# Online Appendix to
# "Patient Versus Provider Incentives in Long-Term Care"

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## A Institutional Details

**Managed Long Term Services and Supports:** States shape the delivery of long-term care services through Section 1115 Demonstrations. States use these demonstrations to implement Managed Long-Term Services and Supports (MLTSS) programs. Their aim is to reduce long-term care expenditures through managed care and, whenever possible, placing Medicaid beneficiaries into Home and Community-Base Services (HCBS). MLTSS also provide nursing home care and typically pay Skilled Nursing Facilities (SNFs) on a episode or capitation basis. The number of states that have MLTSS programs increased from 8 in 2004 to 24 in 2021 (Medicaid and CHIP Payment and Access Commission, 2022). None of the states in our sample had a mandatory MLTSS program during our study period.

**HCBS Waivers:** Stays in Skilled Nursing Facilities (SNF) are expensive. As patients typically also prefer HCBS, states' Medicaid programs have developed and expanded HCBS. In 1991, Medicaid devoted 86% of its total LTC spending for institutional care and only 14% for HCBS. By 2001, HCBC spending had more than doubled to 29%, see Milne, Chang, and Mollica (2004). HCBS waivers—which were authorized under section 1915(c) of the Social Security Act as part of the Omnibus Budget Reconciliation Act (OBRA) of 1987—were a key driver of this expansion.

Table A.1: Eligibility, Out-of-Pocket Prices, and Reimbursement Rates for Nursing Home and Community-Based Long-Term Care

| | Medicare | Medicaid |
|---|---|---|
| **Panel A: General** | | |
| General Eligibility | Age 65 (or disabled),<br>automatic enrollment,<br>federal single payer system | Asset test: CA (\$2000), PA (\$2400), NJ (\$4000), OH (\$1500)<br>"Medically Needy" (MN) income limits:<br>CA (\$600, 83% FPL), PA (\$425; 59% FPL), NJ (\$367, 51% FPL), OH (n/a, \$423 TANF) |
| Eligibility SNF | Up to 100 days of post-acute care after<br>hospital stays of at least three days. | ADL and/or medical condition requiring 24 hour supervision:<br>CA and PA (both), NJ and OH (one of two)<br>Needs allowance: CA (\$35), PA (\$30), NJ (\$35), OH (\$40) |
| Eligibility HCBS | prescribed by physician,<br>for home-bound patients | All states w/ HCBS waivers under Section 1915(c) of the Social Security Act.<br>Idea is to provide Medicaid HCBS to patients who would be eligible for Medicaid in SNF.<br>Asset test: CA (\$2000), PA (\$2000), NJ (\$2000), OH (\$1500)<br>Income limits: CA (MN =\$600); PA, NJ, OH: (300% SSI or \$1635 in 2002)<br>Needs allowance: CA (\$600), PA (\$521), NJ (\$1482), OH (\$964) |
| **Panel B: Patient Incentives** | | |
| Price SNF | After first 100 days, private rate. Per day:<br>CA (\$180); PA (\$170); NJ (n/a); OH (\$148) | Except for allowance, income applied to costs,<br>e.g. (\$647-\$30)/(\$170×30 days)=12% of private rate for PA; |
| Price HCBS | Part-time home health aide by Medicare<br>-certified agency covered. Physical, speech,<br>occupational therapy: no cost-sharing.<br>No coverage of personal (assistance w/ ADL)<br>or household services.<br>20% coins. for durable equipment (walkers,...). | Home health aides, nursing services, medical equipment generally covered.<br>\$1/visit in CA, no copay in other states.<br>Limits on service days in CA (30/4 months) and PA (15/month after 28 days) |
| **Panel C: Provider Incentives** | | |
| Reimbursement SNF | Private rates per day:<br>\$180 (CA); \$170 (PA); NJ (n/a); OH (\$246) | Medicaid rates per day:<br>CA (\$148), PA (\$144), NJ (n/a), OH (\$144).<br>All states pay per diem. PA used case-mix index; OH and NJ based on cost;<br>CA by size, location, level of care. |
| Reimbursement HCBS | see above, limited home health care. | Depends on service provided.<br>Fee for service in all states but NJ where it was cost-based. |

