NBER WORKING PAPER SERIES

INCENTIVIZING BETTER QUALITY OF CARE: THE ROLE OF MEDICAID AND COMPETITION IN THE NURSING HOME INDUSTRY

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Working Paper 24133
http://www.nber.org/papers/w24133

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
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December 2017

I thank my thesis advisers Steven Berry, Philip Haile, and Amanda Kowalski for their invaluable support. I thank seminar and conference participants at Bonn, CESifo, IIOC, INSEAD, the Kelley School of Business, the NBER Summer institute, NYU Stern, PennCorn, Penn State, RAND, the Simon Business School, the St. Louis Fed, Queen's University, UCLA, the University of Maryland, the University of Wisconsin Madison, WEAI, Wharton, Yale, as well as Nikhil Agarwal, Joe Altonji, John Asker, Moshe Buchinsky, Zack Cooper, Camilo Dominguez, Maximiliano Dvorkin, Benjamin Friedrich, Paul Grieco, Nora Hackmann, Tobias Hackmann, Mitsuri Igami, Adam Kapor, Fabian Lange, Frank Limbrock, Adriana Lleras Muney, Costas Meghir, Charlie Murry, Christopher Neilson, Peter Newberry, Vincent Pohl, Maria Polyakova, Ted Rosenbaum, Stephen Ryan, Seth Zimmerman, and three anonymous referees for their thoughtful comments. Jean Roth and Mohan Ramanujan provided invaluable help with the data. Funding from the National Institute on Aging grant #P30 AG012810 is gratefully acknowledged. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 24133
December 2017
JEL No. I11,I18,L13

ABSTRACT

This paper develops a model of the nursing home industry to investigate the quality effects of policies that either raise regulated reimbursement rates or increase local competition. Using data from Pennsylvania, I estimate the parameters of the model. The findings indicate that nursing homes increase the quality of care, measured by the number of skilled nurses per resident, by 8.8% following a universal 10%increase in Medicaid reimbursement rates. In contrast, I find that pro-competitive policies lead to only small increases in skilled nurse staffing ratios, suggesting that Medicaid increases are more cost effective in raising the quality of care.

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A online appendix is available at http://www.nber.org/data-appendix/w24133

1 Introduction

Shortcomings in the quality of care in U.S. nursing homes have been an ongoing public concern for decades. Many studies indicate that nurse-to-resident staffing ratios remain very low (see Harrington et al. (2016)), which may harm a sizable portion of a particularly vulnerable elderly population. Nursing homes provide care for about 1.4 million residents at any given point in time and contribute about 0.9% to GDP. As the U.S. population ages and spending on nursing homes increases, it is important to understand why nursing homes lack incentives to improve the quality of care so that appropriate policy instruments can be designed.

In this paper, I develop a structural model of the nursing home industry to simulate the effects of policies that either raise regulated Medicaid reimbursement rates or increase local competition via directed entry on the quality of care. Using data from Pennsylvania, I find that low Medicaid reimbursement rates are an important contributor to shortfalls in the quality of care. Moderate increases in Medicaid reimbursement rates lead to increases in the quality of care as well as social welfare. On the other hand, I find that an increase in competition has a relatively small positive effect on the quality of care.

These exercises are motivated by two common institutional features of healthcare markets that can result in low quality of care. First, prices for nursing home care are largely regulated. Nationwide, Medicaid and Medicare regulate the reimbursement rates for 62% and 14% of nursing home residents, respectively. Only 24% of residents pay the private rate set by the nursing home. If reimbursement rates are very low, as is commonly claimed for Medicaid, nursing homes have little incentive to compete for Medicaid beneficiaries through better quality of care. Second, competition in the nursing home industry is muted not only because of vertical and horizontal (geographic) product differentiation, but also because state Certificate of Need (CON) laws restrict entry and investment decisions. Spence (1975) shows that quality can be inefficient if there is market power although the direction of the inefficiency is ambiguous within the Spence framework. White (1972) specifically considers the case when prices are regulated, arguing that market power then leads to lower quality, providing an alternative explanation for observed quality shortfalls in this industry. Whether increases in reimbursement or competition increase social welfare is theoretically ambiguous (Gaynor (2006)) and ultimately an empirical question.

I investigate these questions using data on Pennsylvania's nursing home industry, which is in many ways representative of the U.S. One important advantage of this empirical context, besides data availability, is that I can isolate a source of plausibly exogenous variation in Medicaid reimbursement rates. In Pennsylvania, the regulated Medicaid reimbursement rate of each nursing home is based on previously reported costs of all nursing homes in a peer group determined by facility size and region. Each peer group region combines several counties that are commonly assumed to represent locally segmented nursing home markets. My identification strategy isolates the reported cost variation of those nursing homes in the peer group that operate in different counties. Specifically, I assume that, conditional on a rich set of observables, cost shocks to nursing homes located in distant counties affect staffing and pricing decisions of a local nursing home through the reimbursement rule only.

Applying the methodology to the data, I find that an increase in the Medicaid reimbursement rate leads to an economically and statistically significant increase in the number of licensed practical and registered nurses (henceforth skilled nurses) per resident. I find no evidence for changes in other quality inputs. The preliminary evidence suggests a key mechanism through which nursing homes can influence the quality of care: staffing of skilled nurses. The skilled nurse to resident ratio is commonly considered to be a direct quality of care measure. Furthermore, many studies have shown a positive relationship between skilled nurses and quality of care outcomes including improvements in clinical outcomes and reductions in nursing home complaints and deficiencies, see e.g. Kaiser Family Foundation (KFF) (2015).

Building on the preliminary evidence and empirical methods developed in Berry, Levinsohn and Pakes (1995) and Fan (2013), I next develop and estimate a static industry model in which nursing homes compete in the private rate and the skilled nurse staffing ratio as the key input towards better quality of care. The model captures the role of regulated Medicaid and

Medicare reimbursement rates, differences in market structure, and allows for non-pecuniary objectives among not-for-profit and public nursing homes, which may mitigate the quality concerns. To estimate the model, I combine nursing home survey data with administrative resident assessment data from the Long Term Care Minimum Data Set (MDS) and Medicaid and Medicare claims data. I construct additional cost moments from Medicaid cost reports to identify differences in objectives between for-profits, not-for-profits, and publicly operated nursing homes.

My findings indicate that current skilled nurse staffing ratios are inefficiently low. Combining the estimated preferences over quality and private rates, I find that nursing home residents value an additional skilled nurse at $126,000 per year on average. The marginal benefit exceeds the annual cost of employment of $83,000, considering wages and fringe benefits. My estimates also imply that current staffing ratios fall short of the social optimum by 48% on average. These results are supported by several robust exercises. I find no evidence for inefficiently low staffing ratios in the small fraction of nursing homes that do not accept Medicaid residents, suggesting that low Medicaid reimbursement rates are a potentially important contributor to quality shortfalls in this industry.

I revisit this conjecture in the first counterfactual exercise. Here, I simulate the effects of a universal 10% increase in Medicaid reimbursement rates. I find that nursing homes increase the number of skilled nurses per resident by 8.8% and decrease their private rates by 4.9% on average. The decrease in private rates indicates "cost-shifting" between Medicaid beneficiaries and private payers, which has been studied in the hospital industry (see e.g., Frakt (2011)) but not for nursing homes. Combining the effects on consumer surplus, provider profits, and public spending, I find a welfare gain of $68 million per year, about 30% of the increase in Medicaid spending.

I compare these findings to the effects of an increase in local competition via directed entry of a new public nursing home. I find very small changes in incumbent skilled nurse staffing ratios. My results point to a reduction in social welfare as the consumer gains are smaller than the reduction in industry profits, when adding the fixed costs of the new entrants. I also find that new entrants are unable to recover their fixed costs. Considering the annual losses of the new entrants as required additional public spending, I find a return in skilled nurses per resident per $100 million in public spending of only 1.5%. In contrast, I find a return of 3.9% in the former policy counterfactual, which suggests that raising Medicaid reimbursement rates is more cost effective in improving the quality of care.

The main contribution of this paper is to provide new evidence on the dependence of the quality of nursing home care on Medicaid reimbursement rates and local market power. Previous studies investigated the link between Medicaid reimbursement rates and nurse staffing ratios both theoretically (see e.g., Scanlon (1980), Ma (1994), and Rogerson (1994)) and empirically (see e.g., Gertler (1989); Grabowski (2001); Harrington et al. (2008); Feng et al. (2008)).[1] Other studies have investigated the link between measures of concentration and staffing (Lin (2015)) and pricing decisions (Nyman (1988)).

My analysis contributes to this literature in two important ways. First, I explore a novel source of plausibly exogenous variation in the Medicaid reimbursement rate and thereby address the endogeneity concerns of previous related studies. Second, this paper is the first to develop and estimate an explicit model of demand and supply of the nursing home industry using a novel combination of survey and administrative data sources. The model allows me to analyze the welfare consequences of quality shortfalls and to quantify the demand and supply mechanisms through which alternative policies can mitigate these concerns.[2]

My demand analysis is related to Ching, Hayashi and Wang (2015). The authors develop a novel methodology to quantify how binding capacity constraints, induced by a CON law in Wisconsin, restrict access to care for Medicaid beneficiaries. My paper is primarily concerned with the quality of nursing home care. To this end, I simplify their demand model by abstract-

[1] Earlier studies have argued that higher Medicaid rates may lead to lower quality of care if rationing leads to excess demand of Medicaid residents, see Grabowski (2001) for a summary. However, more recent studies, starting with Grabowski (2001), find evidence for a positive relationship in parts because of a decline in nursing home utilization.

[2] My findings also complement the evidence on Medicaid's effect on access to care and quality of care in other health care sectors, where the effects may be different to the extent that Medicaid covers a significantly smaller fraction of the patient population, see KFF (2013) for an overview.

ing away from rationing concerns as well as substitution between different forms of long term care. Instead, I extend their analysis by adding an endogenous quality of care component. I take advantage of rich administrative resident data, which allow me to include Medicare beneficiaries, and model residents with multiple payer sources. I use more precise information on distances to nursing homes, which is a key source of horizontal product differentiation. These institutional details are important in understanding the link between quality, pricing, Medicaid reimbursement rates, and local competition. I estimate the model using data from Pennsylvania, where rationing is perhaps less worrisome, as Pennsylvania does not restrict entry and capacity investments through a CON law. An extensive list of robustness exercises indicates that rationing as well as the availability of other forms of long term care only have a minor impact on the effect of Medicaid rates and entry subsidies on the quality of care.[3]

My supply side analysis is related to Lin (2015), who develops a rich dynamic model of nursing home entry and exit. Lin's paper studies important dynamic considerations in the interdependence between quality choices and market structure, which my paper abstracts away from. My analysis focuses on explaining the large cross-sectional differences in the quality of care. To this end, I adopt a simpler static modeling approach and replace the author's reduced form profit function with an explicit model of demand and supply. Shifting the focus towards separating demand and supply is integral for welfare analysis and for understanding the mechanisms through which Medicaid reimbursements affect staffing and pricing incentives.

A second contribution is the identification of non-pecuniary objectives among non-profit and public nursing homes, which have been argued to be important in this industry, see Chou (2002). Combining the model with marginal cost data allows me to decompose observed quality differences by profit status into differences in local demand, cost structures, and non-pecuniary objectives. This extends previous empirical studies on the hospital industry which have not been able to separate differences in objectives from differences in costs (see, e.g. Gaynor and Vogt (2003)). My findings indicate that non-pecuniary objectives of non-profits can explain quality differences between for-profit and not-for-profit nursing homes.

[3]However, welfare and total spending estimates are affected by the availability of different forms of care.

