

## **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**

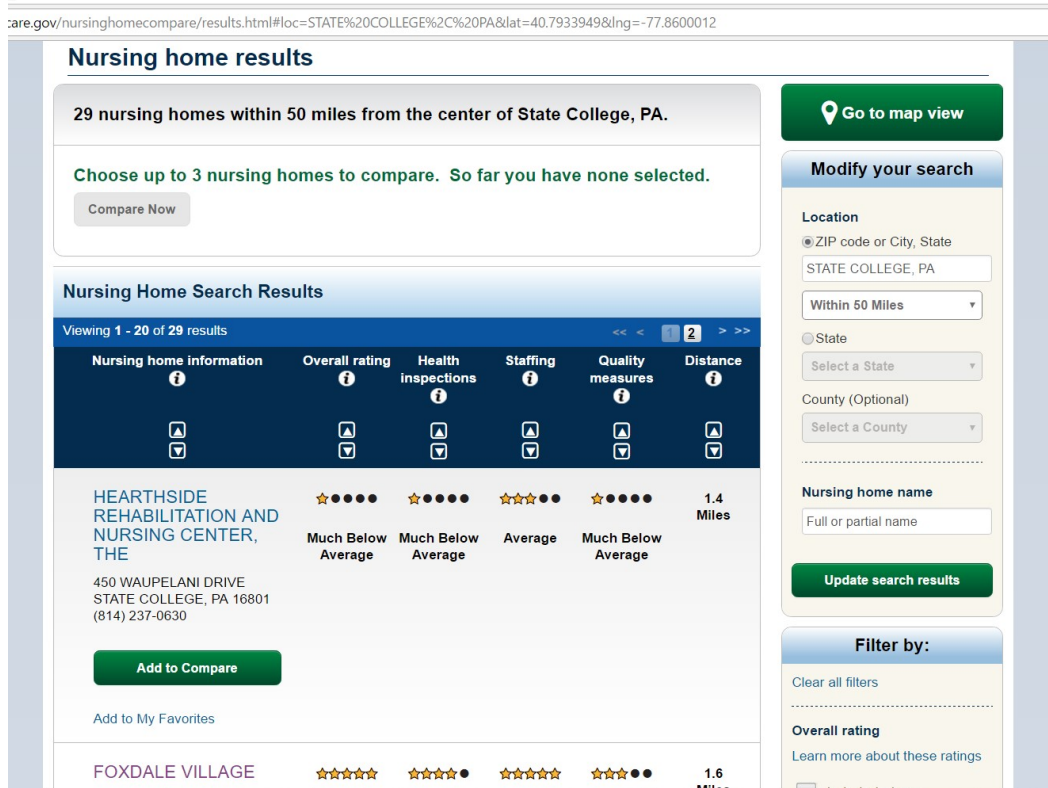
In 1998, the Centers for Medicare and Medicaid (CMS) introduced a web-based nursing home report card initiative (Nursing Home Compare), which subsequently added more quality of care measures including health related deficiencies and nurse staffing levels in 2000. In 2002, the Nursing Home Quality Initiative (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

Figure A.1: Quality Measures on Nursing Home Compare



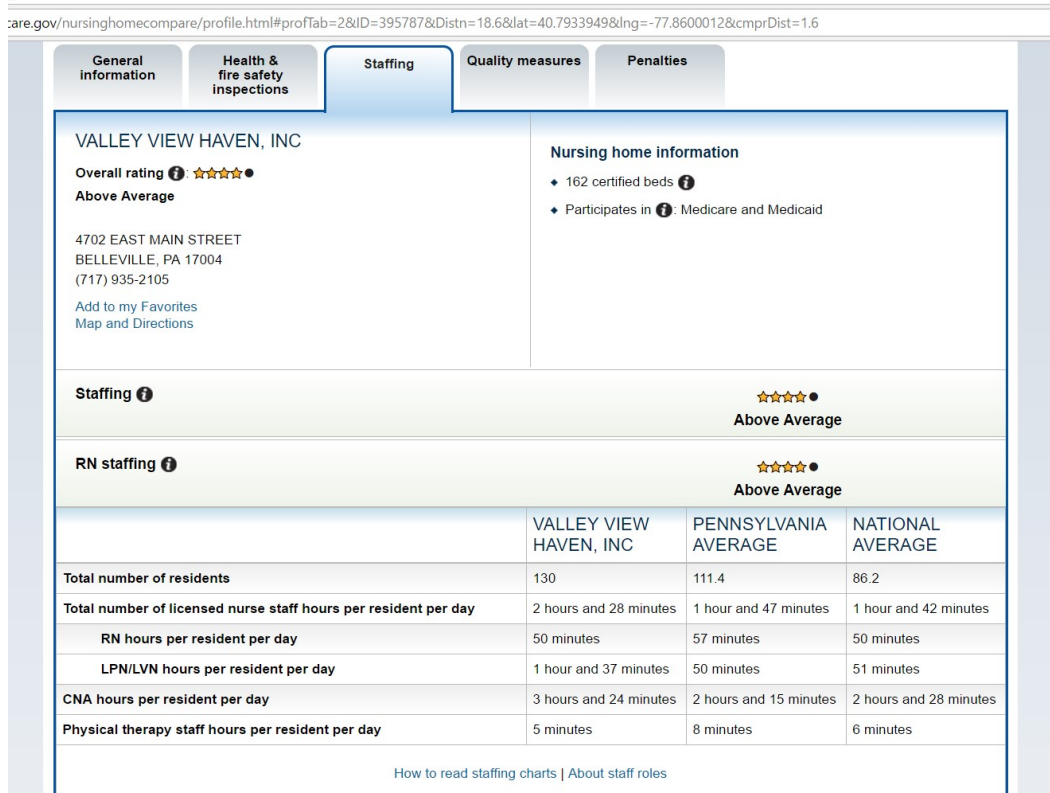
Notes: This screen shot summarizes the outcome of a nursing home search on the nursing home compare web page “<https://www.medicare.gov/nursinghomecompare/>” for the area of State College, PA. Nursing Homes are ordered by distance and ranked in three quality dimensions. Health inspections, which indicates 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.<sup>1</sup> 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

<sup>1</sup>New York (2014): [goo.gl/zvot49](http://goo.gl/zvot49); California (2004): [goo.gl/F3VgRF](http://goo.gl/F3VgRF); Ohio: <http://codes.ohio.gov/oac/5160-3-41v1>; and Florida: [goo.gl/aQaRI3](http://goo.gl/aQaRI3), all last accessed 10/23/16.

Figure A.2: Staffing Quality from Nursing Home Compare Quality Report Cards



Notes: This screen shot summarizes the staffing information for an example nursing home that was listed as one option under the aforementioned nursing home search. The report card provides detailed information on the number of licensed nurses, which correspond to skilled nurses in my analysis.

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.

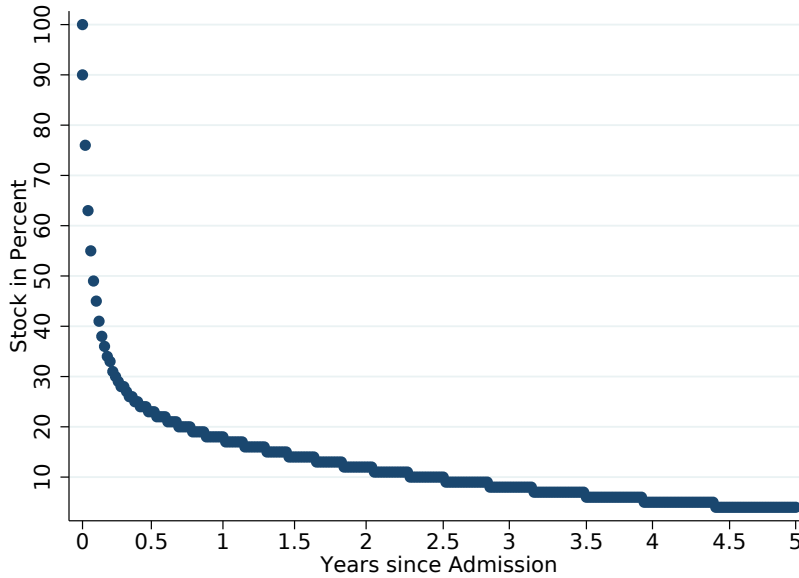
### **A.3 Details on Length of Stay**

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.<sup>2</sup> 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 (*adm*), 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:

<sup>2</sup>See <http://www.pacode.com/secure/data/055/chapter1181/s1181.212.html>, accessed 11/29/2016.

$$\begin{aligned}
R_{jt}^{caid} = & \min \left\{ \begin{array}{l} 1.17 * med \left( \left\{ AC_{k,t-3,4,5}^{rc} \right\}_{p(k)=p(j)} \right), \\ 0.3 * 1.17 * med \left( \left\{ AC_{k,t-3,4,5}^{rc} \right\}_{p(k)=p(j)} \right) + 0.7 * 1.03 * AC_{jt-3,4,5}^{rc} \end{array} \right\} * cmi_{jt}^{MA} \\
& + \min \left\{ \begin{array}{l} 1.12 * med \left( \left\{ AC_{k,t-3,4,5}^{orc} \right\}_{p(k)=p(j)} \right), \\ 0.3 * 1.12 * med \left( \left\{ AC_{k,t-3,4,5}^{orc} \right\}_{p(k)=p(j)} \right) + 0.7 * 1.03 * AC_{jt-3,4,5}^{orc} \end{array} \right\} \\
& + 1.04 * med \left( \left\{ AC_{k,t-3,4,5}^{admc} \right\}_{p(k)=p(j)} \right) \\
& + AC_{jt-3,4,5}^{capc} .
\end{aligned} \tag{A.1}$$

Here,  $AC_{t-3,4,5}^{rc}$  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 ( $AC_{t-3,4,5}^{orc}$ ,  $AC_{t-3,4,5}^{admc}$ , and  $AC_{t-3,4,5}^{capc}$ ) 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  $p(j) \in p_1, p_2, \dots, p_{12}$  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.<sup>3</sup>

## 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.**  $AC_{-c,t-3,4,5}^{p(j)}$  provide a valid set of instruments if the following two assumptions hold:

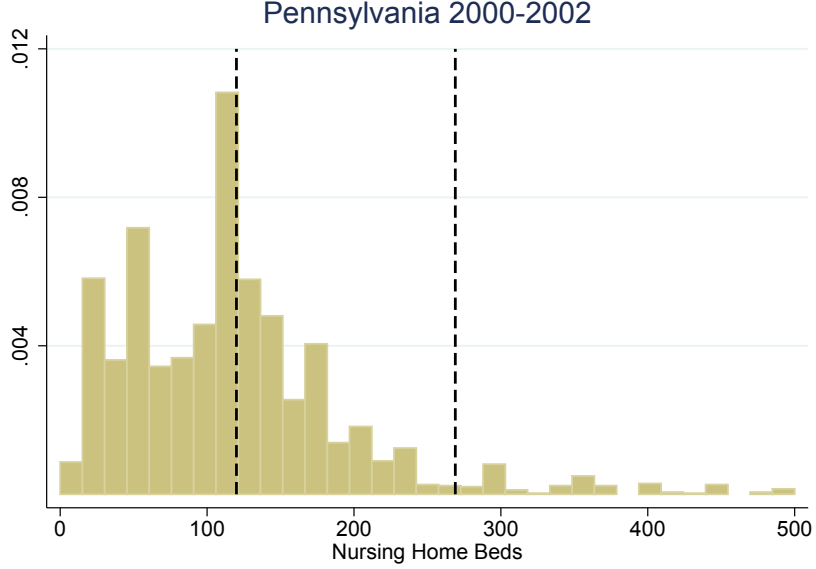
(SP)  $\epsilon_{jt}$  is independent of lagged shocks to providers located in other counties from 3 or more

---

<sup>3</sup>The 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  $\phi_{ct}$ :

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

**(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  $\gamma_1 \neq 0$ :

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

*Proof.* Using equation (3), we can express  $AC_{-c,t-3,4,5}^{p(j)}$  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  $AC_{-c,t-3,4,5}^{p(j)}$  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. Us-

ing equation (2), we can express  $R_{-c,t-3,4,5}$  in terms of  $AC_{-c,t-6,7,8,9,10}^{p(j)}$  and  $AC_{c,t-6,7,8,9,10}^{p(j)}$ . Using the first argument, we can iteratively replace previously submitted average costs  $AC_{-c,t-6,7,\dots}^{p(j)}$  and  $AC_{c,t-6,7,\dots}^{p(j)}$  in terms of  $X_{-ct-6,7,\dots}$ ,  $\phi_{-ct-6,7,\dots}$ ,  $\epsilon_{-ct-6,7,\dots}$ ,  $\eta_{-ct-6,7,\dots}$  and

$$X_{ct-6,7,\dots}, \phi_{ct-6,7,\dots}, \epsilon_{ct-6,7,\dots}, \eta_{ct-6,7,\dots} \quad \square$$

## 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  $Z_{-ct-3,4,\dots}$ ,  $X_{-ct-3,4,\dots}$ ,  $\epsilon_{-ct-3,4,\dots}$ , and  $\eta_{-ct-3,4,\dots}$ .
- Assumption (PT): Supported by the evidence presented in Appendix Section B.4, I assume imperfect pass-through of Medicaid rates onto average costs:  $\frac{\partial \log(AC_{jt})}{\partial \log(R_{jt}^{mcAid})} \leq 1$ .
- Assumption (TS): Average log costs at the county-peer group level, follow an AR(1) process with

$$\overline{\log(AC_{ct}^{p(j)})} = c + \overline{\log(AC_{ct-1}^{p(j)})} + u_{ct}^{p(j),ac},$$

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

$$\epsilon_{ct}^{p(j)} = \overline{\log(AC_{-ct}^{p(j)})} + u_{ct}^{p(j),\epsilon},$$

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

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

$$\log(Y_{jt}) = \gamma_1 \log(R_{jt}^{mcaid}) + \epsilon_{jt} . \quad (\text{B.1})$$

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:

$$R_{jt}^{mcaid} = \pi * \text{median}(AC_{c,t-4}^{p(j)}, AC_{-c,t-4}^{p(j)}) .$$

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:

$$\begin{aligned} \log(R_{jt}^{mcaid}) &= \log(\pi * \text{median}(AC_{c,t-4}^{p(j)}, AC_{-c,t-4}^{p(j)})) \\ &= \log(\pi) + \text{median}\left(\log(AC_{c,t-4}^{p(j)}), \log(AC_{-c,t-4}^{p(j)})\right) \\ &\approx \log(\pi) + \rho_c \overline{\log(AC_{c,t-4}^{p(j)})} + (1 - \rho_c) \overline{\log(AC_{-c,t-4}^{p(j)})} . \end{aligned} \quad (\text{B.2})$$

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  $\rho_c = \rho$ .  $\overline{\log(AC_{c,t-4}^{p(j)})}$  and  $\overline{\log(AC_{-c,t-4}^{p(j)})}$  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:

$$\log(AC_{jt}) = \tilde{\phi}^z \log(Z_{jt}) + \tilde{w} \log(Y_{jt}) + \log(\eta_{jt}) . \quad (\text{B.3})$$

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

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

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

$$\begin{aligned} \frac{\text{cov}(\epsilon_{jt}, (1-\rho)IV_{jt})}{\text{var}((1-\rho)IV_{jt})} &= \frac{\text{cov}(\epsilon_{jt}, (1-\rho)\overline{\tilde{w}\log(Y_{-ct-4}^{p(j)})})}{\text{var}((1-\rho)IV_{jt})} \\ &= \frac{\text{cov}(\epsilon_{jt}, (1-\rho)\overline{\tilde{w}\gamma_1\log(R_{-ct-4}^{mcaid})})}{\text{var}((1-\rho)IV_{jt})} \\ &= \frac{\text{cov}(\epsilon_{jt}, (1-\rho)\overline{\tilde{w}\gamma_1\rho\log(AC_{c,t-8}^{p(j)})})}{\text{var}((1-\rho)IV_{jt})} \\ &+ \tilde{w}\gamma_1 \frac{\text{cov}(\epsilon_{jt}, \overline{\log(AC_{-c,t-8}^{p(j)})})}{\text{var}(IV_{jt})} \end{aligned}$$

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  $\eta_{-ct-3,4..}$ ,  $Z_{-ct-3,4..}$  (first equality) and  $\epsilon_{-ct-3,4..}$  (second equality) on the other. The third equality leverages the additive structure in simplified reimbursement formula.<sup>5</sup> Assumption (TS) implies that (i) the time series in aver-