Sources: O'Keeffe (1999); Kassner and Shirey (2000); O'Keeffe, Tilly, and Lucas (2006); own collection, own illustration. Asset thresholds, personal needs allowance and HCBS maintenance needs allowances are from Kassner and Shirey (2000) and refer to the status as of 2000. ADL and medical requirements are from O'Keeffe (1999). At the time, Ohio was a 209(b) state that did not have a Medically Needy (MN) program; the 209(b) statues allow individuals to spend down to the cash assistance level (State of Ohio, 2001). CA, PA, and NJ all ran MN programs and also had a "special income rule" of 300% of SSI limits to determine financial eligibility for LTC services (Kassner and Shirey, 2000). In 2002, the 300% SSI threshold equaled \$1635 (Social Security Administration, 2019). The MN spent-down rules are typically more generous than the 300% SSI special income rule, which is why we only list the former in the table above. All four states had HCBS waivers at the time but only California applied the medically needy rules to HCBS waivers, whereas PA, NJ and OH allowed HCBS participants to qualify via the 300% SSI special income rule (Kassner and Shirey, 2000). States allow "maintenance need" deductions as listed, before the 300% SSI rule is applied. Medicaid reimbursement rates and the reimbursement methodology are taken from Grabowski et al. (2004), Hackmann (2019) and Kaiser Family Foundation (2003b), also see Section C. Kaiser Family Foundation (2003a) and Kaiser Family Foundation (2003b) also provide details on covered HCBS and nursing home services and copayments for Medicaid beneficiaries in the four states as of 2003. For private and Medicaid SNF rates, we use two nursing home surveys from California and Pennsylvania, (for details, see Hackmann, 2019). The Pennsylvania survey data were provided by the Bureau of Health Statistics and Research of the Pennsylvania Department of Health (2020). California data come from the Office of Statewide Health Planning and Development (2020). The data vary at the facility-year level separately for privately and Medicaid insured. For OH, the rates are from Mehdizadeh and Applebaum (2003). Information of Medicare coverage is from Komisar and Feder (1998) and Centers for Medicare & Medicaid Services (2019b). At the time, there existed also Medicare Savings Programs with slightly higher income thresholds up to 135% FPL and asset limits of \$4,000 (\$6,000 for couples) to determine eligibility (Komisar, Feder, and Kasper, 2005). However, these were programs with numerous barriers, limited Medicaid coverage, and possible estate recovery requirements; for example, only 18% of those eligible for SLMB programs were actually enrolled Medicare Payment Advisory Commission (2004). Because our focus is on asset spent-down as the main route to qualifying for Medicaid, and given the high nursing home costs which would delay eligibility at most by a few weeks in case of slightly higher asset limits, we abstain from these programs.

# B Data Appendix

## A Creation of Main Datasets

For the main analysis, we compile a unique dataset. In our first "fixed-effects" approach, in Section A, we use it at the week-stay level for four states from 2000 to 2005. In our second "event study" approach, in Section B, we aggregate this dataset to the month-stay level and focus on California, see Section E for a detailed explanation.

To produce the baseline working dataset, we merge administrative micro data from the Long-Term Care Minimum Data Set (MDS) with Medicaid and Medicare SNF claims data from 2005 from California, P, OH and NJ from 2000 to 2005. The Centers for Medicare and Medicaid Services (CMS) provide most of these data, which cannot be made publicly available. However, we provide the codes in the Supplementary Materials that also include *READMEgeneratedata.docx*. The file describes in even more detail how we generate our main dataset at the week-stay level using the following input files (a) to (e):

(a) Long Term Care Minimum Data Set (MDS) 2.0 (Centers for Medicare & Medicaid Services, 2022a). The MDS measures the health of all nursing home residents in all U.S. Medicaid or Medicare-certified nursing homes in a standardized manner. This includes about 98% of all U.S. nursing homes. The data contain the exact admission and discharge dates as well as the discharge destination. Section C provides more details on the health assessments.

(b) Medicaid and Medicare claims data contained in Medicaid Analytic Extract (MAX) files. MAX contains every Medicaid beneficiary who was enrolled for at least one month or who had a Medicaid-paid service within the file year (Centers for Medicare & Medicaid Services, 2019a).

(c) 100% Medicare Provider Analysis and Review (MedPAR) files containing claims of Medicare beneficiaries during their SNF stays (Centers for Medicare & Medicaid Services, 2022b).

(d) 100% Denominator Files. The Denominator Files contain all Medicare enrollees from administrative data sources and allow linkages to payer information (Centers for Medicare & Medicaid Services, 2021).

(e) LTC Focus (On-Line Survey, Certification, and Reporting system, OSCAR) data containing the number of licensed beds, see Section C for details on the data.

In secondary analysis, described in *READMEsecondary.docx* we also use the National Long Term Care Survey (NLTCS) as well as data from The Office of Statewide Health Planning and Development

(OSHPD) in California.

## B Characterization of SNF Residents Using the NLTCS

To provide further insights into the economic endowment of our treatment and control group, we use representative data of the National Long Term Care Survey (NLTCS) for 1999 and 2004. The NLTCS also samples individuals who are *currently* residing in nursing homes along with patients living in the community. Moreover, the NLTCS contains information on the payer type at admission *and* at the time of the interview, which allows us to observe payer transitions. Table B.1 shows nursing home residents' average income and assets by payer type.

As in our main sample, we drop residents who were on Medicaid at admission. The first column shows descriptives for those who were private payers initially and then transitioned to Medicaid in the nursing home, whereas the second column shows descriptives for those who are still private payers in nursing homes. The third column reports descriptives for Medicaid beneficiaries with ADL needs in the community.

As seen, while incomes for the relevant groups in columns (1) and (3) overlap to a large extend, their means differ ($819 vs. $669). In robustness checks below, we rescale the hypothetical asset spend-down schedule assuming that the time-to-Medicaid transition would be three times slower that it actually is after patients are discharged to community settings (Table E.5).

## C Discharge Destination, Health Assessments, Occupancy Rates

**Discharge Destination:** The MDS indicates the admission and discharge dates for each resident. This information allows us to construct the exact length of each nursing home stay. Moreover, we observe a discharge code, which provides information on the reason of discharge and the discharge destination. The first column of Table B.2 displays overall and destination-specific discharge probabilities by SNF stays; these are consistent with the literature (Mor et al., 2007b; Arling et al., 2010; Holup et al., 2016; Hass et al., 2018). However, on average, residents who are eventually discharged to the community have shorter stays. Hence, at a given point in time, the fraction of SNF residents that are eventually discharged to the community is smaller than reported in column (1) as the composition of present residents is skewed towards longer stay patients. To see this, we weight nursing home stays by length of stay, see column (2) of Table B.2. As expected, fewer SNF stays end in a home discharges (38.5% vs. 7.4%).