Finally, my counterfactual analysis of the gains from additional entry also relates to a literature on the welfare effects of free entry. Several studies have shown, both theoretically and empirically, that free entry can lead to social inefficiencies if fixed costs are present (see Berry and Waldfogel (1999) for an overview). This study provides new empirical evidence on these inefficiencies, which is particularly interesting in the context of the nursing home industry since CON laws restrict entry of new nursing homes in several states.

The remainder of this study is organized as follows. In Section 2, I discuss the institutional background before I turn to the data and preliminary evidence from Pennsylvania in Section 3. I discuss the empirical industry model in Section 4, and present estimation and counterfactual results in Sections 5 and 6, respectively. Finally, I consider robustness checks in Section 7 and conclude in Section 8. Further details are provided in online appendix sections A.1 - A.20.

2 Institutional Background

2.1 Quality of Care

Quality shortfalls in nursing home care have been an ongoing concern for decades as evidenced by very low nurse staffing ratios, poor clinical outcomes, and a high number of process or outcome based deficiencies, see e.g., Department of Health and Human Services (1999) and Harrington et al. (2016). In an effort to improve the quality of care, various policy attempts have been made including minimum staffing regulations, nursing homes inspections, resident health reporting, reimbursement reform, and public reporting of quality outcomes, with only partial success, see Section A.1 for details.With Medicaid being the primary payer for most nursing home residents, reimbursement rates continue to be a priority policy area for state governments to address low nurse staffing ratios and nursing home deficiencies.

In this paper, I focus on licensed practical and registered nurse (skilled nurse) staffing ratios as the key mechanism through which nursing homes influence the quality of care. I make this modeling choice for three main reasons. First, skilled nurses play an important role in monitoring and coordinating the delivery of care and many studies have found a positive relationship between skilled nurse staffing and better outcomes of care. These include fewer deficiencies, Lin (2014), better clinical outcomes such as improved physical functioning, less antibiotic use, fewer pressure ulcers, catheterized residents, urinary tract infections, less weight loss, and less dehydration, see KFF (2015) for an overview, as well as lower mortality rates, Friedrich and Hackmann (2017). Second, skilled nurse staffing ratios are published on publicly available quality report cards, giving nursing homes an economic incentive to improve staffing in order to attract more residents, see Figure A2 for details. Finally, I provide direct evidence that nursing homes primarily adjust the number of skilled nurses per resident in response to changes in the regulated Medicaid reimbursement rates.[4]

2.2 Market Structure, Regulation, and the Quality of Care

Nursing home expenditures totaled $170 bn in 2016, about 5% of total health care spending, up from 3% in 1965. Over the next decade, nursing home expenditures are expected to grow roughly proportionately to total health care spending at an annual rate of 5.3%.[5] This poses a substantial burden for state budgets given that Medicaid is the primary payer for most nursing home stays. In Pennsylvania (and nationwide), about 62% of residents are covered by Medicaid at any given point in time, who meet the state-specific income and asset criteria. Medicaid pays the nursing home a regulated capitation payment per Medicaid-resident day, the Medicaid reimbursement rate, which is intended to cover the provider's expenses for health care services as well as room and board. Most states, including Pennsylvania, calculate nursing home specific reimbursement rates based on a prospective, risk-adjusted, cost-based reimbursement methodology, which I discuss in greater detail in Section 3.1.

The average Medicaid reimbursement rate per resident and day equals about $189 in Pennsylvania, exceeding the national average by $25 or about one standard deviation in

[4] While registered nurses and licensed practical nurses differ in their training background and skill levels, I combine them as skilled nurses to simplify the following analysis.

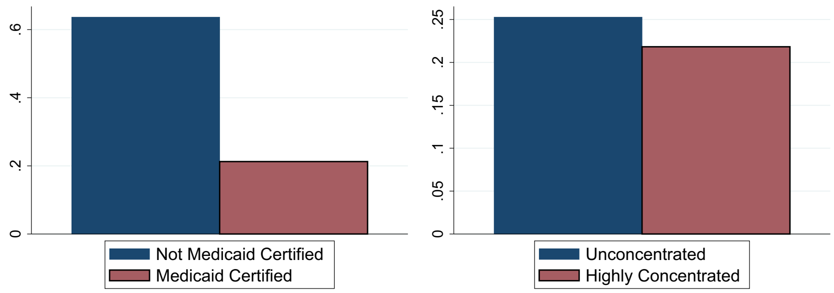
[5] See goo.gl/DHRm6r, last accessed 10/23/16.

state averages, see Section A.2 for more details. The Medicaid rates generally fall short of the private rate, set by the nursing home, which are charged to about 27% of residents in Pennsylvania who pay out-of-pocket (compared to 24% nationwide). In Pennsylvania, private rates exceed the Medicaid reimbursement rate by 17% on average and nursing homes are not allowed to charge Medicaid or Medicare beneficiaries on top of the regulated rate. The residual 11% of residents are generally covered by Medicare and only a very small fraction of residents has private long term-care insurance. Medicare pays the nursing home a more generous reimbursement rate per resident and day but only covers up to 100 days of post-acute care following a qualifying hospital stay.

Medicare's day limit and the asset eligibility criteria for Medicaid also imply that a large fraction of residents transitions between multiple payer sources during a nursing home stay. In Pennsylvania, 52% of residents are covered by Medicare at the time of admission but more than 90% of these residents are covered by Medicaid or pay out-of-pocket at the end of their stay, see Table A3 for details. Also, 34% of residents are initially paying out-of-pocket but almost 60% of these residents are covered by Medicaid at their time of discharge.

Since the daily revenues differ across payer types, nursing homes have an economic incentive to differentiate the quality of care. However, federal regulations require that nursing homes offer the same quality of care to all payer types within a facility. Existing studies have shown that nursing homes comply with the regulation, see Angelleli, Grabowski and Gruber (2008). Therefore, I model quality of care as a public good across different payer types. Nevertheless, one would expect quality differences between nursing homes based on the composition of payer types served. In the left graph of Figure 1, I compare the number of skilled nurses per resident between Medicaid certified nursing homes (93%) and nursing homes that do not accept Medicaid beneficiaries (7%) using national data from LTC focus from 2010. The large staffing difference provides the first evidence that Medicaid reimbursement plays a potentially important role for the quality of care. I revisit this hypothesis in the next section using detailed data on Medicaid reimbursement rates in Pennsylvania.

Figure 1: Skilled Nurses per Resident by Medicaid Certification and Concentration



Note: The vertical axis measures the number of skilled nurses per resident. Following the merger guidelines from the Federal Trade Commission, the right graph divides counties into highly concentrated (HHI>2,500) and unconcentrated (HHI<1,500) markets. The national data come from LTC Focus in 2010.

A competing explanation for quality shortfalls in this industry is a lack of local competition. The average Herfindahl index (HHI), using the county as the market definition, equals 1,200 in Pennsylvania compared to 2,000 nationwide. The difference in concentration (about one standard deviation in state averages) may be partially attributed to CON laws which restrict entry and capacity investments in two thirds of the states but not in Pennsylvania. The HHI measures suggest that the nursing home industry is less concentrated than the hospital industry. However, the county market definition may understate the market concentration if nursing homes compete in more narrowly defined geographic markets. In the right graph of Figure 1, I compare average staffing ratios between highly concentrated markets (29%) and unconcentrated markets (57%). The observed difference suggests that an increase in competition might lead to better quality of care.

Motivated by the evidence from Figure 1, I now turn to a rigorous analysis of the dependence of staffing and pricing decisions on Medicaid reimbursement rates and market structure using detailed data from Pennsylvania.

3 Data and Preliminary Evidence from Pennsylvania

I collect administrative resident level micro data from the Minimum Data Set (MDS), which provides at least quarterly information on a variety of health measures for all nursing home residents in Medicaid or Medicare certified nursing homes, about 98% of all nursing homes. The MDS has become increasingly more popular among researchers who study the health profiles of nursing home residents. However, this is the first study, to the best of my knowledge, which uses the MDS to estimate the demand for nursing home care.

Nursing home residents typically struggle with multiple physical and cognitive disabilities. I focus on a subset of health measures, evaluated at the time of the senior's admission to the nursing home, to model potential differences in the senior's preferences for nursing home characteristics. For instance, I measure whether the resident was diagnosed with Alzheimer's disease and allow for a particular preference for nursing homes with an Alzheimer's unit. I also reduce a large number of health measures and disabilities to a one-dimensional individual case-mix index (CMI). The CMI is used in reimbursement methodologies and summarizes the expected resource utilization relative to the average resident. I use the admission date and the discharge date to calculate the length of the nursing home stay, which is the unit of observation in the empirical analysis.[6] The MDS also provides the zip code of the resident's former address, which allows me to incorporate the role of distance in the demand model.

One disadvantage of the MDS is that the provided payer type information is not particularly accurate. Therefore, I merge the MDS with Medicaid and Medicare claims data, which allow me to specify which days during any stay were covered by Medicaid or Medicare. I assume that the residual days are paid out-of-pocket because only a very small fraction of residents has access to private long-term care insurance.[7]

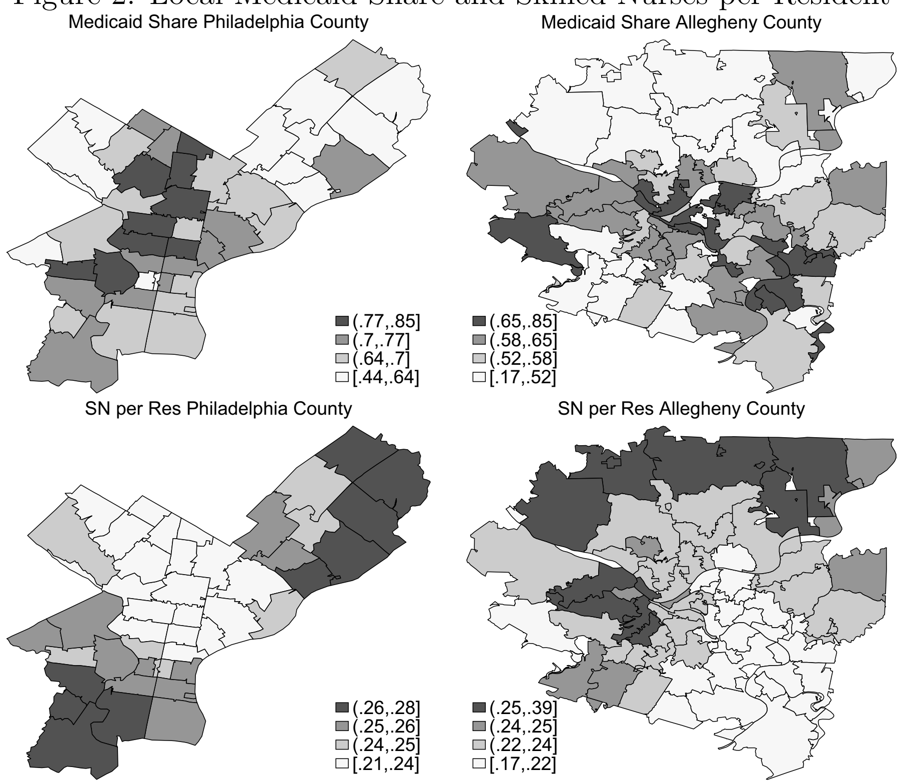
I focus on seniors who were admitted to a nursing home in Pennsylvania in the years 2000-2002, which reduces the sample population to about 287,000 nursing home stays, about

[6]A nursing home stay ends with a permanent discharge, which indicates that a return is not anticipated at the time of the discharge. This can be because the resident deceased. I observe discharge dates up until the end of 2005 and treat the 31st of December in 2005 as the discharge date for those residents who stay beyond this day. This applies to only 4.7% of observations since I focus on admissions between 2000 and 2002, see Figure A3 for more details on the length of stay.

