Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home Industry *

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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 8.7% 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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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. 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 significant increases in the quality of care. 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. 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 Census and 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. Nursing home residents value an additional skilled nurse at $123,000 per year on average, which 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 43% on average. While these calculations abstract away from income effects, I find qualitatively similar results in extensive robustness exercises which build on staffing recommendations and estimated returns on nursing from the literature, or estimated income effects based on observed asset spend-down or bequest decisions. 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 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 8.7% and decrease their private rates by 4.5% 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 $31 million per year, about 9.3% of the increase in Medicaid spending. The welfare gains are muted by an unintended market expansion effect. As the quality of care increases, elderly people substitute from community to nursing home care raising Medicaid spending considerably. The baseline logit model may overstate the market expansion effect as it allows for more elastic substitution between different forms of care, when
compared to a nested logit model (nesting all nursing home goods). In the robustness section, I bound the market expansion effect from below by considering an alternative demand model that does not allow for substitution between different forms of care. This model predicts very similar changes in staffing and pricing but larger increases in social welfare ($68 million).

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 0.4%. In contrast, I find a return of 2.6% in the former policy counterfactual, which suggests that raising Medicaid reimbursement rates is more cost effective in improving the quality of care.

In order to focus the analysis on the interplay of Medicaid rates, competition, and the quality of care, the baseline model abstracts away from capacity constraints. I relax this assumption in the robustness section by estimating alternative demand models that allow for rationing. I also revisit the staffing responses to Medicaid rate changes when excluding nursing homes close to capacity. While each approach relies on strong assumptions, they all indicate that the key findings of the main analysis are robust to potential rationing, perhaps because Pennsylvania does not restrict entry and capacity investments through a CON law.\footnote{\textit{\emph{1}}However, the welfare gains resulting from Medicaid increases are reduced if rationing crowds out seniors who would otherwise derive high utility from nursing home 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)).\footnote{\textit{\emph{2}}Earlier studies have argued that increases in Medicaid rates may lower the quality of care if rationing leads}
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.3

My demand analysis is related to Ching, Hayashi and Wang (2015), who 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 abstracting away from rationing in the baseline analysis. 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.

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

3My findings also complement the evidence on Medicaid’s effect on access to care and the 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.
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.

Finally, my counterfactual entry analysis relates to an older theoretical literature on the social inefficiencies of free entry (Spence (1976); Dixit and Stiglitz (1977); Mankiw and Whinston (1986)). In the presence of fixed costs, free entry can be excessive when entrants steal business from incumbents. Conversely, entry can be insufficient when entrants cannot appropriate all of the consumer surplus. This study provides new empirical evidence on these inefficiencies in a policy relevant context, given that CON laws restrict entry of new nursing homes in several states.

The rest of this study proceeds as follows. Section 2 describes institutional details of the industry with an emphasis on the quality of care. In Section 3, I describe the data and present preliminary evidence from Pennsylvania. 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 Section 8 concludes.

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, Werner and Konetzka (2010). 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 (screen shots are provided in Figures A.1 and A.2) giving nursing homes an economic incentive to improve staffing in order to attract more residents. 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 billion 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

4While registered nurses and licensed practical nurses differ in their training background and skill levels, I combine them as skilled nurses to simplify the analysis.
5See goo.gl/DHRm6r, last accessed 10/23/16.
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 state averages, see Table A.1 for a comparison of Medicaid rates and other institutional 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 A.2 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

Notes: 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 non-concentrated (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 non-concentrated 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 depen-
dence 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.

6A 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 A.3 for more details on the length of stay.
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.  

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 96,000 admissions per year. The top graphs of Figure 2 describe 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.

I combine the MDS with data from annual nursing home surveys, which were provided by the Bureau of Health Statistics and Research of the Pennsylvania Department of Health. 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.

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7Less than 2% of days are covered by private long term care insurance, which compares to 4% nationwide Congressional Budget Office (2004). Furthermore, the average maximum daily benefit of private insurance equals $109 in 2000 (the modal benefit was $100), indicating substantial cost-sharing.

8The Department specifically disclaims responsibility for any analysis, interpretation or conclusions.
Notes: 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 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. 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 including 2,079 observations for the years 2000-2002, summarized in the middle rows of Table

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9Specifically, 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 further robustness exercises available upon request. 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.
Table 1: Summary Statistics 2000-2002

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

Notes: 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.

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." This provides additional evidence that Medicaid reimbursements are a potentially important determinant of the quality of care.

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

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10I 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.
costs to provide nursing home care and are used directly in the Medicaid reimbursement methodology.\textsuperscript{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.\textsuperscript{12} In the empirical model, I assume constant marginal costs, whereby average 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 resident and day, on average.\textsuperscript{13} The annual fixed costs equal $1.1 million on average, which comprise administrative and capital costs, see the last row of Table 1.

Finally, I calculate the county level share of elderly people with long term care needs in nursing home care using complementary population data from the Census 2000 5\% sample. I restrict the Census populations to seniors aged 65 and older, who indicate a physical or mental health condition. These conditions define plausible prerequisites for considering any long term care support and institutional nursing home care in particular. Scaling the sample to the full population, I find that 32\% of the 225,000 seniors with physical or mental conditions live in a nursing home. The standard deviation of county level shares equals 9.4\%.

\section{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:

\begin{equation}
\log(Y_{jt}) = \gamma_1 \log(R_{mcaid}^{jt}) + \alpha X_{jt} + \phi_{ct} + \varepsilon_{jt}.
\end{equation}


\textsuperscript{12}In the structural estimation, I find that the observed variable costs of for-profits are consistent with the variable cost predictions of the pricing first order conditions, corroborating this interpretation.

\textsuperscript{13}All nominal terms in the analysis are denominated in 2009 dollars.
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, \( \phi_{ct} \) captures county-year fixed effects, and \( X_{jt} \) contains additional nursing home specific control variables. The key parameter of interest is \( \gamma_1 \) which denotes the effect of an increase in the log Medicaid reimbursement rate on staffing and pricing decisions.

Before discussing the identification of \( \gamma_1 \), 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.\(^{14}\) 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 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.4 for details:

\[
R_{jt}^{mcaid} = g\left(AC_{jt-3,4,5}, \text{median}(AC_{p(j)}_{c,t-3,4,5}, AC_{p(j)}_{-c,t-3,4,5})\right). \tag{2}
\]

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 \( AC_{p(j)}^{c_{i,t-3,4,5}} \) and, importantly, average costs of nursing homes located in other counties \(-c\), captured by \( AC_{p(j)}^{c_{i,t-3,4,5}} \). 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.

\(^{14}\) 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 A.4 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.
Finally, I decompose average costs into observable cost shocks $Z_{jt} \subset X_{jt}$, which is a subset of $X_{jt}$, staffing decisions $Y_{jt}^{s}$ scaled by input prices $w^{s}$, and unobservable cost shocks $\eta_{jt}$:

$$AC_{jt} = \phi^{s}Z_{jt} + \sum_{s} w^{s}Y_{jt}^{s} + \eta_{jt}.$$  (3)

**Identification:** An empirical challenge to the estimation of $\gamma_{1}$ is the potential correlation between $\log(R_{jt}^{mcaid})$ and $\epsilon_{jt}$, which would add bias to the ordinary least squares estimator. This is of particular concern because $j$'s lagged average costs affect $\log(R_{jt}^{mcaid})$ directly, see the first argument in equation (2). The correlation between $\log(R_{jt}^{mcaid})$ and $\epsilon_{jt}$ 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 \( \log(R_{j,t}^{mcaid}) \) 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, \( AC_{-c,t-3,4,5}^{p(j)} \), 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, \( AC_{-c,t-3,4,5}^{p(j)} \) must be independent of \( \epsilon_{jt} \), conditional on \( X_{jt} \) and \( \phi_{ct} \). As shown in Section B.1, this holds true if the following two assumptions are satisfied:

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

\[
\epsilon_{jt} \perp \perp \{\epsilon_{-ct-k}, \eta_{-ct-k}, X_{-ct-k}, \phi_{-ct-k}\}_{k \in 3,4,5} \mid X_{jt}, \phi_{ct}
\]

**(SE)** \( \epsilon_{jt} \) 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 \( \phi_{ct} \), if \( \gamma_1 \neq 0 \):

\[
\epsilon_{jt} \perp \perp \{\epsilon_{ct-k}, \eta_{ct-k}, X_{ct-k}, \phi_{ct-k}\}_{k \in 6,7,8} \mid X_{jt}, \phi_{ct}
\]
Assumption (SP) may be violated if shocks to staffing decisions, governed by equation (1), are spatially as well as serially correlated. Assumption (SE) may be violated if local staffing shocks are serially correlated, adding bias if they affect the instrumental variable, average costs in other counties, \( AC_{c,t-3,4,5}^{(j)} \), as well. Intuitively, this bias operates through a “feedback loop” in future years. For example, \( \epsilon_{jt-6} \) affects \( Y_{jt-6} \) and consequently \( AC_{jt-6} \), through equations (1) and (3), respectively. This in turn affects \( R_{mcaid}^{maxid} \) through equation (2) and in turn \( Y_{c,t-3,4,5}^{(j)} \) and \( AC_{c,t-3,4,5}^{(j)} \) through (1) and (3). Hence, \( \epsilon_{jt-6} \) may “feed” back into \( R_{mcaid}^{maxid} \) through \( AC_{c,t-3,4,5}^{(j)} \) adding bias if \( \epsilon_{jt-6} \) is correlated with \( \epsilon_{jt} \).

In this context, I find that serial correlation alone can only add a small upward bias to the two stage least squares (2SLS) estimator discussed below. Using a bounding exercise detailed in Section B.2, I find an upward bias of at most 5%. 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 “feedback loop” operates through the median argument in equation (2), which is attenuated by cost shocks from several other counties. Regarding assumption (SP), I find very little spatial correlation in marginal costs and staffing decisions between counties, see Figure B.1, 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:

\[
R_{mcaid,sim}^{maxid} = \frac{1}{N_{sim}} \sum_{i=1}^{N_{sim}} g(x_i, \text{median}(x_i, AC_{c,t-3,4,5}^{(j)}))
\]

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 its rival’s costs, see Section A.4 for details.15

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 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.

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 B.2. 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 Table B.3. 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. For tractability reasons and following the reasons outlined in Section

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15The aggregation method allows me to 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 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.
Table 2: Medicaid Reimbursement Rates, Staffing, and Pricing

<table>
<thead>
<tr>
<th></th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tbody>
<tr>
<td></td>
<td>First Stage</td>
<td>log(SN\textsuperscript{res})</td>
<td>log(NA\textsuperscript{res})</td>
<td>log(Th\textsuperscript{res})</td>
<td>log(P)</td>
</tr>
<tr>
<td>Log Simulated Rate</td>
<td>1.15***</td>
<td>(0.18)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Medicaid Rate</td>
<td>1.17***</td>
<td>(0.29)</td>
<td>0.07</td>
<td>0.66</td>
<td>0.03</td>
</tr>
<tr>
<td>Observations</td>
<td>4022</td>
<td>4022</td>
<td>3872</td>
<td>3307</td>
<td>4022</td>
</tr>
<tr>
<td>R\textsuperscript{2}</td>
<td>0.189</td>
<td>0.090</td>
<td>0.039</td>
<td>0.122</td>
<td>0.101</td>
</tr>
</tbody>
</table>

Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01
Notes: log(SN\textsuperscript{res}), log(NA\textsuperscript{res}), and log(Th\textsuperscript{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.

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.

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 Table B.4.

**Robustness:** Whether potential violations of assumptions (SP) and (SE) add significant bias to $\hat{\gamma}_{1}^{2SLS}$ depends on the specific context. In Section B, 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 “feedback loop” relationship between endogenous staffing and average costs.
in equation (3). I can also relax assumption (SP) as follows: $\epsilon_{jt} \perp \{Z_{-ct-k}\}_{k \in 3,4,...} | X_{jt}, \phi_{ct}$, with $Z_{-ct-k} \subset X_{-ct-k}$. Here, I find a point estimate for skilled nurses of $\hat{\gamma}^{2SLS}_{1} = 1.41$, see column 2 of Table B.5. 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, see Figure B.2. 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 $\hat{\gamma}^{2SLS}_{1} = 1.01$ for skilled nurses, see column 3 of Table B.5.

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 employ a static model of demand for a cohort of seniors considering nursing home care in year $t$.\(^{16}\) I assume that senior $i$ with payer type $\tau$ decides between an outside good and the nursing home $j$ which maximizes her average daily indirect conditional utility:\(^{17}\)

$$u_{it\tau j} = \beta^d_i D_{ij} + \beta^d_2 D_{ij}^2 + \beta^{sn}_i \log(SN_{jt}^{res}) + \sum_x \beta^x_i X_{jt} + \beta^p_\tau P_{jt} + \xi_{jt} + \nu_{ijt}$$  \hspace{1cm} (4)

with $\beta^k_i = \beta^k + \sum_r z_{ir}\beta^k_r$.

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.

\(^{16}\)The model abstracts away from forward looking beliefs regarding potential nursing home switches.

\(^{17}\)Seniors implicitly also maximize the utility of the entire stay, which is simply the product of equation (4) and the length of stay in days, $LOS_i$.  

22
who pay out-of-pocket. $\xi_{jt}$ denotes facility and payer type specific preference shocks which are observed by person $i$ but remain unobserved to the econometrician and $\nu_{ijt}$ refers to an i.i.d. extreme value taste shock. The $\beta_i^k$ 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 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, $\xi_{jt}$, which may capture differences in room amenities.

These differences in preferences between payer types are summarized in the nursing home mean utilities, $\delta_{rjt}$, which vary at the product-payer-type-year level:

$$
\delta_{rjt} = \begin{cases} 
\beta^{sn} \log(SN_{rjt}) + \sum x \beta^x X_{jt} + \beta^p P_{jt} + \xi^p_{jt} & \text{if private payer} \\
\beta^{sn} \log(SN_{rjt}) + \sum x \beta^x X_{jt} + \beta^p P_{jt} + \xi^h_{jt} & \text{if hybrid payer} \\
\beta^{sn} \log(SN_{rjt}) + \sum x \beta^x X_{jt} + \xi^p_{jt} & \text{if public payer}
\end{cases}
$$

Instead of choosing nursing home care, seniors can also remain in their community and demand other formal and informal forms of long term care. I capture the demand for community-based care by an outside good. Senior $i$’s utility from choosing this option is:

$$
u_{it, out} = \varphi_{c(i)} + \nu_{it, out},$$

where $\varphi_c$ captures differences in the quality of the outside good between counties of residence.
Senior i’s probability of choosing nursing home j is then given by:

\[ s_{ijt} = \frac{\exp(\beta_1 D_{ij} + \beta_2 D_{ij}^2 + \sum_{k,r} z_{ir} \beta_k \tilde{X}_{jt} + \delta_{rt})}{\exp(\varphi_c) + \sum_{l \in CS_i} \exp(\beta_1 D_{il} + \beta_2 D_{il}^2 + \sum_{k,r} z_{ir} \beta_k \tilde{X}_{lt} + \delta_{rt})} , \]  

where \( \tilde{X}_{jt} = [X_{jt}, \log(SN_{jt}^{res})] \) to abbreviate notation. \( CS_i \) denotes senior i’s choice set of nursing homes. This 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 Figure C.1.

**Supply:** I consider a static oligopoly model. Nursing homes compete in private rates and the number of skilled nurses per resident for a cohort of seniors who begin their nursing home stay in year t. 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 \( \zeta_{jt} \). 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 potential length of (nursing home) stay in days should she choose any nursing home care. \( FC_{jt} \) denotes fixed costs.\(^{18}\) Combining demand and costs, I can express nursing home profits over cohort t as:

\[ \Pi_{jt} = \sum_i s_{ijt} (P_{jt} Days_i^{priv} + R_{jt}^{mcaid} Days_i^{mcaid} + R_{jt}^{mcare} Days_i^{mcare}) - C_{jt} = \sum_i s_{ijt} LOS_i (\bar{R}_{ijt} - MC_{jt}) - FC_{jt} . \]

Here \( Days_i^{priv} \) refer to days paid out-of-pocket and \( Days_i^{mcaid} \) and \( Days_i^{mcare} \) denote days

\(^{18}\)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.
reimbursed by Medicaid and Medicare respectively, which are known to the nursing home at the beginning of each stay. \( R_{jt}^{medicaid} \) and \( R_{jt}^{medicare} \) 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:

\[
U_{jt} = \alpha_j \Pi_{jt} + (1 - \alpha_j) \sum_i s_{ijt}LOS_i .
\]  

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:

\[
MC_{jt} = \frac{\sum_i s_{ijt} Days_{ijt}^{priv} + \sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} \bar{R}_{ijt} LOS_i}{\sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} LOS_i} + \frac{1 - \alpha_j}{\alpha_j} \sum_i s_{ijt} LOS_i .
\]  

\[
W_{jt} = \frac{\sum_i \frac{\partial s_{ijt}}{\partial SN_{jt}} (\bar{R}_{ijt} - MC_{jt} + \frac{1 - \alpha_j}{\alpha_j}) LOS_i}{\sum_i s_{ijt} LOS_i} .
\]

The non-pecuniary objectives enter equation (8) 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

My estimation strategy proceeds in two steps, similar to Goolsbee and Petrin (2004).

**Step 1:** To recover the nursing home mean utilities, $\delta_{\tau jt}$, as well as preference heterogeneity over nursing home characteristics, $(\beta^k, \beta_1^d, \beta_2^d)$, I first focus on seniors in nursing home care, e.g., seniors who chose an “inside” good. Using the MDS, I construct the share of seniors in a given nursing home as a fraction of seniors in any nursing home. Building on the logit structure, I derive the analogues choice probabilities predicted by the model and estimate $(\delta_{\tau jt}, \beta^k, \beta_1^d, \beta_2^d)$ via Maximum likelihood (ML).\(^{19,20}\) Turning to the outside good, I combine these parameter estimates with the observed county level shares of seniors in community care to recover the outside good parameters, $\varphi_c$, see Section C.2 for details.\(^{21}\)

**Step 2:** In the second step, I use a generalized method of moments (GMM) estimator to recover the remaining mean preferences for nursing home characteristics, see equation (5), as well as the cost and nursing home objective parameters. In the model, nursing home managers observe the unobservable taste shocks, $\xi_{\tau jt}$, 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. Unfortunately, the simulated

\(^{19}\)In the ML approach the first order conditions of the log likelihood function with respect to $\delta_{\tau jt}$ equate the predicted market shares (by the model) and the observed market shares. Therefore, these market shares coincide in the optimum just as in Berry, Levinsohn and Pakes (1995). For natural identification reasons, I need to normalize one mean utility per year and payer type to zero.

\(^{20}\)I weight observations by their length of stay, which is consistent with the profit incentives of nursing homes and implies a plausible representation of the resident population in the consumer welfare analysis.