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

<sup>5</sup>Notice that  $\overline{\log(R_{-ct-4}^{mcaid})}$  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

age costs is weakly stationary with  $\overline{\text{var}(\log(AC_{-c,t-4}^{p(j)}))} = \overline{\text{var}(\log(AC_{-c,t-8}^{p(j)})}$  and that (ii)  $\frac{\overline{\text{cov}(\epsilon_{jt}, \log(AC_{-c,t-k}^{p(j)})}}{\overline{\text{var}(\log(AC_{-c,t-k}^{p(j)})}} = \tau\phi^k$ . These properties allow me to rewrite

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

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:

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

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

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

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

$$\begin{aligned} \overline{\text{var}(\log(AC_{-c}^{p(j)})} &= \overline{\text{var}\left(\frac{\rho}{1 - \rho} \sum_{d=1}^{\frac{1}{\rho}-1} \log(AC_{-d}^{p(j)})\right)} = \frac{\rho}{1 - \rho} \overline{\text{var}(\log(AC_{-d}^{p(j)})} \\ &+ \sum_{d \neq d'} \overline{\text{cov}\left(\frac{\rho}{1 - \rho} \log(AC_{-d}^{p(j)}), \frac{\rho}{1 - \rho} \log(AC_{-d'}^{p(j)})\right)} \\ &\geq \frac{\rho}{1 - \rho} \overline{\text{var}(\log(AC_{-d}^{p(j)})} = \frac{\rho}{1 - \rho} \overline{\text{var}(\log(AC_c^{p(j)})}, \end{aligned}$$

if  $\overline{\text{cov}\left(\frac{\rho}{1 - \rho} \log(AC_{-d}^{p(j)}), \frac{\rho}{1 - \rho} \log(AC_{-d'}^{p(j)})\right)} \geq 0$ . 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  $\overline{\log(AC_{-c,t-8}^{p(j)})}$ .

that  $\overline{\text{var}(\log(AC_{-c}^{p(j)}))} \approx \frac{\rho}{1-\rho} * \overline{\text{var}(\log(AC_c^{p(j)}))}$  is a reasonable approximation. This allows me to rewrite the bias condition as

$$\begin{aligned} \frac{\text{cov}(\epsilon_{jt}, (1-\rho)IV_{jt})}{\text{var}((1-\rho)IV_{jt})} &= \frac{\tilde{w}\gamma_1}{1 - (1-\rho)\tilde{w}\gamma_1\phi^4} \frac{\rho}{1-\rho} \frac{\overline{\text{cov}(\epsilon_{jt}, \log(AC_{ct-8}^{p(j)}))}}{\overline{\text{var}(\log(AC_{ct-8}^{p(j)}))}} \\ &= \frac{\tilde{w}\gamma_1}{1 - (1-\rho)\tilde{w}\gamma_1\phi^4} \frac{\overline{\text{cov}(\epsilon_{jt}, \log(AC_{ct-8}^{p(j)}))}}{\overline{\text{var}(\log(AC_{ct-8}^{p(j)}))}}. \end{aligned}$$

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

$$\frac{\overline{\text{cov}(\epsilon_{jt}, \log(AC_{c,t-8}^{p(j)}))}}{\overline{\text{var}(\log(AC_{c,t-8}^{p(j)}))}} = \frac{\overline{\text{cov}(\log(Y_{jt}), \log(AC_{c,t-8}^{p(j)}))}}{\overline{\text{var}(\log(AC_{c,t-8}^{p(j)}))}} - \gamma_1 \frac{\overline{\text{cov}(\log(R_{jt}^{mcaid}), \log(AC_{c,t-8}^{p(j)}))}}{\overline{\text{var}(\log(AC_{c,t-8}^{p(j)}))}},$$

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

$$\begin{aligned} \text{bias} &= \frac{\tilde{w}\gamma_1}{1 - (1-\rho)\tilde{w}\gamma_1\phi^4} \left[ \frac{\overline{\text{cov}(\log(Y_{jt}), \log(AC_{c,t-8}^{p(j)}))}}{\overline{\text{var}(\log(AC_{c,t-8}^{p(j)}))}} \right. \\ &\quad \left. - \gamma_1 \frac{\overline{\text{cov}(\log(R_{jt}^{mcaid}), \log(AC_{c,t-8}^{p(j)}))}}{\overline{\text{var}(\log(AC_{c,t-8}^{p(j)}))}} \right]. \end{aligned} \tag{B.4}$$

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 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  $d$ :

$$Cov(d) = E[Y_i Y_j | D(L_i, L_j) = d] .$$

The empirical analogue is given by the following kernel estimator:

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

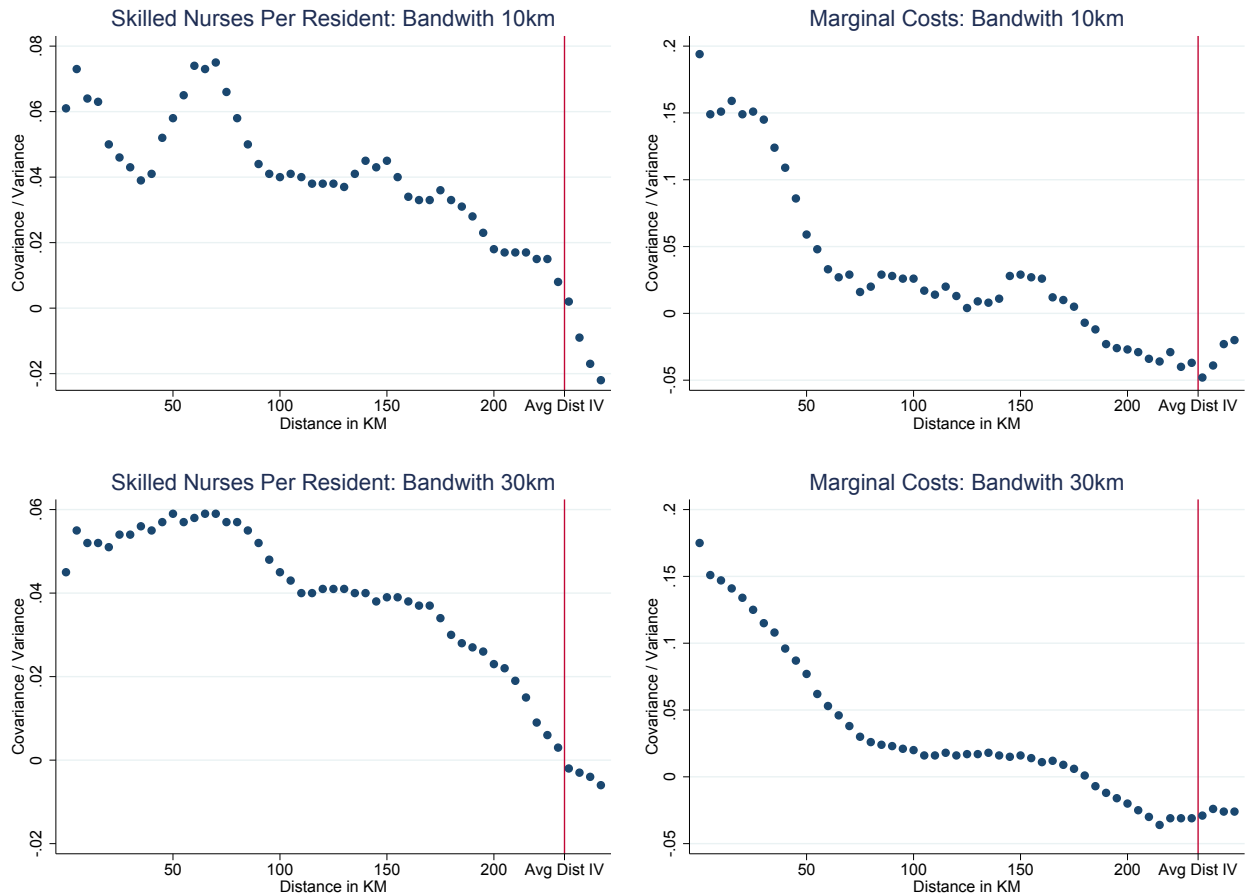
where  $h > 0$  is a bandwidth parameter that essentially smoothes the estimate of the conditional expectation.  $1\{D(L_i, L_j) - d < h\}$  is an indicator function that turns on if the distance between nursing homes  $i$  and  $j$  differs from the pre-specified distance  $d$  by at most  $h$  km. 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 of 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  $\$8.4 / (65\% * \$18.3) = 70\%$  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,  $\log(R^{mcaid})$ , only affect variable costs through skilled nurses. Specifically, I consider:

$$Z \rightarrow \log(R^{mcaid}) \rightarrow \log(SN^{res}) \rightarrow VC^{res,day} \quad (\text{B.5})$$

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.

$$Z \rightarrow \log(SN^{res}) \rightarrow VC^{res,day} \quad (\text{B.6})$$

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

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

where, just as in the preliminary analysis,  $X_{jt}$  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:

$$\left( \log(R^{mcaid}) \rightarrow \log(SN^{res}) \right) \left( \log(SN^{res}) \rightarrow VC^{res,day} \right) = 1.17 * 72.75 = 85.12$$

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,  $SN^{res,day}$ , (just as variable costs) and consider the following model:

$$VC_{jt}^{res,day} = S * SN_{jt}^{res,day} + \alpha X_{jt} + \phi_{ct} + \epsilon_{jt} .$$

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:

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

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,  $A\hat{C}_{jt} = \hat{\phi}^z Z_{jt}$  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 from the baseline analysis.

