

A Online Appendix

A.1 Institutional Details: Quality Concerns and Policy Efforts

The quality of nursing home care has been an ongoing concern for decades. The problem came to the forefront in the early 1970s, when legislative investigations revealed many cases of patient abuse, mistreatment, and inadequate services performed by underqualified personnel, see Giacalone (2000). Persistent quality problems published by the Institute of Medicine (1986) landmark report ultimately led to the 1987 Nursing Home Reform Act as part of the Omnibus Budget Reconciliation Act (1987), see e.g., Werner and Konetzka (2010) for more details. This reform mandated extensive regulatory controls, verified through regular inspections and from mandatory reports of quarterly resident assessments, as well as federal minimum staffing regulations.

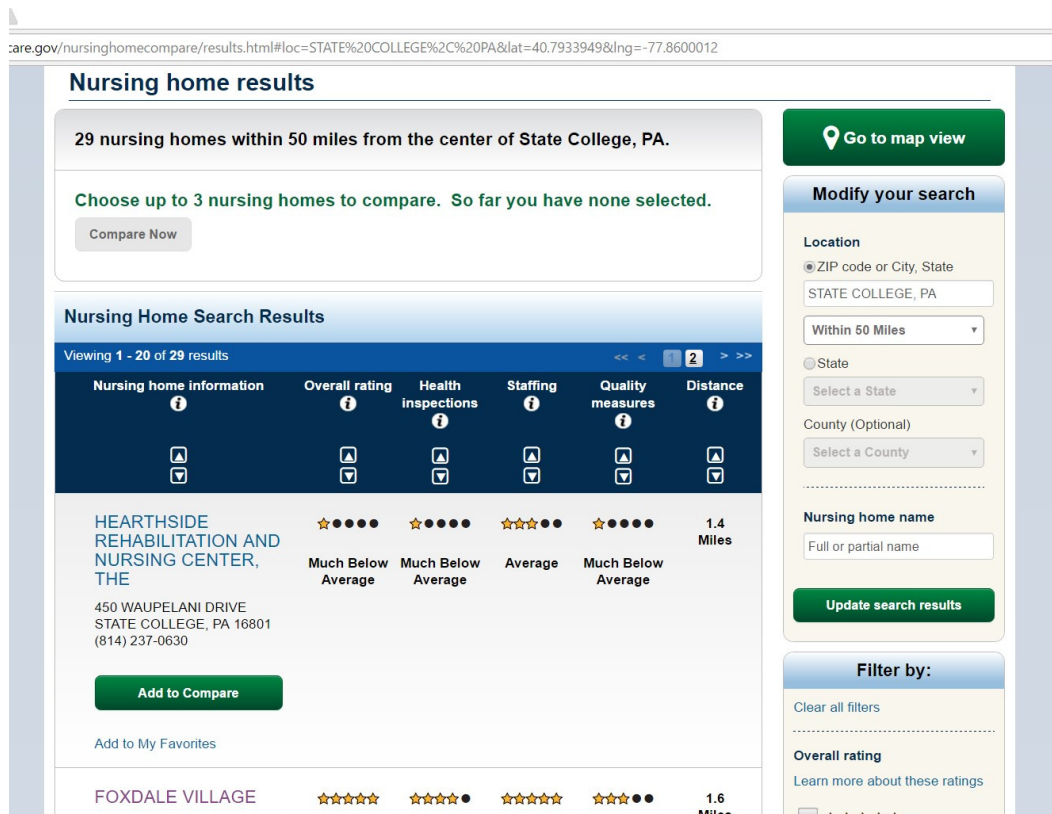
While these regulatory changes have led to improvement in the standards for quality of clinical care and resident safety, quality concerns continued to exist. According to a report from the Department of Health and Human Services from 1999,¹ 13 of 25 quality of care deficiencies had increased in the 1990s. These include a lack of supervision to prevent accidents, improper care for pressure sores, and lack of proper care for activities of daily living. In addition, complaints from residents and relatives, commonly regarding resident care, such as pressure sores and hygiene, had been steadily increasing since 1989. Finally, nurse-to-resident staffing ratios continued to be very low, see Harrington et al. (2000).

In an effort to improve staffing ratios, clinical outcomes, and to reduce deficiencies and complaints, more recent reforms have focused on minimum staffing regulations, public reporting, and Medicaid reimbursement policies. In the late 1990s and early 2000s several states adopted additional staffing requirements, which (in the case of registered nurses) led to a re-

¹See <https://oig.hhs.gov/oei/reports/oei-02-99-00060.pdf>, last accessed October 23rd, 2016.

duction in the total number deficiencies, see Lin (2014). Public reporting of quality outcome measures has been an alternative approach to address quality concerns in the industry. 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 A1 and A2 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).

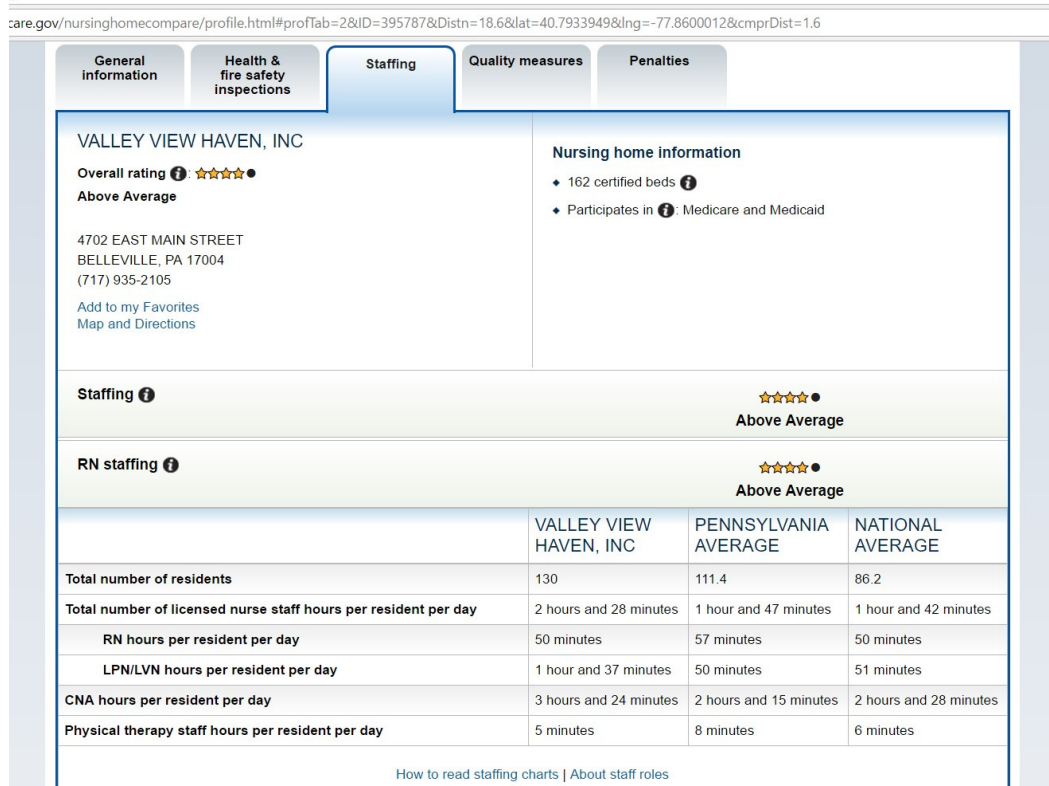
Figure A1: Quality Measures on Nursing Home Compare



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.

Finally, with Medicaid as the primary payer for most nursing home residents, reimburse-

Figure A2: Staffing Quality from Nursing Home Compare Quality Report Cards



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.

ment rates have been a priority policy area for state governments to address low nurse staffing ratios, particularly registered nurse staffing, and nursing home deficiencies. For example, several states including California, Iowa, and Minnesota, have revised their Medicaid reimbursement methodologies in the 2000s in an effort to improve the quality of care, see KFF (2015).² More generally, as economic conditions have improved after the Great Recession, about 40 states aimed to increase their Medicaid reimbursements rates for nursing homes in 2015 hoping to improve the delivery of care.³

²See <http://ltcombudsman.org/uploads/files/library/deficiencies-09-14.pdf>, last accessed 10/13/16.

³See <https://kaiserfamilyfoundation.files.wordpress.com/2014/10/8639-medicaid-in-an-era-of-health-delivery-system-reform3.pdf>, last accessed 10/24/16.

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

In this section, 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 A1. 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 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.⁴ More details on differences in reimbursement rates among states are provided in Table A2. Certificate of Need laws, however, differ from state to state; in 2002, those laws existed in two-thirds of states but not in Pennsylvania.

Nursing homes are, on average, slightly larger in Pennsylvania and the share of for-profit nursing homes falls short of the national average by about one standard deviation. The share of public nursing home is on the other hand quite similar. On average, the nursing home industry appears to be less concentrated in Pennsylvania. The Herfindahl Index (HHI) falls short of the national average by almost one standard deviation. Furthermore, the nursing home industry is generally less concentrated than other health care industries. Gaynor (2011) finds a HHI of more than 3,000 for the hospital industry. The resident composition in Pennsylvania is overall representative. The composition is slightly selected towards older white women, who have slightly worse health profiles as demonstrated by a higher case mix index and a marginally higher average level of need for help with activities of daily living (ADL) such as

⁴New York (2014): goo.gl/zvot49; California (2004): goo.gl/F3VgRF; Ohio: <http://codes.ohio.gov/oac/5160-3-41v1>; and Florida: goo.gl/aQaRI3, all last accessed 10/23/16.

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.

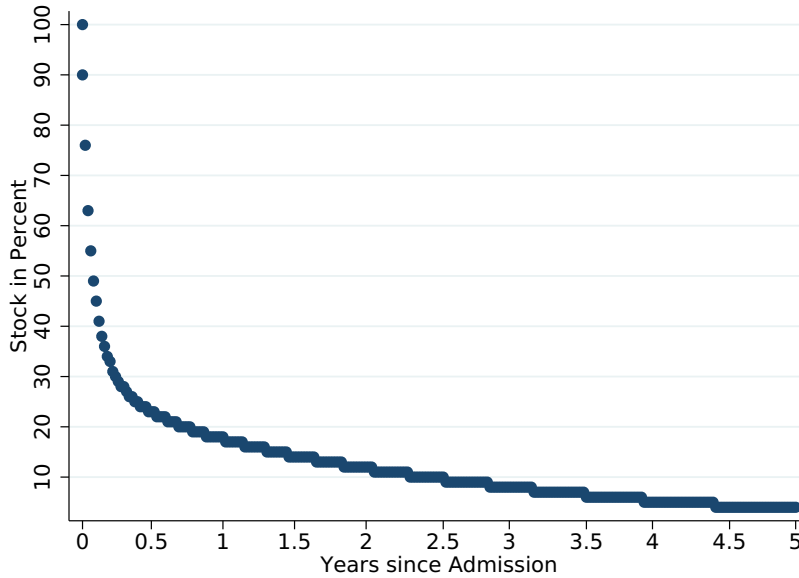
Next, I turn to the comparison of health care quality. Industry experts commonly distinguish between three groups of quality measures. These are nurse staffing levels, clinical outcomes, and deficiencies that are assigned by state surveyors if nursing homes fail to meet process and outcome based nursing home care requirements. While the average total nurse hours are comparable between Pennsylvania and the U.S., Table A1 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 A1 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 A3. 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 A3 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.

Figure A3: Kaplan Meier Survival Curve by Years Since Admission



A.4 Medicare Focus and Sample Selection

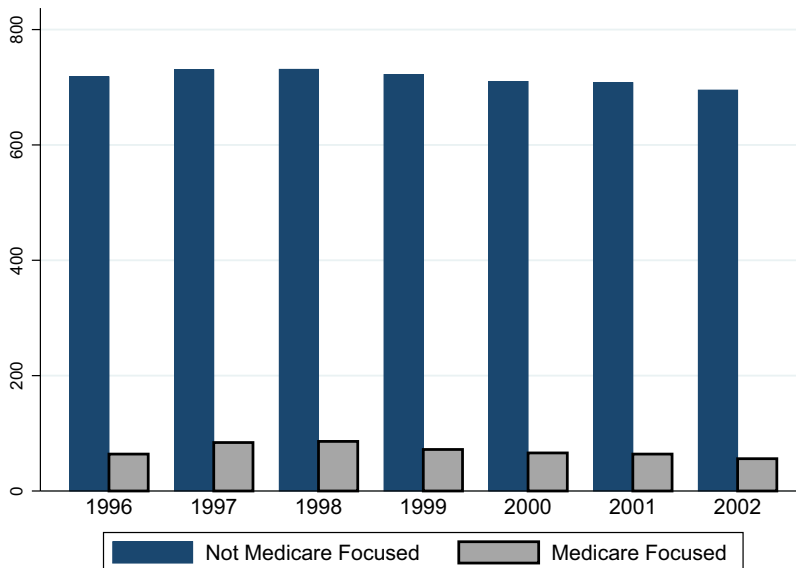
In this section, I investigate potential sample selection resulting from endogenous changes in a nursing home’s Medicare focus following changes in the market structure and the Medicaid reimbursement rate. Overall only 9% of nursing homes in Pennsylvania have a Medicare share of more than 90%, which I consider as Medicare focused. The time series indicated in Figure A4 below indicates that there are only minor year-to-year changes in the number of Medicare focused nursing homes, providing first evidence against sizable and systematic changes in the Medicare focus of nursing homes.

I also explore the potential link between Medicare focus, Medicaid rates, and market entry more directly. Specifically, I add Medicare focused nursing homes back to the sample population and start by revisiting the link between Medicare focus and Medicaid rates. To this end, I estimate the following regression model:

$$Y_{jt} = \gamma_3 * \log(R_{jt}^{mcaid}) + \phi_{ct} + \alpha * X_{jt} + \epsilon_{jt}$$

where Y_{jt} is now an indicator variable, which turns on if nursing home j focuses on Medi-

Figure A4: Robustness Medicare Sample



care residents. $\log(R_{jt}^{medicaid})$ denotes again the log Medicaid reimbursement rate, ϕ_{ct} denotes county-year fixed effects and X_{jt} captures other nursing home specific characteristics. The key parameter of interest is γ_3 . I estimate the model via 2SLS using the log simulated Medicaid reimbursement rate as an instrument for the endogenous log Medicaid reimbursement rate. The IV estimate is presented in the first column of Table A4. The small and statistically insignificant point estimate provides evidence against systematic sample selection in the fraction of Medicare focused nursing homes.

Next, I turn to the potential link between market entry and Medicare focus. To this end, I take advantage of the fact the Pennsylvania repealed its CON law in 1996. Prior to 1996, this CON law restricted entry and capacity investments and may have thereby distorted the nursing home size distribution. I use the regulated market structure in 1995 as a source of entry variation in the following years to explore a potential link between market entry and Medicare focused nursing homes. Specifically, I first construct a Herfindahl index based on the bed distribution in 1995:

$$HHI_c^{95,beds} = \sum_{j=1}^{N_c,1995} \left(\frac{Beds_{j,1995}}{\sum_{j=1}^{N_c,1995} Beds_{j,1995}} \right)^2,$$

where $N^{c,1995}$ is the number of nursing homes in county c in year 1995. Then, I estimate the following regression model:

$$Y_{jt} = \gamma_4 * HHI_c^{95,beds} + \phi_t + \alpha * X_{jt} + \epsilon_{jt} ,$$

where ϕ_t denotes year fixed effects and X_{jt} contains a set of observable nursing home and market characteristics. The estimate for γ_4 is presented in the second column of Table A4. Again, the small and statistically insignificant point estimate provides evidence against systematic sample selection in the fraction of Medicare focused nursing homes.

A.5 Reimbursement Formula and Simulated Reimbursement Rate

In this section, I provide further details on the Medicaid reimbursement methodology and the calculation of the simulated reimbursement rates.

A.5.1 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.⁵ 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:

⁵See <http://www.pacode.com/secure/data/055/chapter1181/s1181.212.html>, accessed 11/29/2016.

$$\begin{aligned}
R_{jt}^{caid} = & \min \left\{ \begin{array}{l} 1.17 * med \left(\left\{ AC_{k,t-3,4,5}^{rc} \right\}_{p(k)=p(j)} \right), \\ 0.3 * 1.17 * med \left(\left\{ AC_{k,t-3,4,5}^{rc} \right\}_{p(k)=p(j)} \right) + 0.7 * 1.03 * AC_{jt-3,4,5}^{rc} \end{array} \right\} * cmi_{jt}^{MA} \\
& + \min \left\{ \begin{array}{l} 1.12 * med \left(\left\{ AC_{k,t-3,4,5}^{orc} \right\}_{p(k)=p(j)} \right), \\ 0.3 * 1.12 * med \left(\left\{ AC_{k,t-3,4,5}^{orc} \right\}_{p(k)=p(j)} \right) + 0.7 * 1.03 * AC_{jt-3,4,5}^{orc} \end{array} \right\} \\
& + 1.04 * med \left(\left\{ AC_{k,t-3,4,5}^{admc} \right\}_{p(k)=p(j)} \right) \\
& + AC_{jt-3,4,5}^{capc} .
\end{aligned} \tag{10}$$

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.5.2 Simulated Reimbursement Rates

In this section, 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 10.