[7]Less than 2% of days are covered by private long term care insurance, which compares to 4% nationwide, see https://www.cbo.gov/sites/default/files/cbofiles/ftpdocs/54xx/doc5400/04-26-longtermcare.pdf, last accessed 11/30/16. Furthermore, the average maximum daily benefit of private insurance equals $109 in 2000 (the modal benefit was $100), which is substantially smaller than the average private rate in 2000 of $220. Therefore, privately insured elderly internalize differences in prices between nursing homes and should, absent of wealth effects, respond as elastically to private rates as seniors who pay the full price out-of-pocket.

96,000 admissions per year. The top row of Figure 2 describes spatial variation in the fraction of Medicaid beneficiaries by zip code of former residence in two urban counties, Philadelphia County and Allegheny County (which includes the city of Pittsburgh). The graphs indicate that there is considerable heterogeneity in the payer mix across zip codes within the same county. This provides rich spatial variation in nursing home's staffing and pricing incentives since the distance between the senior's former residence and the nursing home is critical for the nursing home choice. The first row of Table 1 indicates that the median senior chooses a nursing home within 7km of the senior's former residence. There is also considerable heterogeneity in the length of stay among nursing home residents, see the second row of Table 1. While some residents stay for several years, about 50% are discharged within 1 month.

Figure 2: Local Medicaid Share and Skilled Nurses per Resident



Note: The top graphs summarize the spatial variation in the share of Medicaid beneficiaries by the zip code of their former residence. The lower graphs display distance-weighted averages in the number of skilled nurses per resident. I construct the average over all nursing homes within 10km of the zip code centroids.

I combine the MDS with data from annual nursing home surveys, which were provided by

Table 1: Summary Statistics 2000-2002

	N	Mean	10th	50th	90th
Distance traveled in 100km	287,364	0.11	0.02	0.07	0.23
Length of Stay in Days	287,364	222	8	34	868
Share Medicaid	2,079	0.59	0.14	0.66	0.85
Licensed Practical Nurses per Resident	2,079	0.14	0.07	0.13	0.21
Registered Nurses per Resident	2,079	0.13	0.06	0.11	0.21
Daily Private Rate	2,079	223	175	212	261
Daily Medicaid Rate	1,834	183	158	181	210
Marginal Costs per Resident Day	1,824	159	123	155	194
Fixed Costs per Year in million dollars	1,781	1.25	0.48	1.11	2.05

Note: The top two rows describe the data from the MDS and are based on newly admitted residents between 2000 and 2002. Travel distance is weighted by length of stay. The remaining rows describe the data from the annual nursing home survey and the annual cost reports for the years 2000-2002.

the Bureau of Health Statistics and Research of the Pennsylvania Department of Health.[8] The survey provides information on various nursing home characteristics for all licensed nursing homes in Pennsylvania, including the Medicaid reimbursement rate, the private rates charged to seniors who pay out-of-pocket, and the number of full-time and part-time employees by profession. I aggregate the employment information to full-time equivalent employees by dividing the part-time employees by 2 and adding them to the number of full-time employees.

I use survey data from 1996-2002 for the preliminary analysis on the effect of Medicaid reimbursement rates on staffing and pricing decisions and focus on the years 2000-2002 in the structural estimation. Similar to Feng et al. (2008), I exclude nursing homes that primarily target residents requiring expensive rehabilitative care (provided by specialized therapists) as opposed to support with their chronic disabilities, and thereby compete in a different market.[9] I also exclude nursing homes that focus on out-of-state residents (more than 85% of residents). This reduces the sample population by about 10% to 5,000 nursing home-year observations

[8] The Department specifically disclaims responsibility for any analysis, interpretation or conclusions.

[9] Specifically, I exclude homes whose Medicare share exceeds 90% as well as the 2% of homes that charge the highest daily private rate. Their rates exceed the median daily rate in the sample population by more than 7 standard deviations and they employ more than twice as many therapists per resident than the average nursing home. I address concerns regarding endogenous sample selection in Section A.4. To construct a balanced sample that allows for the estimation of senior preferences, I drop homes that cannot be linked between the survey and the MDS or have fewer than 5 admissions per year.

including 2,079 observations for the years 2000-2002, summarized in the middle rows of Table 1. There is considerable variation in the share of Medicaid residents between nursing homes as indicated by the third row, which is (positively) spatially correlated with the variation in Medicaid beneficiaries across their former residences. About 8% of nursing homes are not Medicaid certified and cannot serve any Medicaid beneficiary. There is also substantial variation in the number of licensed practical and registered nurses per resident across nursing homes. The 90th percentile exceeds the 10th percentile by a factor of three. The lower graphs in Figure 2 summarize the distance-weighted spatial distribution of skilled nurses per resident across zip codes for the two urban example counties. The graphs visualize the negative spatial correlation between skilled nurse staffing ratio and the local share of Medicaid beneficiaries in the two urban counties.[10] This provides additional evidence that Medicaid reimbursements are a potentially important determinant of the quality of care.

Finally, I merge the survey data with detailed cost information for Medicaid certified nursing homes. Every year, certified nursing homes submit reimbursement relevant cost reports to Pennsylvania's Department of Human Services (DHS). Following the detailed Medicaid reimbursement guidelines, the DHS isolates allowable costs, which are considered as necessary costs to provide nursing home care and are used directly in the Medicaid reimbursement methodology.[11] I treat these allowable costs as economic costs, which is consistent with the Medicaid reimbursement goal to cover economic costs. I follow the interpretation of the DHS and treat health related costs (mostly salaries and fringe benefits of health care professionals) and other health related costs (mostly spending on room and board) as variable costs.[12] In the empirical model, I assume constant marginal costs, whereby variable costs and marginal costs per resident and day are equal. Hence, I can recover marginal costs by dividing the total annual variable costs by the number of resident days in the given year, which equal $155 per

[10] I find a negative spatial correlation of -10% (-33%) across all zip codes in Pennsylvania (zip codes in Allegheny and Philadelphia County), which is statistically significant at the 1% level.

[11] See http://www.pacode.com/secure/data/055/chapter1181/s1181.212.html, accessed 11/29/2016.

[12] This interpretation is further supported by a statistically significant positive relationship between variable costs per resident day and the daily private rate. Furthermore, the observed variable costs of for-profits are consistent with the variable cost predictions of the pricing first order conditions, when evaluated at the estimated parameters, see Section 5 and Section A.11 for details.

resident and day, on average. The annual fixed costs equal \$1.1 million on average, which comprise administrative and capital costs, see the last row of Table 1.

3.1 Medicaid Reimbursement, Staffing, and Pricing

In this section, I provide first direct evidence on the effects of regulated Medicaid provider reimbursement rates on staffing and pricing decisions. To this end, I consider the following empirical specification for Medicaid certified nursing homes:

$$log(Y_{jt}) = \gamma_1 * log(R_{jt}^{mcaid}) + \alpha X_{jt} + \phi_{ct} + \epsilon_{jt} \quad . \tag{1}$$

Here, $log(Y_{jt})$ denotes the respective outcome measure in nursing home j and year t, such as the log number of skilled nurses per resident or the log daily private rate for a semi-private room. $log(R_{jt}^{mcaid})$ refers to the log Medicaid reimbursement rate per resident and day, ϕ_{ct} captures county-year fixed effects, and X_{jt} contains additional nursing home specific control variables. The key parameter of interest is γ_1 which denotes the effect of an increase in the log Medicaid reimbursement rate on staffing and pricing decisions.

Before discussing the identification of γ_1, it is important to describe Pennsylvania's reimbursement methodology. The Medicaid reimbursement rate is based on reported costs (from 3-5 years ago) of all nursing homes in a peer group determined by size and region. The DHS distinguishes between small (<120 beds), medium-sized (120-269 beds), and large nursing homes (>269 beds) in each of the four reimbursement regions indicated in Figure 3, defining 12 peer groups.[13] The regions are determined based on the population size of the Metropolitan Statistical areas (MSAs) and combine several counties that are commonly assumed to define separate nursing home markets (Zwanziger, Mukamel and Indridason (2002)).

Specifically, the Medicaid reimbursement rate for nursing home j depends on j's lagged

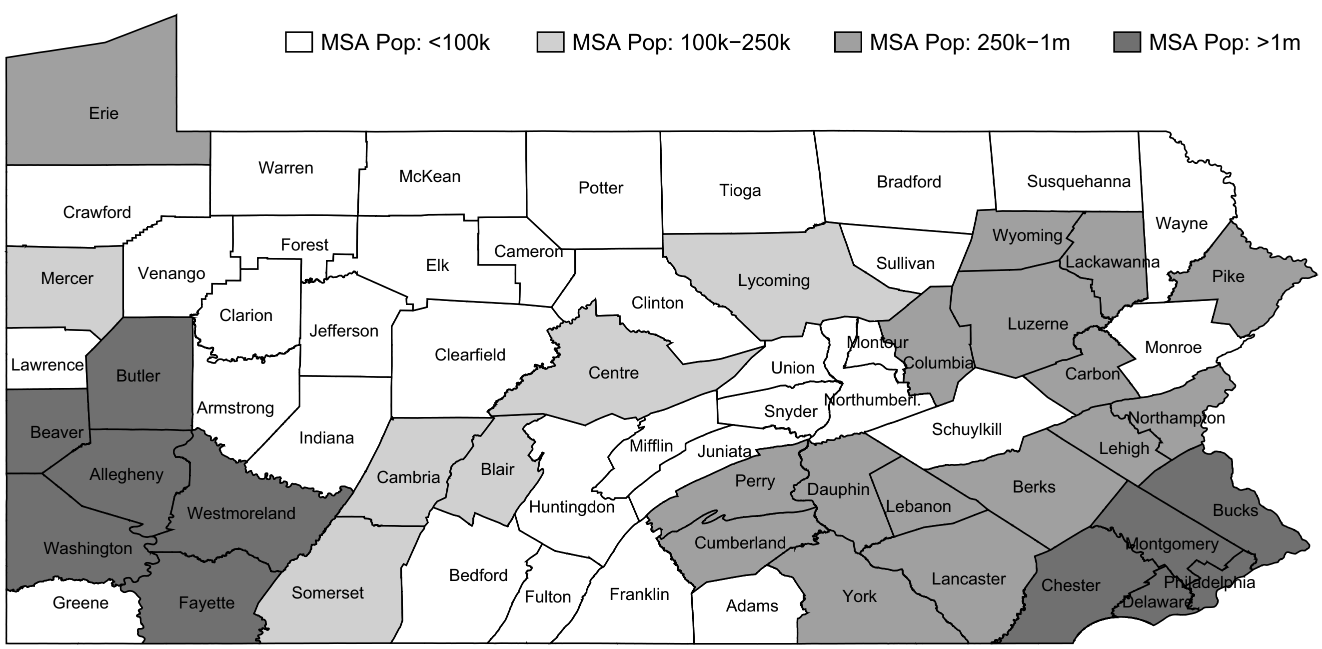
[13] About 45% of nursing homes have fewer than 120 beds, 49% have between 120 and 269 beds, and 6% have more than 269 beds, see Figure A5 for details. The DHS defines two additional peer groups for hospital operated and rehabilitative care providers. These providers target predominantly different rehabilitative care patients and are excluded from this analysis, as discussed earlier.

average costs from 3-5 years ago, $AC_{jt-3,4,5} = \{AC_{jt-3}, AC_{jt-4}, AC_{jt-5}\}$, as indicated by the first argument in the reimbursement formula $g(\cdot)$, see Section A.5 for details:

$$R_{jt}^{mcaid} = g\Big(AC_{jt-3,4,5}, median(AC_{c,t-3,4,5}^{p(j)}, AC_{-c,t-3,4,5}^{p(j)})\Big) \ . \tag{2}$$

Furthermore, R_{jt}^{mcaid} also depends on the median of lagged average costs of all nursing homes in $j's$ peer group, $p(j)$, as indicated by the second argument. This includes average costs of nursing homes located in $j's$ county c, abbreviated by $AC_{c,t-3,4,5}^{p(j)}$ and, importantly, average costs of nursing homes located in other counties $-c$, captured by $AC_{-c,t-3,4,5}^{p(j)}$. For example, the Medicaid reimbursement rate for a nursing home located in Allegheny County (Southwest corner in Figure 3) depends in part on lagged costs of nursing homes located in Bucks County (Southeast corner), if they are of similar size.