## C Details on Structural Estimation

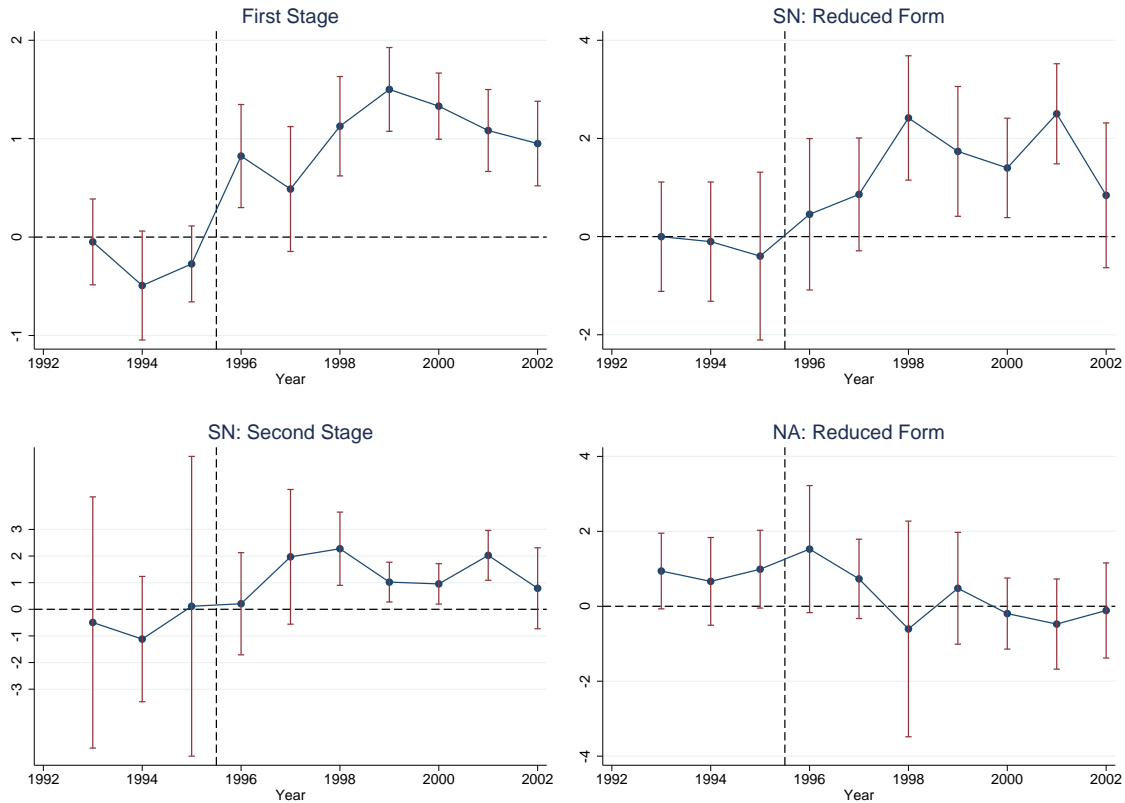
This section provides further details on the structural estimation.

### 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 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:

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

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 be expressed as follows:

$$D_j = \sum_i s_{ij|in} LOS_i$$

$$= \sum_i \phi_i s_{i,in} s_{ij|in} LOS_i .$$

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,  $s_{ij} = s_{i,in} s_{ij|in}$ , which is a product of the inside share and the probability that senior  $i$  chooses any inside good, denoted by  $s_{i,in}$ . Since not every senior decides to demand nursing home care,  $s_{i,in} \leq 1$ , it must be that there are multiple seniors of consumer type  $i$  that trade-off between different forms of care.<sup>6</sup> 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,  $D_{ij}$ :

$$\phi_i = \frac{1}{s_{i,in}} .$$

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  $\phi_i > \frac{1}{s_{i,in}}$  or  $\phi_i < \frac{1}{s_{i,in}}$ , one would overpredict or underpredict the consumer type specific nursing home demand  $D_{ij} = \phi_i s_{i,in} s_{ij|in} LOS_i$ . 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.

---

<sup>6</sup>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

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

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:

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

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

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

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.<sup>7</sup> 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  $G^{Demand}(\theta)$ ,  $G_{1,type}^{Cost}(\theta)$ ,  $G_{2,type}^{Cost}(\theta)$ ,  $G_3^{Cost}(\theta)$ , and  $G_4^{Cost}(\theta)$  outlined in Section 4. I refer to the stacked  $k$ -dimensional row vector over the set of moment conditions as:<sup>8</sup>

$$\begin{aligned} G(\theta) &= \frac{1}{N} \sum_i \left[ g_i^{Demand}(\theta), g_{1,type,i}^{Cost}(\theta), g_{2,type,i}^{Cost}(\theta), g_{3,i}^{Cost}(\theta), g_{4,i}^{Cost}(\theta) \right] \\ &= \frac{1}{N} \sum_i g_i(\theta) . \end{aligned}$$

---

<sup>7</sup>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.

<sup>8</sup>Here,  $k$  is the number of instrumental variables plus three  $G_{1,type}^{Cost}(\theta)$  moments (one for for-profit, not-for-profit, and public nursing homes, respectively) plus three  $G_{2,type}^{Cost}(\theta)$  moments plus one  $G_3^{Cost}(\theta)$  and one  $G_4^{Cost}(\theta)$  moment. So  $k = \dim(IV) + 8$ .

Here, the unit of observation  $i$  is a nursing-home-year-payer type.<sup>9</sup> 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  $\bar{j}$  and year  $\bar{t}$ . Then the demand moments provide three observations (one for each):

$$G(\theta) = \frac{1}{N} * \sum_i \begin{bmatrix} \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \xi_{jt}^{priv} IV_{jt}^{priv} & mc_{\bar{j}\bar{t}} - MC_{\bar{j}\bar{t}} & \cdot & \cdot \\ \xi_{jt}^{hyb} IV_{jt}^{hyb} & mc_{\bar{j}\bar{t}} - MC_{\bar{j}\bar{t}} & \cdot & \cdot \\ \xi_{jt}^{pub} IV_{jt}^{pub} & mc_{\bar{j}\bar{t}} - MC_{\bar{j}\bar{t}} & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{bmatrix}$$

as indicated in the middle three rows of the first columns. Then, for example, I triple the respective marginal cost moment,  $g_{1,type,i}^{Cost}(\theta)$ , 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:

$$\hat{\theta}^{GMM} = \underset{\theta}{argmin} G(\theta)WG(\theta)' ,$$

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:  $\tilde{\theta}$ . I then use

---

<sup>9</sup>For example,  $g_i^{Demand}(\theta) = \xi_i * IV_i$ .

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

$$\begin{aligned} B_0 &= \Gamma_0' W \Gamma_0 \\ \Gamma_0 &= \frac{1}{N} * \sum_i \frac{dg_i(\tilde{\theta})}{d\theta'} \\ \Omega_0 &= \Gamma_0' W V_0 W \Gamma_0 . \end{aligned}$$

### 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.<sup>10</sup> 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.