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 10.

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.5.3 Cost Data from Medicaid Cost Reports

Table A5 provides additional details on nursing home costs. As mentioned earlier, the DHS divides total costs into four cost categories: resident related care costs (see the top panel), other resident related care costs, see the second panel, as well as administrative and capital costs.

The evidence from Table A5 suggests annual fixed costs of about \$1.8 million considering capital and administrative costs. This exceeds the allowable fixed costs from the baseline analysis, that are considered for reimbursement, by about \$0.7 million on average. I only use the fixed costs in the counterfactual entry analysis. This suggests that the gains from entry may be even smaller when considering even larger annual fixed costs.

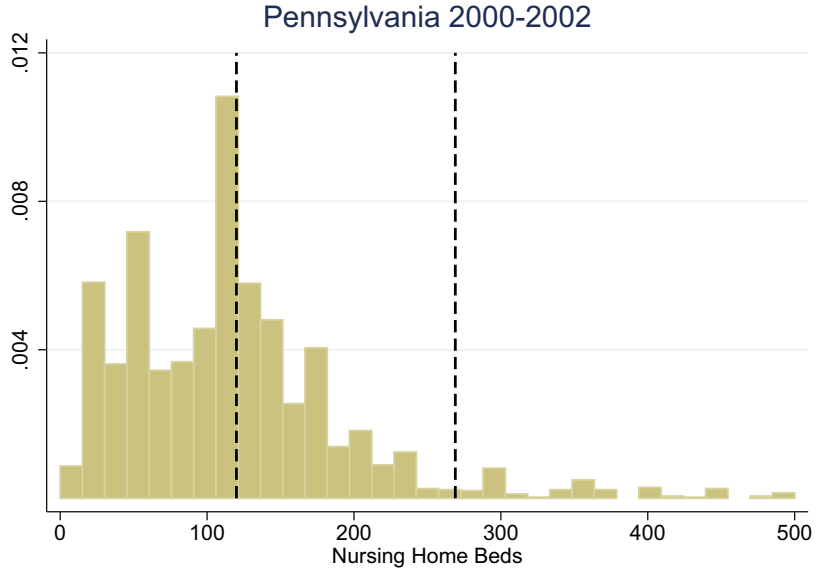
A.6 Nursing Home Size Distribution

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

Figure A5 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.⁶

⁶The 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

Figure A5: Nursing Home Size Distribution in Beds



A.7 Spatial Correlation in Staffing and Marginal Costs

In this section, 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.

my analysis. I summarize the discussion for bunching and the robustness checks in Section A.20.

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.

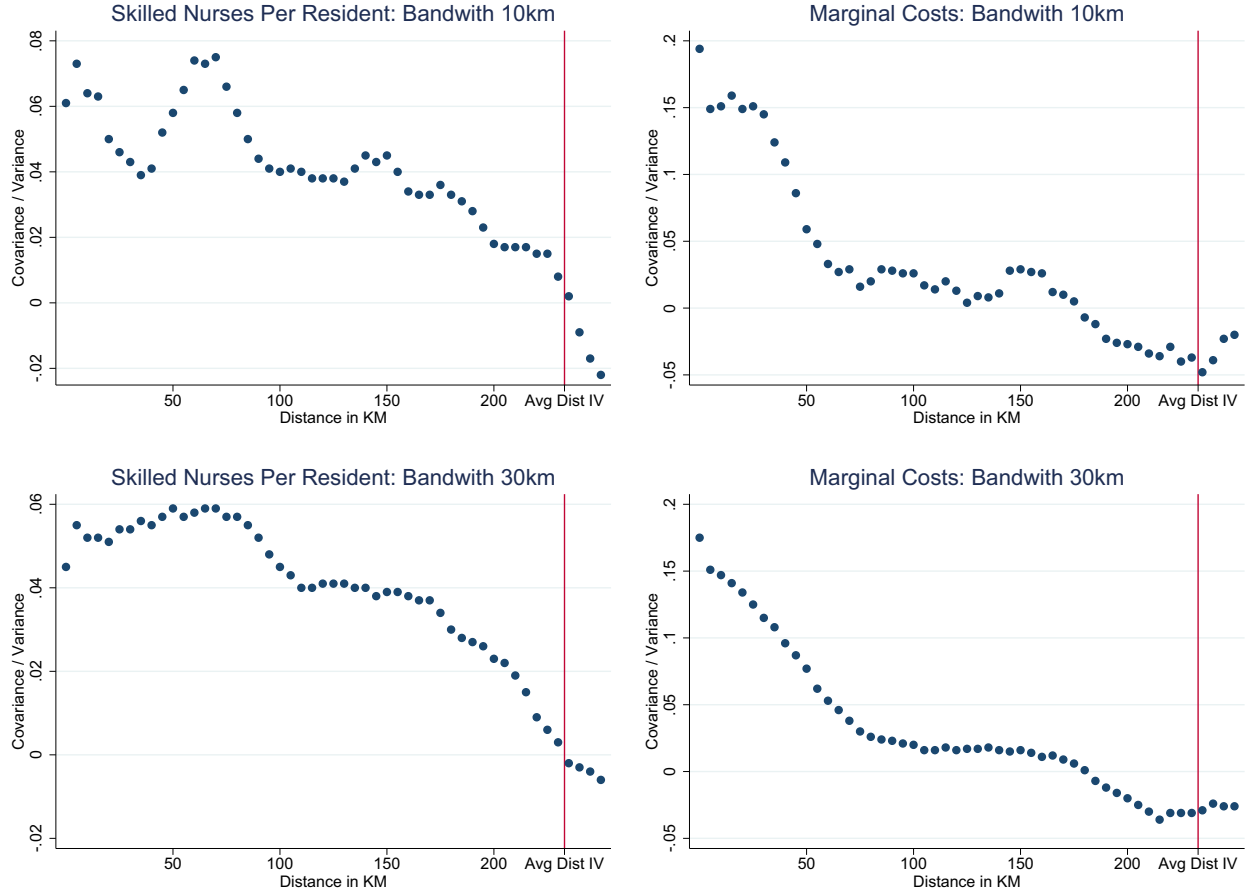
Figure A6 summarizes the spatial correlation in skilled nurses per resident (left graphs) and marginal costs (right graphs) in a correlogram for different bandwidths. The vertical axis denotes Moran's I statistic, Moran (1950), which is the spatial covariance divided by the own variance. The horizontal 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.

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.

A.8 Extension of Preliminary Analysis

In this section, I revisit the preliminary analysis on the effects of changes in the Medicaid reimbursement rates on staffing and pricing decisions. I first discuss the ordinary least squares regression results for equation (1) before I consider a simple leave-one-out estimator, revisit the exclusion restrictions, and consider alternative inputs.

Figure A6: Spatial Correlation in Staffing and Marginal Costs



A.8.1 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) ϵ_{jt} is independent of lagged shocks to providers located in other counties from 3 or more years ago, conditional on X_{jt} and ϕ_{ct} :

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

(SE) ϵ_{jt} is independent of lagged shocks to peer group members located in the focal county

c from six or more years ago, conditional on X_{jt} and ϕ_{ct} , if $\gamma_1 \neq 0$:

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

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 $\gamma_1 = 0$, ϵ_{jt} is mean independent of $AC_{-c,t-3,4,5}^{p(j)}$ if ϵ_{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 ϵ_{jt} and $R_{-c,t-3,4,5}$ as well. Using 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

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

A.8.2 Potential Bias From Serial Correlation in County Average Costs

In this section, 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): ϵ_{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 A.8.6, 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

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

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

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

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

$$\log(Y_{jt}) = \gamma_1 * \log(R_{jt}^{mcaid}) + \epsilon_{jt} . \tag{11}$$

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 8 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:

$$\begin{aligned}
\log(R_{jt}^{mcaid}) &= \log(\pi * \text{median}(AC_{c,t-4}^{p(j)}, AC_{-c,t-4}^{p(j)})) \\
&= \log(\pi) + \text{median}\left(\log(AC_{c,t-4}^{p(j)}), \log(AC_{-c,t-4}^{p(j)})\right) \\
&\approx \log(\pi) + \overline{\rho_c \log(AC_{c,t-4}^{p(j)})} + (1 - \rho_c) * \overline{\log(AC_{-c,t-4}^{p(j)})}. \tag{12}
\end{aligned}$$

Here, the last row uses the approximation, where, ρ_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:

$$\log(AC_{jt}) = \tilde{\phi}^z * \log(Z_{jt}) + \tilde{w} * \log(Y_{jt}) + \log(\eta_{jt}). \tag{13}$$

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.⁷ Consequently, the 2SLS estimator for γ_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 (11)-(13), the bias term can be expressed as

$$\frac{\text{cov}(\epsilon_{jt}, (1 - \rho) * IV_{jt})}{\text{var}((1 - \rho) * IV_{jt})} = \frac{\text{cov}(\epsilon_{jt}, (1 - \rho) * \tilde{w} * \overline{\log(Y_{-ct-4}^{p(j)})})}{\text{var}((1 - \rho) * IV_{jt})}$$

⁷Averaging over the other terms $\log(\pi) + \rho \log(AC_{c,t-4}^{p(j)})$ in equation (12), as proposed in the main text, only adds a constant to the instrument.

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

Here the first and the second equality used assumption (DC), which allows me to ignore the covariance between ϵ_{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.⁸ Assumption (TS) implies that (i) the time series in average 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 nurs-

⁸Notice that $\log(R_{-ct-4}^{mcaid})$ 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 in other counties, which is captured by $\log(AC_{-c,t-8}^{p(j)})$.

ing home share ρ 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

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

if $\text{cov}(\frac{\rho}{1-\rho} \overline{\log(AC_{-d}^{p(j)})}, \frac{\rho}{1-\rho} \overline{\log(AC_{-d'}^{p(j)})}) \geq 0$. The evidence presented in Appendix Section A.8.6, suggests relatively little spatial correlation in average costs across county boundary indicating 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

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

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:

$$\begin{aligned} \text{bias} &= \frac{\tilde{w} * \gamma_1}{1 - (1-\rho) * \tilde{w} * \gamma_1 * \phi^4} * \left[\frac{\overline{\text{cov}(\log(Y_{jt}), \log(AC_{c,t-8}^{p(j)})}}{\overline{\text{var}(\log(AC_{c,t-8}^{p(j)})}} \right. \\ &\quad \left. - \gamma_1 * \frac{\overline{\text{cov}(\log(R_{jt}^{mcaid}), \log(AC_{c,t-8}^{p(j)})}}{\overline{\text{var}(\log(AC_{c,t-8}^{p(j)})}} \right] . \end{aligned} \tag{14}$$

The bias term depends on the true parameter γ_1 . Building on the 2SLS estimator, I search

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

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 (13). 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 γ_1 .

To estimate the AR(1) coefficient ϕ , 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 A6. 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.5 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 A6.

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 γ_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 γ_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-though 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.

A.8.3 Ordinary Least Squares Results

The ordinary least squares regressions are subject to two biases: an omitted variable bias and a bias stemming from a simultaneity problem. To illustrate the effects of these biases, I simplify the Medicaid reimbursement formula and assume that the reimbursement rate is determined as follows:

$$R_{jt} = \eta_{jt} * \sum_k S_{jt}^k * exp(Y_{jt}^k) . \quad (15)$$

The reimbursement rate depends at least in part on previously reported own costs, which is captured by the right hand side variables. Specifically, $exp(Y_{jt}^k)$ denotes the number of employed skilled nurses, therapists, and nursing aides, and S_{jt}^k captures the respective annual compensations. η_{jt} denotes a common multiplicative input price shock, which directly affects staffing and pricing decisions. Combining equation (15) with equation (1) implies that we can express the ordinary least squares estimator for the effect of the log reimbursement rate on staffing and pricing decisions as follows:

$$\hat{\gamma}_1^{k,OLS} = \frac{cov(\log(Y_{jt}^k), \log(R_{jt}))}{var(\log(R_{jt}))} = \gamma_1^k + \frac{cov(\epsilon_{jt}^k, \log(R_{jt}))}{var(\log(R_{jt}))} +$$

$$= \gamma_1^k + \frac{\text{cov}(\epsilon_{jt}^k, \log(\sum_k S_{jt}^k * \exp(Y_{jt}^K)))}{\text{var}(\log(R_{jt}))} + \frac{\text{cov}(\epsilon_{jt}^k, \log(\eta_{jt}))}{\text{var}(\log(R_{jt}))}.$$

The second term captures the simultaneity bias. Y_{jt}^K depends positively on ϵ_{jt}^k , as evidenced by equation (1), which suggests a positive bias. The third term captures the omitted variable bias. Intuitively, a positive input price shock should lead nursing homes to lower staffing levels and to increase private rates. This indicates that the third term is negative for staffing decisions and positive for pricing decisions. Taken together, the total bias may be positive or negative for staffing decisions, depending on whether the simultaneity bias outweighs the omitted variable bias. Both effects indicate a positive bias for the effect on private rates. Table A7 presents the ordinary least squares regression results, which are consistent with this assessment.

A.8.4 Leave-One-Out Estimator

In this section, 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 A8.

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.

A.8.5 Alternative Exclusion Restrictions

In this section, 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 A9. 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.

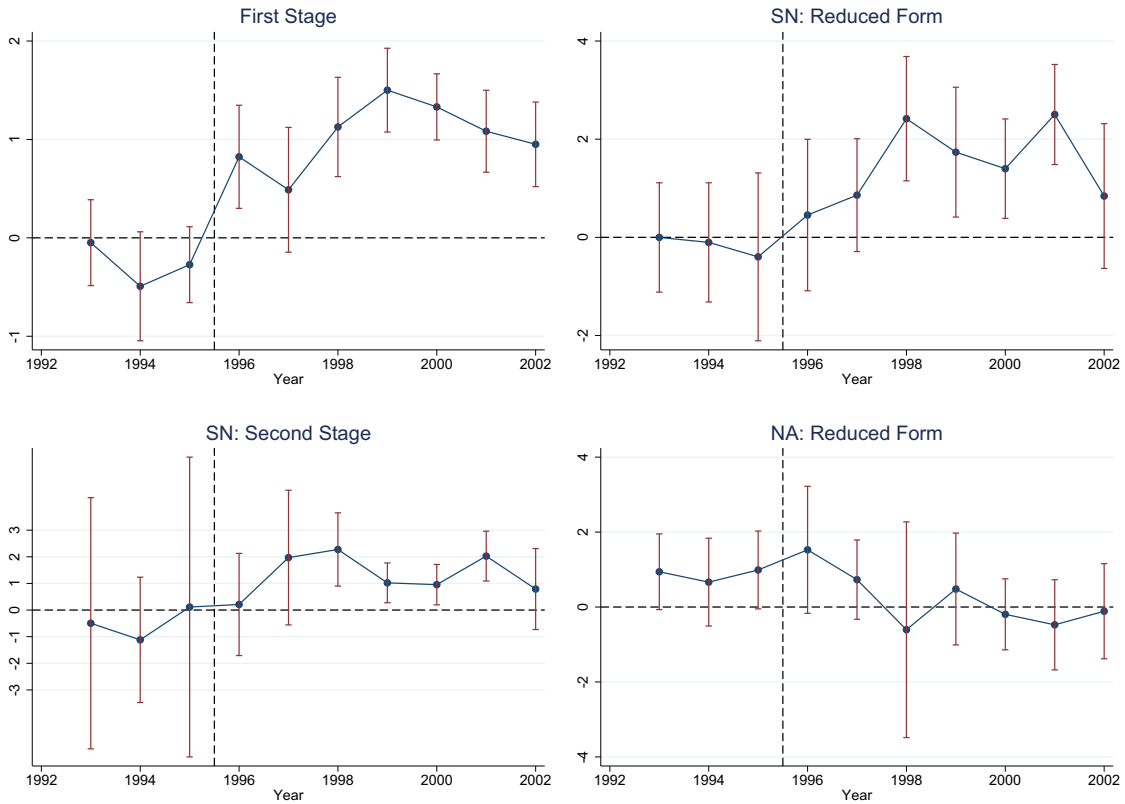
Change in Reimbursement Formula in 1996:

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 A7. 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.