Figure 3: Reimbursement Peer Group Regions in Pennsylvania



Finally, I decompose average costs into observable cost shocks $Z_{jt} \subset X_{jt}$, which is a subset of X_{jt}, endogenous staffing decisions Y_{jt}^s scaled by input prices w^s, and unobservable cost shocks η_{jt}:

$$AC_{jt} = \phi^z * Z_{jt} + \sum_s \left(w^s * Y^s_{jt} \right) + \eta_{jt} \ . \tag{3}$$

Identification: An empirical challenge to the estimation of γ_1 is the potential correlation between $log(R^{mcaid}_{jt})$ and ϵ_{jt}, which would add bias to the ordinary least squares estimator discussed in Section A.8.3. This is of particular concern because $j's$ lagged average costs affect $log(R^{mcaid}_{jt})$ directly, see the first argument in equation (2). The correlation between $log(R^{mcaid}_{jt})$ and ϵ_{jt} can be positive or negative. For example, unobserved positive demand shocks, may increase staffing and consequently average costs and future reimbursement rates, suggesting a positive correlation. Alternatively, unobserved supply shocks, such as higher input prices, may lower staffing but increase costs, suggesting a negative correlation. Furthermore, the staffing decisions of $j's$ local competitors may affect $log(R^{mcaid}_{jt})$ through the median argument in equation (2) if they belong to the same peer group. Rival staffing decisions may also affect $j's$ staffing decisions directly suggesting a positive or negative correlation depending on whether staffing decisions are strategic complements or substitutes. This effect is, however, attenuated by costs of distant non-competitors that enter the median argument as well.

To mitigate these concerns, I assume that nursing homes compete in locally segmented markets both for new residents and inputs (e.g. nurses). In my primary specification, I assume that counties define segmented markets suggesting that lagged costs from nursing homes located in different counties, $AC^{p(j)}_{-c,t-3,4,5}$, do not affect the optimal staffing and pricing decision directly and are therefore excluded from equation (1). However, these costs affect the Medicaid reimbursement rate, see equation (2), and can therefore serve as instrumental variables. For example, the for-profit penetration affects the equilibrium distribution of staffing ratios and private rates and thereby affects the cost distribution of providers in the given county. The exclusion restriction states that the county-specific for-profit penetration does not affect staffing and pricing decisions in other counties, conditional on the for-profit penetration in these distant counties, other than through the reimbursement formula.

More formally, $AC^{p(j)}_{-c,t-3,4,5}$ must be independent of ϵ_{jt}, conditional on X_{jt} and ϕ_{ct}. As shown in Section A.8.1, this holds true if the following two assumptions are satisfied:

(SP) ϵ_{jt} is independent of lagged shocks to providers located in other counties from 3 or more years ago, conditional on X_{jt} and ϕ_{ct}:

$$\epsilon_{jt} \perp\!\!\!\perp \{\epsilon_{-ct-k}, \eta_{-ct-k}, X_{-ct-k}, \phi_{-ct-k}\}_{k\in 3,4,..} |\ X_{jt}, \phi_{ct}$$

(SE) ϵ_{jt} is independent of lagged shocks to peer group members located in the focal county c from six or more years ago, conditional on X_{jt} and ϕ_{ct}, if $\gamma_1 \neq 0$:

$$\epsilon_{jt} \perp\!\!\!\perp \{\epsilon_{ct-k}, \eta_{ct-k}, X_{ct-k}, \phi_{ct-k}\}_{k\in 6,7,..} |\ X_{jt}, \phi_{ct}$$

Assumption (SP) may be violated if cost and staffing shocks are spatially as well as serially correlated. Assumption (SE) may be violated if local cost and staffing shocks are serially correlated, adding bias if they affect the instrumental variable, average costs in other counties, $AC^{p(j)}_{-c,t-3,4,5}$, as well. Intuitively, this bias operates through a "boomerang effect". For example, ϵ_{jt-6} affects Y_{jt-6} and consequently AC_{jt-6}, through equations (1) and (3), respectively. This in turn affects $R^{p(j)}_{-c,t-3,4,5}$ through equation (2) and in turn $Y^{p(j)}_{-ct-3,4,5}$ and $AC^{p(j)}_{-c,t-3,4,5}$ through (1) and (3).

In this context, I find that serial correlation alone can only add a small upward bias (up to 5%) to the two stage least squares (2SLS) estimator discussed below. This is largely because of the long time lag of 6 or more years in assumption (SE) and because I control for serial correlation at the county level through county-year fixed effects. Furthermore, the "boomerang" effect operates through the median argument in equation (2), which is attenuated by cost shocks from several other counties, see Section A.8.2 for details. Regarding assumption (SP), I find very little spatial correlation in marginal costs and staffing decisions between counties, see Section A.7, in parts because the median senior chooses a nursing home within only 7km of her former residence. I return to a more thorough discussion of assumptions (SE) and (SP) at the end of this section.

To use the large number of instrumental variables most effectively, I employ a simulated instrument approach (Currie and Gruber (1996)). This method increases statistical power by exploiting knowledge of the functional relationship between instruments and the endogenous regressor. To apply this method, I use the exact reimbursement formula but simulate an analogue Medicaid reimbursement rate that only varies in exogenous cost components, costs from peer group affiliated nursing homes located in different counties:

$$R_{jt}^{mcaid,sim} = \frac{1}{N^{sim}} \sum_{i=1}^{N^{sim}} g\Big(x_i, median(x_i, AC_{-c,t-3,4,5}^{p(j)})\Big) \quad .$$

Here, x_i is a random average cost draw from the distribution of all nursing homes in the state and N^{sim} is the number of simulation draws. Following Currie and Gruber (1996), this instrument can be thought of as a "convenient parametrization" of the generosity of a nursing home's Medicaid reimbursement rate, purged of variation due to the nursing home's own costs as well as it's rival's costs, see Section A.5 for details.[14]

Table 2 presents the 2SLS regression results. The first column shows the first stage parameter estimate, which indicates that a 1% increase in the simulated reimbursement rate raises the endogenous Medicaid reimbursement rate by 1.15%. The point estimate is statistically significant at the 1% level with an F statistic of 42. The remaining columns present the second stage effects. The estimate in the second column indicates an economically and statistically significant effect for skilled nurses. Nursing homes increase the number of skilled nurses per resident by 1.17% in response to a 1% increase in the Medicaid reimbursement rate. To put this effect into perspective, I assume that a full-time skilled nurse works 2,080 hours per year, which corresponds to 52, 40-hour weeks. The number of skilled nurses per resident equals

[14] An advantage of this aggregation method is that I can exploit identifying cost variation at the county-year-peer group and the county-year level even though I control for county-year fixed effects. This is because peer group size differences among counties imply different county weights in the reimbursement calculation. For example, suppose there are disproportionately many (few) large (small) nursing homes in Allegheny County when compared to its neighbor Westmoreland County. Then the Medicaid reimbursement rates of large nursing homes in Philadelphia County will largely depend on cost shocks to Allegheny County and to a lesser extent on cost shocks to Westmoreland County. The opposite holds true for small nursing homes in Philadelphia County.

0.24 on average, which corresponds to 2,080 *0.24/365=1.37 hours per resident and day. This suggests that a 10% increase in Medicaid rates raises the time a skilled nurse spends per resident and day by about 10 minutes on average.

Table 2: Medicaid Reimbursement Rates, Staffing, and Pricing

	(1) First Stage	(2) $log(SN^{res})$	(3) $log(NA^{res})$	(4) $log(Th^{res})$	(5) $log(P)$
Log Simulated Rate	1.15***				
	(0.18)				
Log Medicaid Rate		1.17***	0.07	0.66	0.03
		(0.29)	(0.49)	(2.25)	(0.20)
Observations	4022	4022	3872	3307	4022
R^2	0.189	0.090	0.039	0.122	0.101

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: $log(SN^{res})$, $log(NA^{res})$, and $log(Th^{res})$ abbreviate the log number of skilled nurses, nurse aides, and therapists per resident, respectively. $log(P)$ is the log daily private rate. All specifications control for county-year fixed effects, ownership type, having an Alzheimer's unit, average distance to closest competitors, local demographics, and a fourth order polynomial in beds interacted with year fixed effects. Standard errors are clustered at the county level.

I find no evidence for systematic changes in other inputs including the number of nurse aides or therapists, see columns 3 and 4, as well as pharmacists, physicians, psychologists, social workers, and dietetic technicians, see Table A.8.6. I also explore the effects on additional inputs captured by overall changes in costs and find that about three quarters of the overall change in costs can be explained by changes in the skilled nurse staffing ratios, see Section A.8.6 for details.[15] While the large standard errors on other staffing measures make it difficult to rule out other endogenous characteristics, the cost estimates suggest that skilled nurses are the most important measure.[16] For tractability reasons and following the reasons outlined in Section 2.1, the structural analysis focuses on a single quality of care measure: the number of skilled nurses per resident.

Finally, column 5 displays the effect on private rates, which equals 0.03 and is statistically insignificant.

[15] I also find that nursing homes spend 53% of the extra Medicaid revenues on additional skilled nurses.

[16] Possibly, this is because the skilled nurse staffing ratio is observed by seniors and their relatives, when they choose a nursing home. I revisit this hypothesis in the following demand analysis.

I repeat the analysis with a leave-one-out instrumental variable approach. Instead of using the exact reimbursement formula, I compute the average over reported costs from providers located in different counties. The findings are qualitatively similar. The first stage coefficient decreases to 0.61 (se=0.16) and the second stage coefficient for skilled nurses decreases to $\hat{\gamma}_1^{2SLS} = 0.83$ (se=0.36). Again, I find no evidence for systematic changes in the number nurse aides per resident, therapists per resident, or the private rate, see Section A.8.4 for details.

Robustness: Whether potential violations of assumptions (SP) and (SE) add significant bias to $\hat{\gamma}_1^{2SLS}$ depends on the specific context. In Section A.8.5, I show in an extensive list of robustness checks that the potential bias from serial and spatial correlation is probably small in this context. With respect to serial correlation, I revisit the point estimates exploring identifying variation in observable distant cost shocks, $Z_{-ct-3,4,5}$, only. These include the number of licensed beds, the ownership type, the distance to a nursing home's closest competitors, and local demographics. This refinement allows me to drop assumption (SE) as I do not have to account for the "boomerang" relationship between endogenous staffing and average costs in equation (3). I can also relax assumption (SP) as follows: $\epsilon_{jt} \perp\!\!\!\perp \{Z_{-ct-k}\}_{k \in 3,4,..} | \ X_{jt}, \phi_{ct}$, with $Z_{-ct-k} \subset X_{-ct-k}$. Here, I find a point estimate for skilled nurses of $\hat{\gamma}_1^{2SLS} = 1.41$. I also consider robustness to concurrent trends at the peer group-county level, which may violate assumption (SE). To this end, I add data from 1993-1995 to the analysis and take advantage of a change in the reimbursement methodology in 1996. The reimbursement rates from 1996 onward are not correlated with staffing ratios prior to 1996, which provides evidence against biases arising from concurrent trends. With respect to spatial correlation, I consider robustness to a more conservative geographic market definition: the MSA. Exploring cost variation of nursing homes located in different MSAs, I find $\hat{\gamma}_1^{2SLS} = 1.01$ for skilled nurses.