---

<sup>10</sup>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

$$MB_j^{res,day}(SN^{res}) = -\frac{MU_{SN_j^{res}}}{MU_P} = -\frac{\frac{\beta^{sn} + \beta_{cmi}^{sn} C\bar{M}I_j}{SN_j^{res}}}{\beta_{priv}^P} = -\frac{\frac{\bar{\beta}_j^{sn}}{SN_j^{res}}}{\beta_{priv}^P}, \quad (C.3)$$

where  $C\bar{M}I_j$  is the average case mix index for residents in nursing home  $j$  and  $MU_{SN_j^{res}}$  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.<sup>11</sup>

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

---

<sup>11</sup>The marginal benefit per resident day of an additional skilled nurse per resident  $MB^{res,day}(SN^{res})$  can be described as follows:  $MB^{res,day}(SN^{res}) = \frac{\Delta MB^{res,day}}{\Delta SN^{res}}$ . Multiplying the nominator and the denominator by the average number of residents at any point in time,  $Res$ , yields:

$$MB^{res,day}(SN^{res}) = \frac{\Delta MB^{res,day} * Res}{\Delta SN^{res} * Res} = \frac{\Delta MB^{day}}{\Delta SN} = MB^{day}(SN) .$$



simply the product of equation (C.3) and the number of calendar days:

$$MB_j(SN) = MB_j^{day}(SN) * 365 = MB_j^{res,day}(SN^{res}) * 365 .$$

#### 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:

$$-\frac{\bar{\beta}_j^{sn}}{SN_j^{res}} * 365 = W_j * 365 \forall j . \quad (C.4)$$

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

$$TS_j = W_j SN_j^{res} \sum_i s_{ijt} LOS_i = W_j SN_j^{res} Resdays_j ,$$

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:

$$TS_j = W_j * 365 * SN_j^{res} Resdays_j / 365 = W_j * 365 * SN_j^{res} Res_j = W_j * 365 * SN_j ,$$

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:

$$-\frac{\bar{\beta}_c^{sn}}{\beta_{priv}^P} * 365 = W_c * 365 * SN_c^{res} \forall c .$$

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

$$-\frac{\bar{\beta}_j^{sn}}{SN_c^{res}} * 365 = W_c * 365 ,$$

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.

## D Robustness of Structural Analysis

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

### D.1 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%:  $R_{t\tau j}^*(Occ_{tj}) = 0$  if  $Occ_{tj} \leq 0.9$ .

These assumptions imply that:

$$S_{t\tau j}(Occ_{tj}) = \begin{cases} A_{t\tau j}^* & \text{if } Occ_{tj} \leq 0.9 \\ A_{t\tau j}^* [1 - R_{t\tau j}^*(Occ_{tj})] & \text{else} \end{cases}, \quad (D.1)$$

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:

$$S_{t\tau j} = \sum_{k=75}^{100} \gamma_{\tau}^k Occ_{jt}^k + \phi_{year,\tau,j} + \epsilon_{t\tau j}. \quad (D.2)$$

Here,  $Occ_{jt}^k$ , 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  $\gamma_{\tau}^k$ . 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  $x$ ,  $E[\sum_{tj, Occ \geq x} A_{t\tau j}^* R_{t\tau j}^*]$ , relative to the total number of observed admissions  $E[\sum_{tj} S_{t\tau j}]$  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:

$$\begin{aligned}
\frac{E[\sum_{tj, Occ_{tj} \geq x} A_{t\tau j}^* R_{t\tau j}^*]}{E[\sum_{tj} S_{t\tau j}]} &= \frac{E[\sum_{tj, Occ_{tj} \geq x} A_{t\tau j}^*] - E[\sum_{tj, Occ_{tj} \geq x} S_{t\tau j}]}{E[\sum_{tj} S_{t\tau j}]} \\
&= \frac{\sum_{tj, Occ_{tj} \geq x} E[A_{t\tau j}^*] - \sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ_{tj} \geq x]}{E[\sum_{tj} S_{t\tau j}]} \\
&= \frac{\sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ = 0.9] - \sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ_{tj} \geq x]}{E[\sum_{tj} S_{t\tau j}]} \\
&= \frac{\sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ_{tj} \geq x]}{E[\sum_{tj} S_{t\tau j}]} \left( \frac{E[S_{t\tau j} | Occ = 0.9]}{E[S_{t\tau j} | Occ_{tj} \geq x]} - 1 \right) \\
&= \frac{E[\sum_{tj, Occ_{tj} \geq x} S_{t\tau j}]}{E[\sum_{tj} S_{t\tau j}]} \left( \frac{\gamma_{\tau}^{90}}{\gamma_{\tau}^{\bar{x}}} - 1 \right) \\
&= \underbrace{\frac{E[\sum_{tj, Occ_{tj} \geq x} S_{t\tau j}]}{E[\sum_{tj} S_{t\tau j}]}_A} \underbrace{\frac{\gamma_{\tau}^{90} - \gamma_{\tau}^{\bar{x}}}{\gamma_{\tau}^{\bar{x}}}}_B. \tag{D.3}
\end{aligned}$$

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,  $\gamma_{\tau}^{90}$  and  $\gamma_{\tau}^{\bar{x}}$  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 from 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,  $\{D_1, D_2, \dots, D_R\}$ .<sup>12</sup> 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.

---

<sup>12</sup>An 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.



### **D.2.3 Medicaid, Staffing, and Pricing**

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.

## **D.3 Marginal Utility of Income: Details for Alternative Approaches**

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.

### **D.3.1 Life Cycle Approach**

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:<sup>13</sup>

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

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  $v(b) = \left( \frac{\phi}{1-\phi} \right)^\sigma \frac{\left( \frac{\phi}{1-\phi} c_b + b \right)^{1-\sigma}}{1-\sigma}$  with  $\phi \in (0, 1)$ . Notice that  $\phi$  determines the risk aversion over bequests.  $\phi = 1$  implies risk neutrality in bequests with  $v(b) = c_b^{-\sigma} * b$ . 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:  $v'(0) = c_b^{-\sigma} = u'(c_b)$ . Hence, with  $c_b > 0$  bequests become luxury goods.

Finally, assets  $\omega_t$  are determined as follows:

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

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

---

<sup>13</sup>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  $t$ :

$$\frac{d}{dc_t}U = u'(c_t) - \sum_{a=t+1}^{T+1} \beta^{a-t} \left( \prod_{s=t}^{a-1} (1 - \delta_s) \right) \delta_a v'(b_a) \left( \prod_{s=t}^{a-1} (1 - r_s) \right) = 0 . \quad (\text{D.4})$$

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

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

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 dividing \$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:

$$MU^\tau = \frac{1}{\#i \in \tau} \sum_{i \in \tau} v'(b_i^\tau) = \frac{1}{\#i \in \tau} \sum_{i \in \tau} \left( \frac{\hat{\phi}}{1 - \hat{\phi}} \right)^{\hat{\sigma}} \left( \frac{\hat{\phi}}{1 - \hat{\phi}} \hat{c}_b + b_i^\tau \right)^{-\hat{\sigma}} .$$

Here,  $\#i \in \tau$  indicates the sample of individuals of payer type  $\tau$  and  $b_i^\tau$  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  $(1 - 27.5\%) * \$126,300 = \$91,600$  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 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  $0.15 * \$126,300 + 0.85 * \$91,600 = \$96,800$ .

### **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.<sup>14</sup> I also add a second interaction term,  $Rich_{it}$ , 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:

$$\begin{aligned}
u_{i\tau jt} &= \beta_1^d D_{ij} + \beta_2^d D_{ij}^2 + \beta_i^{sn} \log(SN_{jt}^{Res}) + \sum_x \beta_i^x X_{jt} + \beta_\tau^p P_{jt} + \xi_{jt}^\tau \\
&+ \beta_{wealth}^p 1\{\tau = private\} Wealth_{it} P_{jt} \\
&+ \beta_{rich}^p Wealth_{it} 1\{\tau = private\} Rich_{it} P_{jt} + \epsilon_{ijt} \quad ,
\end{aligned}$$

where  $Wealth_{it}$  indicates the de-measured predicted tangible wealth level and  $1\{\tau = private\}$  is an indicator variable that turns on for private payers. I present the parameter estimates in column 3 of Table D.7.<sup>15</sup> 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

---

<sup>14</sup>I 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.