Figure A7: Robustness to Change in Reimbursement formula in 1996



A.8.6 Other Inputs

In this section, 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 A10.

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 A11 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:

$$Z \rightarrow \log(R^{mcaid}) \rightarrow \log(SN^{res}) \rightarrow VC^{res,day} \quad (16)$$

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 16.

$$Z \rightarrow \log(SN^{res}) \rightarrow VC^{res,day} \quad (17)$$

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 ϕ_{ct} . I use the simulated Medicaid reimbursement rate as an instrument for skilled nurses. I report the β estimate in the second column of Table A11. 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 A11 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 A11 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.

A.9 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 A8 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 definition in the literature, see Miller et al. (2004) for example. In the bottom left graph of Figure A8, 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.

A.10 Further Details on the Two-Step Estimation Procedure

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 market 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.⁹ 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.

⁹The 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.

A.10.1 Computational Details on Weighting Matrix and Variance Covariance Matrix for Second Step

The second step of the analysis builds on the following five sets of moment conditions:

$$\begin{aligned}
G^{Demand}(\theta) &= \frac{1}{N} \sum_{\tau} \sum_t \sum_j \xi_{jt}^{\tau} * IV_{jt}^{\tau}, \\
G_{1,type}^{Cost}(\theta) &= \frac{1}{N} \sum_{\tau} \sum_t \sum_{j \in type} mc_{jt} - \frac{1}{N} \sum_{\tau} \sum_t \sum_{j \in type} MC_{jt} \\
G_{2,type}^{Cost}(\theta) &= \frac{1}{N} \sum_{\tau} \sum_{j \in type} w_{j,02} - \frac{1}{N} \sum_{\tau} \sum_{j \in type} W_{j,02} \\
G_3^{Cost}(\theta) &= \frac{1}{N} \sum_{\tau} \sum_t \sum_j \left[mc_{jt} - \frac{1}{N} \sum_{\tau} \sum_t \sum_j mc_{jt} \right]^2 - \frac{1}{N} \sum_{\tau} \sum_t \sum_j \left[MC_{jt} - \frac{1}{N} \sum_{\tau} \sum_t \sum_j MC_{jt} \right]^2 \\
G_4^{Cost}(\theta) &= \frac{1}{N} \sum_{\tau} \sum_j \left[\omega_{j,02} - \frac{1}{N} \sum_{\tau} \sum_j \omega_{j,02} \right]^2 - \frac{1}{N} \sum_{\tau} \sum_j \left[W_{j,02} - \frac{1}{N} \sum_{\tau} \sum_j W_{j,02} \right]^2,
\end{aligned}$$

see Section 4 for details. I refer to the stacked k -dimensional row vector over the set of moment conditions as:¹⁰

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

Here, the unit of observation i is a nursing-home-year-payer type.¹¹ 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

¹⁰Here, 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 $k = dim(IV) + 8$.

¹¹For example, $g_i^{Demand}(\theta) = \xi_i * IV_i$.

the demand moments provide three observations (one for each):

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

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_τ 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 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 $\hat{\theta}^{GMM}$, $Vcov$, is given by:

$$Vcov = B_0^{-1}\Omega_0B_0^{-1}$$

where

$$\begin{aligned}
 B_0 &= \Gamma'_0 W \Gamma_0 \\
 \Gamma_0 &= \frac{1}{N} * \sum_i \frac{dg_i(\tilde{\theta})}{d\theta'} \\
 \Omega_0 &= \Gamma'_0 W V_0 W \Gamma_0 .
 \end{aligned}$$

A.11 Goodness of Fit Based on Demand Moments

In this section, I discuss the cost model's cost estimates and the goodness of fit analysis in greater detail. The left graph of Figure A9 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 \$6 (4%) 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 0.5 indicating that a \$1 increase in the predicted marginal costs is associated with \$0.5 increase in observed marginal costs. The R-squared is 40%.

The right graph of Figure A9 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 0.24 and the R-squared decreases to 11%. 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 α_j , I set these parameters to 1, which implies profit-maximization. The left graph of Figure A10 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 3.6%. The difference equals about 11% for for-profits.¹² 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 5% 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.

A.12 Marginal Benefit and Social Planner’s Problem

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

A.12.1 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

¹²Intuitively, 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.

skilled nurse per resident, for residents in nursing home j , is given by

$$MB_j^{res,day}(SN^{res}) = -\frac{MU_{SN_j^{res}}^-}{MU_P} = -\frac{\frac{\beta^{sn} + \beta_{cm_j}^{sn} * C\bar{M}I_j}{SN_j^{res}}}{\beta_{priv}^p} = -\frac{\frac{\bar{\beta}_j^{sn}}{SN_j^{res}}}{\beta_{priv}^p}, \quad (18)$$

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, β_{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 (18) 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.¹³

Finally, the annual marginal benefit of an additional full-time equivalent skilled nurse is simply the product of equation (18) and the number of calendar days:

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

¹³The 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:

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

A.12.2 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:

$$-\frac{\bar{\beta}_j^{sn}}{SN_j^{res}} * 365 = W_j * 365 \forall j . \quad (19)$$

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 (19) 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 (19) 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 A12.

A.13 Minimum Staffing Regulations

The baseline analysis abstracts away from minimum staffing regulations that may affect the nursing home's staffing incentives. The minimum staffing regulation for skilled nurses, a category which comprises registered nurses and licensed nurses, requires 0.3 hours per resident and day in Pennsylvania, see Lin (2012). This translates into a staffing ratio 0.05 skilled nurses per resident assuming that nurses work 40 hours in each of 52 work weeks per year. In my sample, only one nursing home has a smaller staffing ratio of 0.045 skilled nurses per resident. However, a more careful analysis of the minimum staffing regulations indicates that the regulation applies only to registered nurses in Pennsylvania. The model treats registered and licensed practical nurses as perfect substitutes which may understate the importance of minimum staffing regulations to the extent that they are not. Focusing solely on registered nurses increases the fraction of nursing homes with a smaller staffing ratio than 0.05 to only about 3.4%. Figure A11 displays a histogram of the registered nurse staffing ratio for the 25% nursing homes with the smallest registered nurse staffing ratios. The vertical red line indicates the minimum staffing ratio. I find no evidence for bunching around the minimum staffing ratio suggesting that these regulations play only a minor role in my sample population.

A.14 Directed Entry in Urban Counties

In this section, 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 A13 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 \$5.2 million per year as indicated by the third row in the third column. On the other hand, consumer surplus increases by \$6 million per year. The increase stems largely from gains in variety (\$5.6 million) which may be interpreted as an upper bound as discussed in Section 6. Considering the annual increase in public spending of \$0.3 million, I find an annual welfare gain of \$0.5 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 0.3%, which is smaller than the estimated increase based on entry in rural counties (0.5%). Private rates increase slightly by 0.1% whereas they decreased by -0.2% following directed entry in rural counties. To put the staffing estimates into perspective, I construct again 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 A13. I find a return on public spending of only 1.3% when I consider the new entrants' annual losses of \$2.6 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 3. The return of directed entry in urban counties is also smaller than the return of directed entry in rural (potentially less competitive) counties of 1.5%. Finally, considering the entire industry losses as required public spending reduces the return to 0.6% which falls short of the comparable return on Medicaid spending by a factor of $6.5/0.57=11.4$.

A.15 Details on Rationing

In this section, I discuss the role of rationing for my baseline analysis in greater detail.

A.15.1 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 τ 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:

$$S_{t\tau j}(Occ_{tj}) = \begin{cases} A_{t\tau j}^* & \text{if } Occ_{tj} \leq 0.9 \\ A_{t\tau j}^* * [1 - R_{t\tau j}^*(Occ_{tj})] & \text{else} \end{cases} , \quad (20)$$

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 (20) by payer type at the nursing home-week level using the following linear regression model:

$$S_{t\tau j} = \sum_{k=75}^{100} \gamma_{\tau}^k Occ_{jt}^k + \phi_{year,\tau,j} + \epsilon_{t\tau j} . \quad (21)$$

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 A12 presents the estimated fixed effects γ_{τ}^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 (20) and (21), I can express this ratio as follows:

$$\begin{aligned}
\frac{E[\sum_{tj, Occ_{tj} \geq x} A_{t\tau j}^* R_{t\tau j}^*]}{E[\sum_{tj} S_{t\tau j}]} &= \frac{E[\sum_{tj, Occ_{tj} \geq x} A_{t\tau j}^*] - E[\sum_{tj, Occ_{tj} \geq x} S_{t\tau j}]}{E[\sum_{tj} S_{t\tau j}]} \\
&= \frac{\sum_{tj, Occ_{tj} \geq x} E[A_{t\tau j}^*] - \sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ_{tj} \geq x]}{E[\sum_{tj} S_{t\tau j}]} \\
&= \frac{\sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ = 0.9] - \sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ_{tj} \geq x]}{E[\sum_{tj} S_{t\tau j}]} \\
&= \frac{\sum_{tj, Occ_{tj} \geq x} E[S_{t\tau j} | Occ_{tj} \geq x] \left(\frac{E[S_{t\tau j} | Occ = 0.9]}{E[S_{t\tau j} | Occ_{tj} \geq x]} - 1 \right)}{E[\sum_{tj} S_{t\tau j}]} \\
&= \frac{E[\sum_{tj, Occ_{tj} \geq x} S_{t\tau j}]}{E[\sum_{tj} S_{t\tau j}]} * \left(\frac{\gamma_{\tau}^{90}}{\gamma_{\tau}^{\bar{x}}} - 1 \right) \\
&= \underbrace{\frac{E[\sum_{tj, Occ_{tj} \geq x} S_{t\tau j}]}{E[\sum_{tj} S_{t\tau j}]}_A} * \underbrace{\frac{\gamma_{\tau}^{90} - \gamma_{\tau}^{\bar{x}}}{\gamma_{\tau}^{\bar{x}}}}_B. \tag{22}
\end{aligned}$$

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, γ_{τ}^{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 (21) by a single indicator variable that turns on when the occupancy rate exceeds x .

Estimates of factor A are displayed in Table A14 and equal 2% ($x > 100\%$), 15% ($x >$

97%), and 29% ($x > 95\%$) for all payer types as indicated in the first column. Estimates of the second factor, B, are displayed in Table A15, 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.

Finally, I multiply the estimates from Table A14 and A15 as indicated by equation (22). 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 A14 and A15, 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.

A.15.2 Robustness: First Come First Served

First, I consider the effects of a universal capacity constraint for all payer types. Specifically, I consider a capacity limit of 100% occupancy and assume that residents are admitted on a first-come-first-served basis. Consequently, I leave only those nursing homes in the senior's choice set that have at least one open bed on the day the resident was admitted to any nursing

home. Using the revised choice set, I estimate the preference parameters excluding the cost moments in the second step.¹⁴ The parameter results are presented in the third column of Table A16 and are similar to the baseline parameter estimates presented in the fifth column of Table 3. The key parameters differ by at most 26%.¹⁵ The estimates from the third column of Table A16 indicate even larger welfare gains from an increase in Medicaid reimbursement rates for the following two reasons. First, the slightly larger preference parameter for the number of skilled nurses per resident indicates that nursing home demand responds more elastically to the quality of care. This encourages nursing homes to raise their staffing ratios even further. Second, the consumer gains from an increase in the number of skilled nurses are larger as evidenced by the larger marginal benefit estimate, which exceeds the baseline estimate from column 5 of Table 3 by 19%.

A.15.3 Asymmetric Rationing Based On Payer Type

Second, and motivated by heterogeneous reductions in weekly admissions across payer types, I consider an alternative asymmetric rationing models. Here, I add an indicator variable to the indirect conditional utility function, interacted with payer type, that turns on if the average occupancy of the nursing home in the respective week falls short of 97% and 95%, respectively. These interaction terms capture potential access constraints in a reduced form way. Specifically, I extend the indirect conditional utility function from equation (4) as follows:

$$\begin{aligned}
u_{irjt} &= \beta_1^d * D_{ij} + \beta_2^d * D_{ij}^2 + \beta_i^{sn} * \log(SN_{jt}^{Res}) + \sum_x \beta_i^x X_{jt} + \beta_\tau^p * P_{jt} + \xi_{jt}^\tau + \epsilon_{ijt} \\
&+ \vartheta * 1\{occupancy_{ij} < \overline{occ}\} \\
&+ \vartheta_{hyb} * 1\{occupancy_{ij} < \overline{occ}\} * 1\{\tau = hybrid\} \\
&+ \vartheta_{priv} * 1\{occupancy_{ij} < \overline{occ}\} * 1\{\tau = private\} .
\end{aligned}$$

¹⁴Cost moments can be included but require a supply side model that takes rationing into account.

¹⁵The price coefficient for hybrid payers differs by 45% but this coefficient is not relevant for the marginal benefit calculation.

The first row replicates the indirect utility function from the baseline model, see equation (4), but rows 2-4 add the new interaction terms. $1\{occupancy_{ij} < \overline{occ}\}$ is an indicator variable that turns on if nursing home j 's weekly average occupancy rate falls short of the threshold of 97% or 95% in the week in which senior i is admitted to any nursing home. $1\{\tau = hybrid\}$ and $1\{\tau = private\}$ are indicator variables that turn on if senior i is a hybrid or a public payer, respectively.

The results are summarized in columns 5 and 7 of Table A16. The first interaction effect, ϑ , is positive indicating the seniors are, all else equal, more likely to choose a nursing home with an occupancy of less than 97% or 95%. This suggests that capacity constraints restrict access to nursing home care for all payer types, possibly through a first-come-first serve admission process. The interaction terms, ϑ_{hyb} and ϑ_{priv} are negative indicating that rationing is less pronounced for hybrid and private payers. However, these estimates are relatively small when compared to the overall effect suggesting that selective admissions based on payer type play a potentially minor role in the sample period.

Most importantly for my analysis, the implied preference parameters from the first two panels are very similar to the baseline estimates presented in the fifth column of Table 3. Comparing the estimates parameter by parameter, I find that the estimates from Table A16 differ from the baseline estimates by at most 15%. The estimates from columns 5 and 7 in Table A16 also suggest a higher marginal benefit of a skilled nurse, which exceeds the baseline estimates by 11% and 23% in the case of the 97% and the 95% threshold, respectively.

In summary, the presented evidence suggests that controlling for (selective) rationing leaves the main preference parameters and the qualitative conclusions largely unchanged.

A.15.4 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 A17 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.

A.16 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.

A.16.1 Staffing recommendations from the Literature

First, I contrast my findings to staffing recommendations from the literature (Harrington et al. (2000)). In 1998, a group of national experts including nurse researchers, educators and administrators in long term care, consumer advocates, health economists, and health services researchers convened for a conference at New York University, to discuss adequacy in staffing levels in U.S. nursing homes. The expert group recommended that the skilled nurse hours per resident day should at least equal 1.85 hours, which corresponds to a skilled nurse staffing ratio of about 0.32, see the second row of Table A18.¹⁶ This ratio exceeds the average staffing ratio in 2000 of 0.24 by 35%. This estimate corresponds well to the optimal staffing ratio of 0.37, predicted by the social planner's problem which depends directly on the baseline

¹⁶The 1.85 hours recommendation combines 1.15 hours for registered nurses and 0.7 hours for licensed practical nurses per resident and day, see Table 2 in Harrington et al. (2000). Assuming again that nurses work 40 hours per week in 52 weeks of the year, I find a required staffing ratio of $1.85 \cdot 365 / (40 \cdot 52) = 0.32$.

marginal benefit calculation.

A.16.2 Health Returns Approach

Second, I calculate the marginal benefits of an additional skilled nurse by multiplying the health benefits with the statistical value of life. Friedrich and Hackmann (2017) take advantage of a natural experiment in Denmark from 1994 to quantify the mortality effects of an additional skilled nurse. The authors find that a federally funded parental leave program reduced the number of skilled nurses in nursing homes by 670 nurses and increased nursing home mortality by 900 to 1,700 elderly per year. Ignoring other health benefits from higher staffing levels and assuming that the dying elderly lose only one year of their residual life, each skilled nurse saves $900/670=1.34$ to $1,700/670=2.5$ life years per year. I multiply the mortality effect by the quality-of-life-adjusted statistical value of a life year for an 85 year old of \$62,000, see Cutler et al. (1997). This suggests a benefit of an additional skilled nurse of about $900/670*\$62,000=\$83,284$ to $1,700/670*\$62,000=\$157,313$ per year, see the third row of Table A18. These estimates encompass my baseline estimate of \$126,000.