Table B.1: Summary Statistics: Monthly Income and Assets (NLTCS)

| | Private at admission | | |
|---|---|---|---|
| | Currently Medicaid | Currently private | Medicaid beneficiary in the community |
| Total income | 818.7 | 1154.5 | 668.7 |
| | (605.3) | (1567.2) | (425.6) |
| Social Security benefits | 647.1 | 677.5 | 559.3 |
| | (432.3) | (624.9) | (388.5) |
| Other retirement income | 145.0 | 287.5 | 9.572 |
| | (359.7) | (831.7) | (65.80) |
| Supplemental Security Income | 0 | 10.74 | 66.49 |
| | (0) | (102.1) | (196.6) |
| Spouse's Social Security benefits | 13.79 | 121.9 | 22.64 |
| | (66.96) | (477.9) | (129.4) |
| Spouse's other retirement income | 12.82 | 54.44 | 7.027 |
| | (88.83) | (380.2) | (72.41) |
| Spouse's Supplemental Security Income | 0 | 0 | 2.736 |
| | (0) | (0) | (24.14) |
| Welfare payments | 0 | 2.424 | 0.995 |
| | (0) | (39.53) | (9.833) |
| Home ownership | 0.0196 | 0.0374 | 0.223 |
| | (0.140) | (0.190) | (0.418) |
| Observations | 51 | 294 | 135 |

**Notes:** National Long Term Care Survey 1999 and 2004. All amounts are in 2005 dollars. The exact number of observations vary slightly over the income and asset variables due to missings, e.g. we only have total income values for 48,266, and 133 observations, respectively.

Table B.2: Sample Discharge Probabilities by Destination

| | By Stay (1) | By LOS (2) |
|---|---|---|
| Any Discharge | 0.902 | 0.636 |
| Home Discharge | 0.385 | 0.074 |
| Assisted Living Facility | 0.077 | 0.024 |
| Other SNF | 0.126 | 0.063 |
| Hospital | 0.213 | 0.316 |
| Deceased | 0.135 | 0.152 |

**Notes:** The figure summarizes discharge destinations for our sample. *Any discharge* is an indicator that turns on if the stay ends with a discharge. *Home*, *Assisted Living*, *Other SNF*, *Hospital*, and *Deceased* are binary variables indicating if the stay ends with a discharge to the community, to an assisted living facility, a different SNF, a hospitals, or if the resident died in the nursing homes. Column (1) reports the statistics by stay and column (2) by LOS. LOS stands for length of stay. Column (1) weighs the means by stay and column (2) by LOS.

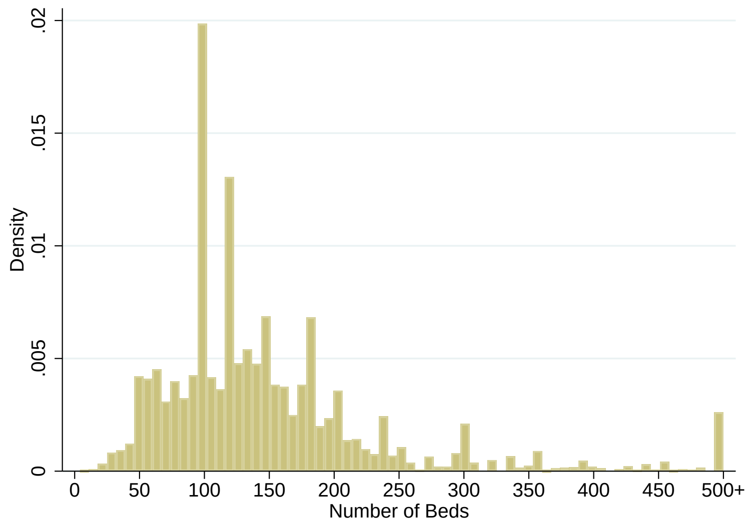
**Health Assessments:** The MDS provides information on residents' health assessments, which typically take place at admission, then on a quarterly basis, and then at discharge. The MDS data include several clinical health measures on a variety of cognitive, physical functional, behavioral, communication, and disease-related conditions. We reduce the wealth of these measures to a few key statistics that are commonly used in Medicaid and Medicare reimbursement methodologies. Most importantly, these include the residents' Case Mix Index (CMI), which is normalized to one and summarizes the expected resource utilization relative to the average resident. We also consider four other health measures that all enter the calculation of the CMI: (i) physical disabilities, measured by the amount of help required with activities of daily living (ADL) such as toileting or assistance with eating, bed mobility, and transferring, (ii) depression, (iii) impaired cognition, and (iv) behavioral problems. Table 1 in the main text lists the summary statistics of all health measures by payer type.

**Occupancy Rates:** To calculate the occupancy rate of each nursing home in a given week, we combine admission and discharge date information from the MDS with information on the number of licensed beds from Long-Term Care: Facts on Care in the U.S. (2020), specifically the On-Line Survey, Certification, and Reporting system (OSCAR). OSCAR provides information from state surveys on all federally-certified Medicaid and Medicare nursing homes in the U.S. (cf, Grabowski, 2001). These are administrative data collected by state agencies during SNF annual certification inspections which are conducted at least every 15 months (Long-Term Care: Facts on Care in the U.S., 2020). Figure B.1 presents a histogram for the number of licensed beds. While about 30% of all SNFs have between 100 and 120 beds, there is substantial variation in facility size.