<sup>15</sup>The 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  $-\hat{\beta}_{priv}^p = 0.018$ , 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

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

<sup>a</sup> Data from 2009, <sup>b</sup> Data from 2002, <sup>c</sup> Data from 2010



Table A.2: Payer Type Transitions (weighted by length of stay)

		Discharge			
Admission		Medicaid	Private	Medicare	Sum
	Medicaid	13.9%	0.0%	0.0%	13.9%
	Private	19.6%	14.5%	0.0%	34.1%
	Medicare	32.6%	14.3%	5.1%	52.0%
	Sum	66.1%	28.8%	5.1%	100.0%

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

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

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

	(1)	(2)	(3)	(4)	(5)
	$\log(\text{Pharma}^{res})$	$\log(\text{Phys}^{res})$	$\log(\text{Psy}^{res})$	$\log(\text{Soc}^{res})$	$\log(\text{Tech}^{res})$
Log Medicaid Rate	-0.44 (0.57)	-0.45 (0.79)	0.05 (0.25)	5.00 (24.86)	0.06 (7.45)
Observations	4022	4022	4022	4022	4015

Standard errors in parentheses

Notes:  $\log(\text{Pharma}^{res})$ ,  $\log(\text{Phys}^{res})$ ,  $\log(\text{Psy}^{res})$ ,  $\log(\text{Soc}^{res})$ , and  $\log(\text{Tech}^{res})$  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

	(1)	(2)	(3)	(4)
	$VC^{res,day}$	$VC^{res,day}$	$VC^{res,day}$	$TC^{res,day}$
Log Medicaid Rate	84.16*** (28.76)			
$\log(SN^{res})$		72.75** (30.01)		
$SN^{res,day}$			105.29** (41.93)	106.91** (42.62)
Observations	3878	3878	3878	3852

Notes:  $VC^{res,day}$  and  $TC^{res,day}$  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

	(1)	(2)	(3)	(4)	(5)
	First	$\log(SN^{res})$	$\log(NA^{res})$	$\log(Th^{res})$	$\log(P)$
Log Simulated Rate	0.61*** (0.16)				
Log Medicaid Rate		0.83** (0.36)	-0.05 (0.61)	-0.86 (2.01)	-0.09 (0.26)
Observations	4022	4022	3872	3307	4022

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

	(1)	(2)	(3)	(4)
	$\log(SN^{res})$	$\log(SN^{res})$	$\log(SN^{res})$	$\log(SN^{res})$
Log Medicaid Rate	1.17*** (0.29)	1.41** (0.43)	1.01*** (0.30)	1.22* (0.56)
NH Market	County	County	MSA	MSA
IV Variation	Full	Shocks	Full	Shocks

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.

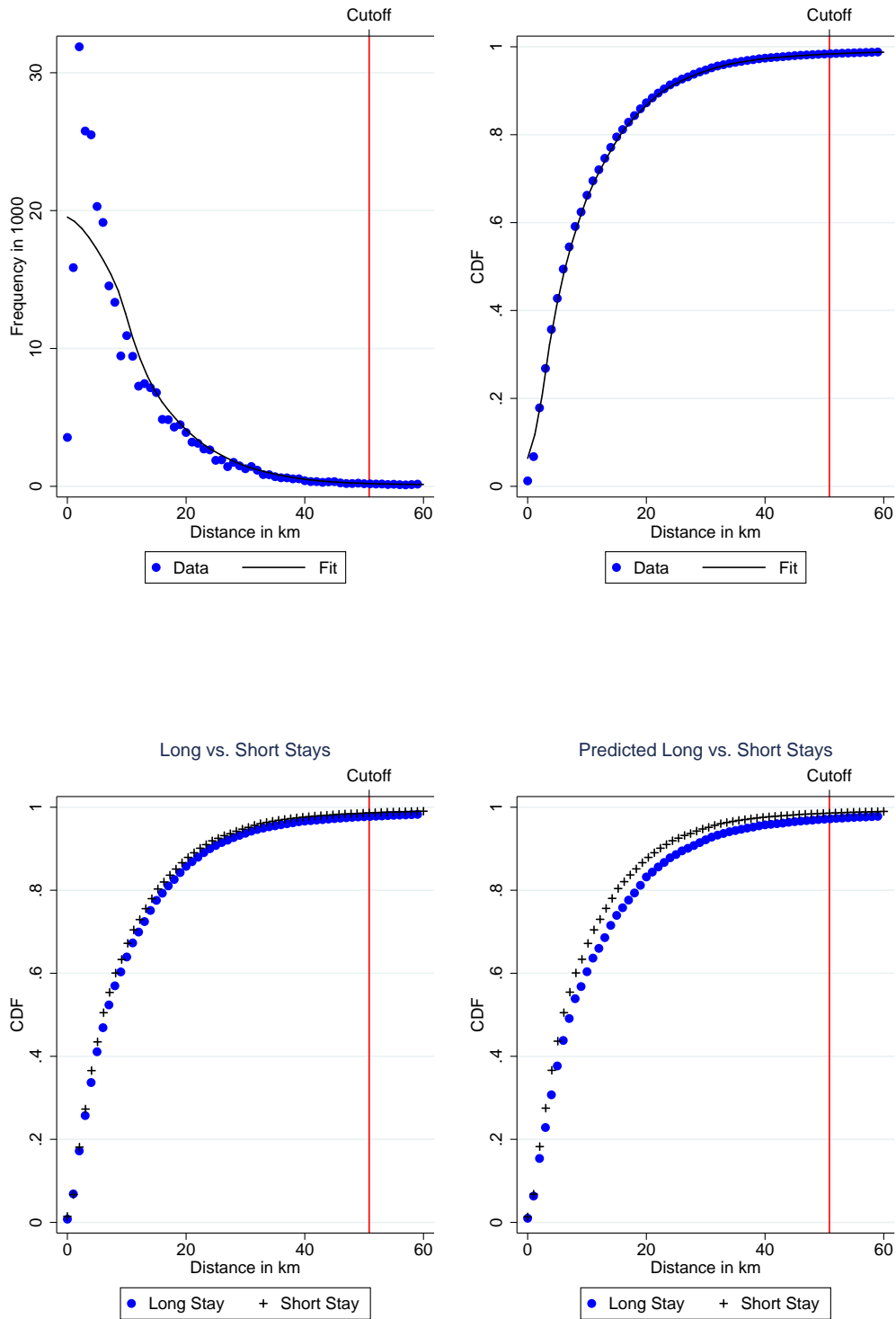
\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

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

	Mean	25th	50th	75th
Avg. SN Staffing Ratio	0.25	0.23	0.25	0.26
Optimal Avg. SN Staffing Ratio	0.36	0.31	0.34	0.40
Ratio: Optimal/ Actual SN Staffing Ratio	1.43	1.30	1.39	1.55
Observations	67			

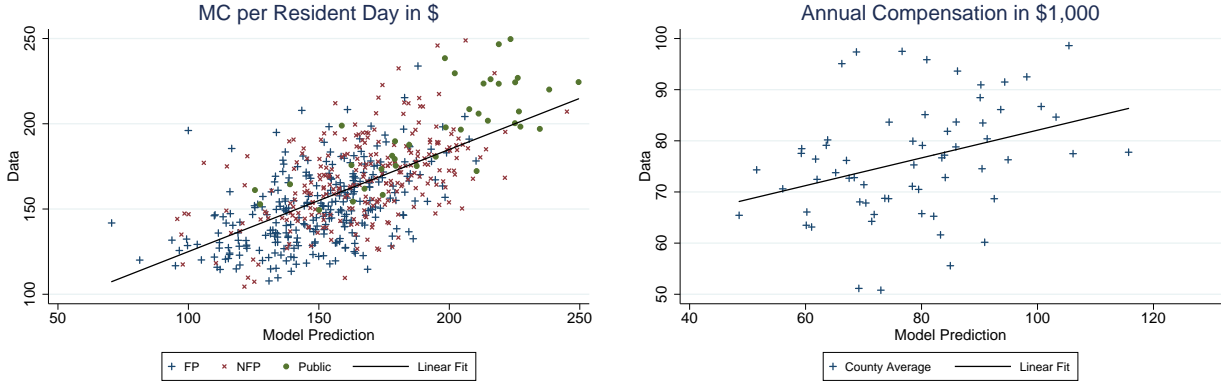
Notes: This table compares observed (first row) and optimal skilled nurse staffing ratios (second row) at the county level.