4 Empirical Model of Demand and Supply

Motivated by the preliminary evidence, I now turn to the empirical industry model, which allows me to analyze the positive and normative implications of counterfactual experiments.

Demand: I consider a static model of demand for a cohort of elderly people, who seek nursing home care in year t.[17] Motivated by the evidence from the literature, my preferred specification does not model substitution between different forms of long term care and treats the length of a nursing home stay as exogenous.[18] I revisit the role of other forms of care in Section 7. Specifically, I assume that senior i with payer type τ chooses the nursing home j which maximizes her average daily indirect conditional utility:[19]

$$u_{i\tau jt} = \beta_1^d * D_{ij} + \beta_2^d * D_{ij}^2 + \beta_i^{sn} * log(SN_{jt}^{res}) + \sum_x \beta_i^x X_{jt} + \beta_\tau^p * P_{jt} + \xi_{jt}^\tau + \epsilon_{ijt} \qquad (4)$$

with

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

Here, D_{ij} measures the distance between the senior's former residence and the nursing home. $log(SN_{jt}^{res})$ denotes the log number of skilled nurses per resident and X_{jt} captures characteristics that remain exogenous in the empirical analysis. These include, for example, the presence of an Alzheimer's unit. P_{jt} captures the daily private rate charged to elderly people who pay out-of-pocket. ξ_{jt}^τ denotes facility and payer type specific preference shocks which are observed by person i but remain unobserved to the econometrician and ϵ_{ijt} refers to an i.i.d. extreme value taste shock. The β_i^k parameters represent the taste of senior i for nursing home characteristic k, which may vary in the senior's health profile (evaluated at admission) and payer type, captured by vector z_i.

I distinguish between three payer types: residents who pay the entire stay out-of-pocket, elderly people who are covered by Medicaid or Medicare for the entire stay, and elderly people

[17] The model abstracts away from forward looking beliefs regarding potential nursing home switches.

[18] An older literature evaluated several long term care interventions from the early 1980s (known as the Channeling demonstration), which sought to substitute community care for nursing home care. Most studies found that the community care interventions had relatively small effects on nursing home utilization suggesting very little substitutability among community and nursing home care, see Rabiner, Stearns and Mutran (1994) for a review. This is consistent with more recent evidence from McKnight (2006) and Grabowski and Gruber (2007), who find that the demand for nursing home care at the extensive margin is relatively inelastic with respect to financial incentives.

[19] Seniors implicitly also maximize the utility of the entire stay, which is simply the product of equation (4) and the exogenous and nursing home independent length of stay in days, LOS_i.

who are partially covered but also pay some days of their stay out-of-pocket. I refer to these payer types as private, public, and hybrid payers, respectively. I allow the price coefficients in equation (4) to differ between payer types. Intuitively, one would expect that hybrid payers respond less elastically to prices than private payers. Finally, I assume that public payers do not respond to private rates and set their price parameter to zero. This is equivalent to setting their price to zero. I also allow for differences in unobserved preference shocks, ξ_{jt}^{τ}, which may capture differences in room amenities. Combining the modeling assumptions, I can express the nursing home choice probabilities for senior i as follows:

$$s_{ijt} = \frac{exp(\beta_1^d * D_{ij} + \beta_2^d * D_{ij}^2 + \beta_i^{sn} * log(SN_{jt}^{res}) + \sum_x \beta_i^x X_j - \beta_\tau^p * P_{jt} + \xi_{jt}^\tau)}{\sum_{k \in CS_i} exp(\beta_1^d * D_{ik} + \beta_2^d * D_{ik}^2 + \beta_i^{sn} * log(SN_{kt}^{res}) + \sum_x \beta_i^x X_{kt} - \beta_\tau^p * P_{kt} + \xi_{kt}^\tau)} \ .$$

Here, CS_i denotes senior $i's$ choice set, which includes all nursing homes in a 50 km radius around the senior's former address. I impose this choice set restriction for computational reasons as it reduces the data memory requirements considerably. However, only 2% of the seniors choose a nursing home that is farther away, see Section A.9 for details.

Supply: I consider a static oligopoly model. Nursing homes compete in private rates and the number of skilled nurses per resident for seniors from cohort t who begin their nursing home stay in the given year. To deal with stays that overlap multiple years, I assume that nursing homes commit to the cohort-specific staffing ratio and private rate throughout the entire stay.

I assume that nursing homes operate under constant marginal costs per resident and day, MC_{jt}, which depend on the skilled nurse staffing ratio, their unobserved input price W_{jt}, and an unobserved cost shifter ζ_{jt}. The total cost of serving residents from cohort t is then:

$$C_{jt} = MC_{jt} * \sum_i s_{ijt} * LOS_i + FC_{jt} = (\zeta_{jt} + W_{jt} * SN_{jt}^{res}) * \sum_i s_{ijt} * LOS_i + FC_{jt} \ .$$

Here, LOS_i denotes resident $i's$ length of stay in days and FC_{jt} denotes fixed costs. Notice that variable costs as well as total skilled nurse compensation are proportional to the total number of resident days because nursing homes choose the number of skilled nurses *per resident*.[20] Combining demand and costs, I can express nursing home profits over cohort t as:

$$\begin{aligned}\Pi_{jt} &= \sum_i s_{ijt} * (P_{jt} * Days_i^{priv} + R_{jt}^{mcaid} * Days_i^{mcaid} + R_t^{mcare} * Days_i^{mcare}) - C_{jt} \\ &= \sum_i s_{ijt} * LOS_i * \left(\bar{R}_{ijt} - MC_{jt}\right) - FC_{jt} \ .\end{aligned}$$

Here $Days_i^{priv}$ refer to days paid out-of-pocket and $Days_i^{mcaid}$ and $Days_i^{mcare}$ denote days reimbursed by Medicaid and Medicare respectively, which are known to the nursing home at the beginning of each stay. R_{jt}^{mcaid} and R_t^{mcare} denote the Medicaid and Medicare reimbursement rates per resident day and $\bar{R}_{ijt}$ captures the average daily revenue rate over the nursing home stay of the elderly i. Hence, the model captures the effect of local variation in demographics and socioeconomic status on staffing and pricing decisions through the combination of detailed payer source information and individual choice probabilities in the profit function.

Nursing Home Objectives: Not all nursing homes are necessarily profit maximizers. 46% of nursing homes are for-profits, 48% are private and not-for-profit, and 6% are public. While there is no agreement in the literature on a general model for non-profits, most models assume an objective function that depends on profits and an additional argument such as quantity or quality (Gaynor and Town (2011)). Following Lakdawalla and Philipson (1998), I assume that not-for-profit as well as public nursing homes maximize a utility function which is additive in profits and output quantity, capturing the motive to provide access to care:

$$U_{jt} = \alpha_j * \Pi_{jt} + (1 - \alpha_j) * \sum_i s_{ijt} * LOS_i \ . \tag{5}$$

[20]Let S and W be the annual and daily compensation per skilled nurse. The total annual compensation then equals $TS = S * SN$, where SN is the number of skilled nurses. Dividing and multiplying by the average number of residents, Res, yields $TS = S * SN^{res} * Res$. The annual number of resident days is simply Res*365 days. Hence, dividing and multiplying by 365 yields

$$TS = S/365 * SN^{res} * Res * 365 = W * SN^{res} * \sum_i s_{ijt} * LOS_i \ .$$

Specifically, I allow $\alpha \neq 1$ for non-profits and public nursing homes. Nursing homes choose private rates and staffing ratios simultaneously. Rewriting the first order conditions yields:

$$MC_{jt} = \frac{\sum_i s_{ijt} * Days_i^{priv} + \sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} * \bar{R}_{ijt} * LOS_i}{\sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} * LOS_i} + \frac{1-\alpha_j}{\alpha_j} \tag{6}$$

$$W_{jt} = \frac{\sum_i \frac{\partial s_{ijt}}{\partial SN_{jt}^{res}} * (\bar{R}_{ijt} - MC_{jt} + \frac{1-\alpha_j}{\alpha_j}) * LOS_i}{\sum_i s_{ijt} * LOS_i} . \tag{7}$$

The non-pecuniary objectives enter equation (6) as a marginal cost shifter. Intuitively, non-profits behave as for-profits with a perceived marginal cost advantage of $\frac{1-\alpha_j}{\alpha_j}$, see Lakdawalla and Philipson (1998).

4.1 Estimation and Identification

To estimate the key parameters of the model, I proceed in two steps following the approach in Goolsbee and Petrin (2004).

Step 1: In the first step, I use a Maximum likelihood estimation (MLE) approach to estimate taste heterogeneity in observable resident characteristics as well as mean utilities, defined below. Specifically, using micro data on each nursing home choice weighted by length of stay, I recover the preference parameters for proximity as well as the taste heterogeneity net of average tastes in the resident population denoted by β_r^k, excluding those parameters that capture heterogeneity across payer types.[21] The mean utilities, $\delta_{\tau jt}$, vary at the product-payer-type-year level and absorb the remaining preference components from the indirect utility function (ignoring the extreme value taste shock):

$$\delta_{\tau jt} = \begin{cases} \beta^{sn} * log(SN_{jt}^{res}) + \sum_x \beta^x X_{jt} + \beta_{priv}^p * P_{jt} + \xi_{jt}^{priv} & if\ private\ payer \\ \beta^{sn} * log(SN_{jt}^{res}) + \sum_x \beta^x X_{jt} + \beta_{hyb}^p * P_{jt} + \xi_{jt}^{hyb} & if\ hybrid\ payer \\ \beta^{sn} * log(SN_{jt}^{res}) + \sum_x \beta^x X_{jt} + \xi_{jt}^{pub} & if\ public\ payer\ . \end{cases} \tag{8}$$

[21] Weighting observations by their length of stay is consistent with the profit incentives of nursing homes and implies a plausible representation of the resident population in the consumer welfare analysis.

One convenient property of the MLE approach is that the first order conditions of the log likelihood function with respect to $\delta_{\tau jt}$ equate the predicted market share (by the model) and the observed market share by payer type. Therefore, these market shares coincide in the optimum just as in Berry, Levinsohn and Pakes (1995), see Section A.10 for details.

Step 2: In the second step, I use a generalized method of moments (GMM) estimator to recover the remaining mean preferences for observable nursing home characteristics as well as the cost and nursing home objective parameters. In the model, nursing home managers observe the unobservable taste shocks, ξ_{jt}^{τ}, before they choose the skilled nurse staffing ratios and the private rates. Therefore, these choices are likely correlated with the unobservables.

To address this endogeneity concern, I employ an instrumental variables approach. Motivated by the preliminary evidence from Table 2, I use the simulated Medicaid reimbursement rate as an instrument for the skilled nurse staffing ratios. I assume that the identifying cost variation (stemming from nursing homes located in different counties) is orthogonal to unobserved preference shocks in the given nursing home county.[22] I use information on region specific price indices interacted with the payer type as instruments for the private rates. Higher input prices raise marginal costs and lead nursing homes to charge higher private rates in equilibrium (the first stage). A common assumption in the industrial organization literature is that these marginal cost shifters do not affect preferences directly, which allows me to exclude them from equation (8). Furthermore, I use observable and exogenous product characteristics of local competitors (ownership type and number of beds), which do not enter the indirect conditional utility function directly. However, they affect the rival's costs, staffing, and pricing decisions and thereby have an indirect effect on staffing and pricing decisions of local competitors through competitive spillover effects. The instrumental variables form the "demand" moment conditions $E[\xi * IV] = 0$ and the following sample analogue:

$$G^{Demand}(\theta) = \frac{1}{N} \sum_{\tau} \sum_{t} \sum_{j} \xi_{jt}^{\tau} * IV_{jt}^{\tau} \ .$$

[22]The simulated Medicaid reimbursement rate could also serve as an instrument for the private rate, see Ching, Hayashi and Wang (2015), but the evidence from the Table 2 suggests a relatively weak first stage.