To avoid a mechanical reverse relationship between the own discharge process and our constructed occupancy rate, we use a leave-one-out measure for the occupancy rate. Specifically, we measure occupancy rate variation in *other* beds and use the lagged occupancy rate, which only varies in other beds as we exclude the first week of the stay. To see this, note that an individual resident only affects the occupancy rate in the weeks when she is admitted and discharged. By dropping the first week of each stay and using the lagged occupancy rate, we remove the variation in the last week of each nursing home stay that is partly due to the resident's own discharge.

**Assessing Measurement Error in Bed Counts and Occupancy:** We also assess potential measurement error in the bed count information, which is key for the construction of nursing home occupancy. For instance, it might be that the federal reports overlook some changes in bed counts from year to year

Figure B.1: Number of Licensed Beds



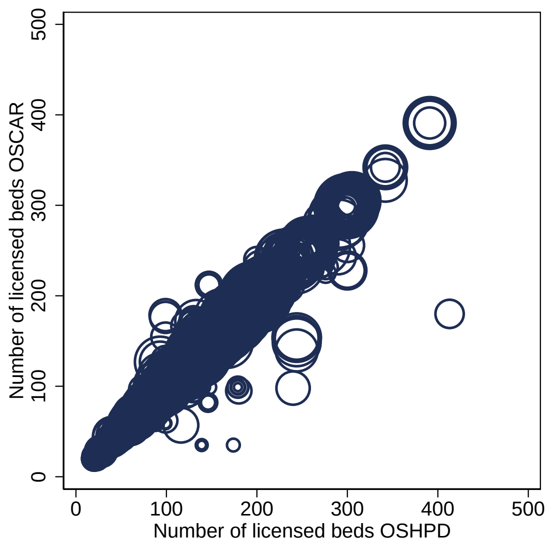

**Source:** Administrative data from Long-Term Care: Facts on Care in the U.S. (2020) linked to MDS data. The figure presents a histogram of the overall number of licensed beds. The unit of observation is the week of the nursing home stay.

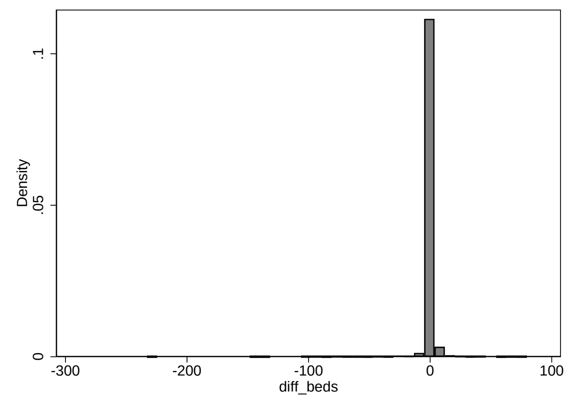
adding measurement error to the bed count and hence our occupancy measure in the baseline analysis. To cross-validate the OSCAR survey data, we benchmark the number of licensed beds with another administrative data source for the state of California. The Office of Statewide Health Planning and Development (2020) (OSHPD) collects detailed information from all nursing homes licensed in California. Each year, SNFs have to submit Long-Term Care Facility Integrated Disclosure and Medi-Cal Cost Reports (FIDCR). These report include key facility indicators such as the number of licensed beds.

Figure Ca correlates the number of reported beds by SNF and year between the two data sources: OSCAR vs. OSHPD. The size of the scatters represent the size of the SNF. The bed counts are not identical as shown in Figure B2, confirming that these are indeed different measures of bed count. That said, the differences are relatively small. Specifically, we note that (a) the deviations appear symmetric, and that (b) the large majority of all values are identical and line up on the 45 degree line in Figure Ca. Plotting the histogram of bed size deviations, Figure Cb corroborates this conclusion. As seen, the overwhelming majority of reported beds are identical between the two data sources.

Finally, to more formerly assess the potential effects of idiosyncratic measurement error in OSCAR's bed count information and hence our baseline occupancy rate for our main findings, we also construct an alternative occupancy measure in California using the OSHPD bed count and use it as an instrument for our baseline LTCfocus occupancy measure. We obtain consistent estimates when both occupancy

Figure B.2: Number of Licensed Beds at Facility Year Level: OSCAR vs. OSHPD Data




**Source:** Long-Term Care: Facts on Care in the U.S. (2020); Office of Statewide Health Planning and Development (2020). The left figure shows the correlation between licensed bed data from OSCAR vs. OSHPD. The size of the scatters indicate the size of the facility. The left figure shows a histogram of the differences in licensed beds from the two data sources. In both cases, the unit of observation is the facility-year.

measures are correlated, as shown in Figure above, and the OSHPD occupancy is uncorrelated with the residual of the structural equation. This requires that the measurement errors in each variable are uncorrelated. We then estimate the pooled fixed effects model via two stage least squares. The structural equation is:

Table B.3: Home Discharges: Instrumental Variables for Occupancy Rates

| | (1) | (2) |
|---|---|---|
| Medicaid × Occupancy ≤ 85% | -0.0168 | -0.0170 |
| | (0.0005) | (0.0004) |
| Medicaid × Occupancy > 85% & ≤ 95% | -0.0188 | -0.0187 |
| | (0.0003) | (0.0002) |
| Medicaid × Occupancy > 95% | -0.0128 | -0.0130 |
| | (0.0008) | (0.0004) |
| Occupancy ≤ 85% | -0.0052 | -0.0049 |
| | (0.0003) | (0.0003) |
| Occupancy > 95% | -0.0009** | -0.0006* |
| | (0.0004) | (0.0003) |
| Observations | 4,766,346 | 4,766,346 |
| R-squared | | 0.1195 |