A.16.3 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:¹⁷

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

subject to the asset constraint listed below. Here, t is the individual's current age. T is the

¹⁷I 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.

maximum possible age, β discounts the future, and δ_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 ϕ 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 ω_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 order condition with respect to consumption at age t :

$$\frac{d}{dc_t} U = u'(c_t) - \sum_{a=t+1}^{T+1} \beta^{a-t} \left(\prod_{s=t}^{a-1} (1 - \delta_s) \right) \delta_a v'(b_a) \left(\prod_{s=t}^{a-1} (1 - r_s) \right) = 0. \quad (23)$$

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 A19 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 (23) 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 A20 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 A20 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 A20.

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 (23). 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 τ and b_i^τ 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 $0.15 * \$126,300 + 0.85 * \$91,600 = \$96,800$.

A.16.4 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 A13 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.¹⁸ I also add a second interaction term, $Rich_{it}$, that turns on for richer private payers with predicted residual tangible wealth levels of more

¹⁸I 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.

than \$140,000. The extended indirect conditional utility function equals:

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

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 A21.¹⁹ 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 A13 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 A21 imply that Medicaid beneficiaries, with a residual tangible 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

¹⁹The estimation strategy only exploits the demand moments in the second step.

5.9%. Following equation (18), I increase the baseline marginal benefit estimate of \$126,320 by 5.9% delivering a new estimate of \$133,750.

A.17 Substitution between different forms of Long Term Care

In this section, I investigate substitution patterns between nursing home care and other forms of community based long term care, which I ignore in the baseline analysis. One potential concern is that quality improvements, triggered by increases in Medicaid reimbursement rates, may lead to a market expansion if seniors substitute away from alternative forms of long term care. This may increase public spending, tighten capacity constraints, and ultimately lower the welfare gains from Medicaid rate increases. Counter to these concerns runs a large body of previous work, which finds that substitution between nursing home and community based forms of long term care is relatively inelastic. Nevertheless, to assess the potential implications in this context, I investigate the role of substitution patterns using Census data from 2000. To this end, I add an outside good to the baseline demand model and revisit the counterfactual experiments. This allows me to shed light on the robustness of my main findings with respect to a potential market expansion. I also revisit the findings under the directed entry counterfactual and conclude with a comparison of the effectiveness in raising the quality of care.

A.17.1 Census Data and Direct Evidence

To provide direct evidence on the significance of substitution patterns between nursing home and other forms of long term care, I exploit data from the 5% sample of the 2000 Census, available through the Integrated Public Use Microdata Series (IPUMS).²⁰ This nationally representative sample provides information on seniors living inside and outside of nursing homes at the county level.²¹ I restrict the sample to seniors aged 65 and older residing in

²⁰<https://usa.ipums.org/usa/>, last accessed September 25th, 2017.

²¹In some instances, the county code only identifies a small group of neighboring counties when the underlying population is too small. In Pennsylvania, I can divide the 67 counties into 40 adjacent regions.

Pennsylvania. Similar to Ching, Hayashi and Wang (2015), I focus on seniors who indicate a “physical or mental health condition that has lasted at least 6 months and makes it difficult for them to take care of their own personal needs, such as bathing, dressing, or getting around inside the home.” This is a plausible pre-requisite for considering any long term care support and institutional nursing home care in particular.²² To distinguish between seniors living inside and outside of nursing homes, I explore residential information collected by the Census, which distinguishes between housing units and group quarters. A group quarter refers to a “group living arrangement , that is owned or managed by an entity or organization providing housing and/or services for the residents.” This includes places as nursing homes, college residence halls, and military barracks, for example.²³ It stands to reason that the group quarter definition provides a plausible proxy for nursing home residence given the sample composition of seniors with physical or mental conditions.

Scaling the sample to the full population, I find that about 30% of the 225,000 seniors with physical or mental conditions live in a nursing home. This is consistent with the evidence from the MDS used in the baseline analysis, as indicated in Figure A14. The figure plots the number of nursing home residents by county, based on the Census data, on the horizontal axis, against the observed number of residents in the MDS in 2000, on the vertical axis. A simple bivariate linear regression model suggests a slope of 0.82 and an R-squared of 87%.

Turning next to the substitutability of different forms of long term care, I investigate the relationship between the overall nursing home demand and the average nursing home quality at the county level. Figure A15 plots the share of seniors in nursing home care on the vertical axis against the average log number of skilled nurses per resident across nursing homes on the horizontal axis.²⁴ I find no evidence for a positive correlation between the quality of care and the overall demand for nursing home care. A simple bivariate regression model suggest a small statistically insignificant coefficient of 0.038 (t-value=0.25) with an R-squared of less

²²This information is collected in variable `diffcare`, see https://usa.ipums.org/usa-action/variables/DIFFCARE#description_section, last accessed September 25th, 2017.

²³See <https://www.nap.edu/read/13387/chapter/4> for more details, last accessed September 25th, 2017.

²⁴Tying this analysis to the baseline sample population, I construct the share of seniors in nursing home care by dividing the resident numbers from the MDS by the overall senior population in the Census data.

than 0.2%.

Of course, unobserved quality attributes of the other forms of long term care and or nursing home care may add bias to the bivariate regression output. To assess this possibility, I also explore an instrumental variables strategy. Unfortunately, I am not able to explore exogenous variation in the Medicaid reimbursement rate as I can not control for confounding cross-sectional variation via county fixed effects. Instead, I use skilled nurse salaries as a source of variation in average nurse staffing ratios between counties. Consistent with the supply side model presented in the baseline analysis, I assume that nursing homes reduce the skilled nurse staffing ratio following an increase in local salaries for skilled nurses. I also assume that nurse salaries do not correlate with other forms of long term care, who rely significantly less on skilled nurses. These assumptions allow me to revisit the OLS evidence in a 2SLS regression model. Turning to the results, the first stage estimates suggest a statistically significant negative effect of local salaries for registered nurses on the skilled nurse staffing ratio (t value=-2.85). However, the second stage estimates remain statistically insignificant (t-value -.56) and now even suggest a negative relationship between the quality of care and the overall demand for nursing home care.

Overall, I find no direct evidence for an elastic market level demand response for nursing home care as the quality of nursing home care changes. Consistent with the existing literature, this may mitigate concerns regarding a substantial market expansion following an increase in Medicaid rates and consequently the quality of nursing home care. However, I acknowledge that remaining concerns regarding the identifying variation in the quality of care may compromise the conclusions from this descriptive analysis. Therefore, I proceed by exploring the potential impacts of a market expansion on the main findings of this study, using a conservative extended demand framework that allows for substitution between different forms of care.

A.17.2 Extended Demand Model with Outside Good

In this section, I extend the baseline demand analysis by adding an outside good, which comprises the demand for other formal and informal forms of long term care. To be conservative, I assume that the utility for the outside good is additive in the mean utility component $\delta_{c(i),out}$, which may differ between counties c , and an extreme value taste shock $\epsilon_{i,out}$, such that

$$u_{i,out} = \delta_{c(i),out} + \epsilon_{i,out} .$$

Specifically, I do not model an additional correlated taste shock among the inside goods, which could be captured in a nested logit framework, as this would reduce the demand elasticity between the outside and the inside goods and thereby weaken the market expansion effect.²⁵

Identification and Estimation: The estimation strategy builds on the baseline strategy outline in the main text. 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

²⁵I have also considered a nested logit specification with

$$\begin{aligned} u_{ij} &= \delta_{ij} + \varsigma_{i,in} + (1 - \sigma)\epsilon_{ij} \\ u_{i,out} &= \delta_{c(i),out} + \varsigma_{i,out} + (1 - \sigma)\epsilon_{i,out} , \end{aligned}$$

where ϵ_{ij} is again identically and independently distributed extreme value. For consumer i , the variable $\varsigma_{i,in}$ is common to all inside goods and has a distribution that depends on σ , with $0 \leq \sigma < 1$. Here, ς is the unique distribution with the property that $\varsigma + (1 - \sigma)\epsilon$ is distributed extreme value, see Cardell (1997). Intuitively, as σ approaches 0, the within group correlation in utility through ς goes to zero and we are back in the logit model. On the other hand, as σ goes to 1, the within nest correlation goes to 1 and there will be relatively little substitution between the inside goods and the outside good. Berry (1994) shows that σ can be recovered from the following simple linear regression model

$$\ln(s_j) - \ln(s_{c,out}) = \delta_j + \sigma \cdot \ln(1 - s_{c,out}) ,$$

where s_j is nursing home j 's market share in the county and $s_{c,out}$ is the share of seniors in the county that choose not to live in a nursing home. The OLS results imply a 95% confidence interval for σ of [0.49, 1.95] suggesting that the logit model with $\sigma = 0$ will considerably overstate the substitution patterns at the extensive margin. Again this finding should be interpreted with caution as it ignores the endogeneity concerns in $\ln(1 - s_{c,out})$.

market shares are commonly referred to as “inside” market shares and given by:

$$s_{ij|in} = \frac{\exp(\delta_{ij})}{\sum_{k \in C_i^{in}} \exp(\delta_{ik})}.$$

Here, δ_{ij} denotes senior i 's indirect conditional utility for nursing home j and C_i^{in} is senior i 's inside choice set, which excludes the outside good. This inside market share in this extended model is equivalent to the nursing home choice probabilities outlined in Section 4 of the baseline analysis. Therefore, I simply repeat the first step from the baseline strategy using the sample of nursing home residents, which leaves the preference parameters governing taste heterogeneity as well as the mean utilities (by payer type τ) for inside goods $\delta_{\tau j}$, defined in equation (8), unchanged.

Turning next to the demand for the outside good, I add the Census information on seniors that remain in the community to identify the mean utility parameters for the outside good. Specifically, I use an inversion technique that holds the demand for each inside good j in days, $D_{j|in}$, fixed:

$$\begin{aligned} D_{j|in} &= \sum_i s_{ij|in} * LOS_i \\ &= \sum_i \phi_i * s_{i,in} * s_{ij|in} * LOS_i . \end{aligned}$$

Here, the first row replicates the baseline prediction, which simply scales the corresponding “inside” share with the senior’s length of stay, LOS_i , summed up over all seniors. The second row introduces the outside good, by considering 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 type i that trade-off between different forms of care. In the estimation, I assume that the number of seniors of type i , ϕ_i , equals the inverse inside share in the sample population. Of course, ϕ_i is policy invariant and held fixed in the counterfactual experiments.

Building on the structure of the demand model, I have:

$$\phi_i = \frac{1}{s_{i,in}} = \frac{1}{\frac{\sum_{j \in CS_i^{in}} \exp(\delta_{ij})}{\exp(\delta_{c,out}) + \sum_{j \in CS_i^{in}} \exp(\delta_{ij})}} = \frac{\exp(\delta_{c,out}) + \sum_{j \in CS_i^{in}} \exp(\delta_{ij})}{\sum_{j \in CS_i^{in}} \exp(\delta_{ij})}, \quad (24)$$

suggesting that the indirect conditional utilities over the “baseline” product characteristics specify ϕ_i . Closing the empirical model, I leverage information on the number of seniors living in the community $Sen_{c,out}$, which I observe in the Census data, to pin down $\delta_{c,out}$. Specifically, I have:

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

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

$$\exp(\delta_{c,out}) = \frac{Sen_{c,out}}{\sum_i \frac{LOS_i}{365 * \sum_{j \in CS_i^{in}} \exp(\delta_{ij})}}. \quad (25)$$

Finally, I update the first order conditions with respect to pricing and staffing decisions to take substitution between different forms of care into account. Importantly, the derivatives of nursing home j 's market share with respect to pricing and staffing decisions change as follows:

$$\frac{\partial s_{ijt}}{\partial Q_{jt}} = \frac{\partial(\phi_i * s_{i,in} * s_{ij|in})}{\partial Q_{jt}} = \underbrace{\phi_i * s_{ij|in} * \frac{\partial s_{i,in}}{\partial Q_{jt}}}_A + \underbrace{\phi_i * s_{i,in} * \frac{\partial s_{ij|in}}{\partial Q_{jt}}}_B.$$

Here, Q_{jt} refers to the private rate or the number of skilled nurses per resident. Term B captures the derivative of the baseline analysis as $\phi_i = \frac{1}{s_{i,in}}$. The new term A captures substitution at the extensive margin. Intuitively, allowing for additional marginal seniors at the extensive margin increases the overall demand elasticity. This in turn implies smaller price markups, which would be rejected by the data. Therefore, the empirical model will rationalize observed markups with smaller price and quality preference coefficients, counteracting the effect of the market expansion on the demand elasticities. I will come back to this point

below.

Computational Details: To incorporate the aforementioned changes, I extend the estimation strategy as follows. The first step of the empirical baseline strategy remains unchanged delivering identical mean utilities for the inside goods and preference coefficients governing preference heterogeneity in observable senior demographics. Building on the mean utilities for the inside goods, I then recover the mean utilities for the outside goods using equation (25) before quantifying ϕ_i using equation (24). Turning to the second step of the empirical strategy, I leave the baseline demand moments, G^{Demand} , unchanged and update the cost moments G_1^{Cost} , G_2^{Cost} , G_3^{Cost} and G_4^{Cost} using the outside good mean utilities and ϕ_i as discussed above. Finally, I estimate the remaining consumer preference, marginal cost, and nursing home objective parameters using the updated moment conditions.

A.17.3 Results

Turning to the results, Table A22 presents the key demand and nursing home objective parameter estimates. As outlined above, the parameter estimates from the first step, presented in the second panel, remain unchanged and are identical to the baseline estimates from Table 3. The estimate for β^{sn} and β_{priv}^p drop by 11% and 15%, respectively. This is as expected, since the model rationalizes observed markups with smaller preference coefficients when the overall market size expands. Importantly, both parameters decrease roughly proportionately, leaving the marginal benefit of a skilled nurse largely unchanged. The new estimate suggests a marginal benefits of about \$123k, which deviates from the baseline estimate by only 2.4%. This implies that the normative implications concerning the observed nurse staffing ratio remain unchanged. The price coefficient for hybrid payers and the objective parameters are almost identical to the baseline estimates.

Universal Medicaid Increase: I now turn to the implications for the counterfactual analysis. To this end, I revisit the exercises from the baseline analysis using the expanded sample and the revised parameter estimates and allowing for substitution between inside goods

and the outside good. The counterfactual results under a universal 10% increase in Medicaid reimbursement rates are presented in the first two columns of Table A23. The average change in the skilled nurse staffing ratio and the price for private payers are remarkably similar to baseline findings, differing by only 0.1 and 0.4 percentage points, respectively. Increases in quality and reductions in private rates increase consumer surplus annually by 212 million, which exceeds the baseline estimate by 4.3%. This is because quality improvements and price reductions now lead to a 6.7% market expansion in the demand for nursing home care.

Nursing home profits increase by 149 million per year which exceeds the estimated increase in the baseline analysis by 59 million per year, in parts because of smaller changes in staffing and pricing but mostly because of the market expansion. This estimate translates approximately into a variable profit margin of about \$45 per day over new nursing home residents.²⁶ To provide a conservative estimate for changes in profits, this estimate is net of changes in variable profits over Medicare beneficiaries because of the market expansion.²⁷

Finally, Medicaid spending increases by \$331 million annually, which exceeds the estimated increase in the baseline analysis by \$105 million because of an additional 790 thousand Medicaid days for seniors, who previously lived in the community. The spending estimate nets out savings in Medicaid spending of \$30,000 per year and beneficiary on home and community based services.²⁸ Overall, the estimates suggest an annual net welfare gain of \$31 million or about 9% of additional Medicaid spending. The estimate falls short of the baseline estimate by \$37 million largely because of an increase in Medicaid beneficiaries who now demand more expensive long term care.

I contrast these estimates to a more conservative analysis of consumer welfare, presented in the latter columns. This analysis takes the potential effect of rationing into account.

²⁶Here, I simply divided the difference in profits by the overall increase in nursing home days: \$59 million/1.31 million = \$45 per day.

²⁷To construct the variable Medicare profits per Medicare day, I take the daily Medicare reimbursement rate and subtract from it the marginal cost estimate for Medicare beneficiaries, which I derive from cost data of hospital based nursing homes which primarily target Medicare beneficiaries. I make this adjustment because I do not consider changes in Medicare spending in the spending analysis.

²⁸See <https://www.kff.org/medicaid/report/medicaid-home-and-community-based-services-programs-2012-data-update/> for details, last accessed October 24th, 2017.

While the demand for nursing home care increases by only 6.7% in the previous exercise, 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, $\{D_1, D_2, \dots, D_R\}$.²⁹ 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.

Entry Analysis: Next, I turn to the counterfactual results under directed entry, which are presented in the top panel of Table A24. Compared to the baseline estimates from Table 5, I find slightly smaller increases in the skilled nurse staffing ratios (0.02% compared to 0.05%) and smaller reductions in the private rate (0.0% compared to -0.02%), as evidenced in the last column. This explains the slightly smaller reduction in provider profits by \$4.9 million

²⁹An 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.

compared to a \$5.5 million reduction in the baseline analysis.

