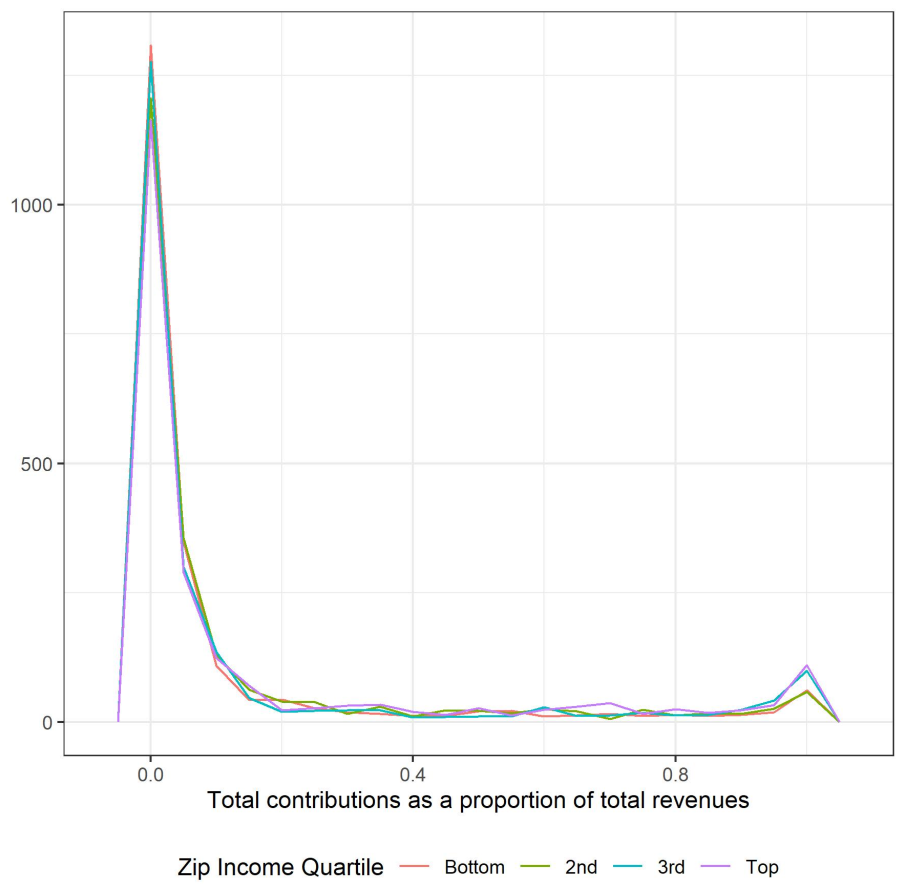


Figure 5: Histogram of contribution rates by zip income quartile, all states, 2010-2018

A.4 Validating in-sample nursing home takeovers

Motivated by papers studying acquisitions and the lack of exit and entry activity in the data, we consider takeover activity in CA in table 5. As facility data do not readily identify ownership, and thus takeovers, we had to hand code takeovers by cross-validating the facility-level data with online sources. To provide some reassurance that we did successfully identify takeovers we conduct an event-study exercise.

Specifically, we estimate the following regression equation for facility j at year t:

$$y_{jt} = \alpha_j + \tau_t + \sum_{k \neq -1} \beta_k \mathbf{1}_{j,k=r(j,t)} + \epsilon_{jt}$$

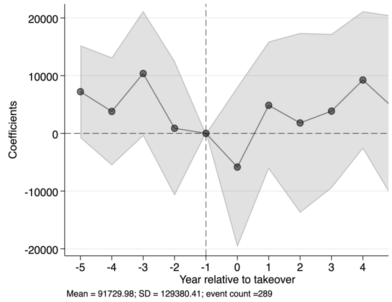
where α_j are facility fixed effects, τ_t are year fixed effects, and $r(j,t)$ is the relative year from when when the facility j was taken over by another facility. Figure 6 reports the estimated coefficients β_k. The sample is relatively small so our estimates are somewhat noisy. Some clear patterns emerge. resident profit which are revenues minus expenses for resident care items increases substantially following a takeover. The reason appears to be that nursing homes shift away from serving Medicaid residents towards serving other resident types while keeping average variable and total costs in check. Since, Medicare and private pay generally pay more, if a nursing home can keep costs fixed when shifting towards Medicare and private pay residents then their resident profitability will increase. Notably, nursing hours and the prices themselves do not significantly change. The result on unchanging nursing hours seems close enough to Gupta et al. (2021) whose results suggest no significant change in nursing hours until much later after the takeover. They do not study changes in prices or the payer-type composition. They also find significant increases in facility fixed costs following a takeover, which in our view is likely attributable to the tunnelling of profits which Gandhi and Olenski (2024) find. Our event study also suggests that fixed costs rise following takeovers, but we do not have enough power to conclude statistical significance.