Source: Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for CA from 2000 to 2005 and Long-Term Care: Facts on Care in the U.S. (2020); Office of Statewide Health Planning and Development (2020). The first column presents estimates for equation (B.1) via two-stage least squares where we construct an alternative occupancy measure, using bed count data from OSHPD as instrument for our baseline occupancy measure, see text for details. The second column presents the baseline OLS results. Standard errors in parentheses. p<0.01, ** p<0.05, * p<0.1.

$$
\begin{aligned}
Y_{ijst} &= \mathbb{1}\{oc^1_{jt-1} \leq 85\%\} \times Mcaid_{is} + \mathbb{1}\{85\% < oc^1_{jt-1} \leq 95\%\} \times Mcaid_{is} + \mathbb{1}\{95\% < oc^1_{jt-1}\} \times Mcaid_{is} \\
&+ \mathbb{1}\{oc^1_{jt-1} \leq 85\%\} + \mathbb{1}\{85\% < oc^1_{jt-1} \leq 95\%\} + \mathbb{1}\{95\% < oc^1_{jt-1}\} \\
&+ \eta_s + \eta_{jy} + \eta_m + \eta_y + Z_i'\alpha + X_{it}'\beta + \epsilon_{ijst} \qquad \text{(B.1)}
\end{aligned}
$$

where $oc^1_{jt-1}$ denotes our baseline occupancy measure based on the OSCAR bed count data. We then instrument all terms involving $oc^1_{jt-1}$ with the occupancy measure obtained using bed count data from the OSHPD, $oc^2_{jt-1}$. For example, we instrument for the interaction between $\mathbb{1}\{oc^1_{jt-1} \leq 85\%\}$ and $Mcaid_{is}$ by interacting $\mathbb{1}\{oc^2_{jt-1} \leq 85\%\}$ and $Mcaid_{is}$. Table B.3 shows the results.

The first column presents the IV model and the second column shows the standard fixed effects model, using data for California only. The key effect sizes denoted in the first three rows are highly similar across the specifications and both (consistent with our main findings) provide evidence for patient incentives (first coefficient smaller than 0), and provider incentives (first coefficient smaller than third coefficient). In conclusion, we find only little scope for idiosyncratic measurement error in the OSCAR bed count information and that these sources of error have only very small effects on the estimated relationship between occupancy and Medicaid home discharges, and hence the implied provider elasticity. We note, however, that there may also be common sources of measurement error in both bed count and hence occupancy measures that our approach cannot address.

## D Payer Types and Transition to Medicaid

To identify specific payers, we combine the MDS with administrative Medicare and Medicaid claims data from the MedPAR and MAX databases. We link the information at the SNF-stay level. Doing so, we can identify the days covered by Medicare and Medicaid. We assume that all others are paid out-of-pocket, given that very few residents have private LTC insurance.

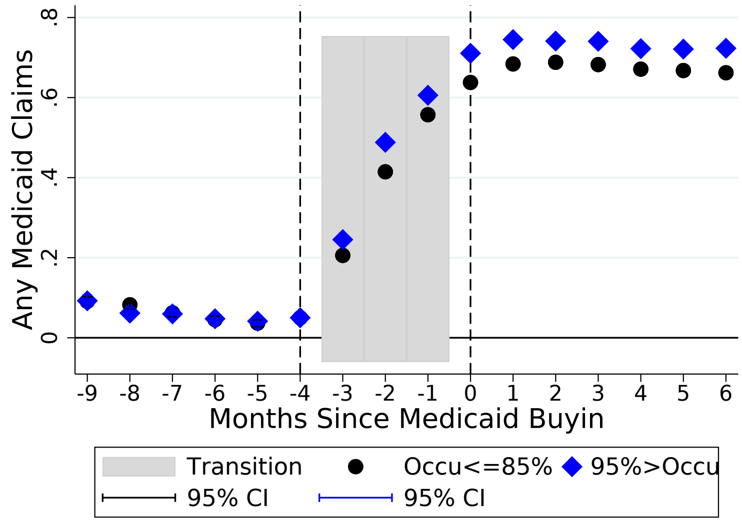
The event study analysis leverages within-patient transitions to Medicaid. It requires us to also observe such transitions outside of SNFs. Thus, we exploit the so called "buyin" indicator, which is an administrative Medicare indicator for dual beneficiaries (Rupp and Sears, 2000; Research Data Assistance Center, 2020), see Section E. However, this indicator is only available at the monthly level. Moreover, for some states, the indicator does not reliably identify all dual beneficiaries. We conducted several cross-validation checks between the weekly SNF payer and the monthly buyin indicator information, using just the population in nursing homes. These checks provide reliable information that both measures consistently identify Medicaid beneficiaries, but only for California.[30] Specifically, we find that 99% of dual beneficiaries also have buyin information. For example, in May 2000, the buyin indicator identifies 45.1% as dual beneficiaries, whereas the information from MedPAR and MAX databases yields a share of 45.8%.