The new entrants incur losses of \$3.3 million per year as their variable profits are not sufficiently high to cover the fixed costs. This estimate is almost identical to the baseline finding largely because the market expands only slightly in this counterfactual. The demand for nursing home care increases by only 0.02% and about 90% of the residents in the newly entering nursing homes substituted away from rival nursing homes. This also explains why the estimated increase in consumer surplus and public spending of \$3.8 million and \$0.3 million, respectively, are almost identical to the baseline estimates. Overall, I find an annual reduction in social welfare of \$1.4 million compared to a \$2.1 million reduction in the baseline analysis.

Finally, I turn to a comparison of the two policy interventions in raising the quality of nursing home care. To provide a conservative comparison of the returns to public spending, I benchmark the quality increases in the Medicaid expansion exercise to the larger spending increase under no rationing. As expected, I find a smaller quality return on increasing Medicaid reimbursement of only 2.63% per extra \$100 million in annual spending, see the first row. While this estimate falls short of the baseline return of 3.9% it still exceeds the baseline return from entry by about 75%. In particular, the return on Medicaid spending compares even more favorably to the return on entry, when allowing for an outside good in the entry analysis as well. Here, I find a return of only 0.6% which is about 4 times smaller than the return on Medicaid spending. Finally, when adjusting for changes in provider profits, that can either be taxed away in case of profits or must be reimbursed in case of losses, I find that the return on Medicaid spending exceeds the return on entry by a factor of 11.7.

Taken together, the presented evidence indicates that allowing for an outside leaves the parameter estimates as well as counterfactual changes in quality and pricing largely unchanged but may reduce the welfare gains from increasing Medicaid reimbursement rates by \$37 to \$54 million per year. However, the welfare effects remain positive and compare favorably to the welfare losses under directed entry. This is further corroborated by the direct comparison of the quality returns on public spending. Therefore, I conclude that the main conclusions of

this study are robust to the potential substitution patterns between different forms of long term care.

A.18 Non-Pecuniary Objectives

In the baseline analysis, I assume that not-for-profits and public nursing homes maximize a weighted average of profits and quantity, see equation (5). In this section, I consider an alternative objective function in which not-for-profits and public nursing homes maximize a weighted average over profits and the quality of care measured by the number of skilled nurses per resident. Specifically, I consider the following objective function:

$$U_{jt} = \alpha_j * \Pi_{jt} + (1 - \alpha_j) * SN_{jt}^{res} , \quad (26)$$

with $\alpha_j = 1$ for for-profit nursing homes.

A.18.1 Different Objective Functions in Theory

Before I turn to the empirical evidence, I first discuss the differences in the implied first order conditions. Starting with private rates, I find the following first order condition in the baseline model:

$$\tilde{R}_{jt} - MC_{jt} = - \frac{\sum_i s_{ijt} * Days_i^{priv}}{\sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} * LOS_i} - \frac{1 - \alpha_j}{\alpha_j} . \quad (27)$$

Here, $Days_i^{priv}$ denotes again the number of days during i 's stay that are paid out-of-pocket. For example, $Days_i^{priv} = 0$ for public payers, who are covered by Medicaid or Medicare throughout their stay, $Days_i^{priv} = LOS_i$ for private payers who pay all days out-of-pocket and $0 < Days_i^{priv} < LOS_i$ for hybrid payers, who pay some but not all days out-of-pocket. \tilde{R}_{jt} is a weighted average price per resident day among residents that pay at least some days out-of-pocket in nursing home j . For example, the price equals simply the private rate if there are no hybrid payers in the nursing home. Mathematically, $\tilde{R}_{jt} = \frac{\sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} * LOS_i * \bar{R}_{ijt}}{\sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} * LOS_i}$ where \bar{R}_{ijt} is the average revenue per resident day for resident i over the course of i 's entire nursing

home stay. Again this would be just the private rate if i is a private payer. Intuitively, the left hand side can be interpreted as a markup over marginal costs. A positive weight on quantity, $0 < 1 - \alpha_j < 1$, can then rationalize a smaller markup for not-for-profits compared to for-profit nursing homes, all else being equal. In other words, a positive weight on quantity in the objective function is equivalent to a reduction in the marginal cost per resident day from the point of view of the nursing home.

This is not true under the alternative objective function that places positive weight on quality as outlined in equation (26). In this case, the first order condition for private rates equals:

$$\tilde{R}_{jt} - MC_{jt} = - \frac{\sum_i s_{ijt} * Days_i^{priv}}{\sum_i \frac{\partial s_{ijt}}{\partial P_{jt}} * LOS_i}, \quad (28)$$

which misses the additive correction term. Hence, this model will have a hard time reconciling potential differences in the markup between for-profits and not-for profits. I will come back to this point below.

Next, I review the first order conditions for the quality of care. In the baseline model, the first order condition for skilled nurses per resident equals:

$$SN_{jt}^{res} = \frac{\sum_i \frac{\partial s_{ijt}}{\partial \log(SN_{jt}^{res})} * (\bar{R}_{ijt} - MC_{jt}) * LOS_i}{W_{jt} * \sum_i s_{ijt} * LOS_i} + \frac{\sum_i \frac{\partial s_{ijt}}{\partial \log(SN_{jt}^{res})} * LOS_i * \frac{1-\alpha_j}{\alpha_j}}{W_{jt} * \sum_i s_{ijt} * LOS_i} \quad (29)$$

where ω_{jt} denotes the compensation of a skilled nurse. Under model (26), the first order condition for skilled nurses equals:

$$SN_{jt}^{res} = \frac{\sum_i \frac{\partial s_{ijt}}{\partial \log(SN_{jt}^{res})} * (\bar{R}_{ijt} - MC_{jt}) * LOS_i}{W_{jt} * \sum_i s_{ijt} * LOS_i} + \frac{\frac{1-\alpha_j}{\alpha_j}}{W_{jt} * \sum_i s_{ijt} * LOS_i} \quad (30)$$

Both first order conditions have a positive additional summand for nonprofits if they place positive weight on profits and quantity or quality, $0 < 1 - \alpha_j < 1$. This holds true in equation (29) because $W_{jt} > 0$ and $\frac{\partial s_{ijt}}{\partial \log(SN_{jt}^{res})} > 0$. In both cases, the positive summand provides suggestive evidence for higher staffing ratios for nonprofits, all else being equal. I will come

back to this point below.

Notice as well, that equations (27), (28), (29), and (30) indicate that the staffing ratios and marginal costs are additively separable in the role of Medicaid rates, which enters through \bar{R}_{ijt} , and the non-pecuniary objective $1 - \alpha_j$. This suggests that the non-pecuniary effects can reconcile cross-sectional differences in staffing ratios and private rates. However, the lack of interaction effects also suggests that the estimated counterfactual staffing effects of changes in the Medicaid reimbursement rate may be robust to alternative non-pecuniary objectives. I will come back to this observation in the empirical analysis.

A.18.2 Empirics on Different Objective Functions

Motivated by the differences in the first order conditions, I start by reviewing differences in markups between for-profits, not-for-profits, and public nursing homes. The top row of Figure A16 compares the average revenue over residents that pay at least some portion of their stay out-of-pocket and the marginal costs per resident and day between nursing homes of different ownership types. These correspond to the left hand side summands in equation (27) and (28). While the average revenues per resident and day are relatively similar across ownership types, the cost reports indicate larger marginal costs for not-for-profits and publicly operated nursing homes in particular.

Combining the evidence on revenues and marginal costs, we see that not-for-profits and public nursing homes have smaller markups than for-profits as evidenced by the left bars in the second row of of Figure A16. The baseline model is able to capture these differences as evidenced by the middle bars through the adjustment term $\frac{1-\alpha_j}{\alpha_j}$ as outlined in equation (27). The baseline estimates from the third column of the second block of Table 3 suggest that the non-pecuniary motives reduce the markup by \$24.66 and \$37.96 per resident and day for not-for-profits and public nursing homes, respectively. In contrast, the alternative model that includes a non-pecuniary quality motive in the objective of not-for-profit and public nursing homes cannot explain the observed differences in markups. The right hand bars in the second

row of Figure A16 indicate larger markups for non-profits and public nursing homes. The mismatch between observed and estimated markups in this model is not particularly surprising since the non-pecuniary objectives do not directly enter the first order condition on prices, see equation (28).

Next, I turn to potential differences in nurse staffing decisions between nursing homes of different ownership types, which are summarized in Figure A17. The top row indicates slight differences in nurse staffing ratios. Not-for-profits have higher staffing ratios than for-profits followed by public nursing homes. Notice, that both models are sufficiently flexible to perfectly reconcile differences in staffing ratios by a different combination of marginal cost shifters and input prices. Hence, to assess the quality of the fit we need to compare the marginal costs and wages predicted by the model to the observed marginal costs and wages from the cost reports. Figure A16 presents evidence on the marginal costs, which suggest that the quality-model is not able to reconcile differences in marginal costs. In the second row of Figure A17, I turn to differences in wages and fringe benefits. Overall, there are only very small differences in the compensation packages for skilled nurses between ownership types, which averages around \$80,000 per year. Public nursing homes appear to pay slightly higher compensations than not-for-profits and for-profits but these differences remain unexplained by the two competing models as indicated by the middle and the right bars. Overall, both models are able to fit the observed salaries on average.

Overall, the presented evidence suggests that the baseline model provides a better fit to the observed differences in costs between nursing homes of different ownership types. Furthermore, the objective parameter estimates for the quality model are statistically insignificant, see the third column of the second panel in Table A25. Therefore, I choose the baseline model as my preferred specification.

A.18.3 Non-Pecuniary Objectives, Staffing and Pricing

Next, I turn to the effects of the non-pecuniary quantity motive in equation (1) on staffing and pricing decisions. As outlined in the theoretical section, not-for-profits may indirectly increase staffing and lower prices in order to increase demand. To investigate this hypothesis, I remove the non-pecuniary objectives of not-for-profit and public nursing homes ($1 - \alpha_j = 0$) and simulate the new equilibrium. The left figure of Figure A18 contrasts the baseline skilled nurse staffing ratios to the counterfactual in which all nursing homes maximize profits. The estimates indicate that not-for-profits and public nursing homes would lower their skilled nurse staffing ratio by 10% and 22%, respectively if they were maximizing profits. This suggests that that not-for-profits act as if they place a positive weight on quality directly. Interestingly, the non-pecuniary motive can explain the observed staffing difference between for-profits and not-for-profits. There is also a small decline in staffing ratios for for-profits (0.3%) because of competitive spillover effects. The decline suggests a strategic complementarity in skilled nurses.

The right figure suggests the inverse pattern for private rates. Not-for-profits and public nursing homes would increase their private rates by 17.5% and 29%, respectively. Overall, not-for-profits and public nursing homes increase markups by raising private rates and by lowering the quality of care, which reduces the marginal cost per resident and day

A.18.4 Implications for the Normative Analysis

Finally, I turn to potential differences in the normative implications of alternative nursing home objective functions. Table A25 displays the implications for the key preference parameters in the top panel. Overall, the preference parameter estimates for prices and skilled nurses per resident are slightly larger in magnitude when compared to the baseline estimates in column 3 of Table 3. One mechanical reason is that the price coefficients in the baseline model aims to reconcile the observed markups among for-profit nursing homes only as differences in markups between ownership types are captured by the objective parameters.

The for-profits' markups are the largest, which are rationalized by a less price elastic demand function, indicated by a smaller price coefficient (in absolute magnitude). However, the normative implications are quite similar between the two models as indicated by the average benefit estimates. The quality model suggests that residents jointly value a skilled nurse at \$128,475 per year, which exceeds the baseline estimate of \$126,320 by only 1.7%.

I also revisit the counterfactual implications of the non-pecuniary motive in the objective function. To this end, I consider an alternative model without pecuniary objectives. In this model, I keep the preference parameter estimates from the baseline model but set the non-pecuniary objective to zero. An alternative model could set a positive weight on quality. However, the presented evidence from Table A25 suggests that the weight on quality is not statistically significant. Using the alternative model without pecuniary motives, I revisit the effects of a universal 10% increase in the Medicaid reimbursement rates. The findings are summarized for different ownership types in columns 4-6 of Table A26. Overall the estimates are very similar to the baseline estimates presented in columns 1-3. For example, the average staffing increase equals 8.7%, which falls short of the baseline estimate of 8.8% by only 1.1% or 0.1 percentage points.

This suggests that the non-pecuniary motives primarily rationalize cross-sectional differences in the cost structure between ownership types. However, the normative implications and the counterfactual results appear to be robust to the exclusion of non-pecuniary motives.

A.19 Additional Endogenous Quality Measure

In this section, I extend the baseline analysis by introducing an additional endogenous quality measure θ . I first discuss the implications for the baseline analysis in theory before I turn to the empirical analysis.

A.19.1 Theoretical Considerations

I assume that the preference coefficients for the new quality measure are proportional to the preference coefficients concerning the number of skilled nurses per residents. This implies the following indirect conditional utility function

$$u_{i\tau jt} = \beta_1^d * D_{ij} + \beta_2^d * D_{ij}^2 + \beta_i^{SN} * \log(SN_{jt}^{res}) + \beta_i^\theta * \log(\theta_{jt}) + \sum_x \beta_i^x X_{jt} + \beta_\tau^p * P_{jt} + \xi_{\tau jt} + \epsilon_{ijt} , \quad (31)$$

which extends equation (4) by the term $\beta_i^\theta * \log(\theta_{jt})$. Here $\beta_i^\theta = \tilde{\beta} * \beta_i^{SN}$, where $\tilde{\beta} \geq 0$ indicates the relative importance of the quality measure θ relative to skilled nurses per resident from the point of view of the elderly. Nursing homes can increase the quality measure θ at a constant input price W_{jt}^θ , which may vary across nursing homes and over time. Hence, I augment the marginal cost function per resident and day as follows:

$$MC_{jt} = \zeta_{jt} + W_{jt}^{SN} * SN_{jt}^{res} + W_{jt}^\theta * \theta_{jt} . \quad (32)$$

The new term is $W_{jt}^\theta * \theta_{jt}$. Nursing homes maximize a weighted average over profits and quantity as outlined in equation (5), and choose private rates, the number of skilled nurses per resident, and the quality measure θ optimally. This implies the following two first order conditions for quality:

$$\begin{aligned} \frac{\partial U_{jt}}{\partial SN_{jt}^{res}} &= \sum_i s_{ijt} * (1 - s_{ijt}) * LOS_i * \frac{\beta_i^{SN}}{SN_{jt}^{res}} \left[\alpha_{jt} * (\bar{R}_{ijt} - MC_{jt}) + (1 - \alpha_{jt}) \right] \\ &- \alpha_{jt} * \sum_i s_{ijt} * LOS_i * W_{jt}^{SN} = 0 \\ \frac{\partial U_{jt}}{\partial \theta_{jt}} &= \sum_i s_{ijt} * (1 - s_{ijt}) * LOS_i * \frac{\tilde{\beta} * \beta_i^{SN}}{\theta_{jt}} \left[\alpha_{jt} * (\bar{R}_{ijt} - MC_{jt}) + (1 - \alpha_{jt}) \right] \\ &- \alpha_{jt} * \sum_i s_{ijt} * LOS_i * W_{jt}^\theta = 0 \end{aligned}$$

Dividing the first order conditions by one another yields:

$$\frac{\theta_{jt}}{SN_{jt}^{res}} = \tilde{\beta} * \frac{W_{jt}^{SN}}{W_{jt}^{\theta}} \iff \theta_{jt} = \tilde{\beta} * SN_{jt}^{res} * \frac{W_{jt}^{SN}}{W_{jt}^{\theta}}. \quad (33)$$

Hence, in the optimum, nursing homes choose skilled nurses per resident and the quality measure θ in a constant proportion. The proportion is determined by the ratio of the input prices and the ratio of the preference parameters, $\tilde{\beta}$. Intuitively, nursing homes prioritize θ over skilled nurses if it is relatively more important to the elderly $\tilde{\beta} > 1$ and/or if the input price is smaller than the compensation paid to a skilled nurse, $W_{jt}^{\theta} < W_{jt}^{SN}$.