Figure 6: Event-study coefficients: Takeover

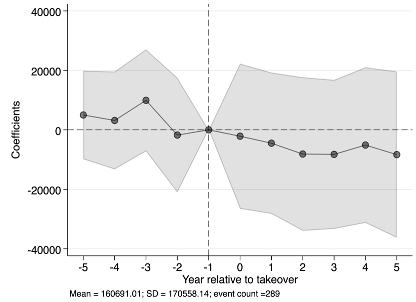
(**a**) resident Profit

figures/takeover_behvior_a

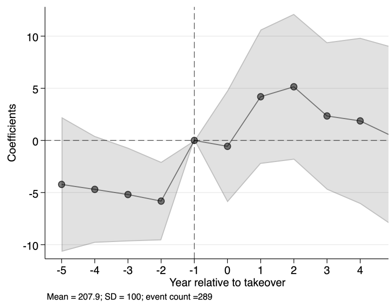
(**b**) Average Total Cost



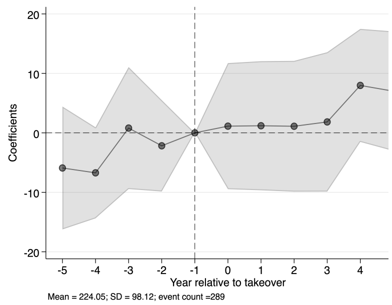
(**c**) Average Variable Cost



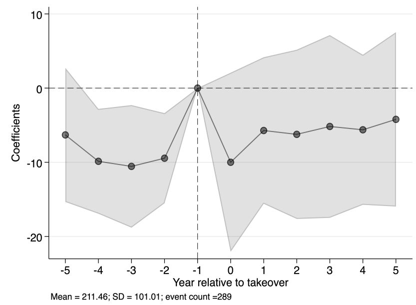
(**d**) Average Medicaid Price



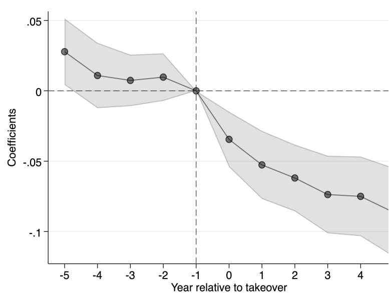
(**e**) Average Medicare Price



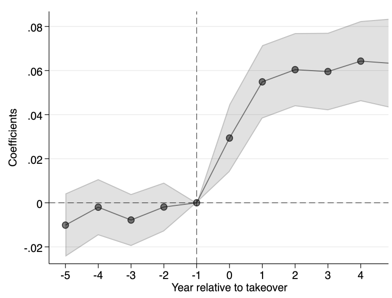
(**f**) Average Private Price



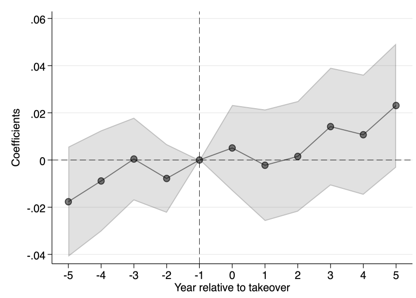
(**g**) Medicaid Share



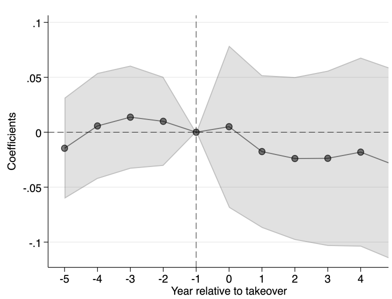
(**h**) Medicare Share



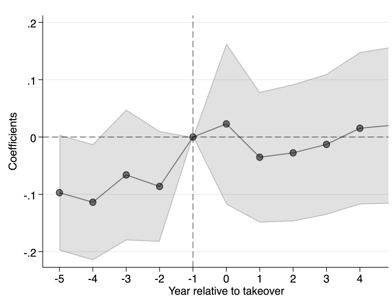
(**i**) Private Share



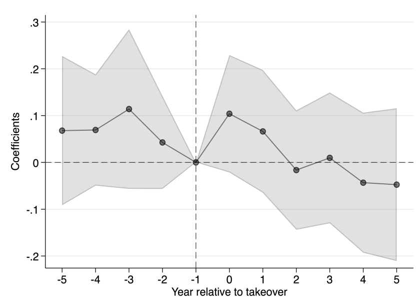
(**j**) Nursing Hours: RN



(**k**) Nursing Hours: LPN



(**l**) Nursing Hours: CNA



Nursing hours are hours per resident per day.