\(^{21}\)To compute the aggregate outside share predicted by the model, I need to integrate the individual choice probabilities over the distribution of senior demographics in the sample population. Unfortunately, I do not observe all choice-relevant demographics in the Census data. Therefore, I cannot measure a consumer type’s population weight directly, which is simply the type’s inverse nursing home share multiplied by the observed number of residents (of that type). For example, if 10 percent of private payers choose nursing home care, then the population of private payers must be 10 times larger than the number of private payers in nursing home care. To address this limitation, I rely on the structure of the demand model and express the type-specific nursing home shares (and consequently the population weights) in terms of preference parameters.
Medicaid rate has no significant effect on private rates, see Table 2. Therefore, I consider two additional sets of instrumental variables to address the price endogeneity concerns. First, I use region specific housing and wage price indices interacted with the payer type. 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 (5). Second, 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 \( E[\xi \cdot IV] = 0 \) and the following sample analogue:

\[
G_{Demand}(\theta) = \frac{1}{N} \sum_{\tau,t,j} \xi_{jt}^\tau IV_{jt}^\tau.
\]

Here, \( \theta \) summarizes the structural parameters and \( N = 3 \cdot 3 \cdot J \), where \( J \) is the number of nursing homes multiplied by 3 payer types and 3 sample years. \( IV_{jt}^\tau \) is the demeaned vector of instruments. 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 (8) and (9), with cost data from Medicaid cost reports by ownership type, own. Let \( J^{own} \) be the set of for-profits (FP), not-for-profits (NFP), or public nursing homes (Pub). The moment conditions are \( E[mc_j - MC_j(\theta)|j \in J^{own}] = 0 \) and \( E[w_j - W_j(\theta)|j \in J^{own}] = 0 \), where lower and upper case

\[\text{To estimate demand, I require instruments that are orthogonal to local demand shocks, } \xi_{jt}^\tau, \text{ but not necessarily to local cost shocks, which was required in Section 3.1 to identify the causal effects of Medicaid rate changes. Hence, I can exploit local cost variation directly, if orthogonal to } \xi_{jt}^\tau, \text{ to estimate preferences.}
\]

\[\text{Following the preliminary analysis, I mitigate the effect of spurious spatial and serial correlation by conditioning on a rich set of control variables. Specifically, I first project the instrumental variables on county fixed effects and nursing home-year specific control variables and use the residuals in this moment condition.}\]
variables refer to data and model predictions, respectively. The sample analogues are:

\[ G^{Cost}_{1, own}(\theta) = \frac{1}{N} \sum_{\tau, t, j \in J_{own}} \left( mc_{jt} - MC_{jt}(\theta) \right), \quad \text{own} \in \{FP, NFP, Pub\} \]

\[ G^{Cost}_{2, own}(\theta) = \frac{1}{N} \sum_{\tau, j \in J_{own}} \left( w_{j,02} - W_{j,02}(\theta) \right), \quad \text{own} \in \{FP, NFP, Pub\}. \]

Here, \( w \) 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.\(^{24}\)

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 \( \text{Var}(mc) = \text{Var}(MC(\theta)) \) and \( \text{Var}(w) = \text{Var}(W(\theta)) \), motivating the following sample analogues:

\[ G^{Cost}_{3}(\theta) = \frac{1}{N} \sum_{\tau, t, j} \left( mc_{jt} - \frac{1}{N} \sum_{\tau, t, j} mc_{jt} \right)^2 - \frac{1}{N} \sum_{\tau, t, j} \left[ MC_{jt}(\theta) - \frac{1}{N} \sum_{\tau, t, j} MC_{jt}(\theta) \right]^2 \]

\[ G^{Cost}_{4}(\theta) = \frac{1}{N} \sum_{\tau, j} \left( \omega_{j,02} - \frac{1}{N} \sum_{\tau, j} \omega_{j,02} \right)^2 - \frac{1}{N} \sum_{\tau, j} \left[ W_{j,02}(\theta) - \frac{1}{N} \sum_{\tau, j} W_{j,02}(\theta) \right]^2. \]

Finally, I stack \( G^{Demand}(\theta), G^{Cost}_{1,type}(\theta), G^{Cost}_{2,type}(\theta), G^{Cost}_{3}(\theta) \), and \( G^{Cost}_{4}(\theta) \) and use the two-step GMM estimator (see Hansen (1982)) of \( \theta \) from the stacked moments.\(^{25}\)

## 5 Results

Table 3 presents relevant demand and firm objective function parameter estimates in column 1. I find that residents value higher skilled nurse staffing ratios (\( \hat{\beta}^{sn} > 0 \)) in particular sicker residents with a higher CMI (\( \hat{\beta}^{sn}_{cmi} > 0 \)). Residents dislike paying higher private rates if they pay at least partly out-of-pocket (\( \hat{\beta}^{p}_\text{hyb} < 0, \hat{\beta}^{p}_\text{priv} < 0 \)).\(^{26}\) Not surprisingly, private payers have

\(^{24}\) Marginal costs and wages are invariant to \( \tau \) and not indexed accordingly, see Section C.2.3 for details.

\(^{25}\) I first weight the moments by the identity matrix to generate an unbiased estimate of \( \theta \). In the second step, I weight by the inverse variance matrix of the sample moment conditions, see Section C.2.3 for details.

\(^{26}\) 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 an even larger marginal benefit from an additional skilled nurse.
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.\(^{27}\) Consistent with the suggestive evidence
from Table 1, I find that residents value proximity to the former residence.\(^{28}\) \(\hat{\beta}_{th}^{1}, \hat{\beta}_{th}^{2}\) and \(\hat{\beta}_{alz}^{alz}\) 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 \((\hat{\beta}_{th}^{2} > 0)\). Also, residents with a diagnosed Alzheimer’s disease
value nursing homes that have an Alzheimer’s unit.

Turning to the firm objective parameters, \(\frac{1-\alpha_{NFP}}{\alpha_{NFP}} > 0\) 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 \((\frac{1-\alpha_{Pub}}{\alpha_{Pub}} >
\frac{1-\alpha_{NFP}}{\alpha_{NFP}} > 0)\). The coefficients indicate that not-for-profits and public nursing homes act, all
else equal, as if they had a marginal cost advantage of $23 and $36, respectively.

In column 2, I present analogous results that only exploit the more traditional demand
moments in the second step of the empirical strategy. This specification also provides a
natural benchmark for further robustness exercises that do not exploit the cost moments
either. 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 \(\hat{\beta}_{sn}\)).
In that sense, adding the additional cost moments primarily increases the precision of the

\(^{27}\) 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.

\(^{28}\) The marginal utility of distance \((-\beta_{d}^{1} + 2\beta_{d}^{2}\text{Distance})\) is negative in the relevant 50km radius bounded from
above by \(-25.79 + 2 \times 22.44 \times 0.5 = -3.35\).
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.

Table 3: Preference and Nursing Home Objective Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta^{\text{sn}}$</td>
<td>log(SN/Resident)</td>
<td>0.888***</td>
<td>1.526**</td>
<td>1.923***</td>
<td>1.786**</td>
</tr>
<tr>
<td>$\beta^{\text{hyb}}$</td>
<td>Price*Hybrid</td>
<td>-0.007***</td>
<td>-0.011***</td>
<td>-0.006***</td>
<td>-0.012***</td>
</tr>
<tr>
<td>$\beta^{\text{priv}}$</td>
<td>Price*Private</td>
<td>-0.011***</td>
<td>-0.018***</td>
<td>-0.019***</td>
<td>-0.019***</td>
</tr>
</tbody>
</table>

| $\beta^{\text{cmi}}$ | log(SN/Resident)*CMI | 0.226*** | 0.226*** | 0.221*** | 0.231*** | 0.230*** |
| $\beta_1$ | Distance in 100km | -25.79*** | -25.79*** | -25.80*** | -25.79*** | -25.79*** |
| $\beta_2$ | Distance$^2$ | 22.44*** | 22.44*** | 22.45*** | 22.44*** | 22.42*** |
| $\beta_3$ | Therapist/Res*Min | -0.124*** | -0.124*** | -0.122*** | -0.124*** | -0.122*** |
| $\beta_4$ | Therapist/Res*Min*Short-Stay | 0.314*** | 0.314*** | 0.312*** | 0.314*** | 0.312*** |
| $\beta_5$ | Alzheimer*Alzheimer Unit | 0.414*** | 0.414*** | 0.413*** | 0.414*** | 0.413*** |
| $\vartheta$ | Occupancy$<\varphi$ | 0.757*** | 0.628*** | 0.312*** | 0.314*** | 0.314*** |
| $\vartheta_{\text{hyb}}$ | Occupancy$<\varphi$ *Hybrid | -0.027*** | -0.088*** | -0.027*** | -0.088*** | -0.088*** |
| $\vartheta_{\text{priv}}$ | Occupancy$<\varphi$ *Private | -0.044*** | -0.058*** | -0.044*** | -0.058*** | -0.058*** |

| $1-\alpha_{\text{NFP}}$ | Non-Profit Objective Parameter | 23.05*** | (1.083) | 30.14*** | (1.902) |
| $1-\alpha_{\text{Pub}}$ | Public Objective Parameter | 36.14*** | (1.902) | 36.14*** | (1.902) |

| Avg Benefit per SN/year | $123,295*** | $139,606*** | $166,511*** | $154,711*** | $171,686*** |
| Avg Wage+Fringe Benefits/SN | $83,171 | $83,171 | $83,171 | $83,171 | $83,171 |
| Benefit-Cost | $40,124** | $56,435 | $83,340 | $71,540 | $88,515 |
| Cost Moments | Y | N | N | N | N |
| Rationing | N | N | 100% | 97% | 95% |

Notes: The table displays the estimated preference and nursing home objective parameters. Column 1 shows the baseline parameter estimates that are identified off from demand and cost moments. Estimates in column 2 are derived from demand moments only. Column 3 presents estimates from a first-come-first-serve rationing model. Columns 4 and 5 allow for asymmetric rationing by payer type when occupancy falls short of 97% and 95%, respectively. Average benefits as well as average wage and fringe benefits per SN are measured in 2002. Th/res, SN/res, and Min abbreviate therapists per resident, skilled nurses per resident, and rehabilitative care minutes respectively. Standard errors are displayed in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.
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 Figures C.2 and C.3.\footnote{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 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.}

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 C.4, 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.\footnote{Medicare beneficiaries face co-payments from the 21st day of their stay onwards but co-pays do not vary across nursing homes.} To address this concern, I assume that all seniors have the same marginal utility of income given by the estimated price parameter of private payers, $\beta_{priv}$. 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 $123,000 per year, see the lower end 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 $40,000 is statistically significant at the 5% level, suggesting that skilled nurse staffing ratios are, on average, inefficiently low.\footnote{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.} 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 95% of the nursing homes as shown by a positive wedge. However, a few nursing
homes have negative wedges. Interestingly, 85% 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 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 $90,000 in Allegheny County. 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).

---

32 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.
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. On average over all counties, the optimal staffing ratio equals 0.36, which exceeds the observed staffing ratio by 43%, see Table C.1 for details.

6 Counterfactuals

Medicaid Rate Increase: First, I study the effects of a universal 10% increase in the Medicaid reimbursement rates.33 The bottom rows of Table 4 display the average change in the skilled nurse staffing ratio and the private rate between the old and the new equilibrium. On average, the staffing ratio increases by 8.7%, which translates into an extra 7.2 skilled nurse minutes per resident and day.34 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. My results indicate that the second effect dominates. On average, I find a 4.5% reduction in the private rate, which indicates “cost-shifting” between Medicaid beneficiaries and private payers (see Frakt (2011)).35 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.

33 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.

34 The top panels of Figure C.4 present the new equilibrium distribution of staffing ratios and private rates.

35 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.
<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>No Market Expansion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Absolute %Δ Spending</td>
<td>Absolute %Δ Spending</td>
</tr>
<tr>
<td>Δ CS</td>
<td>212.0  64.1%</td>
<td>202.6  89.0%</td>
</tr>
<tr>
<td>Δ Profits</td>
<td>149.4  45.2%</td>
<td>103.7  45.5%</td>
</tr>
<tr>
<td>Δ Spending</td>
<td>330.7  100.0%</td>
<td>227.7  100.0%</td>
</tr>
<tr>
<td>Δ Welfare</td>
<td>30.7  9.3%</td>
<td>78.6  34.5%</td>
</tr>
<tr>
<td>Avg Δ SN/Res</td>
<td>8.7%</td>
<td>8.7%</td>
</tr>
<tr>
<td>Avg Δ P</td>
<td>-4.5%</td>
<td>-4.5%</td>
</tr>
</tbody>
</table>

Notes: Absolute values are measured in million dollars. The right panel presents welfare estimates holding nursing home demand (market shares) fixed.

Turning to the welfare implications, Medicaid spending increases by $331 million, see the third row, for two reasons. First, holding nursing home demand fixed, the rate increase raises Medicaid spending by 10% or $228 million as evidenced in the third column. Second, higher staffing ratios and lower private rates lead to a market expansion, increasing the overall demand for nursing home care by 6.7%. This raises Medicaid spending by $103 million because of an additional 790,000 Medicaid days for seniors, who previously lived in the community.36

Nursing homes take advantage of the increase in Medicaid spending: profits increase by $149 million, about 45% of the increase in Medicaid spending. That means that nursing homes pass about 55% 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:

$$\Delta CS_i = \frac{1}{\beta_{priv}^P} \left[ \sum_i \log(\sum_j \exp(\delta_{irjt}^1)) \text{LOS}_i - \sum_i \log(\sum_j \exp(\delta_{irjt}^0)) \text{LOS}_i \right].$$

Here, $\delta_{irjt}^1$ and $\delta_{irjt}^0$ denote the indirect conditional daily utility, net of the extreme value shock, evaluated at new and old product characteristics, respectively. Holding market shares

36 The spending estimate nets out savings in Medicaid spending of $30,000 per year and beneficiary on home and community based services, see https://www.kff.org/medicaid/report/medicaid-home-and-community-based-services-programs- 2012-data-update/ for details, last accessed October 24th, 2017. I also abstract away from the welfare implications of changes in Medicare spending. To this end, I net out the variable profits on additional Medicare days for seniors, who previously lived in the community.
fixed, lower private rates and higher nurse staffing ratios raise consumer surplus annually by about $203 million, see the first entry in the third column. Substitution between community and nursing home care options raises the consumer surplus gains to $212 million.

Combining the overall increase in consumer surplus, provider profits, but also Medicaid spending, I find an annual welfare gain of $31 million, about 9.3% of the increase in Medicaid spending. Ignoring the market expansion effect, the welfare gain increases to $79 million or 34.5% of the increase in Medicaid spending. This is largely because the marginal seniors between substituting from community based care to nursing home care add only 4.4% to the gains in consumer surplus despite their significant impact on Medicaid spending.

The welfare estimates ignore 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 exceeds the baseline return on Medicaid spending. The baseline logit model overstates the substitutability of different forms of care, when compared to a more flexible nested logit model, providing a potential lower bound on the welfare return of increased Medicaid spending. However, the return on Medicaid spending increases to only 34.5% when holding market shares fixed, suggesting that the deadweight loss of taxation is at best fully offset by welfare gains in this industry. I return to the substitution between different forms of care in Section 7.

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 and a disproportionate increase in the overall demand for nursing home 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 A.1 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 each county, I add a publicly operated nursing home located at the size-weighted average of longitude and latitude coordinates of the respective incumbents. 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. On average, incumbents adjust their staffing ratios and private rates by less than 1% in each county as indicated by the top panel of Table 5. Incumbents in Monroe and Jefferson County respond slightly more elastically to entry in parts because the new entrant steals 6% of county demand as opposed to only 3% in Northumberland and Lycoming County.\(^{37}\)

I next turn the results into welfare estimates. The variable annual profits of new entrants vary between $0.2 million and $0.5 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 on net, 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 of $3.6 million per year, see the fourth row of column 5. Holding market shares fixed, changes in incumbent nursing home characteristics raise consumer surplus by only $0.3 million, which is the key object of interest in this exercise. Hence, most of the

\(^{37}\)For more details on the geographic locations of incumbents and entrants as well as heterogeneous responses to entry within counties, see the lower graphs in Figure C.4.
Table 5: Directed Entry and Counterfactual Comparison

<table>
<thead>
<tr>
<th></th>
<th>Northumberland</th>
<th>Lycoming</th>
<th>Monroe</th>
<th>Jefferson</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var. Profit Entrant</td>
<td>0.2</td>
<td>0.3</td>
<td>0.5</td>
<td>0.2</td>
<td>1.1</td>
</tr>
<tr>
<td>Fixed Costs</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
<td>4.4</td>
</tr>
<tr>
<td>Δ Profit</td>
<td>-1.1</td>
<td>-1.0</td>
<td>-1.0</td>
<td>-1.1</td>
<td>-4.2</td>
</tr>
<tr>
<td>Δ CS</td>
<td>0.6</td>
<td>0.8</td>
<td>1.5</td>
<td>0.6</td>
<td>3.6</td>
</tr>
<tr>
<td>Δ Spending</td>
<td>0.4</td>
<td>0.5</td>
<td>0.9</td>
<td>0.3</td>
<td>2.0</td>
</tr>
<tr>
<td>Δ Welfare</td>
<td>-0.9</td>
<td>-0.7</td>
<td>-0.4</td>
<td>-0.8</td>
<td>-2.6</td>
</tr>
<tr>
<td>Avg ΔSN^{res}</td>
<td>0.06%</td>
<td>0.08%</td>
<td>0.88%</td>
<td>0.75%</td>
<td>0.01%</td>
</tr>
<tr>
<td>Avg ΔP</td>
<td>0.02%</td>
<td>0.07%</td>
<td>-0.73%</td>
<td>-0.35%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

Medicaid Expansion with Outside Good | Entry with Outside Good

<table>
<thead>
<tr>
<th>ΔSN^{res}</th>
<th>Δ Spending</th>
<th>ΔSN^{res}/100m</th>
<th>ΔSN^{res}</th>
<th>Δ Spending</th>
<th>ΔSN^{res}/100m</th>
</tr>
</thead>
<tbody>
<tr>
<td>8.70%</td>
<td>331 million</td>
<td>2.63%</td>
<td>0.01%</td>
<td>3.3 million</td>
<td>0.35%</td>
</tr>
<tr>
<td>8.70%</td>
<td>181 million</td>
<td>4.81%</td>
<td>0.01%</td>
<td>4.2 million</td>
<td>0.28%</td>
</tr>
</tbody>
</table>

Notes: The top panel compares the effects of directed entry between rural counties and illustrates the aggregate effects at the state level in the last column. Average staffing and pricing effects are weighted by market 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.

increase in consumer surplus captures gains from variety, which combines the gains from a convenient location and an additional extreme value draw. I interpret this estimate as an upper bound on the consumer welfare gains to the extent that the lack of random coefficients loads unobserved taste heterogeneity onto the extreme value taste shock, see Petrin (2002). Yet, the consumer welfare gains fall short of the additional annual fixed costs of operating the new nursing homes ignoring additional sunk costs of entry. Finally, adding the increase in Medicaid spending (following a 3.6% demand expansion for nursing home care in the four counties) I find an annual welfare loss of $2.6 million.

**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 2.6% per $100 million in additional public spending. Repeating this calculation in the entry counterfactual suggests a return of only 0.35% per
$100 million in public spending when considering new entrants’ annual losses of $3.3 million as required additional public spending. I also analyze the effects of directed entry in four urban counties and find qualitatively similar results. For example, I find a quality return of 0.33% in urban counties, see Table D.1. This comparison indicates that moderate increases in Medicaid rates are about 7.5 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 17 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 23%, 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 increase their private rates by 16% and 29%, respectively. 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.** The baseline analysis abstracts away from capacity constraints, which may introduce bias to the demand and supply elasticities. To assess the role of capacity constraints in this context, I start by quantifying the fraction of seniors who may not access their preferred nursing home due to rationing. Unfortunately, I do not observe rejected seniors directly. Instead, I test for a reduction in observed successful admissions at high occupancy rates which would be indicative of rationing behavior. To mitigate the effect of confounding changes in the arrival rate of seniors, I control for nursing home-year fixed effects and test for a correlation between week-to-week variation in the occupancy rate and the weekly number of newly admitted seniors.\(^{38}\) While I find no evidence for systematic reductions in occupancy rates between 75 and 90% occupancy, I estimate that weekly admissions fall by 12% at occupancy rates exceeding 95%, see Figure D.1 and Table D.2. This reduction is less pronounced among more profitable private payers (-4%). To quantify the potential demand for care absent of rationing, I scale the realized admissions at occupancies exceeding 95% by 12%. About 29% of all admitted seniors enter the nursing home at an occupancy of more than 95%, see Table D.3. Hence, nursing home demand could increase by 29%*12%=3.5% suggesting that only 3.5% of seniors cannot access their preferred nursing home because of rationing.