Here, θ summarizes the structural parameters and $N = 3 \times 3 \times J$, where J denotes the number of nursing homes multiplied by 3 payer types and 3 sample years. IV_{jt}^{τ} is the demeaned vector of instruments.[23] To recover the objective parameters for non-profits and publicly operated nursing homes, I construct additional "cost" moments. Similar to Byrne (2015), I match the cost predictions from the first order conditions, see equations (6) and (7), with cost data from Medicaid cost reports by ownership type. The moment conditions are $E[mc|type] = E[MC|type]$ and $E[w|type] = E[W|type]$, where lower case and upper case variables refer to data and model predictions, respectively. The sample analogues are:

$$G_{1,type}^{Cost}(\theta) = \frac{1}{N}\sum_{\tau}\sum_{t}\sum_{j\in type} mc_{jt} - \frac{1}{N}\sum_{\tau}\sum_{t}\sum_{j\in type} MC_{jt}$$

$$G_{2,type}^{Cost}(\theta) = \frac{1}{N}\sum_{\tau}\sum_{j\in type} w_{j,02} - \frac{1}{N}\sum_{\tau}\sum_{j\in type} W_{j,02} \ .$$

Here, *type* is either the set of for-profits, not-for-profits, or public nursing homes. w and mc denote the observed compensation package for a skilled nurse and marginal costs per resident and day, respectively, see Section 3 for the derivation of marginal costs. Due to data limitations, I only use data on compensation packages from 2002, which is also the base year for the following counterfactual analysis. Finally, I also match variances in marginal costs and compensation packages. The moment conditions are $Var(mc) = Var(MC)$ and $Var(w) = Var(W)$, motivating the following sample analogues:

$$G_3^{Cost}(\theta) = \frac{1}{N}\sum_{\tau}\sum_{t}\sum_{j}\left[mc_{jt} - \frac{1}{N}\sum_{\tau}\sum_{t}\sum_{j} mc_{jt}\right]^2 - \frac{1}{N}\sum_{\tau}\sum_{t}\sum_{j}\left[MC_{jt} - \frac{1}{N}\sum_{\tau}\sum_{t}\sum_{j} MC_{jt}\right]^2$$

$$G_4^{Cost}(\theta) = \frac{1}{N}\sum_{\tau}\sum_{j}\left[\omega_{j,02} - \frac{1}{N}\sum_{\tau}\sum_{j}\omega_{j,02}\right]^2 - \frac{1}{N}\sum_{\tau}\sum_{j}\left[W_{j,02} - \frac{1}{N}\sum_{\tau}\sum_{j} W_{j,02}\right]^2 .$$

Finally, I stack $G^{Demand}(\theta), G_{1,type}^{Cost}(\theta), G_{2,type}^{Cost}(\theta), G_3^{Cost}(\theta)$, and $G_4^{Cost}(\theta)$ and use the two-step GMM estimator (see Hansen (1982)) of θ from the stacked moments.[24]

[23] Following the preliminary analysis, I mitigate the effect of spurious spatial and serial correlation by conditioning on a rich set of control variables. Specifically, I first project the instrumental variables on county fixed effects and nursing home-year specific control variables and use the residuals in this moment condition.

[24] I first weight the moments by the identity matrix to generate an unbiased estimate of θ. In the second

5 Results

Table 3 presents relevant demand and firm objective function parameter estimates in column 3. The estimate in the first row indicates that residents value higher skilled nurse staffing ratios. Sicker residents with a higher CMI value the staffing ratio more than their healthier peers, as evidenced by the fourth row. Residents dislike paying higher private rates if they pay at least partly out-of-pocket, see rows 2 and 3.[25] Not surprisingly, private payers have a higher disutility for private rates than hybrid payers since they pay the private rate on all days, as opposed to only on some days of the stay.[26] Consistent with the suggestive evidence from Table 1, I find that residents value proximity to the former residence, see rows 5 and 6.[27] Rows 7-9 provide further evidence for taste heterogeneity based on observable resident characteristics. For example, residents with a stay of fewer than 100 days have a higher valuation for the number of rehabilitative care therapists per resident if they are assigned a larger number of rehabilitative care minutes, see row 8. Also, residents with a diagnosed Alzheimer's disease value nursing homes that have an Alzheimer's unit.

Turning next to the firm objective parameters, row 10 indicates that non-profits depart from profit maximization. The positive parameter estimate implies that non-profits maximize a weighted average of profits and total resident days. Publicly operated nursing homes depart even further from profit maximization as evidenced by a larger parameter estimate in row 11. The coefficients indicate that not-for-profits and public nursing homes act, all else equal, as if they had a marginal cost advantage of \$25 and \$38 per resident and day, respectively.

I revisit the demand estimates in column 5, which presents analogous results that only

step, I weight by the inverse variance matrix of the sample moment conditions, see Section A.10.1 for details.

[25] I have estimated an alternative demand model in which private and hybrid payers respond proportionately to the private rate based on the fraction of days paid out-of-pocket. This model suggests a smaller price coefficient in absolute magnitudes, implying even larger resident benefits from an additional skilled nurse.

[26] On the other hand, hybrid payers pay on average only 36.4% of their days out-of-pocket. This suggests that hybrid payers are more price elastic then private payers per private pay day, holding choice sets fixed. One reason could be that hybrid payers overestimate their expected length of stay and thereby their expected number of days that are not covered by Medicare.

[27] The marginal utility of traveling farther is always negative in the relevant 50km radius. The marginal utility of distance is given by -25.79+2*22.44*Distance which is bounded from above by -25.79+2*22.44*0.5=-3.35 in the 50km choice set.

Table 3: Preference and Nursing Home Objective Parameters

		Demand and Cost Moments		Demand Moments	
		Parameter	SE	Parameter	SE
β^{sn}:	log(SN/Resident)	0.995***	0.012	1.526**	0.748
β^{p}_{hyb}:	Price*Hybrid	-0.007***	0.000	-0.011***	0.002
β^{p}_{priv}:	Price*Private	-0.013***	0.002	-0.018***	0.004
β^{sn}_{cmi}:	log(SN/Resident)*CMI	0.226***	0.003	0.226***	0.003
β^{d}_{1}:	Distance in 100km	-25.79***	0.014	-25.79***	0.014
β^{d}_{2}:	Distance^2	22.44***	0.037	22.44***	0.037
β^{th}_{rehab}:	Therapist/Res*Rehabmin	-0.124***	0.001	-0.124***	0.001
$\beta^{th}_{rehabXshort}$:	Therapist/Res*Rehabmin*Short-Stay	0.314***	0.007	0.314***	0.007
β^{alz}_{alz}:	Alzheimer*Alzheimer Unit	0.414***	0.002	0.414***	0.002
$\frac{1-\alpha_{NFP}}{\alpha_{NFP}}$	Non-Profit Objective Parameter	24.66***	1.083		
$\frac{1-\alpha_{Pub}}{\alpha_{Pub}}$	Public Objective Parameter	37.96***	1.902		
	Avg Benefit per SN/year in ’02	$126,320***	$13,487	$139,606**	$67,716
	Avg Wage+Fringe Benefits per SN in ’02	$83,171		$83,171	
	Benefit-Cost	$43,149**	$13,487	$56,435	$67,716

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

exploit the more traditional demand moments in the second step of the empirical strategy. The point estimates in the second panel remain unchanged since I have not changed the first step in the estimation algorithm. Therefore, I focus the discussion on the mean parameter estimates listed in the first three rows. The point estimates increase slightly in absolute magnitude, both for private rates and the skilled nurse staffing, but the ratio of the parameters remains almost identical, which is important for the normative implications as discussed below. However, the standard errors increase substantially (in particular for the skilled nurse parameter). In that sense, adding the additional cost moments primarily increases the precision of the point estimates. Another disadvantage of an exclusive analysis of demand moments is that they do not separately identify the firm objective parameters from marginal costs.

Turning to the cost estimates, the predicted marginal costs and annual compensations for skilled nurses coincide closely with their observed counterparts. This also holds true if I exclude the cost moments from the GMM estimation procedure, see Section A.11 for details.[28]

[28] I find implausible marginal cost or salary estimates for only about 5% of all nursing homes of either less than $50 or more than $250 per resident day, and or skilled nurse compensations of less than $10,000 or more than $300,000 per year. This also includes nursing homes whose estimated marginal costs fall short of $60 per resident day and whose estimated compensations exceed $150,000 per year. I hold the staffing and pricing

Normative Implications: Next, I turn to a comparison of the marginal benefit and the marginal cost of an additional skilled nurse. As shown in Section A.12, the marginal benefit per resident is given by the marginal utility of a skilled nurse divided by the marginal utility of income. The latter is inherently difficult to quantify for Medicaid and Medicare residents, who do not pay for their nursing home stays.[29] To address this concern, I extrapolate the estimated price parameter of private payers, who pay the entire stay out-of-pocket, to the entire nursing home population. I revisit this assumption in the robustness check section 7. It is important to note, however, that this assumption does not affect the positive results in the counterfactual analysis. To this end, I also compare the quality returns per public dollar spent of different policy interventions in Section 6.

Aggregating the resident benefits at the nursing home level in 2002 and taking a weighted average by the number of beds, I find a marginal benefit of $126,000 per year, see the lower panel of Table 3. The marginal costs of employing an additional skilled nurse equal only $83,000 per year when considering wages and fringe benefits. The difference of $43,000 is statistically significant at the 5% level, suggesting that skilled nurse staffing ratios are, on average, inefficiently low.[30] To assess potential heterogeneity across nursing homes, I display the distribution of differences between the marginal benefit and the annual compensation in the left graph of Figure 4. The histogram indicates that staffing standards are inefficiently low in about 93% of the nursing homes as shown by a positive wedge. However, a few nursing homes have negative wedges. Interestingly, 82% of these nursing homes do not accept Medicaid residents. This indicates that low Medicaid reimbursement rates may play a relevant role in explaining inefficiently low staffing levels in Medicaid certified nursing homes.

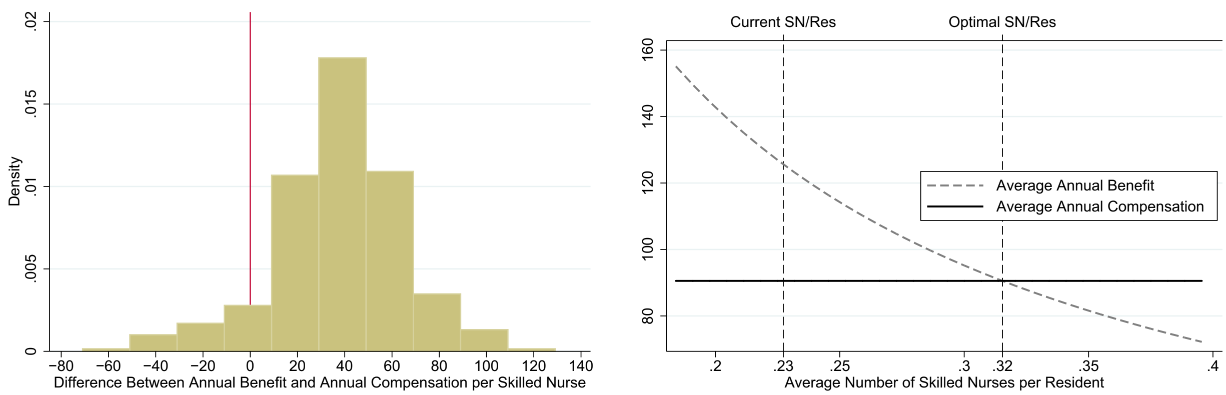
Next, I study the optimal skilled nurse staffing ratios in a simple social planner problem. Here, the social planner allocates residents to nursing homes and chooses the skilled nurse

decisions of this small number of nursing homes fixed in the counterfactual analysis, assuming that the status quo is the best guess for their behavior in the following exercises.