Equation (33) implies that I can express the quality measure θ in terms of the number of skilled nurses per resident. Substituting equation (33) into equations (31) and (32) also allows me to express utilities and marginal costs as a function of the number of skilled nurses per residents:

$$u_{i\tau jt} = \beta_1^d * D_{ij} + \beta_2^d * D_{ij}^2 + \beta_i^{SN} * (1 + \tilde{\beta}) * \log(SN_{jt}^{res}) + \beta_{\tau}^p * P_{jt} + \tilde{\xi}_{\tau jt} + \epsilon_{ijt} \quad (34)$$

$$mc_{jt} = \zeta_{jt} + \omega_{jt}^{SN} * (1 + \tilde{\beta}) * SN_{jt}^{res} \quad (35)$$

with

$$\tilde{\xi}_{\tau jt} = \xi_{\tau jt} + \log\left(\tilde{\beta} * \frac{\omega_{jt}^{SN}}{\omega_{jt}^{\theta}}\right).$$

In this representation, skilled nurses per resident also proxy for θ , which is chosen in constant proportion to skilled nurses. This is reflected by the augmented preference coefficient and input price, both of which are increased by the factor $(1 + \tilde{\beta})$.

A.19.2 Empirical Implications

In this section, I take advantage of the theoretical finding outlined above and revisit the baseline analysis by interpreting skilled nurses per resident as a proxy for skilled nurses per resident and an unobserved endogenous quality measure θ . To this end, I increase the input price for a skilled nurse by the factor $(1 + \tilde{\beta})$, re-estimate senior preferences, and finally revisit the counterfactual results of a universal 10% increase in the Medicaid reimbursement rate.

The evidence in Table A11 from the Section A.8.6 suggests that the increase in skilled nurses following an increase in the Medicaid reimbursement rate raises the variable costs by \$105,290 per skilled nurse and year. This exceeds the observed compensation package of \$83,171 by 26.6%, which implies $\tilde{\beta} = 0.266$. Hence, I simply increase the compensation package of a skilled nurse to \$105,290 in the empirical analysis and re-estimate the demand and nursing home objective parameters under the updated input prices. Table A27 summarizes the key preference parameter estimates. Compared to the baseline estimates presented in the third column of Table 3, I find almost identical price coefficients and nursing home objective parameters. The preference parameter for the log number of skilled nurses per resident exceeds the baseline estimate of 0.995 by 27%, which is consistent with the theoretical prediction. Equation (34) suggests an augmented preference coefficient of $\beta_i^{\tilde{S}N} = \beta_i^{SN} * (1 + \tilde{\beta})$, which exceeds the baseline estimate by 26.6% ($\tilde{\beta} = 0.266$). Consequently, the normative implications remain largely unchanged as the increase in the cost per skilled nurse are offset by the proportional increase in the average benefit. Overall, the average benefit exceeds the cost of employing an additional skilled nurse by \$54,962 per year which also exceeds the baseline difference of \$43,149 by about 27%.

Next, I revisit the counterfactual implications of a universal 10% increase in the Medicaid reimbursement rate. Table A28 summarizes the effects on staffing, pricing, consumer surplus, provider profits, and ultimately on social welfare. Overall, the results are very similar to the baseline estimates presented in Table 4. Comparing the estimates cell by cell, the estimates on staffing, consumer surplus, profits, and welfare in Table A28 (listed the first five rows) deviate from the baseline estimates by at most 7%. The reductions in private rates are about 20% smaller in absolute magnitude.

Overall, the presented evidence suggests that the main findings of this paper are robust to the consideration of multiple endogenous quality measures.

A.20 Bunching at Multiples of 30 beds

The outstanding bars from histogram A5 indicate bunching at multiples of 30 beds, mostly at multiples of 60 beds. This is evidenced for 60, 120, and 180 beds in the left column of Figure A19. While some bunching coincides with Pennsylvania’s peer group threshold at 120 beds, it is unlikely that the bunching is related to Pennsylvania’s Medicaid reimbursement methodology for several reasons. First, there are similar bunching patterns at other multiples of 60 beds but not for the other reimbursement cutoff of 269 beds. Second, the pattern is visible for the years 1993-1995, see the second column of Figure A19, even though the peer-group refinement based on licensed beds was only introduced in 1996. Third, there is a similar bunching pattern at the national level (excluding Pennsylvania) for the years 2000-2002 as indicated by the right most figures.³⁰

Industry regulators, who certify nursing home capacity in Certificate of Need states, referred to this pattern as the “magic 120 bed number in the nursing home industry”. They reckon that the bunching is not a result of federal regulations. Instead, nursing homes commonly indicate that their optimal nursing home size is reached at 120 beds (oftentimes multiples of 30 beds) considering economies of scale and cost efficiencies.

An alternative explanation is a regulatory incentive originating from the Omnibus Budget Reconciliation Act (OBRA) of 1987, which requires skilled nursing homes with more than 120 beds to employ at least one full-time social worker to provide medically-related social services to attain or maintain the highest practicable physical, mental, and psychological well-being of each resident. This suggests that nursing homes with an “optimal” firm size of more than 120 beds have an incentive to downsize to 120 beds in order to forgo the staffing regulation. However, the OBRA conditions do not appear to be a binding constraint in the sample period. The data indicate that between 1996 and 2001, each nursing with a licensed bed number between 110 and 130 employed at least one full time social worker. Furthermore, this regulation does not explain bunching at other multiples of 30 beds.

³⁰The national data come from LTC focus.

A.20.1 Robustness of Main Findings to Bunching

Overall, the bunching at 120 beds is not concerning for my empirical analysis for two reasons. First, nursing homes with 120 beds do not appear to differ systematically from nursing homes of similar size in terms of key variables of interest for this study in the years 1993-1995, see Figure A20. I start by comparing the occupancy rate between nursing homes. If the OBRA regulation distorts nursing homes towards downsizing in capacity, then one might expect a particularly high occupancy rate among nursing homes with 120 beds. This is not the case as evidenced by the top left graph of Figure 2. The occupancy rate equals 0.92 at 120 beds which is only slightly higher than the average of 0.906 for nursing homes between 110 and 130 beds. Nursing homes with 119 beds have a noticeably smaller occupancy rate. But this average is quite noisy given that there are only 2 nursing homes per year with 119 beds. The remaining three graphs indicate that there are no systematic differences in the Medicaid reimbursement rate, the private rate, or the number of skilled nurses per resident either.

Furthermore, the preliminary findings are robust to excluding nursing homes with 120 beds. Table A29 presents the respective preliminary regression estimates, which are qualitatively and quantitatively very similar to the baseline estimates, which include nursing homes with 120 beds, presented in Table 2. For example, the first stage estimate and the elasticity estimate with respect to skilled nurses per resident differ by only 0.04 ($se=0.18$) and 0.18 ($se=0.29$), respectively. In my assessment, bunching at 120 beds is an interesting novel fact about the nursing home industry, which I aim to explore further in future research. However, the evidence also suggests that the bunching is unrelated to the main findings of this paper.

Table A1: External Validity: PA vs. US in 2014

	PA	US	
	Mean	Mean	SD
<i>State Regulations</i>			
Average Daily Medicaid Rate ^a	189	164	28
Casemix Adjustment of Medicaid Rates ^b	1	0.73	0.2
Prospective Medicaid Reimbursement ^b	1	0.76	0.18
Certificate of Need Law ^b	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 ^c	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 ^c	82.17	80.1	1.87
Percent White ^c	91.2	83.7	10.4
Percent Female ^c	72.4	69.9	2.34
Average Casemix Index ^c	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

^a Data from 2009, ^b Data from 2002, ^c Data from 2010

Table A2: Medicaid Reimbursement Rate Variation Between States

	PA	US				
	Mean	Mean	S.D.	10th	50th	90th
2002	\$178.7	\$152.5	\$27.6	\$119.8	\$149.6	\$186.4
2009	\$188.7	\$164	\$28	\$126.1	\$163.9	\$210.65

The rates are denoted in 2009 dollars.

Table A3: 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%

Note: 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 A4: Fraction of Nursing Homes Focusing on Medicare

	(1)	(2)
Log Medicaid Rate	0.04 (0.17)	
$HHI^{95,beds}$		-0.05 (0.05)
Observations	4034	5283

Standard errors in parentheses

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

Table A5: Nursing Home Costs by Cost Category in 2002

	Mean	Median	Share of Total
Resident Care Costs:			
Nursing	4.19	3.51	0.38
Director of Nursing	0.32	0.18	0.03
Related Clerical Staff	0.15	0.07	0.01
Practitioners	0.02	0.00	0.00
Medical Director	0.03	0.02	0.00
Social Services	0.13	0.10	0.01
Resident Activities	0.19	0.15	0.02
Volunteer Services	0.01	0.00	0.00
Pharmacy-Prescription Drugs	0.30	0.22	0.03
Over the Counter Drugs	0.03	0.02	0.00
Medical Supplies	0.20	0.15	0.02
Laboratory and X-rays	0.04	0.03	0.00
Physical, Occupational, and Speech Therapy	0.46	0.39	0.04
Oxygen	0.03	0.01	0.00
Beauty and Barber Services	0.03	0.02	0.00
RC: Minor Movable Property	0.02	0.01	0.00
Nurse Aide Training	0.03	0.00	0.00
Total Resident Care Costs	6.31	5.25	0.57
Other Resident Related Costs:			
Dietary and Food	1.07	0.82	0.10
Laundry and Linens	0.20	0.14	0.02
Housekeeping	0.39	0.28	0.03
Plant Operation and Maintenance	0.66	0.45	0.06
ORC: Minor Movable Property	0.01	0.00	0.00
Total Other Resident Care Costs	2.56	1.75	0.21
Administrative Costs	1.43	1.18	0.13
Capital Costs:			
Real Estate Taxes	0.07	0.05	0.01
Major Movable Property	0.02	0.00	0.00
Depreciation	0.48	0.29	0.04
Interest on Capital Indebtedness	0.29	0.13	0.03
Rent of Facility	0.09	0.00	0.01
Amortization Capital Costs	0.02	0.00	0.00
Total Capital Costs	0.96	0.67	0.08
Total All Costs	11.20	9.27	1.00

Note: The first two columns summarize annual costs in million dollars for nursing homes in 2002. The data come from Medicaid cost reports. Nominal costs are measured in 2009 dollars. The third column displays costs as fraction of total costs.

Table A6: Robustness to Bias from Serial Correlation

	(All)	(RC)	(ORC)	(ADM)
ϕ^4	0.65 (0.14)	0.63 (0.13)	0.6 (0.09)	0.51 (0.09)
$\frac{\overline{\text{cov}(\log(SN_{jt}^{res}), \log(AC_{c,t-8}^{p(j)}))}}{\text{var}(\log(AC_{c,t-8}^{p(j)}))}$	0.3 (0.20)	0.29 (0.19)	0.21 (0.13)	0.06 (0.11)
$\frac{\overline{\text{cov}(\log(R_{jt}), \log(AC_{c,t-8}^{p(j)}))}}{\text{var}(\log(AC_{c,t-8}^{p(j)}))}$	0.19 (0.04)	0.17 (0.04)	0.1 (0.03)	0.06 (0.03)
γ^{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 / γ^{2SLS} (PT<100%)	[0%,4.4%]	[0%,5.0%]	[0%,4.8%]	[-0.1%,0%]
Bounds on γ_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 γ_1</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

Note: 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 A7: Ordinary Least Squares Estimates

	(1)	(2)	(3)	(4)
	$\log(SN^{res})$	$\log(NA^{res})$	$\log(Th^{res})$	$\log(P)$
Log Medicaid Rate	0.83*** (0.11)	0.29** (0.11)	1.25*** (0.27)	0.58*** (0.10)
Observations	4079	3930	3363	4079

Standard errors in parentheses

Note: $\log(SN^{res})$, $\log(NA^{res})$, and $\log(Th^{res})$ abbreviate the log number 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.

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

Table A8: 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

Note: $\log(SN^{res})$, $\log(NA^{res})$, 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 A9: 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

Note: $\log(SN^{res})$ 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 A10: 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

Note: $\log(\text{Pharma}^{res})$, $\log(\text{Phys}^{res})$, $\log(\text{Psy}^{res})$, $\log(\text{Soc}^{res})$, 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 A11: 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

Note: $VC^{res,day}$ 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 A12: 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	0.37	0.31	0.35	0.41
Ratio: Optimal/ Actual SN Staffing Ratio	1.48	1.29	1.43	1.62
Observations	67			

Figure A8: Distance Traveled

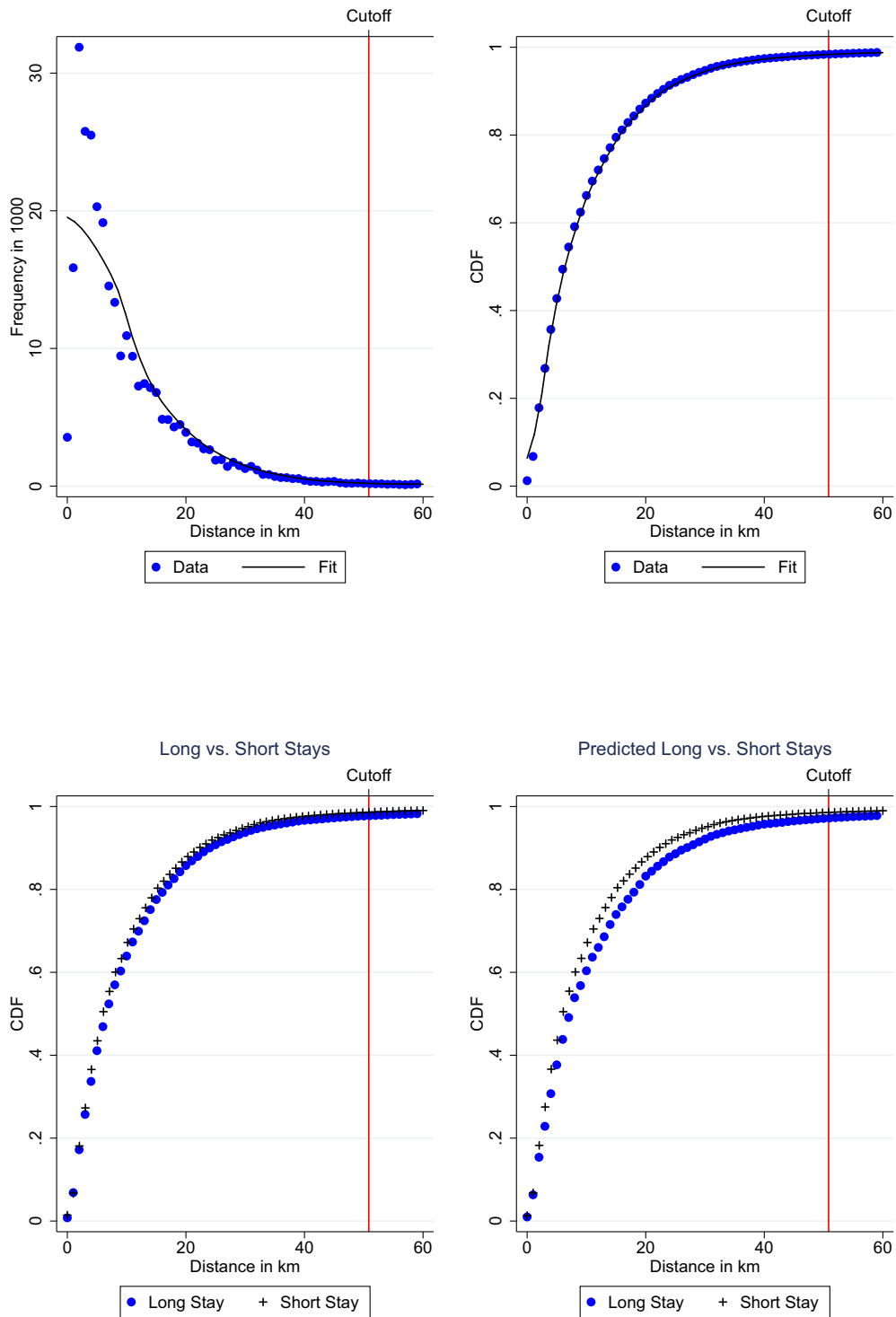
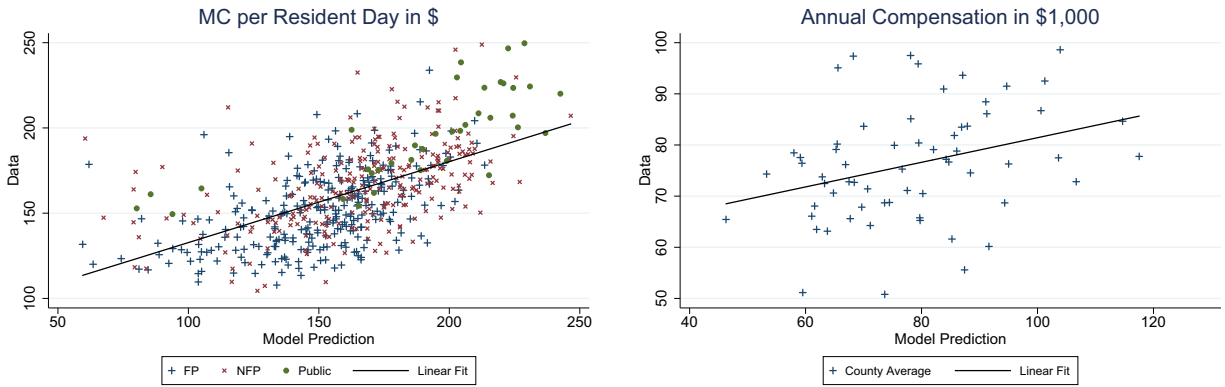