Next, I revisit the demand estimates using two alternative models that allow for rationing. First, I consider a universal capacity limit of 100% occupancy for all payer types and assume that residents are admitted on a first-come-first-serve basis. Consequently, I leave only those nursing homes in the senior’s choice set that have at least one open bed on the day the resident was admitted to any nursing home. Using the revised choice set, I estimate the preference parameters excluding the cost moments in the second step.\(^ {39}\) The parameter estimates are presented in the third column of Table 3. \(\hat{\beta}^{sn}\) and \(\hat{\beta}^{p}_{priv}\) differ by less than 26% from the baseline parameters in column 2 and remain within the respective confidence interval. Importantly, these estimates indicate even larger welfare gains from an increase in

\(^{38}\)See Section D.2 for a formal discussion of the underlying assumptions.
\(^{39}\)Cost moments can be included but require a supply side model that that takes rationing into account.
Medicaid rates as evidenced by the larger marginal benefit estimate.

Second, and motivated by heterogeneous reductions in weekly admissions across payer types, I consider alternative asymmetric rationing models. Here, I add an indicator variable to the indirect conditional utility function from equation (4), interacted with payer type, that turns on if the average occupancy of the nursing home in the respective week, \( oc_{ij} \), falls short of 97% and 95%, respectively:

\[
 u_{i\tau jt}^{AR} = u_{i\tau jt} + \vartheta_1 \{ oc_{ij} < oc \} 1\{ \tau = hyb \} + \vartheta_{hyb1} \{ oc_{ij} < oc \} 1\{ \tau = priv \}.
\]

The results are summarized in columns 4 and 5 of Table 3. The first interaction effect, \( \vartheta \), is positive indicating that seniors are more likely to choose a nursing home with an occupancy of less than 97% or 95%. This suggests that capacity constraints restrict access to nursing home care for all payer types, possibly through a first-come-first-serve admission process. The interaction terms, \( \vartheta_{hyb} \) and \( \vartheta_{priv} \) are negative (although small in relative magnitude) indicating that rationing is less pronounced for hybrid and private payers. Importantly, \( \hat{\beta}_{sn} \) and \( \hat{\beta}_{priv} \) differ by less than 15% from the baseline parameters and suggest again a higher marginal benefit of a skilled nurse.

Despite the larger marginal benefit estimates, the consumer gains from Medicaid increases could be smaller if the overall increase in demand amplifies rationing and leads to a crowd-out of inframarginal seniors with high utility from nursing home care. To investigate this possibility, I combine the baseline preference coefficients with a random rationing model as in Ching, Hayashi and Wang (2015), to predict demand under counterfactual private rates and staffing ratios, see Section D.2.2 for more details. Rationing reduces the gain in consumer surplus to $181 million but also lowers profits and public spending since some of the rationed seniors choose the outside good instead. While the new estimates imply a smaller welfare gain of $14.5 million, they imply a higher return on public spending.

Finally, I also revisit the effect of rationing on the supply side behavior. To this end, I exclude nursing homes with an average occupancy of more than 97% (95%) and re-estimate
the preliminary regression models that investigate the link between Medicaid reimbursement rates, staffing and pricing decisions. The key estimates from the first two columns are differ from the baseline estimates by less than 6%, see Table D.4 for details. This provides further evidence that the main findings of this paper are robust to potential capacity constraints.

Overall, the presented evidence indicates that the key demand and supply elasticities are robust to potential rationing in this context. Nevertheless, the reductions in admissions at high occupancy rates suggest that binding capacity constraints may affect the behavior of nursing homes with very high average occupancy rates.

**Normative Findings.** The consumer welfare estimates rely on the estimated marginal utility of income for private payers. This may understate the marginal utility of income for poorer Medicaid beneficiaries and therefore overstate the marginal benefit of an additional skilled nurse and the optimal staffing ratio. To corroborate my normative findings, I first compare the derived optimal staffing ratio with staffing recommendations from the literature (Harrington et al. (2000)). In 1998, a group of national experts discussed adequacy in staffing levels in U.S. nursing homes and recommended that the skilled nurse hours per resident day should at least equal 1.85 hours. The implied staffing ratio of 0.32, see the second row of Table 6 exceeds the average staffing ratio in 2000 of 0.24 by 35%.

<table>
<thead>
<tr>
<th>Benefit of SN in $1,000</th>
<th>Optimal SN per Res</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline Estimates</td>
<td>126.3</td>
</tr>
<tr>
<td>Harrington et al. (2000)</td>
<td></td>
</tr>
<tr>
<td>Health Returns Approach</td>
<td>157.3</td>
</tr>
<tr>
<td>Life-Cycle Approach</td>
<td>91.6</td>
</tr>
<tr>
<td>Assets Among Private Payers</td>
<td>133.8</td>
</tr>
</tbody>
</table>

Notes: Harrington et al. (2000) recommend a minimum staffing ratio of 0.32.

Second, I revisit the marginal benefit estimate by multiplying the marginal health benefits, estimated in Friedrich and Hackmann (2017), with the statistical value of life. In this paper,

40The 1.85 hours recommendation combines 1.15 hours for registered nurses and 0.7 hours for licensed practical nurses per resident and day, see Table 2 in Harrington et al. (2000).
we find that a federally funded parental leave program in Denmark reduced the number of skilled nurses in nursing homes by 670 nurses and increased nursing home mortality by 1,700 elderly per year, about 2.5 life years per nurse. Considering a quality-of-life-adjusted statistical value of a life year for an 85 year old of $62,000, see Cutler et al. (1997), this suggests a marginal benefit of $157,313 per year, see the third row of Table 6.

Third, I revisit the marginal utility of consumption though the lenses of the calibrated life-cycle model from Lockwood (2014). In this model, individuals trade-off between consumption and bequest motives. Combining the first order condition over consumption and bequest decisions with bequest data from the Health and Retirement Study, I am able to quantify the marginal utility of consumption (income), see Section D.3.1 for details. I find that the marginal utility of consumption for Medicaid payers exceeds the marginal utility of private payers by 27.5%. This would lower the marginal benefit per nurse by 27.5% to $91,600 if all residents were Medicaid beneficiaries, see the fourth row.

Fourth, I test for wealth effects directly by taking advantage of observed asset spend-down patterns in the data. Based on Medicare and Medicaid claims data, I can identify the number of days paid out-of-pocket before the senior becomes eligible for Medicaid. I multiply the number of days with the daily private rate to quantify the amount of tangible assets that are not protected under Medicaid. Next, I assign predicted asset levels to private payers, based on a rich set of demographics, and test for different price elasticities in asset levels. The analysis provides evidence against wealth effects and suggests an annual marginal benefit of $133,800 which exceeds the baseline estimate by 5.9%, see Section D.3.2 for details.\footnote{One reason for this finding is that Medicaid residents have generally longer lengths of stay and are more likely to spend the rest of their lives in the nursing home. The limited consumption opportunities in the nursing home can therefore imply a smaller marginal utility of income despite lower levels of wealth.}

Outside good. The baseline model might overstate substitution between different modes of long term care and thereby reduce the welfare gains from a universal increase in Medicaid rates. To investigate this possibility, I have estimated an alternative demand model that does not allow for an outside good.\footnote{A potential middle ground would be a nested logit model nesting all nursing home goods. Identification} I find very similar average increases in staffing (+8.8%)
and reductions in private rates (-4.9%) following a universal 10% increase in Medicaid reimbursement rates. The welfare gain increases to $68 million (30% of public spending) largely because Medicaid spending increases by only $226 million without the market expansion effect. Turning to the entry counterfactual, I find very small changes in staffing and pricing and an overall welfare loss of $2.1 million per year. Consistent with the baseline results, I find that raising Medicaid rates is about 7.1 times as effective in increasing the quality of care than encouraging local competition via directed entry.

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 8.7% 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 45% of the Medicaid increases as profits and only pass 55% on to residents via higher nurse staffing ratios and lower private rates. A second reason is that increases in the quality of care may lead to a market expansion effect, which may raise Medicaid spending considerably. Therefore, connecting Medicaid payments with the quality of care more directly and containing a potential market expansion effect may provide a more cost-effective approach in addressing quality shortfalls in this industry.

---

of the nesting parameter requires exogenous variation in the characteristics of the outside good in addition to the variation between nursing home goods provided by the simulated Medicaid rate.
References


Foundation, Kaiser Family, ‘What is Medicaid’s impact on access to care, health outcomes, and quality of care?’ (2013).


A Institutional Details

This section provides further institutional details concerning quality report cards, differences in state regulations, and the reimbursement methodology in Pennsylvania.

A.1 Quality Report Cards

In 1998, the Centers for Medicare and Medicaid (CMS) introduced a web-based nursing home report card initiative (Nursing Home Compare), which subsequently added more quality of care measures including health related deficiencies and nurse staffing levels in 2000. In 2002, the Nursing Home Quality Initiative (NHQI) added additional quality indicators. As highlighted earlier, the main quality dimensions are staffing ratios, clinical outcomes, and the number of deficiencies, see Figures A.1 and A.2 for details. However, the evidence on the effects of public reporting on the quality of care remains mixed, see for example Grabowski and Town (2011).

A.2 External Validity: Pennsylvania and the U.S.

In this subsection, I provide more details on how the nursing home industry in Pennsylvania compares to other states and provide additional details on mixed payer sources.

The nursing home industry and the regulatory environment in Pennsylvania is, in many ways, representative for the entire country. While Pennsylvania’s reimbursement rate exceeds the national average by about $25 per resident and day or one standard deviation in state averages, the reimbursement methodology is generally quite comparable among states, as evidenced in the first panel of Table A.1. Like Pennsylvania, about three quarters of all states in 2002 use a per diem reimbursement rate calculation that adjusts for the severity of health conditions based on the resident’s case mix index. Similarly, three quarters use
Notes: This screen shot summarizes the outcome of a nursing home search on the nursing home compare web page “https://www.medicare.gov/nursinghomecompare/” for the area of State College, PA. Nursing Homes are ordered by distance and ranked in three quality dimensions. Health inspections, which indicates potential deficiencies, staffing ratios, and quality measures, which summarize a variety of clinical outcomes. The overall rating indicated in the first column is a weighted average over these statistics.

a prospective cost-based reimbursement methodology, see Grabowski et al. (2004) for more details. Furthermore, several states, including New York, California, Ohio, and Florida, adapted a peer-group based reimbursement methodology, just as in Pennsylvania, over the last decade. Certificate of Need laws, however, differ from state to state; in 2002, those laws existed in two-thirds of states but not in Pennsylvania.

Nursing homes are, on average, slightly larger in Pennsylvania and the share of for-profit nursing homes falls short of the national average by about one standard deviation. The share of public nursing home is on the other hand quite similar. On average, the nursing home industry

---

appears to be less concentrated in Pennsylvania. The Herfindahl Index (HHI) falls short of the national average by almost one standard deviation. Furthermore, the nursing home industry is generally less concentrated than other health care industries. Gaynor (2011) finds a HHI of more than 3,000 for the hospital industry. The resident composition in Pennsylvania is overall representative. The composition is slightly selected towards older white women, who have slightly worse health profiles as demonstrated by a higher case mix index and a marginally higher average level of need for help with activities of daily living (ADL) such as eating, toileting, and bathing. The mix of payer types is again very similar. About 62% of the residents are primarily covered by Medicaid, both in Pennsylvania and at the national level average level. The share of residents who are primarily covered by Medicare, however, is slightly smaller in Pennsylvania indicating a larger fraction of residents who pay out-of-pocket.
Next, I turn to the comparison of health care quality. Industry experts commonly distinguish between three groups of quality measures. These are nurse staffing levels, clinical outcomes, and deficiencies that are assigned by state surveyors if nursing homes fail to meet process and outcome based nursing home care requirements. While the average total nurse hours are comparable between Pennsylvania and the U.S., Table A.1 indicates that licensed practical and registered nurse hours (skilled nurses in my analysis) in Pennsylvania exceed the national average by 6 and 16%, respectively. Consistent with the staffing differences, Table A.1 also indicates that nursing homes in Pennsylvania are less likely to receive deficiency citations, particularly those related to the quality of care.

Finally, I turn to the role of mixed payer types in this industry. The majority of residents use mixed payer sources to pay for nursing home stays. Only about a third of residents, when weighted by length of stay, use the same payer source throughout their nursing home stay, see the diagonal in the right panel of Table A.2. Several seniors are initially covered by Medicare but start paying out-of-pocket once their stay exceeds the covered number of days. Others pay out-of-pocket on the first day but become eligible for Medicaid during their stay once they have spent down their assets.

A.3 Details on Length of Stay

Figure A.3 displays a Kaplan Meier survival curve, which tracks the stock of residents over time since admission. I focus on the cohort of residents, who were admitted in 2000. I am able to track resident stays until the end of 2005, which provides information on 5 full non-censored years for this cohort. Overall, only 4.7% of resident stays in the sample population, admitted in the years 2000-2002, are censored in terms of their length of stay.

A.4 Reimbursement Formula and Simulated Reimbursement Rate

In this subsection, I provide further details on the Medicaid reimbursement methodology and the calculation of the simulated reimbursement rates.
Figure A.3: Kaplan Meier Survival Curve by Years Since Admission

Notes: This figure displays the fraction of seniors that continue to live in the nursing home by the number of years since they were admitted.

A.4.1 Reimbursement Formula

Every year, certified nursing homes submit reimbursement relevant cost information to Pennsylvania’s Department of Human Services (DHS). Following the detailed Medicaid reimbursement guidelines, the DHS isolates allowable costs and groups them into different cost categories.\(^2\) The different cost categories are: resident care costs (rc), which comprise spending on health care related inputs, other resident related care costs (orc), administrative costs (admc), and capital costs (capc). The regulator computes the facility specific arithmetic mean of the reported average costs by category and assigns the peer group-category specific median cost level for all but capital costs to each facility in the peer group. Capital costs are reimbursed directly. The final category specific reimbursement rate for facility \(j\) in year \(t\) depends on the median rate and \(j\)'s previous average costs according to the following formula:

Here, $AC_{rc}^{t-3,4,5}$ denotes the Case Mix Index and inflation corrected average costs for resident care, averaged over the reported cost reports from three, four, and five years ago. Average resident related care costs, average administrative costs, and average capital costs ($AC_{orc}^{t-3,4,5}$, $AC_{admc}^{t-3,4,5}$, and $AC_{capc}^{t-3,4,5}$) are corrected for inflation but not for the Case Mix Index of the residents. Finally, $cmi_{jt}^{MA}$ measures the Case Mix Index of Medicaid residents in facility $j$ and $p(j) \in p_1, p_2, \ldots, p_{12}$ refers to facility $j$’s peer group, defined by size and geographic region. In words, resident care costs, other related care costs and administrative costs are reimbursed according to a weighted average of own costs and the median cost level in the peer group unless own costs exceed the median cost level. In this case, facilities receive the median cost level. This methodology resembles the “yardstick competition” regulatory scheme in which the regulator uses the costs of comparable firms to infer a firm’s attainable cost level.

### A.4.2 Simulated Reimbursement Rates

In this subsection, I discuss the computation of the simulated Medicaid reimbursement rate in further detail. I discuss the simulation strategy for the baseline approach in which I treat counties as locally segmented markets and exploit the full variation in reported costs. I construct separate simulated cost-block reimbursement rates for resident care costs, resident related care costs, and administrative costs following the first three rows of equation A.1.
Specifically, I proceed as follows:

For each cost category, I replace the set of endogenous average costs of providers located in the county under study with a sample of randomly drawn average costs from the population of nursing home observations in Pennsylvania in the given year. Notice, that the number of sampled nursing homes is relevant for the calculation because the reimbursement formula computes the median resident care cost level. For instance, if I sample too many facilities, then the median rate will reflect the median level in Pennsylvania, not the median level in the peer group. This will not bias the parameter estimates, but it will clearly reduce the statistical power of the IV strategy. On the other hand, one may not want to replace the endogenous average resident care costs one by one, as the number of facilities in the county under study may be endogenous. Therefore, I compute the predicted number of facilities per county-peer group based on the underlying number of elderly residents in the county. Specifically, I first predict the number of nursing facilities in the county via ordinary least squares regressions on the number of county residents aged 65 and older by gender. Second, I compute the size group ratio in other counties of the peer group and multiply the predicted number of facilities by this ratio. For instance, if 30% of the facilities in other counties have 269 or more beds, then the predicted number of nursing facilities with 269 or more beds in the county under study equals 30% times the predicted number of facilities in the county. The predicted number of facilities addresses the endogeneity concern and it is sufficiently close to the observed number of facilities, such that the instruments still have substantial statistical power, see the results section.

Using the set of randomly selected and exogenous average costs from other counties, I simulate the cost category-specific reimbursement rate for facility \( j \) multiple times such that each of the sampled average cost observations enters the formula once “as facility \( j \)” and otherwise via a competitor in \( j \)’s county. As a competitor, the sampled average cost observation affects the reimbursement rate through the median rate only. As facility \( j \), the sample average cost observation affects the reimbursement rate through the own costs as well. This distinction is
relevant for resident and resident related care costs. It is not relevant for administrative costs because the reimbursement formula is symmetric in the reported administrative costs of all nursing homes in the respective peer group, see the third row of equation A.1.

Next, I iterate these steps 200 times to minimize the simulation error and keep the arithmetic mean of these 200 simulated instruments. Finally, I add the cost-block specific reimbursement rates together, which delivers a county-peer-group-year specific simulated Medicaid reimbursement rate.

A.5 Nursing Home Size Distribution

This subsection provides additional details on the nursing home size distribution.

Figure A.4 displays a histogram of nursing home beds in Pennsylvania for the years 2000-2002. The histogram is censored at 500 beds; fewer than 1% of nursing homes have more than 500 beds. Since 1996, Pennsylvania’s Medicaid reimbursement formula distinguishes between small (<120 beds), medium-sized (120-269 beds), and large nursing homes (>269 beds), as indicated by the two vertical dashed lines.3

B Robustness of Reduced Form Analysis

This section provides further details on the robustness exercises for the preliminary analysis.

B.1 Details on Exclusion Restriction

Proposition 1. \( AC_{-c,t}^{p(j)} \) provide a valid set of instruments if the following two assumptions hold:

\[(SP) \; \epsilon_{jt} \text{ is independent of lagged shocks to providers located in other counties from 3 or more} \]

\[\text{years.} \]

3The outstanding bars from the histogram indicate bunching at multiples of 30 beds. However, I have extensively investigated robustness of my findings to the bunching and concluded that it is unimportant for my analysis. Details are available upon request.
Figure A.4: Nursing Home Size Distribution in Beds

Notes: This figure displays a histogram of the nursing home bed distribution in Pennsylvania for the years 2000-2002. The vertical dashed lines delineate the size groups defined in Pennsylvania’s Medicaid reimbursement methodology.

years ago, conditional on $X_{jt}$ and $\phi_{ct}$:

$$
\epsilon_{jt} \perp \{\epsilon_{ct-k}, \eta_{ct-k}, X_{ct-k}, \phi_{ct-k}\}_{k \in 3,4,5} | X_{jt}, \phi_{ct}
$$

(SE) $\epsilon_{jt}$ 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 $\phi_{ct}$, if $\gamma_1 \neq 0$:

$$
\epsilon_{jt} \perp \{\epsilon_{ct-k}, \eta_{ct-k}, X_{ct-k}, \phi_{ct-k}\}_{k \in 6,7,8} | X_{jt}, \phi_{ct}
$$

Proof. Using equation (3), we can express $AC_{C}^{\phi(j)}$ in terms of $Z_{c,t-3,4,5}$, $\eta_{c,t-3,4,5}$, and $log(Y_{c,t-3,4,5})$. Next, we can express $log(Y_{c,t-3,4,5})$ in terms of $X_{c,t-3,4,5}, \phi_{c,t-3,4,5}, \epsilon_{c,t-3,4,5}$, as well as $log(R_{c,t-3,4,5})$ if $\gamma_1 \neq 0$. Hence, if $\gamma_1 = 0$, $\epsilon_{jt}$ is mean independent of $AC_{C}^{\phi(j)}$ if $\epsilon_{jt}$ is independent of $\epsilon_{c,t-3,4,5}, \eta_{c,t-3,4,5}, X_{c,t-3,4,5}, \phi_{c,t-3,4,5}$, considering that $Z_{c,t-3,4,5}$ is by construction a subset of $X_{c,t-3,4,5}$.