[29]Medicare beneficiaries face co-payments from the 21st day of their stay onwards but co-pays do not vary across nursing homes.

[30]I find a very similar marginal benefit if I drop the cost moments in the estimation strategy exceeding the baseline estimate by only 10%, see the fifth column of the lowest panel. However, the difference between the marginal benefit and marginal costs becomes statistically insignificant.

Figure 4: Normative Implications in 2002 (in $1,000)



staffing ratio in order to maximize the sum of consumer surplus and provider profits. To simplify the analysis, I assume that annual earnings for skilled nurses are constant within a county. In the optimum, the marginal cost of an additional skilled nurse (the compensation package) equals the marginal benefit in each nursing home. Finally, I take an average of these optimality conditions over nursing homes in each county.

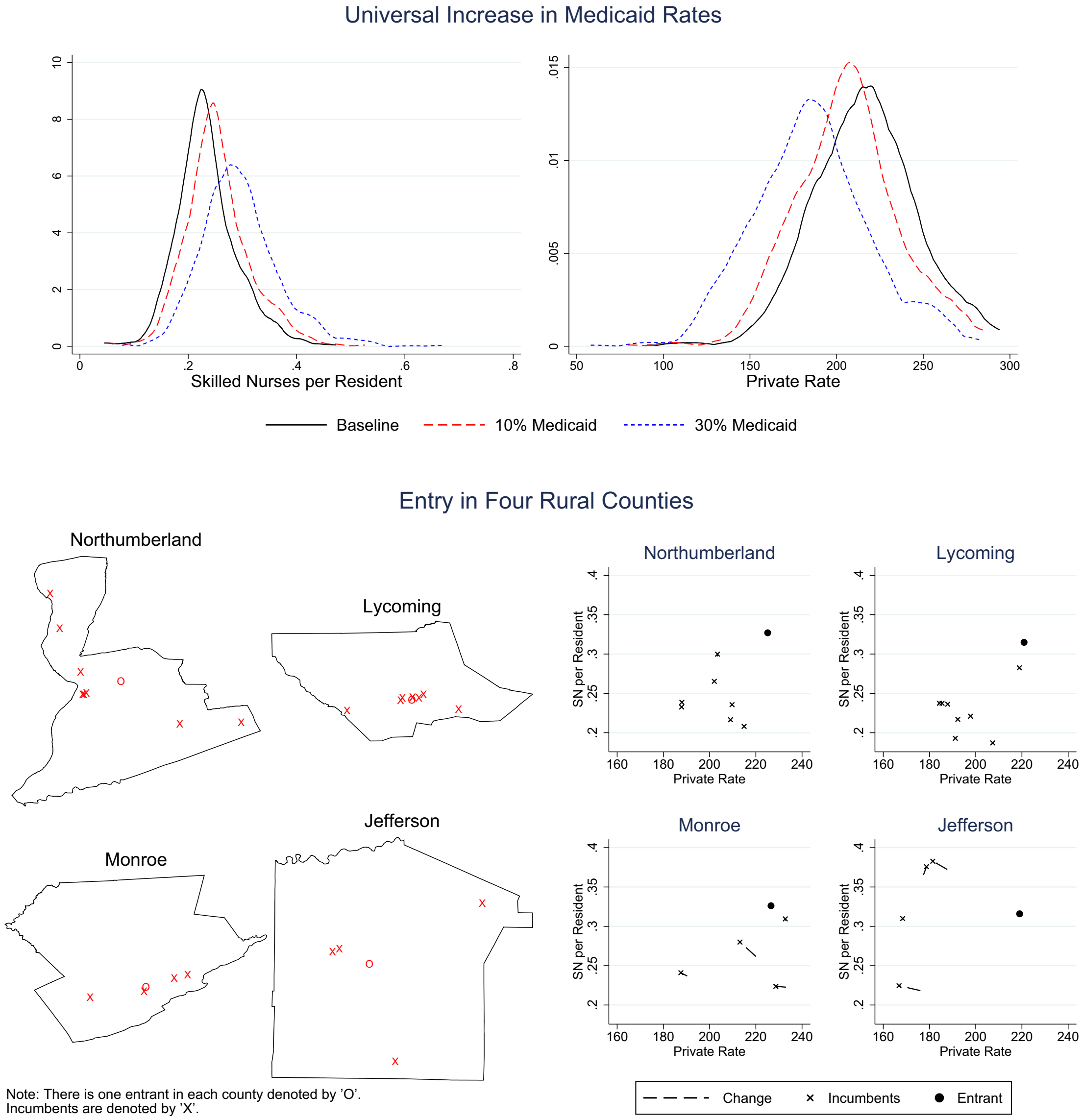
In the right graph of Figure 4, I test the condition in Allegheny County, which lies within the Pittsburgh MSA. The horizontal line indicates the marginal cost of employing an additional skilled nurse, assuming perfectly elastic labor supply, which equals $90,500 in Allegheny County.[31] The downward sloping curve indicates the marginal benefit of an additional skilled nurse. The benefit curve decreases in the staffing ratio because of diminishing marginal utilities. The optimality condition suggests a nurse staffing ratio of 0.32 (1.8 hours per resident and day), as indicated by the right vertical line. This estimate exceeds the observed average staffing ratio of 0.23 in 2002 (1.3 hours per resident and day), indicated by the left vertical line, by 39%. Both observed and optimal staffing ratios are substantially higher than the regulated minimum staffing ratio of 0.07, see the Section A.13 for details. On average over all counties, observed staffing ratios fall 48% short of the optimum, see Table A12 for details.

[31] The assumption of a perfectly elastic labor supply curve may understate the marginal cost of employing an additional skilled nurse and thereby overstate the optimal skilled nurse staffing ratio. However, nursing homes employ only 9% and 13% of all registered and licensed practical nurses, respectively, which is why I abstract from general equilibrium effects on wages. See http://www.bls.gov/oes/current/oes291141.htm and http://www.bls.gov/oes/current/oes292061.htm, last accessed on 11/23/16.

6 Counterfactuals

Medicaid Rate Increase: First, I study the effects of a universal 10% increase in the Medicaid reimbursement rates.[32] The top panels of Figure 5 present the new equilibrium distribution of skilled nurse staffing ratios as well as private rates.[33]

Figure 5: Counterfactual Exercises



On average, the staffing ratio increases by 8.8%, see the fifth row of Table 4, which

[32] Universal changes in Medicaid reimbursement rates are commonly used to balance state budget fluctuations. The state of Pennsylvania, for example, has been using a common base budget adjustment factor since 2005, which scales the Medicaid reimbursement rates to meet a state budget target.

[33] I use an iterative procedure based on the first order conditions to find the new equilibrium. I find that staffing and pricing decisions converge smoothly to the new equilibrium in all policy simulations.

translates into an extra 7.2 skilled nurse minutes per resident and day. This estimate falls into the 95% confidence interval from the preliminary analysis, which suggests a staffing increase of 11.7%, see Table 2.

The sign of the effect on private rates is theoretically ambiguous. The increase in skilled nurses raises marginal costs, which encourages nursing homes to raise their private rates. However, an increase in Medicaid rates also raises the profitability of hybrid payers who are partially covered by Medicaid, partially pay out-of-pocket, and who respond to changes in private rates. Hence, nursing homes have an incentive to lower their private rates in order to attract additional hybrid payers. The results in the right panel of Figure 5 indicate that the second effect dominates. On average, I find a 4.9% reduction in the private rate, see the 6th row of Table 4, which indicates "cost-shifting" between Medicaid beneficiaries and private payers (see Frakt (2011)).[34] While common theories rationalize cost-shifting with revenue or income targets of health care providers, my context provides a novel mechanism: multiple payer sources among hybrid payers.

The effect on skilled nurses is more pronounced in larger (more competitive) counties, see columns 3 and 4, which may stem from strategic complementarities in quality. Private rates and markups on the other hand decrease slightly more in smaller counties.

Table 4: Counterfactual: Universal 10% Increase in Medicaid Rates

	Absolute	%Δ Spending	Large Counties	Small Counties
Δ CS	203.2	89.9%	92.5%	79.6%
Δ Profits	90.8	40.2%	38.1%	48.0%
Δ Spending	226.0	100.0%	100.0%	100.0%
Δ Welfare	67.9	30.0%	30.7%	27.6%
Avg Δ SN/Res	8.8%		9.2%	7.5%
Avg Δ P	-4.9%		-4.8%	-5.7%

Note: Absolute values are measured in million dollars per year. Large counties have at least 10 nursing homes, small counties have fewer than 10 nursing homes. Average staffing and pricing effects are weighted by market shares.

[34]The baseline estimate from Table 2 suggests a statistically insignificant positive effect of 0.3%, with a 95% confidence interval ranging between -3.6% and 4.2%. A larger price effect in the preliminary analysis is consistent with the larger staffing effect, which raises marginal costs further.

Next, I turn to the welfare implications. I find that the increase in Medicaid reimbursement rates raises annual Medicaid spending by $226 million, see the third row of Table 4. Nursing homes take advantage of the increase in Medicaid rates, as profits increase by $91 million, about 40% of the increase in Medicaid spending. That means that nursing homes pass about 60% on to residents through lower private rates and higher nurse staffing ratios. To evaluate the effects on consumer surplus, I again extrapolate the price coefficient of private payers to the entire nursing home population, which implies:

$$\Delta CS_t = \frac{1}{\beta^P_{priv}} \Big[\sum_i log(\sum_j exp(\delta^1_{i\tau jt})) * LOS_i - \sum_i log(\sum_j exp(\delta^0_{i\tau jt})) * LOS_i \Big] \ .$$

Here, $\delta^1_{i\tau jt}$ and $\delta^0_{i\tau jt}$ denote the indirect conditional daily utility, net of the extreme value shock, evaluated at new and old product characteristics, respectively. Lower private rates and higher nurse staffing ratios raise consumer surplus annually by about $203 million. Combining the increase in consumer surplus, provider profits, but also Medicaid spending, I find an annual welfare gain of $68 million, about 30% of the increase in Medicaid spending. This estimate ignores the deadweight loss of higher taxes, which are required to fund the additional Medicaid spending. Common estimates of the deadweight loss of taxation cluster around 30% of tax revenues (Poterba (1996)), which indicates that small increases in Medicaid reimbursement rates can be welfare improving, even when considering the distortionary effects of taxation. I also revisit the entire analysis for a greater increase in Medicaid rates of 30%. The findings are generally very similar. However, I find smaller welfare gains, relative to Medicaid spending, because of diminishing marginal utilities in the quality of care. This suggests that increases in Medicaid rates can lead to larger welfare gains in other U.S. states, given that the average Medicaid reimbursement rate in Pennsylvania exceeds the national average by 17%. Finally, the estimated Medicaid elasticities also indicate that differences in Medicaid rates can fully explain the observed 11% difference in skilled nurse staffing ratios between Pennsylvania and the national average, see Table A1 for details.