Moreover, as an additional test, we run our standard event study regression, but use a flag for the first Medicaid SNF claim as the outcome variable; the event time defined by the buyin indicator is the key explanatory variable. The result is in Figure B.3. It denotes months since the buyin indicator records dual eligibility status on the x-axis, and having any Medicaid claim on the y-axis.

The claims data lead the buyin indicator by up to three full months, increasing from only a few percentage points at $\mu_{-4}$ to about 70% at $\mu_0$. Specifically, the increase from $\mu_{-1}$ to $\mu_0$ denotes the share of successful Medicaid applications that were processed within a month (or 30 days) of the application date and approved in $\mu_0$. Likewise, the increase from $\mu_{-2}$ to $\mu_{-1}$ captures incremental applications with a

[30] For the other three states, institutional differences prevent us from using the buyin indicator to reliably identify dual beneficiaries. For example, for New Jersey, the dual beneficiary shares are 39.3% vs. 44.5%; for Pennsylvania, they are 20.7% vs. 37.4%.

Figure B.3: Medicaid Transition Over Three Month




**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section E. The figure plots $\sum_{\iota=-9}^{6} \mu_t$ of a model similar to equation (3) but uses a dummy for Medicaid claims as the dependent variable. Thus the x-axis indicates the relative "buyin" time in months. It shows since when the Medicare "buyin" indicator records the dual eligibility status. The transition period indicates the increase in approval rates from $\mu_{-4}$ to $\mu_0$. For example, the increase from -1 to 0 denotes the share of successful Medicaid applications that were processed within a month (filed at $\mu_{-1}$ and approved at $\mu_0$).

processing time of between one and two months (30-59 days). Lastly, the increase from $\mu_{-4}$ to $\mu_{-3}$captures the increase in processing times from 3 to 4 months (90-119 days).

Hence, the large majority of Medicaid applications are processed within three months as requested by law. We therefore lead the buyin indicator by three months in the event study and normalize the coefficient for $\mu_{-4}$ since buyin to $\mu_{-1}$. We then interpret the first three months in the event study analysis as transition period between the Medicaid application and the approval date. We note that the share of patients with any Medicaid claims peaks at about 70-80% in Figure B.3. This points to remaining measurement differences (besides the timing difference) between the buyin indicator and the Medicaid claims. Hence the event study analysis may yield slightly smaller point estimates than the fixed effects approach.

## E Private and Medicaid SNF Rates

For daily private and Medicaid SNF rates, we use two nursing home surveys from California and Pennsylvania, (for details, see Hackmann, 2019). The Pennsylvania survey data were provided by the Bureau of Health Statistics and Research of the Pennsylvania Department of Health (2020). California data come from the Office of Statewide Health Planning and Development (2020).

For California, we infer daily private and Medicaid rates by dividing SNF's annual revenue by the number of resident-days for each payer type. The average daily private rates amount to \$170 for Pennsylvania and \$180 for California. The Medicaid rates are \$144 for Pennsylvania and \$148 for California (also see Table A.1).

# C Details for Theoretical Discussion

This section describes the key predictions of our model in greater detail. As discussed in Section A, we start from the theoretical discharge equation (1) and assume that exogenous discharge factors $\epsilon$ are uniformly distributed. This allows us to express the discharge probability per period as:

$$\Pr[D = 1|e^{SNF}, e^{res}] = D^{other,\tau} + \alpha \times e^{SNF}[\text{FinInc}^{SNF}(\tau, oc)] + \beta \times e^{res}[\text{FinInc}^{res}(\tau)]. \tag{C.1}$$

Here, $D$ denotes any discharge, which includes endogenous community discharges (our focus) but also discharges to a hospital, a different nursing home, or death—all captured by $D^{other,\tau}$, which we assume to be exogenous to discharge efforts.

## A Optimal Resident Effort

**No Patient Free-Riding:** The discharge probability depends on $D^{other,\tau}$ and resident's expectations about $e^{SNF}$, captured by "$\cdot$" in $\Pr[D = 1|\cdot, e^{res}]$.

However, these factors do not affect the resident's optimal effort because efforts are additively separable, $D^{other,\tau}$ is exogenous to efforts, and because of the uniform distribution of $\epsilon$, see equation (1). This shuts down potential patient free-riding incentives on provider effort (and hence restricts the strategic interactions between patients and providers) as shown by the first order condition:

$$e^{res,*}(\tau, \eta) = \begin{cases} c_e^{-1}\left(\frac{\beta}{\kappa} \times \big(W(\tau, D = 1, \eta) - W(\tau, D = 0, \eta)\big)\right) & \text{if } W(\tau, D = 1, \eta) \\ & \quad > W(\tau, D = 0, \eta) \ , \\ 0 & \text{otherwise} \end{cases} \tag{C.2}$$

where $c_e^{-1}(\cdot)$ is the inverse marginal cost of effort function. We further assume $c(e) = \gamma \times e^2$, which allows us to express optimal resident effort as follows:

$$e^{res,*}(\tau, \eta) = \begin{cases} \frac{1}{2\gamma}\left(\frac{\beta}{\kappa} \times \big(W(\tau, D = 1, \eta) - W(\tau, D = 0, \eta)\big)\right) & \text{if } W(\tau, D = 1, \eta) \\ & \quad > W(\tau, D = 0, \eta) \ \cdot \\ 0 & \text{otherwise} \end{cases} \tag{C.3}$$

**Scale Normalizations and Additional Modeling Assumptions:** In addition to the functional form assumptions laid out beforehand, we need to impose further simplifying assumptions to achieve identification. First, we require an additional scale normalization on either the cost of effort, $c(e) = \gamma \times e^2$, or the effects of patient effort on discharge, $\beta$, as we cannot separately identify them from the observable relationship between out-of-pocket prices $p^P$ and discharge rates. To see this, consider again the resident's optimal effort choice in equation (C.3), which implies $\partial Pr[D = 1]/\partial p^P = \beta \times \partial e^{res,*}/\partial p^P = \beta^2/2\gamma$. This suggests that increasing $\gamma$ and $\sqrt{\beta}$ in proportion leaves the predicted relationship between out-of-pocket prices $p^P$ and discharge rates unchanged. We therefore normalize the marginal dollar cost of effort by setting $\gamma = 1$, which implies $c(e) = e^2$.