If $\gamma_1 \neq 0$, then we need to consider the relationship between $\epsilon_{jt}$ and $R_{c,t-3,4,5}$ as well. U-
ing equation (2), we can express \( R_{c,t-3,4,5} \) in terms of \( AC^{p(j)}_{c,t-6,7,8,9,10} \) and \( AC^{p(j)}_{c,t-6,7,8,9,10} \). Using the first argument, we can iteratively replace previously submitted average costs \( AC^{p(j)}_{c,t-6,7,..} \) and \( AC^{p(j)}_{c,t-6,7,..} \) in terms of \( X_{ct-6,7,..}, \phi_{ct-6,7,..}, \epsilon_{ct-6,7,..}, \eta_{ct-6,7,..} \) and

\[
X_{ct-6,7,..}, \phi_{ct-6,7,..}, \epsilon_{ct-6,7,..}, \eta_{ct-6,7,..}.
\]

\[\square\]

### B.2 Bias From Serial Correlation in County Average Costs

In this subsection, I provide a back-of-the-envelope calculation to bound the potential bias in the key estimate of interest, \( \hat{\gamma}_1^{2SLS} \), that may be introduced through serial correlation in average costs at the county-year-peer group level. To this end, I impose the following three assumptions:

- **Assumption (DC):** \( \epsilon_{jt} \) is (conditionally) mean independent of \( Z_{ct-3,4,..}, X_{ct-3,4,..}, \epsilon_{ct-3,4,..} \), and \( \eta_{ct-3,4,..} \).

- **Assumption (PT):** Supported by the evidence presented in Appendix Section B.4, I assume imperfect pass-through of Medicaid rates onto average costs: \( \frac{\partial \log(AC_{jt})}{\partial \log(R_{mcaid})} \leq 1 \).

- **Assumption (TS):** Average log costs at the county-peer group level, follow an AR(1) process with

\[
\log(AC^{p(j)}_{ct}) = c + \phi \log(AC^{p(j)}_{ct-1}) + u^{p(j),ac}_{ct},
\]

with \( u^{p(j),ac}_{ct} \sim iid(0, \sigma^2) \). Unobserved staffing shocks at the county-peer group level, \( \epsilon^{p(j)}_{ct} \), depend on average log costs from other counties, \( \log(AC^{p(j)}_{ct}) \) as follows

\[
\epsilon^{p(j)}_{ct} = \tau \log(AC^{p(j)}_{ct}) + u^{p(j),\epsilon}_{ct},
\]

with \( u^{p(j),\epsilon}_{ct} \sim iid(0, \sigma^2) \).

Assumption (DC) rules out spatial correlation, whereby I can solely focus on the bias from serial correlation. Assumption (PT) provides a plausible upper bound for the effect of Medicaid rates on average costs and ultimately staffing decisions. I will come back to this point
below. Finally, assumption (TS) imposes structure on the serial correlation in average costs, which allows me to provide a quantitative assessment of the potential bias.

**Additional Simplifying Assumptions:** For the purpose of analytical tractability and ease of notation, I impose several additional simplifying assumptions. To tighten the exposition, I ignore the controls in equation (1), such that

\[ \log(Y_{jt}) = \gamma_1 \log(R_{jt}^{mcaid}) + \epsilon_{jt} . \]  

(B.1)

More importantly, I simplify the Medicaid reimbursement formula along several dimensions. First, I ignore the direct effect of own costs on future reimbursement rates. I revisit this simplification in footnote 5 below. Replacing the lag series (-3,-4,-5) by the average lag of relevant cost reports (-4) allows me to simplify the reimbursement formula as follows:

\[ R_{jt}^{mcaid} = \pi \times \text{median}(AC_{j}^{p(j)}_{c,t-4}, AC_{-j}^{p(j)}_{c,t-4}) . \]

Again, \( AC_{c}^{p(j)} \) and \( AC_{-c}^{p(j)} \) denote the sequence of reported average costs from peer-group members located in \( j \)'s county \( c \) and other counties \( -c \), respectively.

Second, I approximate the median function by the arithmetic mean, which implies that the log reimbursement rate is additively separable in average costs as outlined below:

\[
\begin{align*}
\log(R_{jt}^{mcaid}) & = \log(\pi \times \text{median}(AC_{j}^{p(j)}_{c,t-4}, AC_{-j}^{p(j)}_{c,t-4})) \\
& = \log(\pi) + \text{median}(\log(AC_{j}^{p(j)}_{c,t-4}), \log(AC_{-j}^{p(j)}_{c,t-4})) \\
& \approx \log(\pi) + \rho_c \log(AC_{j}^{p(j)}_{c,t-4}) + (1 - \rho_c) \log(AC_{-j}^{p(j)}_{c,t-4}) . \\
\end{align*}
\]  

(B.2)

Here, the last row uses the approximation, where, \( \rho_c \) captures the share of nursing homes in the peer-group that are located in \( j \)'s county \( c \). Third, I assume that all counties in the peer group have equally many nursing homes such that \( \rho_c = \rho \). \( \log(AC_{j}^{p(j)}_{c,t-4}) \) and \( \log(AC_{-j}^{p(j)}_{c,t-4}) \) capture the overall average over log average costs among nursing homes located in county \( c \).
or other counties \(-c\), respectively.

Finally, I approximate log average costs as follows:

\[
\log(AC_{jt}) = \tilde{\phi}z \log(Z_{jt}) + \tilde{w} \log(Y_{jt}) + \log(\eta_{jt}).
\]  

\[(B.3)\]

**Bias in the 2SLS estimator:** In the simplified framework, \((1-\rho)IV_{jt} = (1-\rho)\log(AC_{-c,t-4}^{p(j)})\), qualifies as the simulated instrument.\(^4\) Consequently, the 2SLS estimator for \(\gamma_1\) can be expressed as

\[
\hat{\gamma}^{2SLS}_1 = \frac{\text{cov}(\log(Y_{jt}), (1-\rho)IV_{jt})}{\text{var}((1-\rho)IV_{jt})} = \gamma_1 + \frac{\text{cov}(\epsilon_{jt}, (1-\rho)IV_{jt})}{\text{var}((1-\rho)IV_{jt})}. \tag{bias}
\]

Using the structure from equations (B.1)-(B.3), the bias term can be expressed as

\[
\frac{\text{cov}(\epsilon_{jt}, (1-\rho)IV_{jt})}{\text{var}((1-\rho)IV_{jt})} = \frac{\text{cov}(\epsilon_{jt}, (1-\rho)\tilde{w}\log(Y_{-c,t-4}^{p(j)}))}{\text{var}((1-\rho)IV_{jt})}
\]

\[
= \frac{\text{cov}(\epsilon_{jt}, (1-\rho)\tilde{w}\gamma_1\log(R_{mcaid}^{p(j)}))}{\text{var}((1-\rho)IV_{jt})}
\]

\[
= \frac{\text{cov}(\epsilon_{jt}, (1-\rho)\tilde{w}\gamma_1\rho\log(AC_{-c,t-8}^{p(j)}))}{\text{var}((1-\rho)IV_{jt})}
\]

\[
+ \tilde{w}\gamma_1 \frac{\text{cov}(\epsilon_{jt}, \log(AC_{-c,t-8}^{p(j)}))}{\text{var}(IV_{jt})}
\]

Here the first and the second equality used assumption (DC), which allows me to ignore the covariance between \(\epsilon_{jt}\) on the one hand and \(\eta_{-c,t-3,4...}, Z_{-c,t-3,4...}\) (first equality) and \(\epsilon_{-c,t-3,4...}\) (second equality) on the other. The third equality leverages the additive structure in simplified reimbursement formula.\(^5\) Assumption (TS) implies that (i) the time series in averaging over the other terms \(\log(\pi) + \rho\log(AC_{-c,t-4}^{p(j)})\) in equation (B.2), as proposed in the main text, only adds a constant to the instrument.

\(^{4}\)Averaging over the other terms \(\log(\pi) + \rho\log(AC_{-c,t-4}^{p(j)})\) in equation (B.2), as proposed in the main text, only adds a constant to the instrument.

\(^{5}\)Notice that \(\log(R_{mcaid}^{p(j)})\) generally also depends on the “own” reported costs of the focal nursing home, which I assumed away for the purpose of analytical tractability. However, since I am considering an average over all nursing homes in other counties, the “own” effect would correspond to an average over reported costs.
Taking this term on the left hand side and rearranging, we have

\[
\text{cov}(\epsilon_{jt}, \log(AC_{c,t-8})) = \tau \phi^k.
\]

These properties allow me to rewrite

\[
\frac{\text{cov}(\epsilon_{jt}, \log(AC_{c,t-8}))}{\text{var}(IV_{jt})} = \frac{\text{cov}(\epsilon_{jt}, \log(AC_{c,t-8}))}{\text{var}(\log(AC^{p(j)}_{c,t-4}))} = \phi^4 \frac{\text{cov}(\epsilon_{jt}, \log(AC^{p(j)}_{c,t-4}))}{\text{var}(\log(AC^{p(j)}_{c,t-4}))},
\]

where the first equality and the second equality use properties (i) and (ii), respectively. Hence, we can express the last row of the bias term equation as:

\[
(1 - \rho)\tilde{w}\gamma_1 \phi^4 \frac{\text{cov}(\epsilon_{jt}, (1 - \rho)IV_{jt})}{\text{var}((1 - \rho)IV_{jt})}.
\]

Taking this term on the left hand side and rearranging, we have

\[
\frac{\text{cov}(\epsilon_{jt}, (1 - \rho)IV_{jt})}{\text{var}((1 - \rho)IV_{jt})} = \frac{\tilde{w}\gamma_1 \rho}{1 - (1 - \rho)\tilde{w}\gamma_1 \phi^4} \frac{\text{cov}(\epsilon_{jt}, \log(AC^{p(j)}_{c,t-8}))}{\text{var}(IV_{jt})}.
\]

Next, I replace \( \text{var}(IV_{jt}) = \text{var}(\log(AC^{p(j)}_{c,t-4})) \) in terms of the variance of average log average costs in the focal county, \( \text{var}(\log(AC^{p(j)}_{c,t-8})) = \text{var}(\log(AC^{p(j)}_{c,t-4})) \). A county nursing home share \( \rho \) implies that there are \( \frac{1}{\rho} \) counties in a given peer group. We can express \( \text{var}(\log(AC^{p(j)}_{c,t-4})) \) as the variance over the other \( \frac{1}{\rho} - 1 \) county averages, \( \log(AC^{p(j)}_{d}) \) with \( d \in \{1, \frac{1}{\rho} - 1\} \). Specifically, we have

\[
\text{var}(\log(AC^{p(j)}_{c,t-4})) = \text{var}(\frac{1}{1 - \rho} \sum_{d=1}^{\frac{1}{\rho} - 1} \log(AC^{p(j)}_{d})) = \frac{\rho}{1 - \rho} \text{var}(\log(AC^{p(j)}_{c,t-4}))
\]

\[
+ \sum_{d \neq d'} \text{cov}(\frac{\rho}{1 - \rho} \log(AC^{p(j)}_{d}), \frac{\rho}{1 - \rho} \log(AC^{p(j)}_{d'}))
\]

\[
\geq \frac{\rho}{1 - \rho} \text{var}(\log(AC^{p(j)}_{c,t-4})) = \frac{\rho}{1 - \rho} \text{var}(\log(AC^{p(j)}_{c,t-4})),
\]

if \( \text{cov}(\frac{\rho}{1 - \rho} \log(AC^{p(j)}_{d}), \frac{\rho}{1 - \rho} \log(AC^{p(j)}_{d'})) \geq 0 \). The evidence presented in Appendix Section B.4, suggests relatively little spatial correlation in average costs across county boundary indicating in other counties, which is captured by \( \log(AC^{p(j)}_{c,t-8}) \).
that \( \text{var}(\log(AC_{c,t}^{p(j)})) \approx \frac{\rho}{1-\rho} \times \text{var}(\log(AC_{c,t}^{p(j)})) \) is a reasonable approximation. This allows me to rewrite the bias condition as

\[
\frac{\text{cov}(\epsilon_{jt}, (1-\rho)IV_{jt})}{\text{var}((1-\rho)IV_{jt})} = \frac{\tilde{w}\gamma_1}{1-(1-\rho)\tilde{w}\gamma_1\phi^4} \frac{\rho}{1-\rho} \frac{\text{cov}(\epsilon_{jt}, \log(AC_{ct-8}^{p(j)}))}{\text{var}(\log(AC_{ct-8}^{p(j)}))} \\
= \frac{\tilde{w}\gamma_1}{1-(1-\rho)\tilde{w}\gamma_1\phi^4} \frac{\text{cov}(\epsilon_{jt}, \log(AC_{ct-8}^{p(j)}))}{\text{var}(\log(AC_{ct-8}^{p(j)}))}.
\]

Using the structure of the model, I can express the remaining covariance term as:

\[
\frac{\text{cov}(\epsilon_{jt}, \log(AC_{ct-8}^{p(j)}))}{\text{var}(\log(AC_{ct-8}^{p(j)}))} = \frac{\text{cov}(\log(Y_{jt}), \log(AC_{ct-8}^{p(j)}))}{\text{var}(\log(AC_{ct-8}^{p(j)}))} - \gamma_1 \frac{\text{cov}(\log(P_{mc}^{mcoid}), \log(AC_{ct-8}^{p(j)}))}{\text{var}(\log(AC_{ct-8}^{p(j)}))},
\]

where both right hand side covariance terms can be estimated directly. Finally, I have:

\[
\text{bias} = \frac{\tilde{w}\gamma_1}{1-(1-\rho)\tilde{w}\gamma_1\phi^4} \left[ \frac{\text{cov}(\log(Y_{jt}), \log(AC_{ct-8}^{p(j)}))}{\text{var}(\log(AC_{ct-8}^{p(j)}))} \right. \\
- \left. \gamma_1 \frac{\text{cov}(\log(P_{mc}^{mcoid}), \log(AC_{ct-8}^{p(j)}))}{\text{var}(\log(AC_{ct-8}^{p(j)}))} \right]. \tag{B.4}
\]

The bias term depends on the true parameter \( \gamma_1 \). Building on the 2SLS estimator, I search for the largest upward (downward) bias that satisfies the implied sign constraint \( \text{sign}(\text{bias}) = \text{sign}(\gamma_1^{2SLS} - \gamma_1) \), the magnitude equality \( |\text{bias}| = |\gamma_1^{2SLS} - \gamma_1| \), and the imperfect pass-through condition stated in assumption (PT). I refer to these biases as \( \text{bias}^{up} \) and \( \text{bias}^{down} \), which imply the following bounds on the true parameter \( \gamma_1 \in [\gamma_1^{2SLS} - \text{bias}^{up}, \gamma_1^{2SLS} + \text{bias}^{down}] \).

**Quantifying the bias:** I focus the discussion on the effects for skilled nurses per resident, which is the primary endogenous outcome measure of interest. The detailed cost overview indicates that nurse salaries and fringe benefits comprise about 38% of overall costs. If so, a one 1% increase in licensed nurse staffing only leads to increase in costs of weakly less than 0.38%, or \( \tilde{w} \leq 0.38 \), see equation (B.3). I conservatively choose \( \tilde{w} = 0.38 \) and also \( \rho = 0 \). Assumption (PT) requires \( \tilde{w}\gamma_1 < 1 \), which then implies \( \gamma_1 < \frac{1}{0.38} \), providing an upper bound
for $\gamma_1$.

To estimate the AR(1) coefficient $\phi$, I construct log average costs at the county-year-peer group level and regress current averages on the four year lag. The four year lag marks the average lag over relevant cost reports from 3, 4 and 5 years ago. I control for nursing home and market characteristics as well as county-year fixed effects as stated in equation (1). I use four different cost measures presented in the four columns of Table B.1. The first column presents the preferred specification, which uses overall average costs, including resident care costs (RC), other related care costs (ORC), and administrative costs (ADM), which are all used in the simulated instrument approach, see Section A.4 for details. The remaining columns exploit variation from any of these cost categories in isolation. The point estimates suggest serial correlation over 4 years of at most 0.65.

To quantify the covariance terms, I regress $\log(Y_{jt})$ (log skilled nurses per resident) and $\log(R_{jt}^{mcaid})$ on the eight year lag in log average costs in the corresponding county-peer group, which again marks the corresponding average lag over relevant cost reports from 6, 7,...,10 years ago. The point estimates are displayed in the second and third row of Table B.1.

Finally, I turn to the bias estimates. The preferred estimates are displayed in the second row block of the Table. These estimates leverage assumption (PT), which provides an upper bound for $\gamma_1$. The estimates suggest that serial correlation may bias the 2SLS estimate upward by about 0.06 or 5% of the baseline estimate. I do not find a downward bias that satisfies the constraints, explaining why the upper bound on $\gamma_1$ equals the 2SLS estimate. This observation is robust to different values for $\hat{\gamma}_1^{2SLS}$. Reducing (increasing) the baseline estimate of 1.17 by one standard error (0.29), see Table 2, suggest an upward bias of at most 0.056 (0.025). Again, I do not find a downward bias that satisfies the constraints.

However, if we relax assumption (PT), then there may be a downward bias of up to 2.28, suggesting that the true parameter may exceed the 2SLS estimate by 195%. This implies a path-through of more than 125%, which is implausibly large. Importantly, both approaches suggest that serial correlation is unlikely to lead to a substantial upward bias in the 2SLS
estimate.

B.3 Spatial Correlation in Staffing and Marginal Costs

In this subsection, I test for spatial correlation in staffing ratios and marginal costs. I consider the covariance in the respective outcome measure between nursing homes that are spatially separated by the distance $d$ (in km). Let $L_i$ and $L_j$ refer to nursing home $i$’s and $j$’s location, respectively. Then, I consider the covariance between outcome measures $Y_i$ and $Y_j$, which are deviations from the annual mean, conditional on distance $d$:

$$\text{Cov}(d) = E[Y_iY_j|D(L_i, L_j) = d] .$$

The empirical analogue is given by the following kernel estimator:

$$\hat{\text{Cov}}(d) = \frac{1}{N_{d,h}} \sum_{i<j} 1\{D(L_i, L_j) - d < h\} Y_iY_j ,$$

where $h > 0$ is a bandwidth parameter that essentially smoothes the estimate of the conditional expectation. $1\{D(L_i, L_j) - d < h\}$ is an indicator function that turns on if the distance between nursing homes $i$ and $j$ differs from the pre-specified distance $d$ by at most $h$ km. For example if one is interested in the conditional covariance at a distance $d$ of 10km and suppose the bandwidth $h$ equals 10km, then the operator simply takes an average over all cross-products of nursing homes that are within 0km and 20km of reach. The indicator implies equal weighting of all observations within the bandwidth but can be replaced by alternative kernels.

Figure B.1 summarizes the spatial correlation in skilled nurses per resident (left graphs) and marginal costs (right graphs) in a correlogram for different bandwidths. The vertical axis denotes Moran’s I statistic, Moran (1950), which is the spatial covariance divided by the own variance. The horizontal line displays distance between nursing homes in kilometers. The top left figure indicates that there is only very little spatial correlation in skilled nurse
staffing ratios. The spatial correlation ranges only between -2% and 8% and decreases in distance. The bottom left figure revisits the evidence with a larger bandwidth. Again, the level estimates are generally very small. Finally, the vertical line marks the average distance of nursing homes that belong to the same peer group but are located in a different county. The average equals 233km.

Figure B.1: Spatial Correlation in Staffing and Marginal Costs

Notes: This figure displays spatial correlation in skilled nurse staffing ratios (left graphs) and marginal costs (right graphs). The bottom graphs use a larger bandwidth “smoothing” parameter in the underlying kernel estimator. The vertical axis denotes the spatial correlation in these outcome measures between nursing homes that are spatially separated by the distance (in km) denoted on the horizontal axis. The vertical lines indicate the average distance of nursing homes from different counties that belong to the same peer group.