Directed Entry: Next, I simulate the effects of a new public nursing home in four rural counties in an effort to understand the gains from competition in a market with only a hand full of providers. Furthermore, the rural elderly continue to be of particular policy interest to the extent that the lack of healthcare professionals impedes access to health care services. In this exercise, I revisit the implied welfare effects from entry by comparing the gains from variety, better quality, and lower private rates, with losses in provider profits and increased public spending.[35] I discuss the effects in urban counties in Section A.14.

In each county, I add a publicly operated nursing home located at the size-weighted average of longitude and latitude coordinates of the respective incumbents. The bottom left graph of Figure 5 summarizes the locations of incumbents and new entrants, marked by X's and O's, respectively. To calculate the product characteristics and the cost structure of new entrants, I regress these variables on a polynomial in licensed beds, county population, and ownership types and assign the predicted values assuming that new entrants operate with 100 licensed beds. I use the structural model to calculate the private rate and staffing ratio distribution in the new equilibrium, holding the staffing ratios and the private rates of the new entrants fixed. The bottom right graph of Figure 5 presents the county specific results in a private rate (horizontal axis) and skilled nurse staffing ratio (vertical axis) diagram. The x's correspond to the post-entry pricing and staffing decisions of incumbent nursing homes. The dashed line connects the pre-entry and the post-entry staffing and pricing bundle. Finally, the solid dot refers to the staffing ratio and the private rate of the new entrant. The responses of incumbents are quite heterogeneous. Incumbent nursing homes in Northumberland and Lycoming County leave their staffing and pricing decisions almost unchanged, in part because the new entrant steals only about 3% of county demand. In Northumberland, skilled nurse staffing ratios and private rates increase by only 0.5% and 0.1% on average, see the top panel of Table 5. In Monroe County, on the other hand, the new entrant steals about 10% of the market, which explains why incumbents respond more elastically. Here, incumbents increase the number of skilled nurses by 3.7% and lower private rates by 1.9%.

[35] In a robustness exercise, see Section A.17 for details, I find that the directed entry leads to a very small increase in overall nursing home demand, which I abstract away from in the baseline analysis.

Table 5: Directed Entry and Counterfactual Comparison

	Northumberland	Lycoming	Monroe	Jefferson	PA
Var. Profit Entrant	0.2	0.3	0.4	0.2	1.1
Fixed Costs	1.1	1.1	1.1	1.1	4.4
Δ Profit	-1.3	-1.2	-1.6	-1.3	-5.5
Δ CS_1	0.0	0.1	0.6	0.3	1.0
Δ CS_2	0.5	0.6	1.1	0.5	2.8
Δ Spending	0.0	0.2	0.2	0.1	0.3
Δ Welfare	-0.8	-0.6	-0.1	-0.6	-2.1
Avg ΔSN^{res}	0.51%	0.31%	3.69%	2.59%	0.05%
Avg Δ P	0.09%	0.08%	-1.87%	-2.38%	-0.02%

Medicaid Expansion			Entry		
ΔSN^{res}	Δ Spending	ΔSN^{res}/100m	ΔSN^{res}	Δ Spending	ΔSN^{res}/100m
8.80%	226 million	3.90%	0.05%	3.3 million	1.50%
8.80%	135 million	6.50%	0.05%	5.5 million	0.91%

Note: The top panel compares the effects of directed entry between counties and illustrates the aggregate effects at the state level in the last column. Average staffing and pricing effects are weighted by markets shares. The lower panel compares the return on public spending between directed entry in rural counties and a 10% increase in Medicaid rates. Absolute values are measured in million dollars. SN^{res} indicates skilled nurses per resident.

I next turn the results into welfare estimates. The variable annual profits of new entrants vary between \$0.2 million and \$0.4 million, see the first row of Table 5. Assuming that new entrants incur annual fixed costs of \$1.1 million, the median fixed costs displayed in Table 1, I conclude that the new entrants accumulate annual losses of \$3.3 million. This finding is consistent with recent industry trends that indicate net exit of nursing homes in Pennsylvania as well as nationwide. Industry losses are even larger not only because incumbents raise staffing ratios and lower private rates, but also because the variable profits of new entrants stem from "business stealing", see the third row. This compares with potential gains in consumer surplus that can be divided into two components:

$$\Delta CS_t = \frac{1}{\beta^P_{priv}} \Big[\sum_i log(\sum_{j \in J^{old}} exp(\delta^1_{i\tau jt})) * LOS_i - \sum_i log(\sum_{j \in J^{old}} exp(\delta^0_{i\tau jt})) * LOS_i \Big]$$

$$+ \quad \frac{1}{\beta^P_{priv}}\Big[\sum_i log(\sum_{j\in J^{new}} exp(\delta^1_{i\tau jt})) * LOS_i - \sum_i log(\sum_{j\in J^{old}} exp(\delta^1_{i\tau jt})) * LOS_i\Big] \ . \quad (9)$$

The first row isolates the gains from changes in incumbent product characteristics (summarized by the set J^{old}), which is the key object of interest in this exercise. At the state level, this consumer gain equals about \$1 million per year, see the fourth row of column 5. The second row of equation (9) describes the consumer gains from variety as indicated by an extended choice set J^{new}. This component combines the gains from a convenient location, at least for some seniors, as well as an additional extreme value draw. This gain is larger and equals about \$2.8 million per year at the state level, see the fifth row of column 5. I interpret this estimate as an upper bound on the gains from variety to the extent that the lack of random coefficients loads unobserved taste heterogeneity onto the extreme value taste shock, see Petrin (2002). Yet, the gains from variety fall short of the additional annual fixed costs of operating the new nursing homes ignoring additional sunk costs of entry. Finally, adding the cost of additional Medicaid spending, which stems from a re-sorting of residents among nursing homes with different Medicaid rates, I find an annual welfare loss of \$2.1 million. While the effects differ in magnitudes between counties, I find that all entrants incur losses and a reduction in social welfare in each county.

Quality Returns on Spending: Finally, I compare the quality returns on public spending between raising Medicaid reimbursement and directed entry. This exercise does not require an assumption on the marginal utility of income. The results are summarized in the lower panel of Table 5. Dividing the increase in skilled nurse staffing by the increase in Medicaid spending suggests a skilled nurse return of 3.9% per \$100 million in additional public spending. Repeating this calculation in the entry counterfactual suggests a return of only 1.5% per \$100 million in public spending when considering new entrants' annual losses of \$3.3 million as required additional public spending. In the four urban counties, I find a quality return of only 1.3%. This comparison indicates that moderate increases in Medicaid rates are about 2.6 times as effective in raising the quality of care than encouraging local competition via directed entry in rural (urban) counties.

In the second row, I revisit this comparison considering the effects on incumbent profits. Here, I adjust public spending by the change in incumbent profits, which are relevant if the state has to compensate incumbents for their incurred losses in the case of directed entry. Conversely, I assume that the increase in profits following an increase in Medicaid rates can be levied via additional taxes. This comparison indicates that a 10% increase in Medicaid rates is about 7.1 times as effective in raising the quality of care than encouraging local competition via directed entry in rural counties.

Non-Pecuniary Objectives, Staffing, and Pricing: I also revisit the role of non-pecuniary quantity motives, which may give non-profits an incentive to raise the quality of care and to lower private rates in order to increase demand. To investigate this hypothesis, I remove the non-pecuniary objectives of not-for-profit and public nursing homes $(1 - \alpha_j = 0)$ and simulate the new equilibrium. I find that not-for-profits and public nursing homes would lower the skilled nurse staffing ratio by 10% and 22%, respectively, if they were maximizing profits. Furthermore, the non-pecuniary objectives can fully explain the observed difference in staffing ratios between for-profits and not-for-profits in Pennsylvania. I also find that not-for-profits and public nursing homes would also increase their private rates by 17.5% and 29%, respectively. For more details see Section A.18.3.

Nationwide, about 70% of nursing homes are for-profit compared to only 50% in Pennsylvania providing an alternative explanation for quality differences between states. However, the difference in staffing ratios between for-profits and not-for-profits scaled by differences in for-profit penetration among states can only explain a 2% difference (out of an 11% difference) in staffing ratios between Pennsylvania and the national average.

7 Robustness

Rationing. A potential concern for the empirical analysis is the role of capacity constraints, which may introduce bias to the demand elasticities. While occupancy rates have been falling over the last decades, Ching, Hayashi and Wang (2015) argue that CON laws in Wisconsin can constrain access to care for Medicaid beneficiaries in particular.[36] To assess the effect capacity constraints on access to care in this context, which is not affected by CON laws, I test whether weekly admissions by payer type decline at high occupancy rates. I find very little evidence to support this concern and conclude that only 3.5% of seniors cannot access their preferred nursing home because of rationing. I also estimate alternative demand models that allow for rationing, which deliver similar preference parameter estimates. The key parameter estimates differ by at most 26% from the baseline estimates . On the supply side, I find that staffing and pricing responses to Medicaid increases deviate by less than 6% when excluding nursing homes with average occupancy rates of less than 97% and 95%. Details on these robustness exercises are reported in Section A.15.

Normative Findings. The consumer welfare estimates rely on the estimated marginal utility of income for private payers, which may be inaccurate for poorer Medicaid beneficiaries. To corroborate my normative findings, I revisit the marginal benefit estimate and the optimal skilled nurse staffing ratio using alternative approaches and references from the literature. Specifically, I contrast my findings to staffing recommendations from industry experts. I also provide alternative marginal benefit estimates using external evidence on the effect of nurses on resident mortality, or alternative marginal utility of income estimates based on bequest decisions or wealth data from observed assets spend-downs. These approaches deliver remarkably similar marginal benefit estimates and all suggest that current skilled nurse staffing ratios are inefficiently low. I discuss these approaches in detail in Section A.16.

Substitution between different forms of care. The baseline model ignores potential substitution between nursing home and other forms of long term care. To assess the impact of this simplification on the main findings of this study, I add data on seniors living inside and outside of nursing homes from the Census 2000 5% sample. I then estimate an extended demand model that allows for an outside good, capturing community based long term care,

[36] According to Strahan (1997), the national mean occupancy rate has declined from 93% in 1977 to 87% by 1995 and further down to 83% by 2003 (Gibson et al. (2004)). Between 2003 and 2015, the overall number of nursing home residents has remained relatively constant, see goo.gl/fKZtaq, last accessed Oct 31, 2017.

and revisit the counterfactual exercises. The estimated preference and nursing home objective parameters as well as the counterfactual changes in staffing and pricing are very similar to the baseline results. In the Medicaid exercise, I find that the quality increase leads to a market expansion of 7%, which increases annual Medicaid spending by an extra $100 million. As a result, I find a smaller annual welfare gains of $31 million. Importantly, increasing Medicaid rates continues to be significantly more effective in raising the quality of care than encouraging local competition via directed entry, see Section A.17 for details.

Finally, for a discussion of robustness to alternative non-pecuniary nursing home objectives and an additional endogenous quality measure see Sections A.18 and A.19, respectively.

8 Conclusion

This paper investigates the dependence of the quality of care in nursing homes on Medicaid reimbursement rates and local competition. Combining detailed industry data from Pennsylvania with a model of demand and supply, I find that low Medicaid reimbursement rates are a key contributor to quality shortfalls in this industry. Specifically, I find that nursing homes increase the number of skilled nurses, who play an integral role in monitoring and coordinating the delivery of care, by 8.8% following a universal 10% increase in Medicaid reimbursement rates. On the other hand, I find that an increase in competition has relatively small positive effects on the quality of care.

At the same time, raising the quality of care via increases in the Medicaid reimbursement rates poses a burden on tight state budgets. This is in parts because nursing homes keep 40% of the Medicaid increases as profits and only pass 60% on to residents via higher nurse staffing ratios and lower private rates. Therefore, targeting Medicaid raises towards more competitive markets or connecting Medicaid payments with the quality of care more directly, may provide a more cost-effective approach in addressing quality shortfalls in this industry.

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