B Supplements to structural estimation

B.1 Full demand parameter estimates

Table 15: Full demand parameter estimates

	Baseline	Age	Los 30-100	Los 100+	Resp. Non-self	Payment Self	Payment Medicaid	Payment Medicare
Distance	-0.1650 (0.00004)	-0.0013 (0.00003)	-0.0001 (0.00008)	0.0018 (0.00008)	0.0250 (0.00004)			
Distance Sq	0.0016 (0.00002)	0.0000 (0.00000)	0.0001 (0.00001)	0.0002 (0.00001)	-0.0004 (0.00001)			
Quality	1.3341 (0.0194)	0.0009 (0.00008)	-0.1064 (0.00001)	-0.4595 (0.00003)	-0.2616 (0.00003)		-0.2100 (0.00000)	-0.0020 (0.00003)
Price	-0.0395 (0.0003)	0.0000 (0.00000)	-0.0002 (0.00002)	0.0002 (0.00002)	-0.0006 (0.00001)	-0.0025 (0.00003)		
Inertia	5.4225 (0.0012)							
NFP	1.2705 (0.0129)							

	DRS	CPS	ADL	CLN	Has Alz.	Female	Non-white	Bachelor Educated
Quality	-0.0788 (0.00000)	-0.0440 (0.00015)	0.0297 (0.00039)	0.0496 (0.00004)	-0.0531 (0.00002)	0.0158 (0.00002)	-0.2283 (0.00004)	0.0733 (0.00000)
Price								0.0006 (0.00002)

Note: These results use individual-level data from 2000-2010 in California. Standard errors boostrapped using 250 iterations

B.2 Full supply parameter estimates

Table 16: Full supply estimates

	FP	NFP
Quantity Motive	9.32	32.94
	(5.91)	(9.26)
Quality Cost	1.09	0.59
	(0.45)	(0.42)
Convex	0.09	0.38
Quality Cost	(0.20)	(0.16)
Normalised Quality	0.09	0.75
Fixed Cost	(0.28)	(0.53)
Total Beds	0.50	0.46
	(0.07)	(0.12)
Total Beds Sq	-0.09	-0.08
	(0.02)	(0.04)
Agg ADL	2.17	0.85
	(0.37)	(0.95)
Agg CMI	63.59	73.75
	(10.42)	(27.59)
Prop. Other	70.85	-62.98
	(13.22)	(19.71)
Private Payer	90.23	132.62
	(15.07)	(41.67)
Private Payer Sq	-0.003	-0.001
	(0.0005)	(0.0008)
Medicaid Payer	-25.85	44.14
	(4.72)	(32.70)
Medicaid Payer Sq	-0.0006	-0.0008
	(0.0003)	(0.0004)
Medicare Payer	80.41	278.18
	(34.04)	(69.24)
Medicare Payer Sq	0.005	-0.016
	(0.002)	(0.007)
N	7460	886

Note: These results use facility-level data from 2000-2010 in California. Standard errors do not take into account demand parameter uncertainty.

B.3 Provider Selection, Capacity Constraints and Dynamic Pricing Incentives

Identification of supply parameters relies on the inversion of first-order-conditions being correct. Or in other words, that the supply model is correct. While we believe that the first-order economic forces explaining quality and access patterns can be captured in a static framework, we still need to be sure that ignoring dynamics will not bias our supply parameter estimates. Since nursing homes are capacity-constrained and resident stays are long-lived, dynamic pricing incentives could arise from the option-value of beds varying with occupancy. That is, as occupancy approaches capacity, the option value of retaining a vacant spot increases, because the chance that you may have to forgo serving a higher profitability consumer increases. These incentives have been studied in the hotels literature (Cho et al., 2018; Farronato and Fradkin, 2022; McClure, 2023).

In this setting, dynamic considerations can also arise because residents can vary substantially in profitability. Gandhi (2023) finds evidence that nursing homes are selective in their admissions despite this being forbidden by regulation. In this section, we check for robustness of our supply parameters to dynamic pricing incentives. Regarding selective admissions, modelling provider selection or rationing in an oligopoly setting is very challenging as it would involve adding even more endogenous provider choices. On the other hand, estimates in Gandhi (2023) suggest that although present, the ability of a nursing home to be selective in their admissions is limited. For example, according to his structural estimate in figure 7, a nursing home which is almost full still admits a Medicaid-eligible resident with 70% probability. For this reason, we think it is reasonable to abstract from provider selection.