In the case of marginal costs, the spatial correlation drops below 5% after 50km, see the top right figure. The bottom right graph provides qualitatively similar evidence. Again, there is only very little spatial correlation between peer-group affiliated counties given that
the nursing homes are on average more than 200km apart. This supports the instrumental variables approach of this paper, which only exploits cost variation from other counties.

B.4 Other Inputs

In this subsection, I consider the effects of changes in the Medicaid reimbursement rate on additional staffing measures including the number of pharmacists, physicians, psychologists and psychiatrists, medical social workers, and dietetic technicians per resident. Again, I do not find evidence or a statistically and economically significant increase following a 1% increase in the Medicaid reimbursement rate, see columns 1-5 from Table B.2.

While the previous tests fail to find empirical evidence for changes in other staffing measures, it could still be the case that nursing homes adjust inputs that are difficult to observe from the point of view of the econometrician. To investigate this possibility, I have also considered an alternative approach that directly investigates the effects of Medicaid rate changes on variable costs, which comprise expenditures on health care related services as well as room and board and account for 87% of total costs. I also consider the effects on total costs, which add capital and administrative expenditures. I consider variable costs as a summary measure which absorbs the effects of all input changes (including unobservable input changes) following a change in the Medicaid reimbursement rate. Hence, the goal of this exercise is to investigate which fraction of the overall effect on variable costs can be explained by the observed changes in skilled nurses per resident.

Using the cost report information, I first construct the variable costs per resident and day at the nursing home year level. Next, I apply the 2SLS regression model outlined in the preliminary analysis section to investigate the effect of a plausibly exogenous increase in the Medicaid reimbursement rate on variable costs per resident and day. The point estimate in the first column of Table B.3 suggests that a 10% increase in the Medicaid reimbursement rate increases the variable costs by about $8.4 (5%) per resident and day. To put this estimate into perspective, notice that a 10% increase in the Medicaid rate corresponds to a $18.3 increase
per resident and day. About 65% of residents are covered by Medicaid suggesting that nursing homes spend about $8.4/(65\% \times 18.3) = 70\%$ of the additional Medicaid revenues on inputs and keep 30\% as profits.

Next, I investigate whether the overall increase in variable costs can be explained by the observed increase in skilled nurses per resident. To this end, I consider a model in which log Medicaid reimbursement rates, $\log(R_{\text{medicaid}})$, only affect variable costs through skilled nurses. Specifically, I consider:

$$Z \rightarrow \log(R_{\text{medicaid}}) \rightarrow \log(SN_{\text{res}}) \rightarrow VC_{\text{res,day}}$$

(B.5)

where $Z$ is now the simulated Medicaid reimbursement rate, the source of exogenous variation. Since the model is not overidentified, skilled nurses will absorb the overall effect of Medicaid rate changes on variable costs. To see this, I estimate the following simplified variant of model B.5.

$$Z \rightarrow \log(SN_{\text{res}}) \rightarrow VC_{\text{res,day}}$$

(B.6)

via 2SLS. Here, the second stage is given by

$$VC_{j,t}^{res,day} = \beta \log(SN_{j,t}^{res}) + \alpha X_{j,t} + \phi_{ct} + \epsilon_{j,t}$$

where, just as in the preliminary analysis, $X_{j,t}$ controls for observable nursing home characteristics in addition to county-year fixed effects captured by $\phi_{ct}$. I use the simulated Medicaid reimbursement rate as an instrument for skilled nurses. I report the $\beta$ estimate in the second column of Table B.3. If we now multiply this point estimate with the effect of log Medicaid reimbursement rates on the log number of skilled nurses per resident, see column 2 of Table 2, then we find:

$$\left( \log(R_{\text{medicaid}}) \rightarrow \log(SN_{\text{res}}) \right) \left( \log(SN_{\text{res}}) \rightarrow VC_{\text{res,day}} \right) = 1.17 \times 72.75 = 85.12$$
which only differs from the estimate in column (1) from Table B.3 because of differences in the sample populations. Therefore, this test is not informative.

However, I can also investigate the implied factor price of a skilled nurse and contrast this estimate to the observed compensation package of a skilled nurse. If skilled nurses simply act as a proxy for other inputs, then we would expect a relatively large effect of an additional skilled nurse on variable costs. To simplify the interpretation, I construct the number of skilled nurses per resident and day, \( SN_{\text{res,day}} \), (just as variable costs) and consider the following model:

\[
VC_{\text{res,day}} = S \times SN_{\text{res,day}} + \alpha X_{jt} + \phi_{ct} + \epsilon_{jt}.
\]

Here, \( S \) can be interpreted as the implied annual compensation for a skilled nurses if the increase in variable costs can solely be attributed to the increase in the number of skilled nurse. The point estimate in column 3 of Table B.3 implies an annual compensation of $105,290 for a skilled nurse, which exceeds the observed compensation in the data of $83,170 by only 26.6%. This suggests that skilled nurses can explain almost three quarters of the overall effect on variable costs. The evidence is very similar if I consider total costs as opposed to variable costs per resident and day as indicated by the point estimate in column 4.

### B.5 Leave-One-Out Estimator

In this subsection, I replace the simulated instrument by a leave-one-out instrument, which is simply the average over reported average costs from providers located in different counties. More specifically, the instrument is constructed as follows:

\[
R_{\text{mcaind,iv}}^{\text{mcaid,iv}} = \frac{1}{\#(p(j) \cap -c)} \sum_{i \in \#(p(j) \cap -c)} AC_{i,t-3,4,5}
\]

where \( p(j) \cap -c \) denotes the set of nursing homes that belong to \( j \)'s peer group \( p(j) \) but are located in a different county \( -c \). \( \#(p(j) \cap -c) \) denotes the number of nursing homes in
this set. Finally, I estimate equation (1) via 2SLS using $\log(R_{jt}^{mcaid,iv})$ as an instrument for $\log(R_{jt}^{mcaid})$. The results are presented in Table B.4.

The first stage coefficient is smaller in magnitude compared to the baseline estimate but remains positive and statistically significant at the 1% level. The second stage estimate for skilled nurses suggests that a 10% increase in the Medicaid reimbursement rate increases the skilled nurse staffing ratio by 8.3%. This estimate falls short of the predicted 11.7% from the baseline analysis but it is still within the 95% confidence interval of the baseline estimate and is statistically significant at the 5% level. Again, I do not find evidence for systematic changes in the number nurse aides per resident, therapists per resident, or the private rate which is consistent with the baseline results.

### B.6 Alternative Exclusion Restrictions

In this subsection, I consider more conservative sources of identifying variation to address remaining concerns regarding spatial correlation. I first consider a more conservative market definition. Specifically, I extend the market definition from the county level to the MSA level. In this approach, I only explore cost variation of peer-group affiliated nursing homes that are located in different MSAs as opposed to different counties.

Second, I consider a more conservative approach that only explores variation in observable cost shifters. The baseline approach explores the full variation in average costs and thereby assumes that both observable cost shifters, $Z_{-ct-3,4,5}$, as well as unobserved cost shifters, $\eta_{-ct-3,4,5}$, from other counties only affect staffing and pricing decisions through the reimbursement formula. In this approach, I impose this assumption for only a subset of observable and distant cost shifters, $Z_{-ct-3,4,5}$, including the number of licensed beds, the ownership type distribution, the county population share of people aged 65 and older by gender and other demographic characteristics, the average distance to the closest competitors, and whether the nursing home has an Alzheimer’s unit. One key advantage of this approach is that I can control for spurious spatial correlation in these cost shifters explicitly by controlling for the local
cost shifters $Z_{jt}$ in equation (1). Therefore, this approach only exploits observable differences in facility and market characteristics between peer-group affiliated counties. To implement this approach, I first estimate equation (3) via OLS and then use the predicted reported costs, $\hat{AC}_{jt} = \hat{\phi}^z Z_{jt}$ as instrumental variables.

Finally, I re-estimate the preliminary regression model outlined in equation (1) using these alternative instrumental variables approaches. The results are summarized in Table B.5. The first column reproduces the baseline estimate from Table 2. Columns 1 and 2 consider the county as a locally segmented market, whereas columns 3 and 4 extend the market definition to the MSA. Furthermore, columns 2 and 4 explore variation in observable cost shifters only as opposed to the full variation in costs. These specifications yield similar elasticities for skilled nurses ranging from 1% to 1.4%, which remain within the 95% confidence interval of the baseline estimate. This supports the exclusion restrictions from the baseline analysis.

**Change in Reimbursement Formula in 1996:**

I have also collected and digitized data for the years 1993-1995 to take advantage of a change in the reimbursement formula in 1996. The change in the reimbursement formula allows me to test for a spurious correlation between the simulated instrument and Medicaid rates or staffing decisions in the pre-reform years 1993-1995. While it is difficult to find exact documentation on the reimbursement methodology prior to 1996, different sources indicate that the former approach was also cost-based but that the inputs to the reimbursement formula were more recent cost estimates. More importantly, the methodology reform in 1996 refined the peer group definition. Pennsylvania’s Department of Human Services formerly grouped nursing homes based on the geographic location, but in 1996, the department refined, to the best of my knowledge, the peer group definition to condition not only on the region but also on the number of licensed beds. This changed the peer group composition and consequently altered the Medicaid reimbursement rates of nursing homes.

In this exercise, I construct the simulated Medicaid reimbursement rate based on the 1996 onwards formula and interact this rate with year-fixed effects (I interact the 1996 rate
with the 1993-1995 year dummies to capture potential placebo effects). Finally, I add this series of interaction terms to the baseline regression model and investigate the effects on Medicaid reimbursement rates and staffing decisions for the years 1993-2002. The year-specific parameter estimates are summarized in Figure B.2. The vertical dashed lines delineate the pre-reform years 1993-1995 from the baseline sample years 1996-2002. The top left graph indicates the year-specific effects on the Medicaid reimbursement rate, which corresponds to the first stage in the post-reform years. The top right graph displays the effects on skilled nurses per resident, which can be interpreted as the reduced form in the post-reform years. This placebo or lead test corroborates the exclusion restriction. There is no evidence for a concurrent pre-trend and the parameters estimate gradually increase from 0 in the pre-reform years to the recovered magnitudes in the baseline analysis over the post-reform period. The bottom left graph shows the second stage estimates for skilled nurses, which support the evidence from the top graphs. Here, the estimates are a bit noisier. Finally, as a robustness check, I plot the reduced form coefficients for nurse aides in the bottom right graph. I do not find evidence for a systematic change around 1996, which is consistent with the baseline estimates. Overall, the presented evidence corroborates the evidence form the baseline analysis.

C Details on Structural Estimation

This section provides further details on the structural estimation.

C.1 Details on Distance Traveled

About 81% of the elderly choose a nursing home within their county of residence. Fewer than 2% travel farther than 50km. The top graphs in Figure C.1 show a frequency histogram (based on discrete distances) and the cdf of distances traveled.

The travel distance distribution is similar between short and long-stay residents defined by a length of stay that is within and exceeds 90 days, respectively. This is a common
Figure B.2: Robustness to Change in Reimbursement formula in 1996

Notes: This figure displays the parameters of an extended model that interacts the simulated year-specific log Medicaid reimbursement rate with year fixed effects. For the years 1993-1995, the parameters correspond to the log simulated Medicaid rate from 1996 interacted with year fixed effects. The top left graph shows the effects on the log Medicaid rate (first stage). The top right graph documents the effects on the log skilled nurse staffing ratio (reduced form). The bottom left graph presents the implied year-specific second stage effects. The bottom right graph shows the reduced form effects on the log number of nurse aides per resident.

definition in the literature, see Miller et al. (2004) for example. In the bottom left graph of Figure C.1, I simply compare the observed length of stay. In the bottom right graph, I first estimate a probit model to determine the probability of a long-stay based on health measures at admission. I classified a person as a short-stay and a long-stay person, whenever the predicted probability falls short of 40% or exceeded 60% respectively. The results are very similar if I compare 30% to 70%. Long-stayers travel longer distances, their median travel distance is about 20% higher. Yet, they both value proximity and are very unlikely to travel long distances exceeding 50km.
C.2 Details on the Two-Step Estimation Procedure

C.2.1 Identification and Estimation in First Step

To show that the observed conditional nursing home market shares, conditional on choosing any nursing home, and the unconditional outside good’s market share identify mean utilities, outside good parameters, and population weights, I break the analysis down into two interim steps.

First, I take advantage of the independence of irrelevant alternatives (IIA) property of the extreme value shocks, whereby I can recover some preference parameters based on conditional nursing home market shares, conditional on choosing any nursing home. These market shares are commonly referred to as “inside” market shares and given by:

\[ s_{ij|\text{in}} = \frac{\exp(\delta_{ij})}{\sum_{k \in CS_i} \exp(\delta_{ik})}, \]

where I have omitted time subscripts to simplify the notation. Here, \( \delta_{ij} \) denotes senior \( i \)'s indirect conditional utility for nursing home \( j \), see equation (4) net of the extreme value shock. The only difference between the inside share and the choice probability from Section 4 in the main text is that it excludes the outside good in the denominator. Importantly, these inside shares can be constructed based on the subset of seniors in nursing home care and do not depend on the population weights. Hence, I can estimate taste heterogeneity over nursing home characteristics, as outlined in the main text, as well as the mean utilities, \( \delta_{\tau j} \), specified in equation (5) via MLE. To ensure identification, I normalize one mean utility per payer type to zero.

Next, I introduce the demand for the outside good to the analysis. Let \( \sum_i \) denote the sum over seniors in nursing home care and let \( D_j \) be the total demand for nursing home \( j \) in days, which can expressed as follows:

\[ D_j = \sum_i s_{ij|\text{in}} LOS_i \]
\[ = \sum_i \phi_i s_{i,\text{in}} s_{ij|\text{in}} LOS_i. \]

The first row considers the set of seniors in nursing home care and sums their inside market shares weighted by their respective length of stay in days, \( LOS_i \). The second equation expands on this idea by considering the unconditional market share, \( s_{ij} = s_{i,\text{in}} s_{ij|\text{in}} \), which is a product of the inside share and the probability that senior \( i \) chooses any inside good, denoted by \( s_{i,\text{in}} \). Since not every senior decides to demand nursing home care, \( s_{i,\text{in}} \leq 1 \), it must be that there are multiple seniors of consumer type \( i \) that trade-off between different forms of care.\(^6\) This idea is captured by the population weight of consumer type \( i \), denoted by \( \phi_i \). As evidenced in the second row, scaling the unconditional market shares by the population weights and the length of stay must also correspond to the overall demand for a given nursing home in days.

Unfortunately, the Census data do not provide information on relevant population weights since several senior demographics, including the payer type, are only observed among nursing home residents through the MDS. To overcome this challenge I build on the observation that the population weights must equal the inverse inside market share in order to rationalize the consumer type specific nursing home demands in days, \( D_{ij} \):

\[ \phi_i = \frac{1}{s_{i,\text{in}}}. \]

For example, if 10 percent of private payers choose nursing home care, then the population of private payers must be 10 times larger than the number of private payers in nursing home care. Conversely, if \( \phi_i > \frac{1}{s_{i,\text{in}}} \) or \( \phi_i < \frac{1}{s_{i,\text{in}}} \), one would overpredict or underpredict the consumer type specific nursing home demand \( D_{ij} = \phi_i s_{i,\text{in}} s_{ij|\text{in}} LOS_i \). Importantly, the inside market shares can be expressed in terms of primitives of the demand model, providing an opportunity to use the structure of the demand model to help fill in the unobserved population weights. Of course, \( \phi_i \) is policy invariant and held fixed in the counterfactual experiments.

\(^6\)Here, consumer type is more broadly defined as the payer type, \( \tau \), defined in the main text.
Specifically, the structure of the demand model implies that

$$\phi_i = \frac{1}{s_{i,in}} = \frac{1}{\sum_{j \in CS_i} \exp(\delta_{ij}) / \exp(\varphi_c(i)) + \sum_{j \in CS_i} \exp(\delta_{ij})} = \frac{\exp(\varphi_c(i)) + \sum_{j \in CS_i} \exp(\delta_{ij})}{\sum_{j \in CS_i} \exp(\delta_{ij})}.$$ (C.1)

Closing the empirical model, I leverage information on the unconditional number of seniors living in the community $Sen_{c, out}$, which I observe in the Census data, to pin down $\varphi_c$. Specifically, I have:

$$Sen_{c, out} = \sum_i \phi_i s_{i, out} \frac{LOS_i}{365} = \sum_i \frac{\exp(\varphi_c) \cdot LOS_i}{\sum_{j \in CS_i} \exp(\delta_{ij}) / 365},$$

where the length of stay in days divided by 365 provides an annualized estimate of nursing home residents. Rearranging terms, it follows that:

$$\exp(\varphi_c) = \frac{Sen_{c, out}}{\sum_i \frac{LOS_i}{365} \cdot \sum_{j \in CS_i} \exp(\delta_{ij})}.$$ (C.2)

Hence, as indicated in equation (C.2), knowledge about the number seniors living in the community, as well as the conditional nursing home market shares, which pin down the nursing home mean utilities, are sufficient to identify $\varphi_c$.

C.2.2 Relationship to Micro BLP

The two-step approach deviates slightly from the estimation method proposed by Berry, Levinsohn and Pakes (2004), henceforth “MicroBLP”, and offers two advantages. First, the MLE approach uses the large number of nursing home choices, about 90,000 per year efficiently. Second, and more importantly, the approach improves the computational performance in two dimensions. First, I am able to provide the analytic gradient and hessian, which reduces the number of necessary objective function evaluations considerably. Second, I do not have to solve a contraction mapping problem for each guess of preference parameters, which equates the predicted and observed markets shares by payer types. While the predicted and
observed market shares (by payer type) still coincide in the solution, the differences define some of the first order conditions in the MLE problem and are set to zero in the optimum, they do not have to coincide at each step in the optimization routine. A disadvantage of this approach is that it cannot nest random coefficients on endogenous product characteristics since they are not separately identified from the mean utilities in this first step. Yet, I show in Section 5 that the modeled preference heterogeneity based on distance, health profiles, and payer types is rich enough to explain variation in marginal costs between nursing homes.

The proposed approach is expected to yield very similar point estimates as the MicroBLP method. In both cases, predicted market shares equal observed market shares in the optimum suggesting very similar mean utilities. The parameters governing heterogeneity in senior preferences may differ between the approaches to the extent that the first order conditions from the MLE approach differ from the micro moment conditions imposed under the MicroBLP approach and to the extent that the weighting of moments differs between the approaches.

C.2.3 Weighting Matrix and Variance Covariance Matrix

The second step of the analysis builds on the following five sets of moment conditions \( G^{\text{Demand}}(\theta), G^{\text{Cost, type}}(\theta), G^{\text{Cost, type}}(\theta), G^{\text{Cost, type}}(\theta), \) and \( G^{\text{Cost}}(\theta) \) outlined in Section 4. I refer to the stacked \( k \)-dimensional row vector over the set of moment conditions as:

\[
G(\theta) = \frac{1}{N} \sum_i \left[ g_i^{\text{Demand}}(\theta), g_i^{\text{Cost, type}}(\theta), g_i^{\text{Cost, type}}(\theta), g_i^{\text{Cost}}(\theta), g_i^{\text{Cost}}(\theta), g_i^{\text{Cost}}(\theta) \right]
\]

\[
= \frac{1}{N} \sum_i g_i(\theta).
\]

---

7 The identification of random coefficients on endogenous product characteristics requires exclusion restrictions, which are introduced in the second step (but not in the first step) to identify the mean preference parameters.