Figure A9: Goodness of Fit: MC and Annual Compensation in 2002



Note: 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 A10: Goodness of Fit: MC and Annual Compensation in 2002

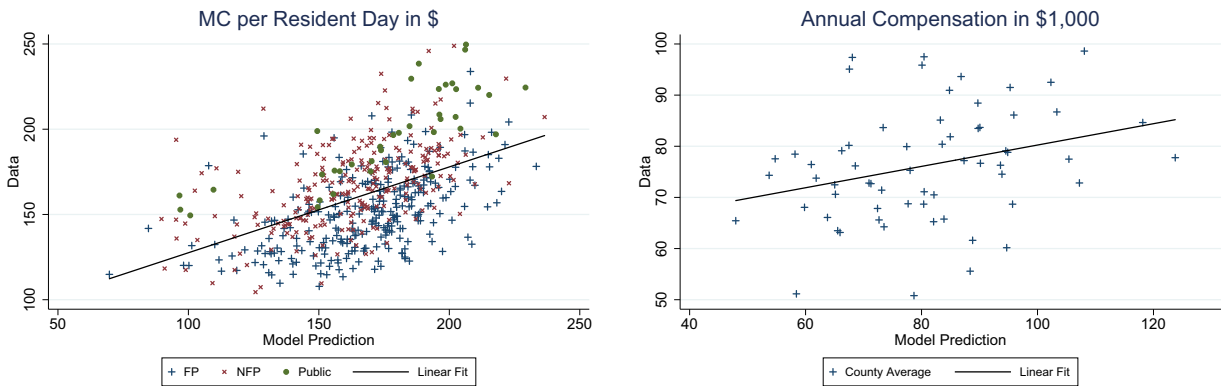


Figure A11: Registered Nurses per Resident

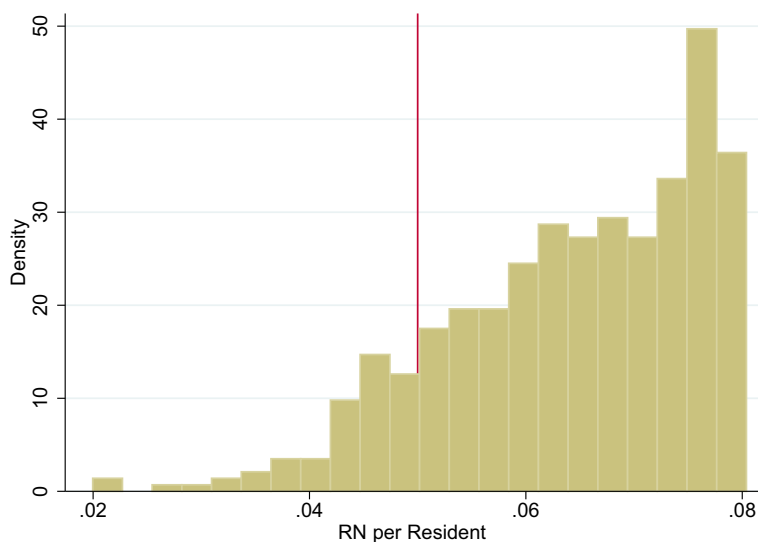


Table A13: Directed Entry in Urban Counties and Counterfactual Comparison

	Pittsburgh Area	Philadelphia Area	PA
Var. Profit Entrant	1.2	0.6	1.8
Fixed Costs	2.2	2.2	4.4
Δ Profit	-2.8	-2.4	-5.2
ΔCS_1	0.2	0.1	0.4
ΔCS_2	3.3	2.3	5.6
Δ Spending	0.2	0.2	0.3
Δ Welfare	0.6	-0.1	0.5
Avg ΔSN^{res}	0.12%	0.09%	0.03%
Avg ΔP	-0.01%	0.04%	0.01%

Medicaid Expansion			Entry		
ΔSN^{res}	Δ Spending	$\Delta SN^{res}/100m$	ΔSN^{res}	Δ Spending	$\Delta SN^{res}/100m$
8.80%	226 million	3.90%	0.03%	2.6 million	1.27%
8.80%	135 million	6.50%	0.03%	5.2 million	0.57%

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

Figure A12: Number of Weekly Admissions by Occupancy and Payer Type

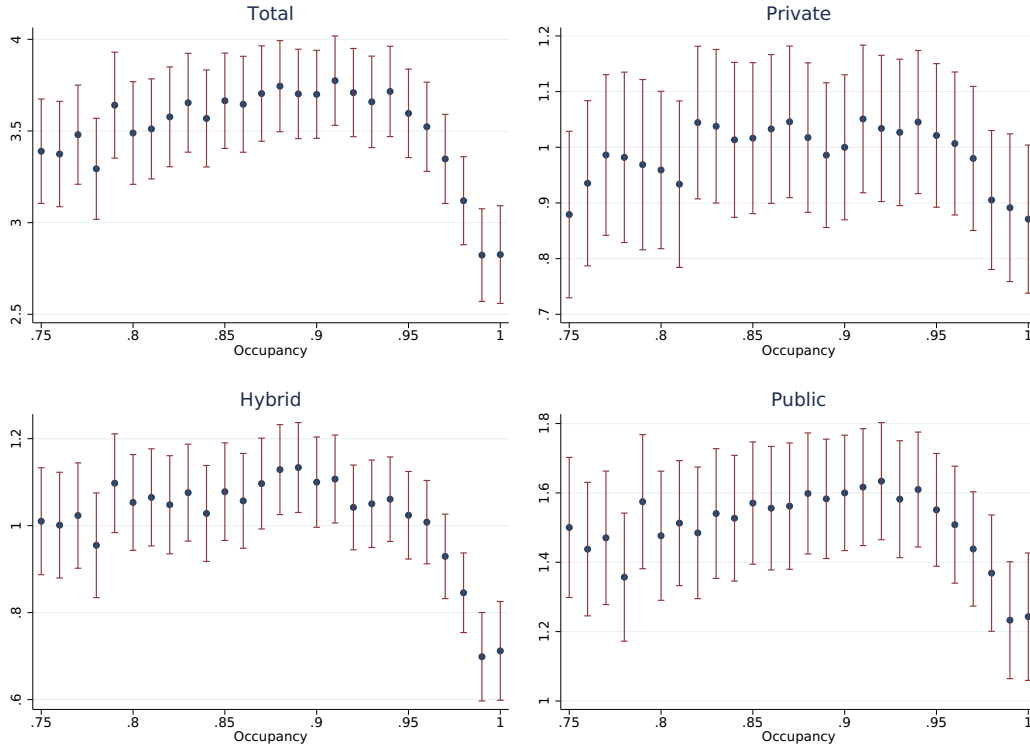


Table A14: Share of Seniors Admitted at High Occupancy Rates

	(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

This table displays the fraction of seniors whose nursing home's occupancy rate exceeds the indicated occupancy threshold at the day of admission.

Table A15: 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.

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

Table A16: Robustness to Rationing: Preference Parameters

	Rationing 100 %		Asym. Rationing 97 %		Asym. Rationing 95%	
	Parameter	SE	Parameter	SE	Parameter	SE
β^{sn} :	log(SN/Res)	1.923***	1.786**	0.82	1.878**	0.844
β_{hyb}^p :	Price*Hybrid	-0.006***	-0.012***	0.002	-0.012***	0.002
β_{priv}^p :	Price*Private	-0.019***	-0.019***	0.004	-0.018**	0.004
β_{cmi}^{sn} :	log(SN/Res)*CMI	0.221***	0.231***	0.003	0.230***	0.003
β_1^d :	Distance in 100km	-25.85***	-25.80***	0.014	-25.79***	0.014
β_2^d :	Distance ²	22.47***	22.45***	0.041	22.42***	0.037
β_{rehab}^{th} :	Th/Res*Rehabmin	-0.133***	-0.122***	0.001	-0.122***	0.001
$\beta_{rehabXshort}^{th}$:	Th/Res*Rehabmin*Short-Stay	0.306***	0.312***	0.007	0.312***	0.007
β_{alz}^{alz} :	Alzheimer*Alzheimer Unit	0.419***	0.413***	0.002	0.413***	0.002
ϑ :	Occupancy < \overline{oc}		0.757***	0.002	0.628***	0.002
ϑ_{hyb} :	Occupancy < \overline{oc} *Hybrid		-0.027***	0.003	-0.088***	0.002
ϑ_{priv} :	Occupancy < \overline{oc} *Private		-0.044***	0.005	-0.058***	0.004
	Avg Benefit per SN/year	\$166,511***	\$154,711**	\$72,552	\$171,686**	\$81,230
	Avg Wage+ Benefits per SN	\$83,171	\$83,171	\$83,171	\$83,171	\$83,171
	Benefit-Cost	\$83,340	\$73,139	\$71,540	\$72,552	\$88,515
				\$72,552		\$81,230

This table displays the estimated preference coefficients under alternative rationing models. Going from left to right, the first model restricts choice set to nursing homes, with an occupancy of less than 100 percent. The second and the third model do not exclude nursing homes from the choice set but add an indicator variable to the indirect conditional utility function, interacted with payer types, which turns on if the average occupancy of the nursing home in the given week is smaller than 97% and 95%, respectively. Th/res SN/res abbreviate therapists and skilled nurses per resident, respectively.

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

Table A17: 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 A18: Normative Estimates Using Alternative Approaches/ Benchmarks

	Benefit of SN in \$1,000	Optimal SN per Res
Baseline Estimates	126.3	0.37
Harrington et al. (2000)		≥ 0.32
Health Returns Approach	83.3 to 157.3	
Life-Cycle Approach	96.8	
Assets Among Private Payers	133.8	

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

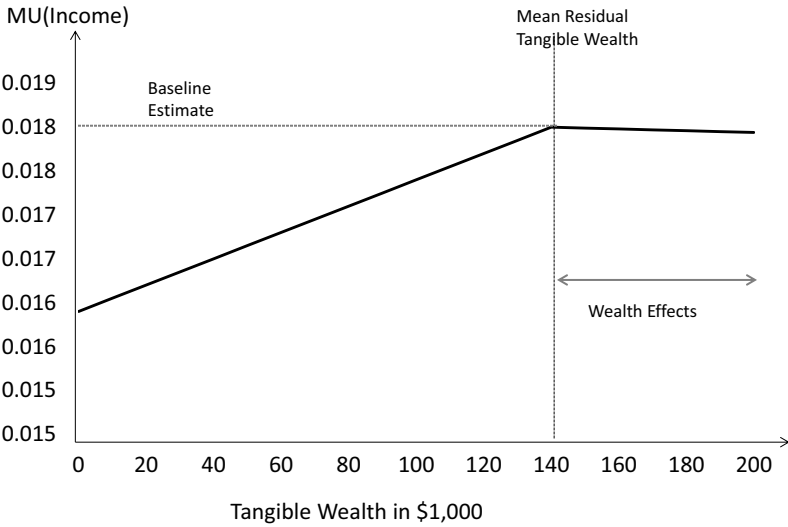
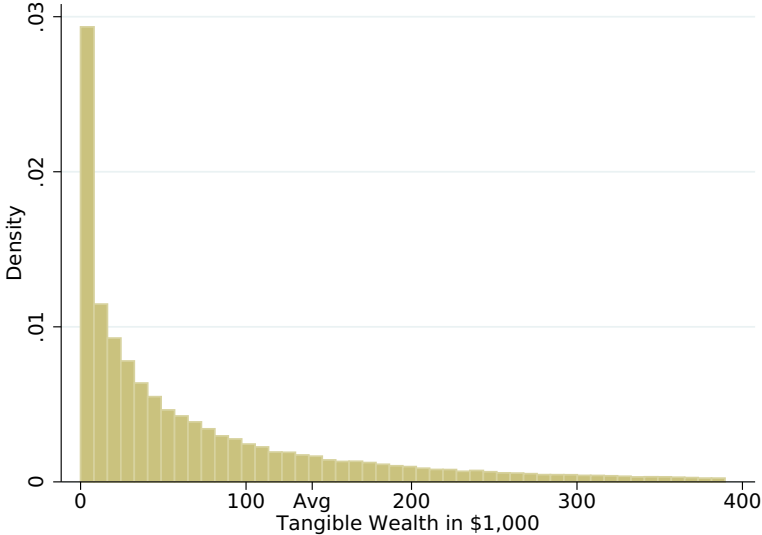
Table A19: Key Parameter Estimates from Lockwood (2016)

Parameter	Point Estimate	Standard Error
ϕ : 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
σ : risk aversion	3	0.05

Table A20: 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 A13: 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 A21: Preference Parameters Considering Wealth Effects

		Wealth Effects	
		Parameter	SE
β^{sn} :	log(SN/Resident)	1.534***	0.748
β_{hyb}^p :	Price*Hybrid	-0.012***	0.002
β_{priv}^p :	Price*Private	-0.018***	0.004
β_{cmi}^{sn} :	log(SN/Resident)*CMI	0.226***	0.003
β_1^d :	Distance in 100km	-25.79***	0.014
β_2^d :	Distance ²	22.45***	0.027
β_{rehab}^{th} :	Therapist/Res*Rehabmin	-0.125***	0.001
$\beta_{rehabXshort}^{th}$:	Therapist/Res*Rehabmin*Short-Stay	0.311***	0.007
β_{alz}^{alz} :	Alzheimer*Alzheimer Unit	0.414***	0.002
β_{wealth}^p :	Wealth Effects in \$1m	-0.015***	0.001
β_{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

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

Figure A14: PA Nursing Home Residents by County in 2000

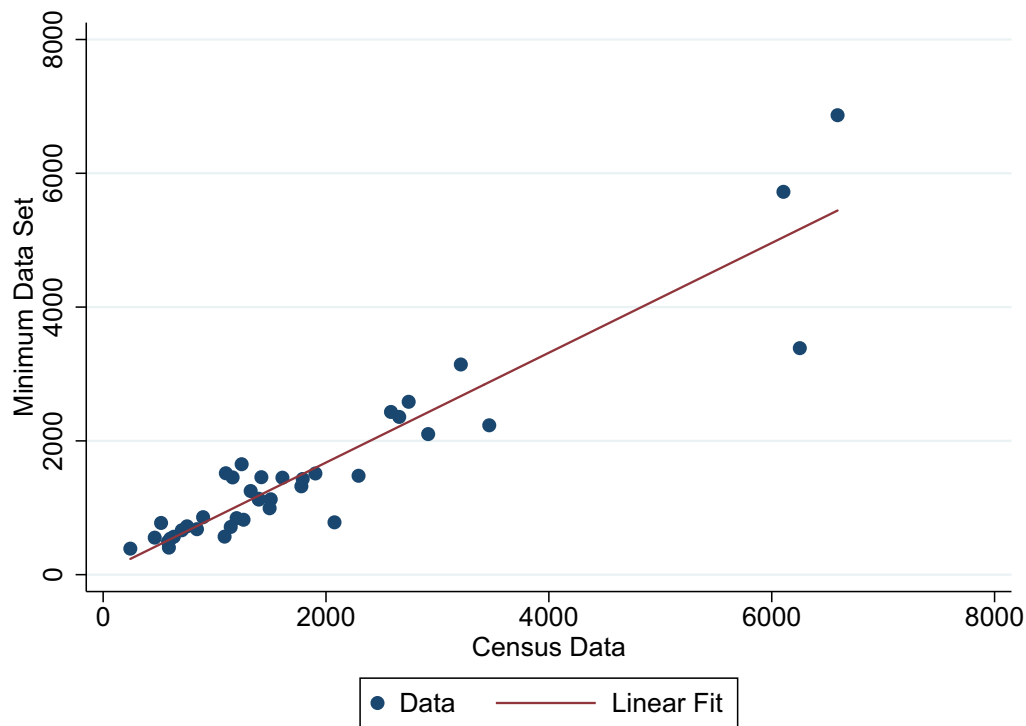
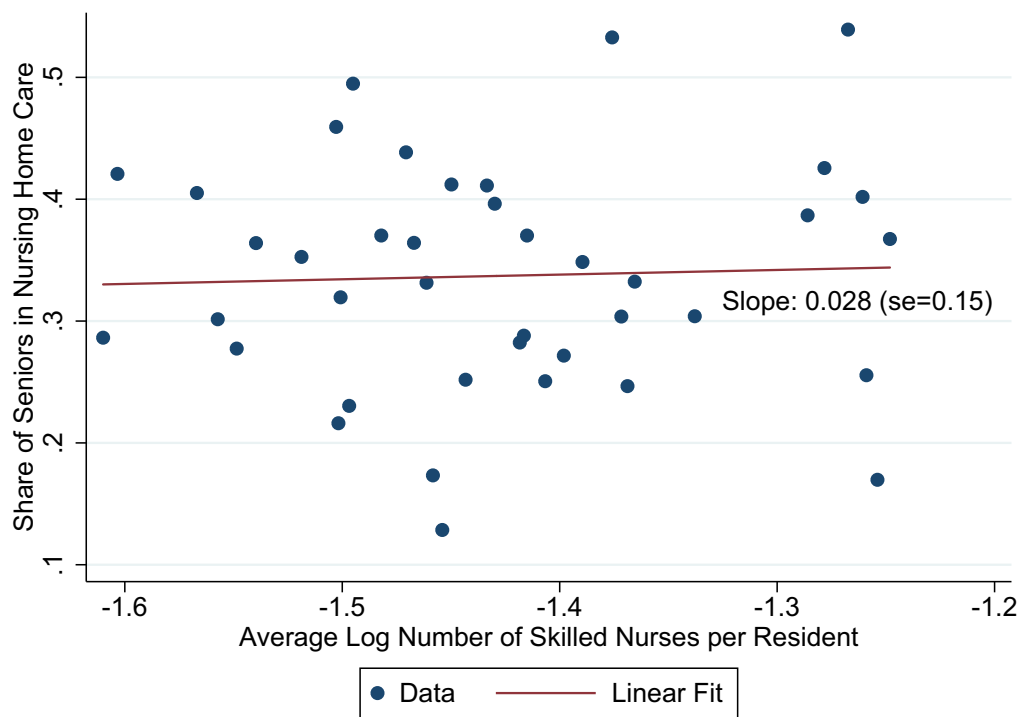


Figure A15: County-level nursing home quality does not predict overall nursing home demand



Note: This figure plots the county-level share of seniors that live in a nursing home on the vertical axis against the county-level average quality of nursing home care, measured by the log number of skilled nurses per resident, on the horizontal axis. Data are from 2000 and come from the 5% sample of the 2000 Census, the MDS, and the Pennsylvania nursing home survey, see Section 3 for details.