Figure C.1: Distance Traveled



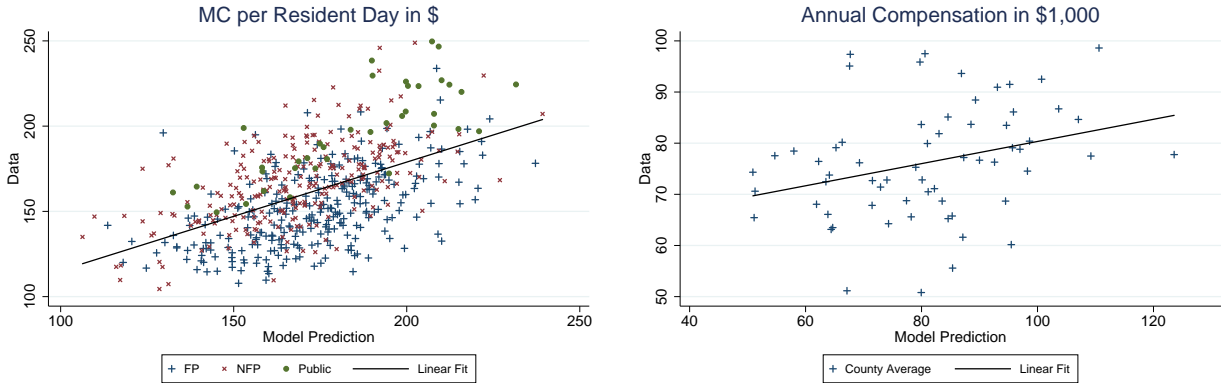
Notes: The top panel summarizes the distance between a senior's former residence and the chosen nursing home. The vertical red lines mark the the 50km threshold used in the demand analysis. Here, I only consider nursing homes in a senior's choice set that are within 50km of their former residence. The bottom panel explores heterogeneity between short stay ( $\leq 90$  days) and long stay ( $> 90$  days) residents.

Figure C.2: Goodness of Fit: MC and Annual Compensation in 2002



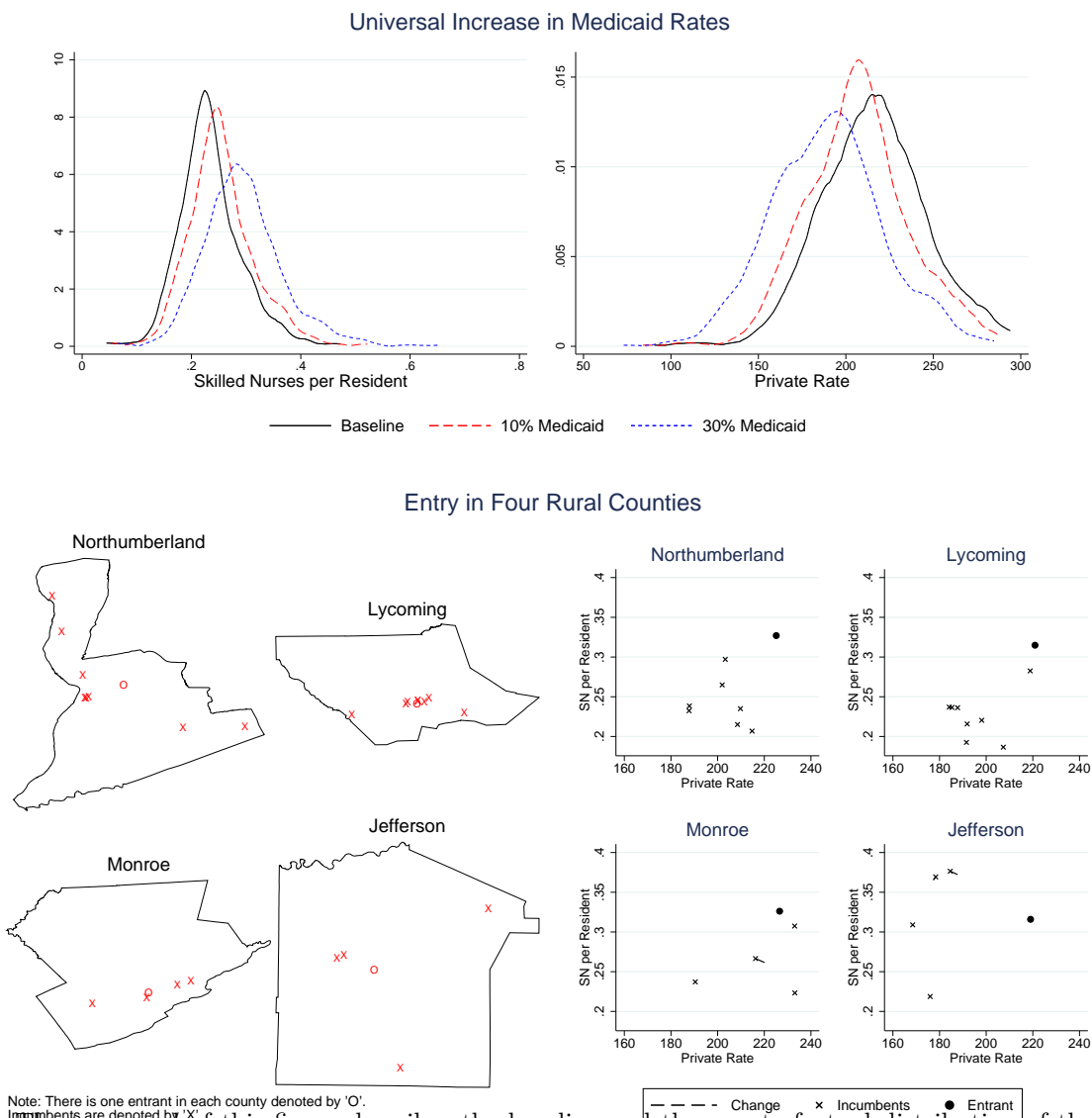
Notes: The figure compares predicted and observed marginal costs and annual nurse compensations to assess the goodness focuses of fit. Marginal costs and annual compensations are measured at the nursing home and the county level, respectively. The figure focuses on Medicaid certified nursing homes with 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.

Figure C.4: Counterfactual Exercises



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

	Pittsburgh MSA	Philadelphia MSA	PA
Var. Profit Entrant	0.6	0.1	0.7
Fixed Costs	2.2	2.2	4.4
$\Delta$ Profit	-2.7	-2.6	-5.4
$\Delta CS$	3.9	2.7	6.7
$\Delta$ Spending	1.6	1.7	3.3
$\Delta$ Welfare	-0.4	-1.6	-2.0
Avg $\Delta SN^{res}$	0.05%	0.03%	0.01%
Avg $\Delta P$	0.02%	0.02%	0.01%

Medicaid Expansion			Entry		
$\Delta SN^{res}$	$\Delta$ Spending	$\Delta SN^{res}/100m$	$\Delta SN^{res}$	$\Delta$ Spending	$\Delta SN^{res}/100m$
8.70%	331 million	2.63%	0.01%	3.7 million	0.33%
8.70%	181 million	4.81%	0.01%	5.4 million	0.23%

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.  $SN^{res}$  indicates skilled nurses per resident.

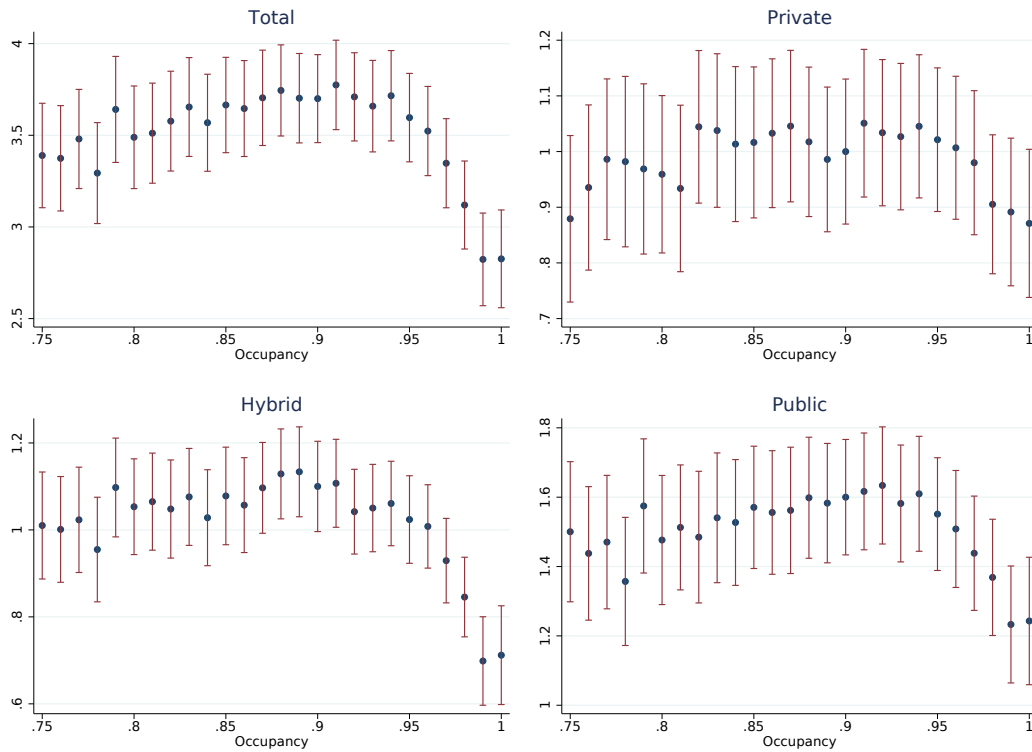
Table D.2: Weekly Admissions by Occupancy and Payer Type