8 Here, \( k \) is the number of instrumental variables plus three \( G^{\text{Cost, type}}(\theta) \) moments (one for for-profit, not-for-profit, and public nursing homes, respectively) plus three \( G^{\text{Cost, type}}(\theta) \) moments plus one \( G^{\text{Cost}}(\theta) \) and one \( G^{\text{Cost}}(\theta) \) moment. So \( k = \text{dim}(IV) + 8. \)
Here, the unit of observation $i$ is a nursing-home-year-payer type. This defines $N = 3 \times 3 \times J$ observations, for 3 payer types in 3 years and $J$ nursing homes. The first set of moments (Demand) covers the universe of observations. In contrast, the latter four sets of moment conditions are aggregated at the nursing home-year level. To match the observations across moments by nursing home and year, I triple each observation in the latter set of moment conditions. For example, consider the three payer types in nursing home $\tilde{j}$ and year $\tilde{t}$. Then the demand moments provide three observations (one for each):

\[
G(\theta) = \frac{1}{N} \sum_{i} \begin{bmatrix}
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot \\
\xi_{\tilde{t}\tilde{j}}^{\text{priv}} IV_{\tilde{t}\tilde{j}}^{\text{priv}} & mc_{\tilde{t}\tilde{j}} - MC_{\tilde{t}\tilde{j}} & \cdot \\
\xi_{\tilde{t}\tilde{j}}^{\text{hyb}} IV_{\tilde{t}\tilde{j}}^{\text{hyb}} & mc_{\tilde{t}\tilde{j}} - MC_{\tilde{t}\tilde{j}} & \cdot \\
\xi_{\tilde{t}\tilde{j}}^{\text{pub}} IV_{\tilde{t}\tilde{j}}^{\text{pub}} & mc_{\tilde{t}\tilde{j}} - MC_{\tilde{t}\tilde{j}} & \cdot \\
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot 
\end{bmatrix}
\]

as indicated in the middle three rows of the first columns. Then, for example, I triple the respective marginal cost moment, $g_{1,\text{type},i}^{\text{Cost}}(\theta)$, for the focal nursing home and match the moments as indicated in the second column. Mathematically, this is captured by the first sum operator $\sum_{\tau}$ in the cost moment conditions.

If the nursing home-year from the first set of moments does not appear in the latter moment at all then I assign a zero. For example, a for-profit nursing home will not appear in the cost moments for not-for-profits. Finally, the GMM estimator is given by:

\[
\hat{\theta}_{GMM}^{GMM} = \arg\min_{\theta} G(\theta)WG(\theta)',
\]

where $W$ denotes a weighting matrix. As mentioned in the main text, I adopt a 2-step approach starting with the identity matrix to generate an unbiased estimate: $\hat{\theta}$. I then use

---

\[^{9}\text{For example, } g_{i}^{\text{Demand}}(\theta) = \xi_{i} \ast IV_{i}.\]
this estimate to construct:

\[ V_0(\tilde{\theta}) = \frac{1}{N} \sum_i g_i(\tilde{\theta})' g_i(\tilde{\theta}) , \]

and use the efficient weighting matrix \( W = V_0^{-1}(\tilde{\theta}) \).

Finally, the variance covariance matrix for \( \hat{\theta}^{GMM} \), \( V_{cov} \), is given by:

\[ V_{cov} = B_0^{-1}\Omega_0 B_0^{-1} \]

where

\[
\begin{align*}
B_0 &= \Gamma_0' W \Gamma_0 \\
\Gamma_0 &= \frac{1}{N} \sum_i \frac{dg_i(\tilde{\theta})}{d\theta'} \\
\Omega_0 &= \Gamma_0' W \Omega_0 W \Gamma_0 .
\end{align*}
\]

### C.3 Goodness of Fit Based on Demand Moments

In this subsection, I discuss the cost model’s cost estimates and the goodness of fit analysis in greater detail. The left graph of Figure C.2 contrasts the predicted marginal costs of the model on the horizontal axis with the observed marginal costs per resident day from the Medicaid cost reports on the vertical axis in the year 2002. On average, they coincide closely at about $160 per day. While the difference between the marginal costs marks a moment condition in the empirical analysis, it is important to note that the predicted marginal costs exceed actual costs on average by only $12 (7%) if I exclude the cost moments from the analysis, as shown below. Furthermore, the model is able to predict the heterogeneity in observed marginal costs, which has not been imposed in the estimation strategy. The slope of the linear regression line equals 0.6 indicating that a $1 increase in the predicted marginal costs is associated with $0.6 increase in observed marginal costs. The R-squared is 44%.

The right graph of Figure C.2 presents analogous evidence for predicted and observed average annual compensations for skilled nurses in 2002 at the county level. On average,
they coincide at about $83,000 even when I exclude the cost moments from the empirical analysis (this would imply a 5% difference). There is also a positive, albeit less pronounced, relationship between the two measures, which indicates that the model is able to explain some of the heterogeneity in compensation between counties. Here the slope is 0.27 and the R-squared decreases to 12%. Presumably, the relationship is less stark for annual compensation because of considerable measurement error at the facility and even at the county level. Overall, the cost data support the imposed demand and supply modeling assumptions, which are particularly important for the counterfactual analysis.

**More conservative empirical strategy.** I revisit the goodness of fit using a more conservative estimation strategy. In this approach, I drop the cost moments in the second step of the empirical strategy and only use the demand moments to estimate the model parameters. Since the demand moments do not identify the nursing home objective parameters $\alpha_j$, I set these parameters to 1, which implies profit-maximization. The left graph of Figure C.3 compares the predicted marginal costs by the model on the horizontal axis with the observed average marginal costs per resident day from the Medicaid cost reports. Overall the model fits the average variable cost data very well. The model overstates the observed average variable costs of per resident day of $161 by only 7%. The difference equals about 15% for for-profits.\(^\text{10}\) The right figure compares the predicted average compensation for skilled nurses at the county level on the horizontal axis with the observed average compensation from the Medicaid cost reports. The model overstates the observed annual compensation by only 6% on average.

Overall, the predicted marginal costs and compensations coincide closely with external data from Medicaid cost reports, which supports the modeling assumptions of the structural analysis.

\(^\text{10}\)Intuitively, this difference explains some of the differences in the demand estimates presented in Table 3. The presented parameters in column 5 overstate the marginal costs of for-profits. To match the marginal costs for for-profits, the baseline model assigns a smaller preference parameter for private rates as evidenced by the fourth row in column 3.
C.4 Marginal Benefit and Social Planner’s Problem

In this subsection, I provide additional details for the marginal benefit calculation and the planner’s problem presented in Section 5.

C.4.1 Marginal Benefits

Equation (4) specifies the average indirect conditional utility (over the course of the stay) per resident and day. Hence, the average marginal benefit per resident and day of an additional skilled nurse per resident, for residents in nursing home \( j \), is given by

\[
MB_{res,day}^{SN_{res}} = - \frac{MU_{SN_{res}}^j}{MU_P} = \frac{\beta_{sn} + \beta_{cmi}^S \tilde{CMI}_j}{\beta_{priv}} = - \frac{\beta_{sn}^S}{\beta_{priv}}, \tag{C.3}
\]

where \( \tilde{CMI}_j \) is the average case mix index for residents in nursing home \( j \) and \( MU_{SN_{res}}^j \) and \(-MU_P\) refer to the average marginal utility of skilled nurses per resident (which differs among residents based on their case mix index) and the marginal utility of income, respectively. Again, I extrapolate the marginal utility of income of private payers, \( \beta_{priv}^P \), to all payer types.

Skilled nurses per resident are defined as the number of full-time equivalent skilled nurses per average number of present residents at a given point in time. Total resident days per year can be written as the average number of present residents multiplied by the number of calendar days, 365. Therefore, equation (C.3) also indicates the marginal benefit per calendar day of an additional full-time equivalent skilled nurse, \( MB_{day}^{SN} \). This can be derived by multiplying marginal benefits per resident day and skilled nurses per resident by the average number of present residents.\(^{11}\)

Finally, the annual marginal benefit of an additional full-time equivalent skilled nurse is

\[^{11}\text{The marginal benefit per resident day of an additional skilled nurse per resident } MB_{res,day}^{SN_{res}} \text{ can be described as follows: } MB_{res,day}^{SN_{res}} = \frac{\Delta MB_{res,day}^{SN_{res}}}{\Delta SN_{res} \ast Res} \text{. Multiplying the nominator and the denominator by the average number of residents at any point in time, } Res, \text{ yields:} \]

\[
MB_{res,day}^{SN_{res}} = \frac{\Delta MB_{res,day}^{SN_{res}} \ast Res}{\Delta SN_{res} \ast Res} = \frac{\Delta MB_{day}^{SN}}{\Delta SN} = MB_{day}^{SN} \text{.}
\]
simply the product of equation (C.3) and the number of calendar days:

\[ MB_j(SN) = MB_j^{\text{day}}(SN) \times 365 = MB_j^{\text{res,day}}(SN^{\text{res}}) \times 365. \]

### C.4.2 Social Planner’s Problem

A necessary condition for optimal skilled nurse staffing ratios is that marginal benefits equal marginal costs of an additional skilled nurse in every nursing home:

\[ -\frac{\bar{\beta}_{sn}^{\text{res}}}{\beta_{\text{priv}}} \times 365 = W_j \times 365 \quad \forall j. \tag{C.4} \]

Here, the left hand side denotes the annual marginal benefit and the right hand side denotes the annual marginal cost of employing an additional skilled nurse. \( W_j \) is defined in the cost equation from Section 4 and corresponds to the compensation package per calendar day. To see this, notice that total salaries for skilled nurses, as defined by the cost function, equal

\[ TS_j = W_j S_{\text{res}}^{\text{res}} \sum_i s_{ijt} LOS_i = W_j S_{\text{res}}^{\text{res}} Resdays_j, \]

where \( Resdays_j \) denotes the total number of resident days in nursing home \( j \). Dividing and multiplying the equation by the number of calendar days yields:

\[ TS_j = W_j \times 365 \times S_{\text{res}}^{\text{res}} Resdays_j / 365 = W_j \times 365 \times S_{\text{res}}^{\text{res}} Res_j = W_j \times 365 \times SN_j, \]

where \( Res_j \) is the average number of residents at a given point in time, and \( SN_j \) is the overall number of skilled nurses. Hence, I multiply \( W_j \) with the number of calendar days in equation (C.4) to quantify annual marginal costs.

To simplify the planner’s problem analysis, I assume that compensations for skilled nurses are constant within a county \( c \), \( W_j = W_c \). Multiplying equation (C.4) by the number of skilled
nurses per resident and taking averages at the county level delivers:

\[- \frac{\hat{\beta}_{sn}^{i}}{\beta_{priv}} \times 365 = W_{c} \times 365 \times SN_{res} \forall c.\]

Finally, dividing the expression by the average number of skilled nurses per resident at the county level delivers

\[- \frac{\hat{\beta}_{sn}^{i}}{\beta_{priv}} \times \frac{SN_{res}}{SN_{res}} \times 365 = W_{c} \times 365 ,\]

which I evaluate in section 5. On average, observed staffing ratios fall 48% short of the social optimum, see Table C.1.

### C.5 Further details on Medicaid and Entry Counterfactual

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 C.4 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 C.4 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. Overall, incumbents hardly respond to entry.
Robustness of Structural Analysis

This section provides further details on the robustness exercises for the structural analysis.

Directed Entry in Urban Counties

In this subsection, I discuss the effects of directed entry in four urban counties: Allegheny, Westmoreland, Philadelphia, and Montgomery County. The first two counties are located in the Pittsburgh MSA, the second two counties are located in the Philadelphia MSA, see Figure 3. In the top panel of Table D.1 I first summarize the findings at the MSA level and show the overall effects at the state level in the last column. Again, entrants are not able to recover their fixed costs through variable profits as indicated by the first two rows. Industry profits decrease again even further mostly because of rival’s increases in the number of skilled nurses and because variable profits of new entrants come from business stealing. Overall industry profits decrease by $5.4 million per year as indicated by the third row in the third column. On the other hand, consumer surplus increases by $6.7 million per year. The increase stems largely from gains in variety ($6.6 million) which may be interpreted as an upper bound as discussed in Section 6. Considering the annual increase in public spending of $3.3 million, I find an annual welfare loss of $2 million. This estimate is also an upper bound because it does not consider the fixed costs of entry, I only consider the annual fixed costs of operating the new nursing homes.

Most importantly, I turn to the effect on staffing and pricing. At the state level, I find a positive effect on skilled nurse staffing of 0.1%, which is very similar to the estimated increase based on entry in rural counties (0.1%). Private rates increase slightly by 0.1% again very similar to the findings in rural counties. To put the staffing estimates into perspective, I construct the return on public spending between raising Medicaid reimbursement rates and subsidizing entry in urban counties. The estimates are summarized in the lower panel of Table D.1. I find a return on public spending of only 0.33% when I consider the new entrants’ annual losses of $3.7 million as required additional public spending. In comparison, the return
of directed entry falls short of the return on Medicaid spending by a factor of 8. The return of directed entry in urban counties is almost identical to the return of directed entry in rural counties of 0.35%. Finally, considering the entire industry losses as required public spending reduces the return to 0.23% which falls short of the comparable return on Medicaid spending by a factor of $4.81/0.23=20.9$.

D.2 Details on Rationing

In this subsection, I provide more details on the rationing robustness analysis summarized in Section 7.

D.2.1 Empirical Evidence on Rationing

To assess the empirical relevance of rationing in this context, I start by quantifying the potential fraction of seniors in the sample population, who may not be able to access their preferred nursing home because of rationing. Unfortunately, I do not observe arrivals of potential residents directly. Instead I only observe successful admissions. Hence, I need to impose additional assumptions to infer the prevalence of rationing in this context from observed admissions.

Without loss of generality, I assume that the number of successful weekly admissions of patient type $\tau$ at nursing home $j$ and week $t$, $S_{t\tau j}$, is multiplicative in the number of weekly arrivals (or potential residents), $A^*_{t\tau j}$, and the share of arrivals that were not rejected (rationed), $1 - R^*_{t\tau j}$:

$$S_{t\tau j} = A^*_{t\tau j}(1 - R^*_{t\tau j}).$$

Here, the star superscripts emphasize that arrivals and the rationing probability are latent variables, which are not observed by the econometrician. To infer rationing behavior from observed admissions, $S_{t\tau j}$, I make the following two assumptions:

(A1) Within nursing home and year (week-to-week) variation in the occupancy rate, $Occ_{tj}$, affects the rationing behavior, $R^*_{t\tau j}$, but is independent of weekly arrivals, $A^*_{t\tau j}$.
(A2) There is no rationing at occupancies of less than 90%: $R_{trj}^*(Occ_{tj}) = 0$ if $Occ_{tj} \leq 0.9$.

These assumptions imply that:

\[
S_{trj}(Occ_{tj}) = \begin{cases} 
A_{trj}^* & \text{if } Occ_{tj} \leq 0.9 \\
A_{trj}^*[1 - R_{trj}^*(Occ_{tj})] & \text{else}
\end{cases}
\]

which allows me to separately identify arrivals and rationing behavior.

Assumption (A1) states that the occupancy rate may affect the admission decisions of nursing homes. An extreme case is an occupancy of 100%. In this case, the fully occupied nursing home might have to reject every potential resident of any payer type. More generally, nursing homes that operate close to their capacity limit may selectively restrict access for less profitable payer types, whereby the remaining beds can be occupied by more profitable residents. With respect to resident preferences, I assume that the week-to-week variation in occupancy is not observed by potential residents and therefore does not affect the arrival rate. In the empirical analysis, I control for nursing home-year fixed effects such that a correlation between consumer demand and the average occupancy rates (more “popular” nursing homes have higher occupancies on average) does not confound the results. Assumption (A2) provides a level normalization. Supported by the evidence presented below, I consider a threshold of 90%.

I estimate equation (D.1) by payer type at the nursing home-week level using the following linear regression model:

\[
S_{trj} = \sum_{k=75}^{100} \gamma^k_{\tau} Occ^k_{jt} + \phi_{year,\tau,j} + \epsilon_{trj} .
\]

Here, $Occ^k_{jt}$ capture occupancy fixed effects ranging from 75%-100%, which turn on if the average weekly occupancy rate in nursing home $j$ equals the respective percentage. $\phi_{year,\tau,j}$ contain nursing home-year fixed effects, whereby I isolate week-to-week variation in occupancy in a given nursing home and year.

Figure D.1 presents the estimated fixed effects $\gamma^k_{\tau}$. The top left graph summarizes the
overall number of weekly admissions and the subsequent figures break admissions down by payer type. The decreasing weekly admissions provide evidence for some rationing at occupancies exceeding 95%. The decline is slightly more pronounced among hybrid and public payers, who are partially (hybrid) or fully (public) covered by public insurance. I find no evidence for a systematic reduction in weekly admissions between 75 and 90%. Combined with the observed decline at higher occupancies, this suggests that rationing is not prevalent at occupancies below 90% as stated in assumption (A2).

To assess the empirical significance of rationing in this context, I now quantify the overall number seniors that are rationed out at occupancies exceeding \( x \), relative to the total number of observed admissions \( E[\sum_{tj} S_{trj}] \) by payer type. I interpret this ratio as the fraction of seniors in the sample population, who are affected by rationing. Notice, that the expectation operators are conditional on nursing home-year fixed effects, which are ignored here to simplify the exposition.

Combining equations (D.1) and (D.2), I can express this ratio as follows:

\[
\frac{E[\sum_{tj,occ_{tj} \geq x} A^*_{trj} R^*_{trj}]}{E[\sum_{tj} S_{trj}]} = \frac{E[\sum_{tj,occ_{tj} \geq x} A^*_{trj}] - E[\sum_{tj,occ_{tj} \geq x} S_{trj}]}{E[\sum_{tj} S_{trj}]} = \frac{\sum_{tj,occ_{tj} \geq x} E[A^*_{trj}]}{E[\sum_{tj} S_{trj}]} - \frac{\sum_{tj,occ_{tj} \geq x} E[S_{trj}]}{E[\sum_{tj} S_{trj}]} E[\sum_{tj} S_{trj}] = \frac{\sum_{tj,occ_{tj} \geq x} E[S_{trj} | Occ = 0.9] - \sum_{tj,occ_{tj} \geq x} E[S_{trj} | Occ \geq x]}{E[\sum_{tj} S_{trj}]} E[\sum_{tj} S_{trj}] = \frac{E[\sum_{tj,occ_{tj} \geq x} S_{trj} | Occ \geq x]}{E[\sum_{tj} S_{trj}]} \left( \frac{E[S_{trj} | Occ = 0.9]}{E[S_{trj} | Occ \geq x]} - 1 \right) = \frac{E[\sum_{tj,occ_{tj} \geq x} S_{trj}]}{E[\sum_{tj} S_{trj}]} \left( \frac{\gamma^90 - \gamma^x}{\beta} \right).
\]

Hence, the fraction of rationed seniors can be expressed as the product of two factors. The first factor, \( A \), denotes the fraction of all observed admissions that occur at occupancies exceeding \( x \). Intuitively, this measures the empirical frequency of high occupancies. The
second factor, B, denotes the relevance of rationing conditional on operating at high occupancies. Here, $\gamma^90_\tau$ and $\gamma^x_\bar{x}$ denote the average number of weekly admission at 90% occupancy or occupancy rates exceeding $x$, respectively. To estimate the latter, I replace the series of fixed effects for occupancy rates exceeding $x$ in equation (D.2) by a single indicator variable that turns on when the occupancy rate exceeds $x$.

Estimates of the second factor, B, are displayed in Table D.2, which is structured into two panels. In each panel, the first row summarizes the number of weekly admissions at occupancies exceeding $x$, the denominator of factor B. The nominator of B is displayed in the second row and the third row displays the ratio, which corresponds to B directly. The last row displays the p-value of a simple hypothesis test on whether the nominator is statistically different from zero. The findings form the first column suggest that in the absence of rationing, admissions would be on average 12% or 21% higher at occupancy rates exceeding 95% and 97%, respectively.

Estimates of factor A are displayed in Table D.3 and equal 2% ($x > 100\%$), 15% ($x > 97\%$), and 29% ($x > 95\%$) for all payer types as indicated in the first column.