Table A22: Preferences and Nursing Home Objectives with Outside Good

		Parameter	SE
β^{sn} :	log(SN/Resident)	0.888***	0.01
β_{hyb}^p :	Price*Hybrid	-0.007***	0.000
β_{priv}^p :	Price*Private	-0.011***	0.001
β_{cmi}^{sn} :	log(SN/Resident)*CMI	0.226***	0.003
β_1^d :	Distance in 100km	-25.79***	0.014
β_2^d :	Distance ²	22.44***	0.037
β_{rehab}^{th} :	Therapist/Res*Rehabmin	-0.124***	0.001
$\beta_{rehabXshort}^{th}$:	Therapist/Res*Rehabmin*Short-Stay	0.314***	0.007
β_{alz} :	Alzheimer*Alzheimer Unit	0.414***	0.002
$\frac{1-\alpha_{NFP}}{\alpha_{NFP}}$	Non-Profit Objective Parameter	23.05***	0.944
$\frac{1-\alpha_{Pub}}{\alpha_{Pub}}$	Public Objective Parameter	36.14***	1.659
	Avg Benefit per SN^* /year in '02	\$123,295***	\$14,430
	Avg Wage+Fringe Benefits per SN^* in '02	\$83,171	
	Benefit-Cost	\$40,124***	\$14,430

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

Table A23: Counterfactual: Universal 10% Increase in Medicaid Rates with Outside Good

	No Rationing		Rationing	
	Absolute	% Δ Spending	Absolute	% Δ Spending
Δ CS	212.0	64.1%	181.1	58.3%
Δ Profits	149.4	45.2%	144.0	46.4%
Δ Spending	330.7	100.0%	310.6	100.0%
Δ Welfare	30.7	9.3%	14.5	4.7%
Avg Δ SN/Res		8.7%		8.7%
Avg Δ P		-4.5%		-4.5%

Note: Absolute values are measured in million dollars. Average staffing and pricing effects are weighted by markets shares.

Table A24: Directed Entry and Counterfactual Comparison with Outside Good

	Northumberland	Lycoming	Monroe	Jefferson	PA
Var. Profit Entrant	0.2	0.3	0.4	0.2	1.1
Fixed Costs	1.1	1.1	1.1	1.1	4.4
Δ Profit	-1.2	-1.2	-1.3	-1.2	-4.9
ΔCS	0.6	1.0	1.9	0.6	3.8
Δ Spending	0.0	0.1	0.1	0.0	0.3
Δ Welfare	-0.6	-0.4	0.6	-0.5	-1.4
Avg ΔSN^{res}	0.15%	0.16%	1.33%	0.95%	0.02%
Avg ΔP	0.05%	0.04%	-0.86%	-0.08%	0.00%

Medicaid Expansion with Outside Good			Entry with Outside Good		
ΔSN^{res}	Δ Spending	$\Delta SN^{res}/100m$	ΔSN^{res}	Δ Spending	$\Delta SN^{res}/100m$
8.70%	331 million	2.63%	0.02%	3.3 million	0.61%
8.70%	181 million	4.81%	0.02%	4.9 million	0.41%

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

Table A25: Quality Objectives

		Parameter	SE
β^{sn} :	log(SN/Resident)	1.282***	0.01
β_{hyb}^p :	Price*Hybrid	-0.010***	0.000
β_{priv}^p :	Price*Private	-0.016***	0.001
β_{cmi}^{sn} :	log(SN/Resident)*CMI	0.226***	0.003
β_1^d :	Distance in 100km	-25.79***	0.014
β_2^d :	Distance ²	22.44***	0.037
β_{rehab}^{th} :	Therapist/Res*Rehabmin	-0.124***	0.001
$\beta_{rehabXshort}^{th}$:	Therapist/Res*Rehabmin*Short-Stay	0.314***	0.007
β_{alz}^{alz} :	Alzheimer*Alzheimer Unit	0.414***	0.002
$\frac{1-\alpha_{NFP}}{\alpha_{NFP}}$	Non-Profit Objective Parameter	-0.504	9,548
$\frac{1-\alpha_{Pub}}{\alpha_{Pub}}$	Public Objective Parameter	-3.357	37,718
	Avg Benefit per SN^* /year in '02	\$128,475***	\$8,048
	Avg Wage+Fringe Benefits per SN^* in '02	\$83,171	
	Benefit-Cost	\$45,304***	\$8,048

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

Figure A16: Prices, Marginal Costs, and Markups by Ownership Type in 2002



Table A26: 10 Percent Medicaid Expansion Under Alternative Objective Functions

	Baseline			No non-pecuniary motive		
	All	FP	NFP	All	FP	NFP
Avg Δ SN/Res	8.8%	9.5%	8.3%	8.7%	9.3%	8.2%
Avg Δ P	-4.9%	-4.6%	-5.2%	-5.2%	-4.9%	-5.5%

Figure A17: Nurse Staffing and Ownership Types

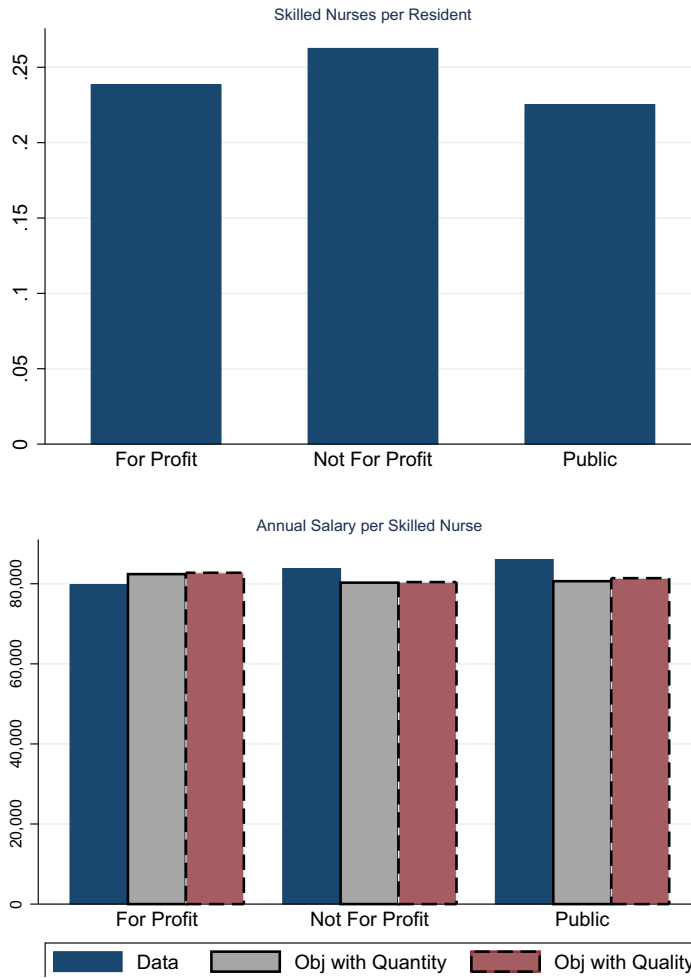


Figure A18: Quantity Motive, Staffing, and Pricing

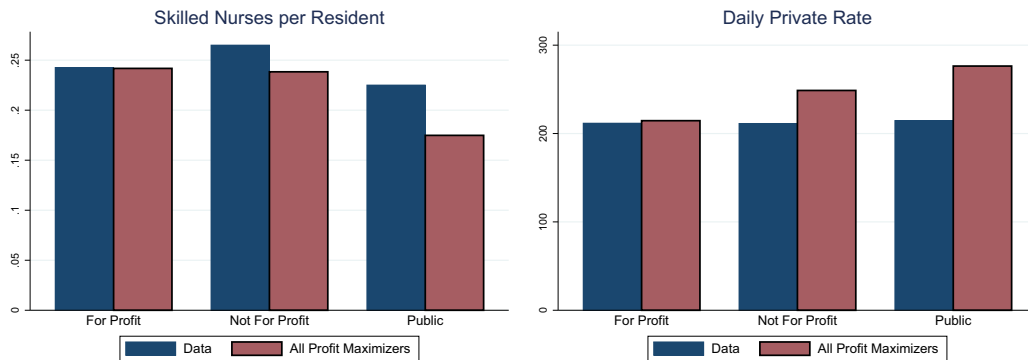


Table A27: Robustness: Preference Parameters in Augmented Quality Model

		Parameter	SE
β^{sn} :	log(SN/Resident)	1.264***	0.015
β_{hyb}^p :	Price*Hybrid	-0.007***	0.000
β_{priv}^p :	Price*Private	-0.013***	0.002
β_{cmi}^{sn} :	log(SN/Resident)*CMI	0.226***	0.003
β_1^d :	Distance in 100km	-25.79***	0.014
β_2^d :	Distance ²	22.44***	0.037
β_{rehab}^{th} :	Therapist/Res*Rehabmin	-0.124***	0.001
$\beta_{rehabXshort}^{th}$:	Therapist/Res*Rehabmin*Short-Stay	0.314***	0.007
β_{alz}^{alz} :	Alzheimer*Alzheimer Unit	0.414***	0.002
$\frac{1-\alpha_{NFP}}{\alpha_{NFP}}$	Non-Profit Objective Parameter	24.67***	1.08
$\frac{1-\alpha_{Pub}}{\alpha_{Pub}}$	Public Objective Parameter	37.88***	1.90
	Avg Benefit per SN^* /year in '02	\$160,252***	\$17,627
	Avg Wage+Fringe Benefits per SN^* in '02	\$105,290	
	Benefit-Cost	\$54,962***	\$17,627

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

Table A28: Universal 10% Increase in Medicaid Rates in Augmented Quality Model

	Absolute	% Δ Spending	Large Counties	Small Counties
Δ CS	213.8	95.0%	97.7%	84.5%
Δ Profits	83.6	37.1%	35.0%	45.2%
Δ Spending	225.1	100.0%	100.0%	100.0%
Δ Welfare	72.3	32.1%	32.8%	29.7%
Avg Δ SN/Res		8.3%	8.6%	7.1%
Avg Δ P		-4.1%	-4.0%	-4.8%

Note: Absolute values are measured in million dollars.

Figure A19: Nursing Home Size Distribution in Beds: PA and US

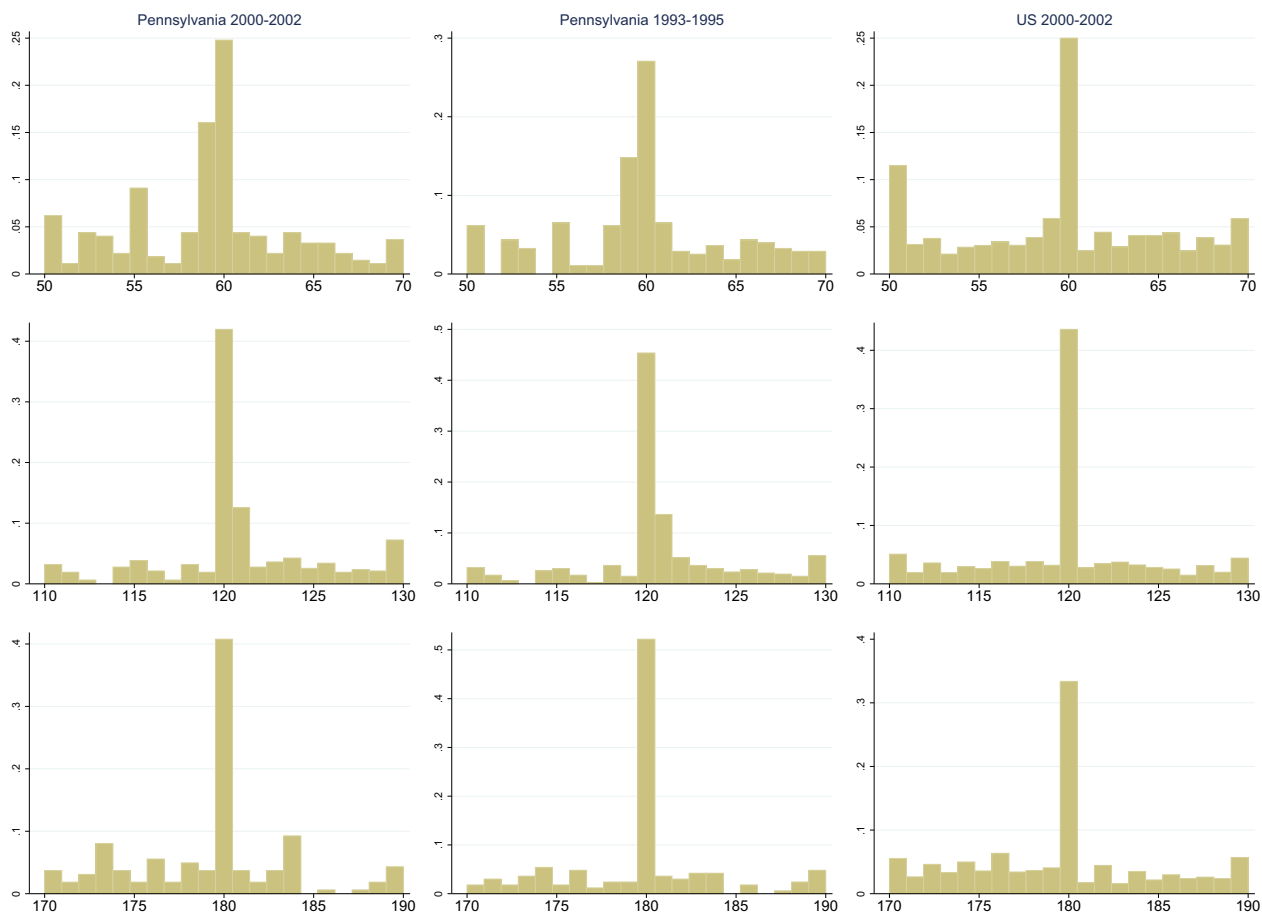


Table A29: Baseline Regressions Excluding Nursing Homes with 120 Beds

	(1)	(2)	(3)	(4)	(5)
	First	$\log(SN^{res})$	$\log(NA^{res})$	$\log(Th^{res})$	$\log(P)$
Log Simulated Rate	1.11*** (0.19)				
Log Medicaid Rate		0.99*** (0.31)	-0.14 (0.54)	0.38 (2.74)	-0.06 (0.23)
Observations	3607	3607	3477	2937	3607

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Figure A20: Nursing Home Comparison by Number of Licensed Beds