	(1)	(2)	(3)	(4)
	Total	Private	Hybrid	Public
98% – 100%	3.2	.9	1.1	1.2
90% – $\overline{(98\% - 100\%)}$	.68	.1	.3	.28
$\frac{90\% - \overline{(98\% - 100\%)}}{98\% - 100\%}$	.21	.11	.28	.23
p-value 90% – $\overline{(98\% - 100\%)}$	0	0	0	0
96% – 100%	3.3	.9	1.1	1.2
90% – $\overline{(96\% - 100\%)}$	.4	.04	.19	.17
$\frac{90\% - \overline{(96\% - 100\%)}}{96\% - 100\%}$	.12	.04	.17	.14
p-value 90% – $\overline{(96\% - 100\%)}$	0	.16	0	0

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,  $\gamma_{\tau}^k$ , 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

	(1)	(2)	(3)	(4)
	Total	Private	Hybrid	Public
More than 100%	.02	.02	.02	.03
More than 97%	.15	.15	.17	.14
More than 95%	.29	.29	.33	.27

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

	(1)	(2)	(3)	(4)	(5)
	First	$\log(SN^{res})$	$\log(NA^{res})$	$\log(Th^{res})$	$\log(P)$
Log Simulated Rate	1.22*** (0.21)				
Log Medicaid Rate		1.17*** (0.30)	0.06 (0.51)	-0.45 (2.34)	0.04 (0.20)
Observations	3227	3227	3120	2617	3227

	(1)	(2)	(3)	(4)	(5)
	First	$\log(SN^{res})$	$\log(NA^{res})$	$\log(Th^{res})$	$\log(P)$
Log Simulated Rate	1.14*** (0.26)				
Log Medicaid Rate		1.13*** (0.39)	-0.29 (0.65)	-1.22 (3.02)	-0.04 (0.26)
Observations	2461	2461	2377	1990	2461

Standard errors in parentheses

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.

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

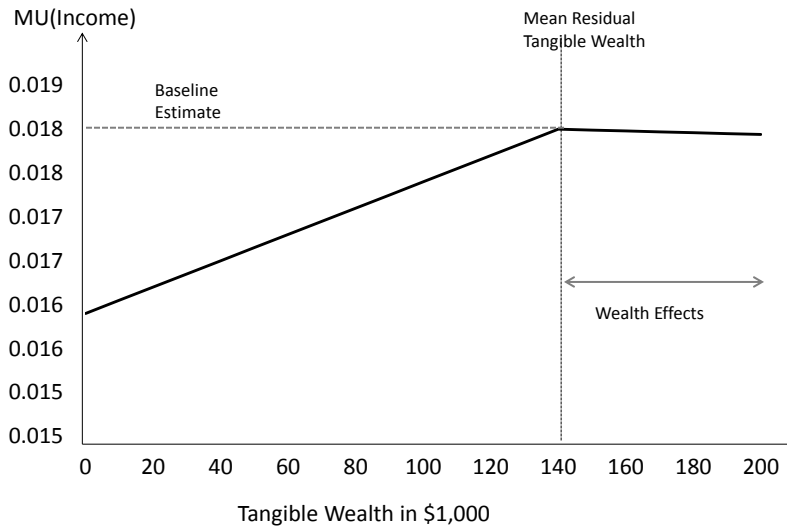
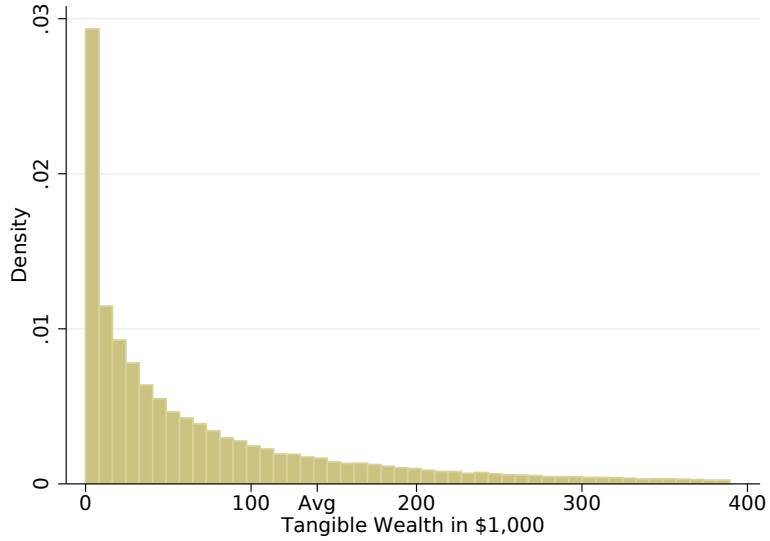
Table D.5: Key Parameter Estimates from Lockwood (2016)

Parameter	Point Estimate	Standard Error
$\phi$ : bequest motive	0.95	0.01
$c_b$ : bequest motive (\$1,000)	16.1	1.4
$c_{pub}$ : public care value NH (\$1,000)	18.3	4.7
$\sigma$ : risk aversion	3	0.05

Table D.6: Nursing Home Residents, HRS 1998-2008

	N	Mean	10th	50th	90th
Medicaid					
Household Income	1149	12835	4932	9948	23160
Assets in \$1,000	1149	26	0	0	70
Pr. Bequests > 0 in %	171	12	0	0	75
Pr. Bequests > 10k in %	192	10	0	0	50
Pr. Bequests > 100k in %	191	2	0	0	0
Estimated Pr. Bequests in \$1,000	1149	13	0	0	34
Private					
Household Income	1384	26534	6720	17650	50500
Assets in \$1,000	1384	219	0	62	604
Pr. Bequests > 0 in %	274	51	0	50	100
Pr. Bequests > 10k in %	381	46	0	50	100
Pr. Bequests > 100k in %	367	25	0	0	100
Estimated Pr. Bequests in \$1,000	1384	72	0	0	224
Observations	2533				

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

		Wealth Effects	
		Parameter	SE
$\beta^{sn}$ :	log(SN/Resident)	1.534***	0.748
$\beta_{hyb}^p$ :	Price*Hybrid	-0.012***	0.002
$\beta_{priv}^p$ :	Price*Private	-0.018***	0.004
$\beta_{cmi}^{sn}$ :	log(SN/Resident)*CMI	0.226***	0.003
$\beta_1^d$ :	Distance in 100km	-25.79***	0.014
$\beta_2^d$ :	Distance <sup>2</sup>	22.45***	0.027
$\beta_{rehab}^{th}$ :	Therapist/Res*Rehabmin	-0.125***	0.001
$\beta_{rehabXshort}^{th}$ :	Therapist/Res*Rehabmin*Short-Stay	0.311***	0.007
$\beta_{alz}^{alz}$ :	Alzheimer*Alzheimer Unit	0.414***	0.002
$\beta_{wealth}^p$ :	Wealth Effects in \$1m	-0.015***	0.001
$\beta_{rich}^p$ :	Wealth Effects for richer priv. payers in \$10m	0.016***	0.001
	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.  $\beta_{wealth}^p$  denotes the interaction between the private rate and tangible wealth.  $\beta_{rich}^p$  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.

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