To check for dynamic pricing incentives, we consider specifications of the cost function where we allow for a nonlinear term reflecting that a nursing home's perceived marginal cost can vary with occupancy. As occupancy approaches capacity, opportunity costs increase. We follow McClure (2023) and capture this by allowing in the cost function:

$$\frac{(Q_{jt} + \tilde{Q}_{jt})}{1+\rho} \left(\frac{(Q_{jt} + \tilde{Q}_{jt})}{\psi K_{jt}} \right)^{\rho}$$

Here, ψ can be interpreted as a soft-capacity constraint, reflecting that nursing homes may have a regular capacity below full capacity that they prefer operating at. For example, $\psi = 0.9$ could be interpreted as the nursing home preferring to operate at 90% capacity. ρ controls how severe the nursing home views violating the soft-capacity constraint. A larger ρ increases the severity of violating the constraint. This function is quite flexible and accommodates a large variety of ways in which the dynamic pricing incentive could manifest.

Table 17 reports the results of our supply estimates when the capacity term is included. Although the capacity term is flexible, one choice has to be made about its sign. In the hotels literature there is not much ambiguity. As the option-value of retaining a room increases the closer a hotel is to capacity, the sign should be positive. For nursing homes, it is conceivable that it could be negative. If the nursing home values especially values residents who pay the private-price at some point during their stay, one way to ensure the nursing home serves more of these residents is to lower their private price. In this case, the perceived marginal cost of serving another bed-day should decline the closer to capacity the facility is. We estimate specifications allowing for either, however we find that the estimator has significant problems when a $+$ sign is included in front of the capacity term instead of a $-$, indicative of especially poor fit.[60] Thus, we ignore the case with a $+$ sign. Focusing on the bottom of the table, we see that the capacity parameters are odd in size and magnitude. The soft capacity constraints far exceed 1, while the severity parameters are negative and large. In fact, these parameters appear to be attempts by the model to shrink these effects to 0. In the last row, I compute the implied at the margin capacity effect for each firm-year and show the largest absolute value effect. They are all null. Parameter estimates for all other parameters are roughly the same with small deviations. We interpret these results as suggesting it is fine to ignore dynamic pricing and quality effects that could arise due to capacity constraints.

[60]Specifically, the algorithm tends towards parameters which make the actual capacity effect very small, but with extreme values which make it difficult to evaluate moment conditions and run the second step in the GMM estimator.

Table 17: Supply Estimates with Capacity Effects

	FP		NFP	
Capacity Specification	None	-	None	-
Quantity Motive	9.32	21.07	32.94	36.95
Quality Cost	1.09	0.99	0.59	-0.07
Convex Quality Cost	0.09	0.20	0.38	0.35
Norm. Quality Fixed Cost	0.09	0.0001	0.75	0.0014
Total Beds	0.50	0.25	0.46	0.52
Total Beds Sq	-0.09	-0.08	-0.08	-0.09
ADL	2.17	2.34	0.85	1.06
CMI	63.59	72.72	73.75	85.96
Prop Other	70.85	83.29	-62.98	-47.94
Private Payer	90.23	59.00	132.62	100.73
Private Payer Sq	-0.003	0.0008	-0.001	0.0004
Medicaid Payer	-25.85	-19.37	44.14	25.80
Medicaid Payer Sq	-0.0006	0.0001	-0.0008	-0.0010
Medicare Payer	80.41	112.87	278.18	240.13
Medicare Payer Sq	0.005	0.0032	-0.016	-0.012
Soft Capacity Constraint		2.49		4.41
Severity		-5.71		-14.32
Largest abs. At the Margin Capacity Effect		-2.1×10^{-4}		-2.7×10^{-10}

Note: '-' refers to the specification where capacity term enters with a minus sign in front. Largest abs. at the margin capacity effect refers to the largest absolute value over any nursing-home year of $\frac{1}{1+\rho}\left(\frac{(Q_{jt}+\tilde{Q}_{jt})}{\psi K_{jt}}\right)^{\rho}$ evaluated at observed quantities. These results use facility-level data from 2000-2010 in California. No standard errors included as the capacity parameters make the variance-covariance matrix non-invertible.

B.4 Takeover Counterfactual Sensitivity Test

Table 18: Takeovers under the social planner's problem with only changes in quality costs

	Takeover w profit cons.	
	Mean	Median
Change in CS ($m)	1.4	-1.7
Change in average price	169.0	151.7
Change in average quality	1.8	1.0
Change in medicaid quantity ('000 bed-days)	-2.7	-1.3
	Takeover w obj. cons.	
Change in CS ($m)	2.8	-0.7
Change in average price	82.4	43.1
Change in average quality	0.2	0.0
Change in medicaid quantity ('000 bed-days)	-1.3	-0.08

Note: All markets with at most 10 nursing homes and at least one NFP in 2005. Each scenario corresponds to one market with one set of targeted FP providers. The sets of targeted FP providers for a given market consist of a set with the lowest quality FP provider, a set with the lowest quality and second lowest quality FP provider, and so on, with the largest set being all FP providers. Changes are computed relative to the Nash-Bertrand equilibrium with all firms in the market. Since costs are heterogeneous, the changes need not be monotonic in the number of targeted FP providers.