Finally, I multiply the estimates from Table D.2 and D.3 as indicated by equation (D.3). Using the 97% occupancy benchmark, I find that only about 15%*21%=3.2% of all seniors in the sample population are rationed out. Repeating the steps for different payer types, as indicated in columns 2-4 of Tables D.3 and D.2, I find that 1.7% of private payers, 5.1% of hybrid payers, and 3.9% of public payers are rationed out. These estimates may understate the amount of rationing to the extent that rationing starts at lower occupancy rates. Therefore, I repeat the analysis at a threshold of 95%. But this only increases the overall fraction of seniors that are affected by rationing to 29%*12%=3.5%. By payer type, the rationing estimates increase to 1.2% for private payers, 5.6% for hybrid payers and 3.8% for public payers, respectively.

Overall, this suggests that rationing affects only a very small fraction of seniors. Nevertheless, I consider robustness of my demand and supply estimates to potential rationing in
the following subsections.

**D.2.2 Rationing in Medicaid Counterfactual**

In this subsection, I revisit welfare gains from an increase in Medicaid reimbursement rates taking the potential effect of rationing into account. While the demand for nursing home care increases by only 6.7% in the baseline counterfactual analysis, it is possible that at least some nursing homes now reach their physical capacity limit forcing them to restrict access to at least some seniors. To provide a conservative assessment of the potential implications for consumer welfare, I consider a random rationing model, which does not prioritize seniors based on their preferences for nursing home care. I use this model to predict the new demand for nursing home care under the improved nurse staffing ratio and lower private rates, discussed above. Specifically, and related to Ching, Hayashi and Wang (2015), I place seniors in a random sequence and assume that seniors subsequently choose from the remaining nursing home options. This allows me to partition seniors into $R$ groups, $\{D_1, D_2, ..., D_R\}$. Following Ching, Hayashi and Wang (2015), these partitions are divided such that after each group of seniors chooses between nursing home options and the outside good, precisely one additional nursing home will just reach its capacity limit. For example, the first group of seniors, $D_1$, can choose from all nursing homes (that are located within 50km of the senior’s former residence, see Section 4). The second group has access to all but one nursing home when ignoring the location constraints.

As expected, I find a smaller gain in consumer surplus of only $181$ million per year. I also find slightly smaller increases in profits and public spending suggesting that some seniors who rationed out of their preferred nursing home now choose the outside good instead. In fact, I find that the market expands by only 5.5% in this calculation because of rationing. Combining the effects on consumer surplus, provider profits, and public spending, I find a smaller welfare gain of $14.5$ million per year or about 5% of additional spending.

12An important difference to Ching, Hayashi and Wang (2015) is that the rationing affects all payer types in my context as opposed to Medicaid beneficiaries only.
Finally, I also revisit the effect of rationing on the supply side behavior. To this end, I exclude nursing homes with an average occupancy of more than 97% (95%) and re-estimate the preliminary regression models that investigate the link between Medicaid reimbursement rates, staffing and pricing decisions. Table D.4 presents the regression results for nursing homes with less than 97% and 95% occupancy in the top and the bottom panel, respectively. The key estimates from the first two columns are differ from the baseline estimates by less than 6%. This provides further evidence that the main findings of this paper are robust to potential capacity constraints.

Extrapolating the estimated marginal utility of income for private payers onto the entire nursing home population may understate the marginal utility of income for poorer Medicaid beneficiaries, in the presence of wealth effects, and therefore overstate the marginal benefit of an additional skilled nurse. If so, the baseline estimates may be interpreted as an upper bound of the marginal benefit. To assess the empirical relevance of this concern, I now provide details on four alternative approaches that aim to corroborate the normative implications of my analysis.

Third, I combine a calibrated life-cycle model with bequest data from the Health and Retirement Study (HRS) to assess differences in the marginal utility of consumption between private and public payers.

I consider a simplified version of the life cycle model in Lockwood (2014) in which agents
choose their consumption profile optimally to maximize the following utility function:\textsuperscript{13}

\[ U = u(c_t) + \sum_{a=t+1}^{T+1} \beta^{a-t} \left( \Pi_{s=t}^{a-1} (1 - \delta_s) \right) [1 - \delta_a] u(c_a) + \delta_a v(b_a) \]

subject to the asset constraint listed below. Here, \( t \) is the individual’s current age. \( T \) is the maximum possible age, \( \beta \) discounts the future, and \( \delta_s \) is the probability that an \( s-1 \) year old will die before reaching the age of \( s \). The utility from consumption satisfies constant relative risk aversion \( u(c) = \frac{c^{1-\sigma} - 1}{1-\sigma} \) and the utility from bequests is \( v(b) = \left( \frac{\phi}{1-\phi} \right)^{\sigma} \left( \frac{v(b_1)}{1-\sigma} \right) \) with \( \phi \in (0, 1) \). Notice that \( \phi \) determines the risk aversion over bequests. \( \phi = 1 \) implies risk neutrality in bequests with \( v(b) = c_b^{-\sigma} \). In this case, preferences are quasilinear. \( \phi = 0 \), on the other hand, implies that people are equally risk-averse over consumption and bequests. \( c_b \geq 0 \) is a threshold consumption level below which, under conditions of perfect certainty or with full, fair insurance, people do not leave bequests: \( v'(0) = c_b^{-\sigma} \). Hence, with \( c_b > 0 \) bequests become luxury goods.

Finally, assets \( \omega_t \) are determined as follows:

\[ \omega_{t+1} = (1 + r_t) \left[ \omega_t + y - m_t - c_t + c_{pub} \right] \]

where \( y \) denotes income, \( m_t \) are medical out-of-pocket expenditures, and \( c_{pub} \) denotes the consumption value of free room and board for Medicaid beneficiaries. Finally, upon death, a person bequests her entire wealth, so \( b_t = \omega_t \).

**First Order Condition:**

I consider the case where an individual consumes weakly more than the consumption floor, \( c_b \), which is supported by the data discussed below. In this case, we have the following first

\textsuperscript{13}I only consider uncertainty in life expectancy, whereas Lockwood also considers uncertainty over medical expenditures. This would complicate the implementation as I would have to integrate over medical expenditures as well.
order condition with respect to consumption at age $t$:

$$\frac{d}{dc_t} U = u'(c_t) - \sum_{a=t+1}^{T+1} \beta^a(\delta^a) \delta_a v'(b_a) \left( \Pi_s^{a-1} (1 - \delta_s) \right) = 0.$$  \hspace{1cm} (D.4)

To simplify the analysis, I assume that $\beta (1 + r) = 1$. This allows me to rewrite the first order condition as follows:

$$u'(c_t) = \sum_{a=t+1}^{T+1} Pr[Death at age a] \ast v'(b_a).$$

This equation indicates that I can express the marginal utility of consumption by combining the estimated parameters from Lockwood (2016) with bequest data from the HRS.

**Parameter Calibration and Data:**

Table D.5 summarizes the key parameter estimates from Lockwood (2014), who uses data from the HRS for the years 1998-2008. The estimates indicate a consumption threshold for bequests of $16,100 per year. The threshold is not binding for Medicaid beneficiaries in nursing homes since the consumption value of room and board alone, $c_{pub}$, exceeds the threshold. To provide a conservative estimate for differences in marginal utilities, I assume that the floor is not binding for private payers either. Therefore, equation (D.4) provides an accurate description of the individual’s first order condition over current consumption.

Next, I turn to the data. The HRS is a representative longitudinal survey of the U.S. population aged 50 and older. In this exercise, I focus on individuals who are living in a nursing home at the time of the interview. I distinguish between Medicaid beneficiaries (at the time of the interview) and other residents, who I treat as private payers. Following Lockwood (2014), I focus on the years 1998-2008. Table D.6 summarizes annual income, assets, and bequest information for the two payer type groups. On average, the annual household income of private payers equals about $26,000 which is about twice as large as the income of Medicaid beneficiaries. Private payers also hold considerably more assets than Medicaid beneficiaries as indicated by the larger mean. The HRS also collects information...
on predicted bequests. Specifically, the elderly is asked to indicate the probability of leaving a bequest of more than $0, $10,000, and $100,000, respectively. The rows 3-5 summarize this information, which indicate that more private payers expect to leave small and large bequests. Unfortunately, the survey data provide only three data points of the underlying bequest distribution function. I follow Hurd and Smith (2002) and extrapolate the survey information based on the observed asset distribution. Intuitively, I construct the bequest over asset ratio by payer type at fixed percentiles of the bequest distribution. Then, I estimate predicted bequests in between these percentiles by multiplying the ratio with the observed asset amount. I start with the largest bequest amounts. The fifth row of the second panel in Table D.6 suggests that the 75th percentile of the bequest distribution for private payers equals $100,000. I construct the bequest ratio at that percentile by diving $100,000 by the 75th percentile of the asset distribution for private payers (which equals $270,000). I then multiply the higher percentiles in the asset distribution with this ratio to construct the right tail in the predicted bequest distribution for private payers. I repeat the analysis for bequests between $10,000 and $100,000. Specifically, I construct the analogous ratio at $10,000 and use a weighted average of this and the former ratio to fill in the bequest percentiles. Finally, I assume that bequests between $0 and $10,000 equal $5,000. I repeat the analysis for Medicaid beneficiaries and summarize the distributions in the sixth row of Table D.6.

Results:

Next, I construct the marginal utility for each payer type by applying the estimated bequest distribution and parameter values from Lockwood (2014) to equation (D.4). Specifically, I calculate the marginal utility of consumption by integrating the calibrated marginal utility of bequests over the empirical distribution of bequests:

$$MU^\tau = \frac{1}{\#i \in \tau} \sum_{i \in \tau} \nu'(b^\tau_i) = \frac{1}{\#i \in \tau} \sum_{i \in \tau} \left( \frac{\hat{\phi}}{1 - \hat{\phi}} \right)^{\underline{\sigma}} \left( \frac{\hat{\phi}}{1 - \phi} \right)^{\hat{\sigma}} \left( \frac{\hat{\phi}}{1 - \phi} \hat{\phi} + b^\tau_i \right)^{-\hat{\sigma}}.$$ 

Here, $\#i \in \tau$ indicates the sample of individuals of payer type $\tau$ and $b^\tau_i$ is person $i$’s predicted bequest. Most importantly, I construct the ratio of marginal utilities between private and
public payers.

My estimates suggest that the marginal utility of consumption for Medicaid payers exceeds the marginal utility of private payers by 27.5%. Considered through the lenses of my baseline model, this suggests that the marginal utility of income for Medicaid beneficiaries, which is denoted by the magnitude of the price coefficient, is actually 27.5% smaller. In regards to the extrapolation exercise, this implies that the baseline estimate for the benefit of a skilled nurse overstates the benefit in a nursing home that only hosts Medicaid beneficiaries by 27.5%. In absolute terms, this exercise suggests that residents jointly value an additional skilled nurse by at least $(1 - 27.5\%) \times \$126,300 = \$91,600$ which still exceeds the cost of employing a skilled nurse by 10%. In the data, about 50% are public payers, 35% are hybrid payers, and the remaining 15% are private payers. To provide a conservative estimate for the benefit of an additional skilled nurse, I assume the that the marginal utility of consumption for Medicaid beneficiaries applies to public and hybrid payers. This implies a lower bound on the benefit of an additional skilled nurse of $0.15 \times \$126,300 + 0.85 \times \$91,600 = \$96,800$.

D.3.2 Asset Spend Down

Fourth, I provide additional details on the asset spend down test, discussed in Section 7. As mentioned in the main text, I can identify the number of days paid out-of-pocket before the senior becomes eligible for Medicaid using Medicare and Medicaid claims data. I multiply the number of days paid out-of-pocket with the daily private rate to quantify the amount of tangible assets that are not protected under Medicaid; those assets must be spent down before the senior becomes eligible. Unfortunately, tangible assets are censored in the data since several seniors are never eligible for Medicaid during their nursing home stays.

To address this concern, I assume that tangible assets follow an exponential distribution, whose mean depends on observable resident characteristics including age, gender, race and zip code. I estimate the conditional means across payer types, taking censoring into account. The top graph of Figure D.2 displays a histogram of the estimated tangible wealth distribution.
In a second step, I interact the recovered mean tangible wealth estimates with the private rate in the private payer’s indirect conditional utility function. I de-mean the tangible wealth (by subtracting the private payer mean of $140,000) to simplify the comparison of the parameter estimates with the baseline estimates. I also add a second interaction term, \( \text{Rich}_{it} \), that turns on for richer private payers with predicted residual tangible wealth levels of more than $140,000. The extended indirect conditional utility function equals:

\[
\begin{align*}
 u_{irjt} &= \beta_{d1} D_{ij} + \beta_{d2} D_{ij}^2 + \beta_{en} \log(SN_{jt}^{Res}) + \sum \beta_{x} X_{jt} + \beta_{P} P_{jt} + \xi_{jt} \\
&+ \beta_{wealth}^{P} \mathbb{1}\{\tau = \text{private}\} Wealth_{it} P_{jt} \\
&+ \beta_{rich}^{P} Wealth_{it} \mathbb{1}\{\tau = \text{private}\} \text{Rich}_{it} P_{jt} + \epsilon_{ijt},
\end{align*}
\]

where \( Wealth_{it} \) indicates the de-meaned predicted tangible wealth level and \( \mathbb{1}\{\tau = \text{private}\} \) is an indicator variable that turns on for private payers. I present the parameter estimates in column 3 of Table D.7. The average price effect displayed in the third row is almost identical to the baseline estimate presented in the fifth column of Table 3 but masks heterogeneity in price sensitivities among private payers with different wealth levels. The negative first point estimates in the lower panel indicates that wealthier private payers respond more elastically to private rates than private payers with lower wealth levels. This is indicated by the positive slope in the lower graph of Figure D.2 between $0 and $140,000. This provides evidence against wealth effects. Among richer private payers whose tangible wealth level exceeds $140,000, there is no meaningful relationship between the price coefficient and the residual tangible wealth as indicated by the flattened relationship. The difference is very small, but positive, \(-0.015 + 0.016 = 0.001\) which provides evidence for minor wealth effects among richer private payers.

The estimates from Table D.7 imply that Medicaid beneficiaries, with a residual tangible

---

14I interact the private rate with the mean wealth estimate instead of a random draw from the respective wealth distribution in order to reduce the computational effort. While this simplification introduces a conceptual inconsistency in this nonlinear model, it removes the computational burden of integrating out the random wealth levels.

15The estimation strategy only exploits the demand moments in the second step.
wealth of $0, have a marginal utility of income of 0.016 which is smaller than the marginal utility of income of private payers with average residual wealth (0.018) and smaller than the baseline estimate of \(-\hat{\beta}_{\text{priv}} = 0.018\), displayed in the third row of the fifth column in Table 3. To provide a conservative marginal benefit estimate of a skilled nurse, I assume that public payers (50%) have a marginal utility of income of 0.016 and assign the baseline value of 0.018 to hybrid and private payers. This implies an average marginal utility of income of 50\%*0.016+50\%*0.018=0.017. The baseline estimate exceeds this estimate by 5.9\%. Following equation (C.3), I increase the baseline marginal benefit estimate of $126,320 by 5.9\% delivering a new estimate of $133,750.
Table A.1: External Validity: PA vs. US in 2014

<table>
<thead>
<tr>
<th></th>
<th>PA</th>
<th>US</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>State Regulations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Daily Medicaid Rate(^a)</td>
<td>189</td>
<td>164</td>
<td>28</td>
</tr>
<tr>
<td>Casemix Adjustment of Medicaid Rates(^b)</td>
<td>1</td>
<td>0.73</td>
<td>0.2</td>
</tr>
<tr>
<td>Prospective Medicaid Reimbursement(^b)</td>
<td>1</td>
<td>0.76</td>
<td>0.18</td>
</tr>
<tr>
<td>Certificate of Need Law(^b)</td>
<td>0</td>
<td>0.65</td>
<td>0.23</td>
</tr>
<tr>
<td><strong>Nursing Home/Market Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beds</td>
<td>126</td>
<td>109</td>
<td>23.4</td>
</tr>
<tr>
<td>Share For-Profit</td>
<td>54.4</td>
<td>68.8</td>
<td>14.6</td>
</tr>
<tr>
<td>Share Public</td>
<td>4.45</td>
<td>6.22</td>
<td>6.49</td>
</tr>
<tr>
<td>Herfindahl Index/10,000(^c)</td>
<td>0.11</td>
<td>0.24</td>
<td>0.14</td>
</tr>
<tr>
<td><strong>Resident Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share Medicaid</td>
<td>62.3</td>
<td>61.9</td>
<td>5.51</td>
</tr>
<tr>
<td>Share Medicare</td>
<td>10.6</td>
<td>14</td>
<td>3.09</td>
</tr>
<tr>
<td>Average Age(^c)</td>
<td>82.17</td>
<td>80.1</td>
<td>1.87</td>
</tr>
<tr>
<td>Percent White(^c)</td>
<td>91.2</td>
<td>83.7</td>
<td>10.4</td>
</tr>
<tr>
<td>Percent Female(^c)</td>
<td>72.4</td>
<td>69.9</td>
<td>2.34</td>
</tr>
<tr>
<td>Average Casemix Index(^c)</td>
<td>1.11</td>
<td>1.06</td>
<td>0.04</td>
</tr>
<tr>
<td>Level of Need with ADL</td>
<td>5.86</td>
<td>5.8</td>
<td>0.27</td>
</tr>
<tr>
<td><strong>Nurse Staffing</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Nurse Hours per RD</td>
<td>4.04</td>
<td>4.03</td>
<td>0.23</td>
</tr>
<tr>
<td>RN Hours per RD</td>
<td>0.92</td>
<td>0.79</td>
<td>0.15</td>
</tr>
<tr>
<td>LPN Hours per RD</td>
<td>0.85</td>
<td>0.8</td>
<td>0.15</td>
</tr>
<tr>
<td><strong>Deficiencies</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deficiencies per NH</td>
<td>7.24</td>
<td>7.98</td>
<td>2.6</td>
</tr>
<tr>
<td>Percent Homes No Deficiency</td>
<td>8.75</td>
<td>7.35</td>
<td>5.72</td>
</tr>
<tr>
<td>Percent Homes with Deficiencies Related to Quality of Care</td>
<td>7.13</td>
<td>10.6</td>
<td>4.35</td>
</tr>
<tr>
<td><strong>Clinical Outcomes/Resident Health</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Residents Pressure Sores</td>
<td>6.03</td>
<td>6.09</td>
<td>1.19</td>
</tr>
<tr>
<td>Percent Residents with Physical Restraints</td>
<td>1.28</td>
<td>1.74</td>
<td>0.74</td>
</tr>
<tr>
<td>Percent Residents Receiving Psychoactive Medication</td>
<td>64.2</td>
<td>64.3</td>
<td>4.73</td>
</tr>
</tbody>
</table>

\(^a\) Data from 2009, \(^b\) Data from 2002, \(^c\) Data from 2010
Table A.2: Payer Type Transitions (weighted by length of stay)

<table>
<thead>
<tr>
<th>Admission</th>
<th>Medicaid</th>
<th>Private</th>
<th>Medicare</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medicaid</td>
<td>13.9%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>13.9%</td>
</tr>
<tr>
<td>Private</td>
<td>19.6%</td>
<td>14.5%</td>
<td>0.0%</td>
<td>34.1%</td>
</tr>
<tr>
<td>Medicare</td>
<td>32.6%</td>
<td>14.3%</td>
<td>5.1%</td>
<td>52.0%</td>
</tr>
<tr>
<td>Sum</td>
<td>66.1%</td>
<td>28.8%</td>
<td>5.1%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Notes: This table compares the resident’s payer source at admission and discharge. The data come from Minimum data set combined with Medicaid and Medicare claims data for residents, who were admitted between 2000-2002 and discharged by the end of 2005.