Second, we need to impose further restriction on either the flow utility parameter $u$, or the return on effort, $\beta$, as only the product of the two determines optimal effort. To see this, note that the numerator in equation (C.3) is $\beta \times \Big(W(\tau, D = 1, \eta) - W(\tau, D = 0, \eta)\Big) = \beta \times \Big(\eta^{home} - u + \kappa p^\tau - \eta^{SNF}\Big)$ . We assume $u$ =0.5 per day.

Building on these assumptions, we then recover $\beta$ and $\kappa$ from home discharge rates at low occupancy rates for Medicaid and private pay patients. To see this, note that predicted community discharge rates for Medicaid patients at low occupancy rates are given by:

$$Pr[D = 1|\tau = M, oc = low] = \beta \times E_\eta[e^{res,*}(M, \eta)] = \frac{\beta^2}{2 \times \kappa} \times E_\eta[\max\{\eta^{home} - u - \eta^{SNF}, 0\}], \quad \text{(C.4)}$$

where expectations are taken over the type-1 extreme value preference shocks $\eta$. Hence, given $u$, we can infer $\frac{\beta^2}{2\times\kappa}$ from Medicaid discharge rates at low occupancy rates, $Pr[D = 1|\tau = M, oc = low]$. Likewise, predicted home discharge rates at low occupancy rates for private pay patients are given by

$$Pr[D = 1|\tau = P, oc = low] = \frac{\beta^2}{2 \times \kappa} \times E_\eta[\max\{\eta^{home} - u + \kappa p^\tau - \eta^{SNF}, 0\}] \ . \quad \text{(C.5)}$$

The ratio of the two discharge rates is then informative about $\kappa$. And with $\kappa$ at hand, we can infer $\beta$ from $\frac{\beta^2}{2\times\kappa}$.

**Discussion:** As stated beforehand, we impose several strong assumptions to achieve identification. In particular, our functional form assumptions rule out differences in the cost of effort, $c(e) = e^2$ and also differences in the effects of patient effort on discharge outcomes, $\beta$, between payer types. These assumptions are key to the identification of $\kappa$ and $\beta$ absent variation in financial incentives within payer types. While demographic and health measures are similar between payer types, we note that Medicaid patients are more likely to be depressed or cognitively impaired (Table D.2), which might suggest that they find it more difficult to respond to financial incentives. This is consistent with the slightly smaller patient elasticities for Medicaid patients that we find when exploring alternative sources of variation in financial incentives within Medicaid patients (see Table E.2). In this case, we might overstate their responsiveness to financial incentives but corroborating our main point that patients respond less elastically to incentives than providers. We also assume that $D^{other,\tau}$ is exogenous to effort and constant across payer types in our baseline analysis. However, we find that relaxing these assumptions, e.g. allowing non-community discharges to vary by payer source and occupancy, has only small effects on the estimated patient (and provider) elasticities, see Section A for details.

## B Provider Effort

Here, we show that the Medicaid discharge rate increases in the occupancy rate above some occupancy threshold $oc^*$—as shown in Figure 1 in the main text—under simplifying assumptions that yield a closed-form solution. Specifically, we assume that the occupancy rate is fixed, that newly admitted residents are private payers, that there are no payer type transitions, and that the exogenous discharge rate and residents' discharge efforts are zero. Hence, a resident is only discharged if the nursing home provides strictly positive effort. The focal bed can either be empty, $\tau = 0$, or filled with a private payer or Medicaid beneficiary: $\tau = P, M$. We assume that providers exert discharge effort during the period, but that discharges continue to be stochastic and are realized at the end of the period. We can then define the following Bellman equation:

$$V(\tau, oc) = \begin{cases} \frac{\Pi(P)}{1-\delta} & \text{if } \tau = P \\ \max_{e \geq 0} \{\Pi(M) - c(e) + D(e)V(0, oc) + (1 - D(e))\delta V(M)\} & \text{if } \tau = M \\ \delta[\phi(oc)V(P, oc) + (1 - \phi(oc))V(0, oc)] & \text{if } \tau = 0 \end{cases}$$

where $\Pi(\tau)$ is the payer-specific per-period profit, $c(e)$ denotes the cost of effort, $D(e)$ is the discharge probability as a function of the nursing home's effort, $\Phi(oc)$ is the probability of refilling a vacant bed, and $\delta$ is the discount factor. Note that nursing homes never have an incentive to discharge private payers in this model, which leads to the functional form of $V(P, oc)$.