Table B.1: Robustness to Bias from Serial Correlation

<table>
<thead>
<tr>
<th></th>
<th>(All)</th>
<th>(RC)</th>
<th>(ORC)</th>
<th>(ADM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi^4$</td>
<td>0.65</td>
<td>0.63</td>
<td>0.6</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.13)</td>
<td>(0.09)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>$\frac{\text{cov}(\log(SN_{jt}, \log(AC_{c,t-8}^{(p(j)}))}{\text{var}(\log(AC_{c,t-8}^{(p(j)}))})$</td>
<td>0.3</td>
<td>0.29</td>
<td>0.21</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.19)</td>
<td>(0.13)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>$\frac{\text{cov}(\log(R_{jt}, \log(AC_{c,t-8}^{(p(j)}))}{\text{var}(\log(AC_{c,t-8}^{(p(j)}))}$</td>
<td>0.19</td>
<td>0.17</td>
<td>0.1</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>$\gamma^{2SLS}$</td>
<td>1.17</td>
<td>1.17</td>
<td>1.17</td>
<td>1.17</td>
</tr>
<tr>
<td>Max Bias (PT&lt;100%)</td>
<td>[0,0.052]</td>
<td>[0,0.058]</td>
<td>[0,0.056]</td>
<td>[-0.01,0]</td>
</tr>
<tr>
<td>Max Bias / $\gamma^{2SLS}$ (PT&lt;100%)</td>
<td>[0%,4.4%]</td>
<td>[0%,5.0%]</td>
<td>[0%,4.8%]</td>
<td>[-0.1%,0%]</td>
</tr>
<tr>
<td>Bounds on $\gamma_1$ (PT&lt;100%)</td>
<td>[1.12,1.17]</td>
<td>[1.11,1.17]</td>
<td>[1.11,1.17]</td>
<td>[1.17,1.18]</td>
</tr>
<tr>
<td>Max Bias 125%</td>
<td>[-2.12,0.052]</td>
<td>[-2.28,0.052]</td>
<td>[0,0.052]</td>
<td>[-0.01,0]</td>
</tr>
<tr>
<td>PT</td>
<td>125%</td>
<td>131%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bounds on $\gamma_1$</td>
<td>[1.12,3.28]</td>
<td>[1.11,3.46]</td>
<td>[1.11,1.17]</td>
<td>[1.17,1.18]</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

Notes: The first column displays the serial correlation and the covariance term estimates based on overall average costs, which include resident care, other related care, and administrative costs. The second-fourth column display the analogue estimates based on resident care costs (RC), other related care (ORC), or administrative costs (ADM) in isolation. $SN_{res}$ denotes the number of skilled nurses per resident.
### Table B.2: Evidence on other Staffing Inputs

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Pharma&lt;sub&gt;res&lt;/sub&gt;)</td>
<td>-0.44</td>
<td>-0.45</td>
<td>0.05</td>
<td>5.00</td>
<td>0.06</td>
</tr>
<tr>
<td>Log Medicaid Rate</td>
<td>(0.57)</td>
<td>(0.79)</td>
<td>(0.25)</td>
<td>(24.86)</td>
<td>(7.45)</td>
</tr>
<tr>
<td>Observations</td>
<td>4022</td>
<td>4022</td>
<td>4022</td>
<td>4022</td>
<td>4015</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

Notes: log(Pharma<sub>res</sub>), log(Phys<sub>res</sub>), log(Psy<sub>res</sub>), log(Soc<sub>res</sub>), and log(Tech<sub>res</sub>) abbreviate the log number of pharmacists, physicians, psychologists and psychiatrists, medical social workers, and dietetic technicians per resident, respectively. All specifications control for county-year fixed effects, ownership type, having an Alzheimer’s unit, average distance to closest competitors, and a fourth order polynomial in beds interacted with year fixed effects. Standard errors are clustered at the county level.

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

### Table B.3: Medicaid Rates and Variable Costs

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VC&lt;sub&gt;res,day&lt;/sub&gt;</td>
<td>84.16***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(SN&lt;sub&gt;res&lt;/sub&gt;)</td>
<td></td>
<td>72.75**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SN&lt;sub&gt;res,day&lt;/sub&gt;</td>
<td></td>
<td></td>
<td>105.29**</td>
<td>106.91**</td>
</tr>
<tr>
<td>Observations</td>
<td>3878</td>
<td>3878</td>
<td>3878</td>
<td>3852</td>
</tr>
</tbody>
</table>

Notes: VC<sub>res,day</sub> and TC<sub>res,day</sub> denote variable and total costs per resident and day. All specifications control for county-year fixed effects, ownership type, having an Alzheimer’s unit, average distance to closest competitors, and a fourth order polynomial in beds interacted with year fixed effects. Standard errors are clustered at the county level.
Table B.4: Medicaid, Staffing, and Pricing using Leave-One-Out Estimator

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>First log</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>log(SN_{res})</strong></td>
<td>0.61***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>log(NA_{res})</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>log(Th_{res})</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>log(P)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Simulated Rate</td>
<td>0.61***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.16)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Medicaid Rate</td>
<td>0.83**</td>
<td>-0.05</td>
<td>-0.86</td>
<td>-0.09</td>
<td></td>
</tr>
<tr>
<td>(0.36)</td>
<td>(0.61)</td>
<td>(2.01)</td>
<td>(0.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4022</td>
<td>4022</td>
<td>3872</td>
<td>3307</td>
<td>4022</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
Notes: log(SN_{res}), log(NA_{res}), and log(Th_{res}) abbreviate log 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, and a fourth order polynomial in beds interacted with year fixed effects. Standard errors are clustered at the county level.

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

Table B.5: Preliminary Evidence Using Alternative Exclusion Restrictions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>log(SN_{res})</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Medicaid Rate</td>
<td>1.17***</td>
<td>1.41**</td>
<td>1.01***</td>
<td>1.22*</td>
</tr>
<tr>
<td>(0.29)</td>
<td>(0.43)</td>
<td>(0.30)</td>
<td>(0.56)</td>
<td></td>
</tr>
<tr>
<td>NH Market</td>
<td>County</td>
<td>County</td>
<td>MSA</td>
<td>MSA</td>
</tr>
<tr>
<td>IV Variation</td>
<td>Full</td>
<td>Shocks</td>
<td>Full</td>
<td>Shocks</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
Notes: log(SN_{res}) denotes the log number of skilled nurses per resident. All specifications control for county-year fixed effects, ownership type, having an Alzheimer’s unit, average distance to closest competitors, and a fourth order polynomial in beds interacted with year fixed effects. Standard errors are clustered at the county level.

* p < 0.05, ** p < 0.01, *** p < 0.001

Table C.1: Current vs. Optimal Staffing in 2002: All Counties

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. SN Staffing Ratio</td>
<td>0.25</td>
<td>0.23</td>
<td>0.25</td>
<td>0.26</td>
</tr>
<tr>
<td>Optimal Avg. SN Staffing Ratio</td>
<td>0.36</td>
<td>0.31</td>
<td>0.34</td>
<td>0.40</td>
</tr>
<tr>
<td>Ratio: Optimal/ Actual SN Staffing Ratio</td>
<td>1.43</td>
<td>1.30</td>
<td>1.39</td>
<td>1.55</td>
</tr>
<tr>
<td>Observations</td>
<td>67</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table compares observed (first row) and optimal skilled nurse staffing ratios (second row) at the county level.
Figure C.1: Distance Traveled

Notes: The top panel summarizes the distance between a senior’s former residence and the chosen nursing home. The vertical red lines mark the the 50km threshold used in the demand analysis. Here, I only consider nursing homes in a senior’s choice set that are within 50km of their former residence. The bottom panel explores heterogeneity between short stay (≤90 days) and long stay (>90 days) residents.
Figure C.2: Goodness of Fit: MC and Annual Compensation in 2002

Notes: The figure compares predicted and observed marginal costs and annual nurse compensations to assess the goodness focuses of fit. Marginal costs and annual compensations are measured at the nursing home and the county level, respectively. The figure focuses on Medicaid certified nursing homes with observed marginal costs between $100 and $250 per day and whose predicted and observed marginal costs fall between $50 and $250. This applies to about 97% of all Medicaid nursing homes with cost report information in 2002.

Figure C.3: Goodness of Fit: MC and Annual Compensation in 2002

Notes: The figure compares predicted and observed marginal costs and annual nurse compensations to assess the goodness focuses of fit. The estimation of the empirical model, which provides predicted marginal costs and annual nurse compensations, only exploits the demand moments $G^{Demand}(\theta)$ in the second step of the estimation strategy. Marginal costs and annual compensations are measured at the nursing home and the county level, respectively. The figure focuses on Medicaid certified nursing homes with observed marginal costs between $100 and $250 per day and whose predicted and observed marginal costs fall between $50 and $250. This applies to about 97% of all Medicaid nursing homes with cost report information in 2002.
Notes: The top panel of this figure describes the baseline and the counterfactual distribution of the skilled nurse staffing ratio (left graph) and the private rate (right graph) following a universal increase in Medicaid reimbursement rates. The red dashed distributions summarize the counterfactual outcomes following a universal 10% increase in Medicaid reimbursement rates. The blue dotted distributions summarize outcomes following a 30% increase in Medicaid reimbursement rates. The bottom panel summarizes the counterfactual changes in the staffing ratio and the private rates following directed entry in four rural counties.
Table D.1: Directed Entry in Urban Counties and Counterfactual Comparison

<table>
<thead>
<tr>
<th>Pittsburgh MSA</th>
<th>Philadelphia MSA</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var. Profit Entrant</td>
<td>0.6</td>
<td>0.1</td>
</tr>
<tr>
<td>Fixed Costs</td>
<td>2.2</td>
<td>2.2</td>
</tr>
<tr>
<td>Δ Profit</td>
<td>-2.7</td>
<td>-2.6</td>
</tr>
<tr>
<td>Δ CS</td>
<td>3.9</td>
<td>2.7</td>
</tr>
<tr>
<td>Δ Spending</td>
<td>1.6</td>
<td>1.7</td>
</tr>
<tr>
<td>Δ Welfare</td>
<td>-0.4</td>
<td>-1.6</td>
</tr>
<tr>
<td>Avg ΔSNres</td>
<td>0.05%</td>
<td>0.03%</td>
</tr>
<tr>
<td>Avg ΔP</td>
<td>0.02%</td>
<td>0.02%</td>
</tr>
</tbody>
</table>

Notes: The top panel compares the effects of directed entry between urban counties. I consider entry in 4 urban counties: Allegheny, Westmoreland, Philadelphia, and Montgomery County. The first two and the latter two counties are located in the Pittsburgh MSA and the Philadelphia MSA, respectively. Aggregate effects at the state level are illustrated 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 urban counties and a 10% increase in Medicaid rates. Absolute values are measured in million dollars. SNres indicates skilled nurses per resident.

Table D.2: Weekly Admissions by Occupancy and Payer Type

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>Private</td>
<td>Hybrid</td>
<td>Public</td>
</tr>
<tr>
<td>98% – 100%</td>
<td>3.2</td>
<td>.9</td>
<td>1.1</td>
</tr>
<tr>
<td>90% – (98% – 100%)</td>
<td>.68</td>
<td>.1</td>
<td>.3</td>
</tr>
<tr>
<td>90% – (98% – 100%)</td>
<td>.21</td>
<td>.11</td>
<td>.28</td>
</tr>
<tr>
<td>p-value 90% – (98% – 100%)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>96% – 100%</td>
<td>3.3</td>
<td>.9</td>
<td>1.1</td>
</tr>
<tr>
<td>90% – (96% – 100%)</td>
<td>.4</td>
<td>.04</td>
<td>.19</td>
</tr>
<tr>
<td>90% – (96% – 100%)</td>
<td>.12</td>
<td>.04</td>
<td>.17</td>
</tr>
<tr>
<td>p-value 90% – (96% – 100%)</td>
<td>0</td>
<td>.16</td>
<td>0</td>
</tr>
</tbody>
</table>

This table summarizes the number of weekly admissions of different payer types at different occupancy rates. The two panels summarize differences in weekly admissions between occupancy levels. Each panel shows the mean number of weekly admissions, absolute difference, the relative difference, and the p-value for a difference test between the regression coefficients. 

* p < 0.10 ** p < 0.05 *** p < 0.01
Figure D.1: Number of Weekly Admissions by Occupancy and Payer Type

Notes: This figure presents the (mean-adjusted) estimated effects of occupancy fixed effects on overall weekly admissions, \( \gamma_k \), as outlined in equation D.2. The top left graph presents the estimated coefficients for any admission. The remaining graphs present analogous coefficients for admissions of private, hybrid, and public payers, respectively.

Table D.3: Share of Seniors Admitted at High Occupancy Rates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>Private</td>
<td>Hybrid</td>
<td>Public</td>
</tr>
<tr>
<td>More than 100%</td>
<td>.02</td>
<td>.02</td>
<td>.02</td>
<td>.03</td>
</tr>
<tr>
<td>More than 97%</td>
<td>.15</td>
<td>.15</td>
<td>.17</td>
<td>.14</td>
</tr>
<tr>
<td>More than 95%</td>
<td>.29</td>
<td>.29</td>
<td>.33</td>
<td>.27</td>
</tr>
</tbody>
</table>

Notes: This table displays the fraction of admitted seniors whose nursing home’s occupancy rate exceeds the indicated occupancy threshold at the day of their admission. The first column presents these fractions for all admitted seniors. Columns 2-4, present analogous fractions for private, hybrid, and public payers respectively.
Table D.4: Preliminary Evidence for Nursing Homes with lower Occupancy Rates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First</td>
<td>log(SN(^{res}))</td>
<td>log(NA(^{res}))</td>
<td>log(Th(^{res}))</td>
<td>log(P)</td>
</tr>
<tr>
<td>Log Simulated Rate</td>
<td>1.22*** (0.21)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Medicaid Rate</td>
<td>1.17***</td>
<td>0.06</td>
<td>-0.45</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.30)</td>
<td>(0.51)</td>
<td>(2.34)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Observations</td>
<td>3227</td>
<td>3227</td>
<td>3120</td>
<td>2617</td>
<td>3227</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First</td>
<td>log(SN(^{res}))</td>
<td>log(NA(^{res}))</td>
<td>log(Th(^{res}))</td>
<td>log(P)</td>
</tr>
<tr>
<td>Log Simulated Rate</td>
<td>1.14*** (0.26)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Medicaid Rate</td>
<td>1.13***</td>
<td>-0.29</td>
<td>-1.22</td>
<td>-0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.39)</td>
<td>(0.65)</td>
<td>(3.02)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Observations</td>
<td>2461</td>
<td>2461</td>
<td>2377</td>
<td>1990</td>
<td>2461</td>
</tr>
</tbody>
</table>

Note: I exclude nursing homes with an average annual occupancy rate of more than 97% and 95% in the top and the bottom panel, respectively. \(\log(SN\(^{res}\)), \log(NA\(^{res}\)),\) and \(\log(Th\(^{res}\))\) abbreviate log 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, and a fourth order polynomial in beds interacted with year fixed effects. Standard errors are clustered at the county level.

* \(p < 0.10\), ** \(p < 0.05\), *** \(p < 0.01\)

Table D.5: Key Parameter Estimates from Lockwood (2016)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Point Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\phi): bequest motive</td>
<td>0.95</td>
<td>0.01</td>
</tr>
<tr>
<td>(c_b): bequest motive ($1,000)</td>
<td>16.1</td>
<td>1.4</td>
</tr>
<tr>
<td>(c_{pub}): public care value NH ($1,000)</td>
<td>18.3</td>
<td>4.7</td>
</tr>
<tr>
<td>(\sigma): risk aversion</td>
<td>3</td>
<td>0.05</td>
</tr>
</tbody>
</table>
Table D.6: Nursing Home Residents, HRS 1998-2008

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>10th</th>
<th>50th</th>
<th>90th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medicaid</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household Income</td>
<td>1149</td>
<td>12835</td>
<td>4932</td>
<td>9948</td>
<td>23160</td>
</tr>
<tr>
<td>Assets in $1,000</td>
<td>1149</td>
<td>26</td>
<td>0</td>
<td>0</td>
<td>70</td>
</tr>
<tr>
<td>Pr. Bequests &gt; 0 in %</td>
<td>171</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>75</td>
</tr>
<tr>
<td>Pr. Bequests &gt; 10k in %</td>
<td>192</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>Pr. Bequests &gt; 100k in %</td>
<td>191</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Estimated Pr. Bequests in $1,000</td>
<td>1149</td>
<td>13</td>
<td>0</td>
<td>0</td>
<td>34</td>
</tr>
<tr>
<td>Private</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household Income</td>
<td>1384</td>
<td>26534</td>
<td>6720</td>
<td>17650</td>
<td>50500</td>
</tr>
<tr>
<td>Assets in $1,000</td>
<td>1384</td>
<td>219</td>
<td>0</td>
<td>62</td>
<td>604</td>
</tr>
<tr>
<td>Pr. Bequests &gt; 0 in %</td>
<td>274</td>
<td>51</td>
<td>0</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Pr. Bequests &gt; 10k in %</td>
<td>381</td>
<td>46</td>
<td>0</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Pr. Bequests &gt; 100k in %</td>
<td>367</td>
<td>25</td>
<td>0</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Estimated Pr. Bequests in $1,000</td>
<td>1384</td>
<td>72</td>
<td>0</td>
<td>0</td>
<td>224</td>
</tr>
<tr>
<td>Observations</td>
<td>2533</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure D.2: Wealth Effects

Notes: The top graph displays a histogram of the estimated tangible wealth for private payers. The distribution is censored at the 95th percentile. The bottom graph summarizes the estimated marginal utilities of price among private payers (multiplied by -1), which can be interpreted as the marginal utility of income, by tangible wealth.
## Table D.7: Preference Parameters Considering Wealth Effects

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Wealth Effects</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta^a_{sn}$:</td>
<td>log(SN/Resident)</td>
<td>1.534***</td>
</tr>
<tr>
<td>$\beta^p_{hyb}$:</td>
<td>Price*Hybrid</td>
<td>-0.012***</td>
</tr>
<tr>
<td>$\beta^p_{priv}$:</td>
<td>Price*Private</td>
<td>-0.018***</td>
</tr>
<tr>
<td>$\beta^a_{cmi}$:</td>
<td>log(SN/Resident)*CMI</td>
<td>0.226***</td>
</tr>
<tr>
<td>$\beta^d_1$:</td>
<td>Distance in 100km</td>
<td>-25.79***</td>
</tr>
<tr>
<td>$\beta^d_2$:</td>
<td>Distance$^2$</td>
<td>22.45***</td>
</tr>
<tr>
<td>$\beta^p_{rehab}$:</td>
<td>Therapist/Res*Rehabmin</td>
<td>-0.125***</td>
</tr>
<tr>
<td>$\beta^p_{rehabXshort}$:</td>
<td>Therapist/Res<em>Rehabmin</em>Short-Stay</td>
<td>0.311***</td>
</tr>
<tr>
<td>$\beta^p_{alz}$:</td>
<td>Alzheimer*Alzheimer Unit</td>
<td>0.414***</td>
</tr>
<tr>
<td>$\beta^p_{wealth}$:</td>
<td>Wealth Effects in $1m$</td>
<td>-0.015***</td>
</tr>
<tr>
<td>$\beta^p_{rich}$:</td>
<td>Wealth Effects for richer priv. payers in $10m$</td>
<td>0.016***</td>
</tr>
</tbody>
</table>

| Avg Benefit per SN/year in '02 | $133,750*** | $66,606 |
| Avg Wage+Fringe Benefits per SN in '02 | $83,171 |
| Benefit-Cost | $50,579 | $66,606 |

Notes: The table displays the estimated preference parameters allowing for differential price coefficients among private payers with different wealth levels. $\beta^p_{wealth}$ denotes the interaction between the private rate and tangible wealth. $\beta^p_{rich}$ captures the interaction between the private rate, tangible wealth, and an indicator that turns on if the tangible wealth exceeds $140k. The parameter estimates are identified off from demand moments. Average benefits as well as average wage and fringe benefits per SN are measured in 2002. Th/res, SN/res, and Min abbreviate therapists per resident, skilled nurses per resident, and rehabilitative care minutes respectively. Standard errors are displayed in parentheses.

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