Below occupancy level $oc < oc^*$, for Medicaid-covered residents, the nursing home has no incentive to exert strictly positive effort because the refill probability is too low and the option value of vacating a bed does not compensate for forgone Medicaid profits. Hence, $V(M, oc) = \frac{\Pi(M)}{1-\delta}$ for $oc < oc^*$. For $oc \geq oc^*$, we have the first order condition:

$$c'(e) = D'(e)[V(0, oc) - \delta V(M, oc)].$$

Assuming $c(e) = e^2$ and with $D'(e) = \alpha$, we have

$$e^* = \frac{\alpha}{2}[V(0, oc) - \delta V(M, oc)],$$

and

$$V(M, oc) = \frac{\Pi(M) - c(e^*)}{1 - \delta(1 - D(e^*))} + \frac{D(e^*)}{1 - \delta(1 - D(e^*))} V(0, oc),$$

Defining:

$$F = e^* - \frac{\alpha}{2}[V(0, oc) - \delta V(M, oc)] = 0,$$

we have $dF/de^* = 1$ as $V(M, oc)/de^* = 0$ because of the first order condition. We also have

$$\frac{dF}{doc} = -\frac{\alpha}{2}\left[1 - \frac{\delta D(e^*)}{1 - \delta(1 - D(e^*))}\right]\frac{dV(0, oc)}{doc}.$$

As $dV(0, oc)/doc > 0$ and $\left[1 - \frac{\delta\mu}{1-\delta(1-\mu)}\right] > 0$, we get $dF/doc < 0$. This implies $de^*/doc > 0$ based on the implicit function theorem. Hence, provider efforts and consequently Medicaid discharge rates increase in the occupancy rate for $oc \geq oc^*$.

## C Estimation and Inference

We estimate $\theta = (\alpha, \beta, \kappa, mc)$ by minimizing the sum of squared differences between discharge rates predicted by the model, $D_{\tau,oc}(\theta)$ and observed home discharge rates $\hat{D}_{\tau,oc}$ (shown in Figure 3):

$$\hat{\theta} = \arg\min_{\theta} \sum_{\tau=P,M} \sum_{oc=65}^{99} \left(D_{\tau,oc}(\theta) - \hat{D}_{\tau,oc}\right)^2. \tag{C.6}$$

The estimation algorithm proceeds as follows: First, for an initial parameter guess $\theta_0$, we solve the provider value function given by equations (8) to (11) and the implied optimal effort function of the nursing home via contraction mapping. This allows us to predict home discharge rates $D_{\tau,oc}(\theta_1)$ using $\Pr[D = 1|e^{SNF}, \tau] = D^{other,\tau} + \alpha \times e^{SNF} + \beta \times E_{\eta}[e^{res,*}|\tau]$. We then update the parameter vector and iterate until the least squares criterion in equation (C.6) attains its minimum.

**Inference:** We conduct inference via bootstrapping. One computational limitation of this procedure is that estimating equation (2) is very time and memory consuming due to the large number of fixed effects and about 13.5 million observations. Instead, we leverage the observation that the OLS estimator for the vector $\nu = [\gamma^{75}, ..., \gamma^{100}, \delta^{75}, ..., \delta^{100}]$ is jointly normally distributed, $\hat{\nu} \sim N\Big(\nu, \Sigma\Big)$. Therefore, we only estimate the variance-covariance matrix for the entire vector, $\Sigma$, once and then draw discharge coefficients. For each bootstrap iteration $b = 1, ..., B$, we draw $\hat{\nu}^b \sim N\Big(\hat{\nu}, \hat{\Sigma}\Big)$ and then re-estimate the parameters $mc, \alpha, \beta$ and $\kappa$, and set $B = 99$. Finally, we obtain 95% confidence intervals by ordering bootstrapped parameters, which are re-centered around the respective point estimates, and report the 2.5th and the 97.5th percentile.

# D Machine Learning and Permanent SNF Residents

This section provides more details on the Machine Learning (ML) approach to identify and discard the 10% of SNF residents who are the least likely to ever be discharged to the community. We use CART regression tree (Breiman, 1984; Mullainathan and Spiess, 2017; Athey and Imbens, 2019) to predict whether a nursing a home stay will ever end in a community discharge.

As predictors, we use 174 demographic and health variables, all of which are taken at the resident's first SNF assessment and plausibly exogenous to the discharge decision. Demographics include race, gender, and marital status. Health variables include medical conditions, cognitive ability indicators, as well as types and amounts of therapies and prescriptions drugs that the resident is receiving. We also include indicators for the location from where the resident was admitted. To mitigate concerns of overfitting, we choose a maximum tree depth of 10 and choose the complexity parameter that maximizes an out-of-sample $R^2$ via 10-fold cross-validation. The complexity parameter denotes the minimum $R^2$ that every additional leaf on the regression tree needs to add to be included in the regression tree. That means that a smaller complexity parameter yields a more complex regression tree. We find an optimal complexity parameter of 0.00018. We then prune our regression tree by removing splits that increase the cross validation $R^2$ by less then this optimal complexity parameter.

Out of the 174 predictors, 101 are used by the final tree. These include, for example, the cognitive skill and the ability to maintain personal hygiene and to take a bath. These variables are proxies for residents' long-term care needs and how well they could cope with living in the community. Our final tree has an overall $R^2$ of 0.59. The CART algorithm then assigns each resident a probability that her stay ends with a community discharge, as predicted at the time of the first assessment. The mean probability is 0.48 and it has a standard deviation of 0.24.

Finally, we exclude the 10% of SNF stays with the smallest predicted probability of ever being discharged to the community. Table D.1 provides the summary statistic for this excluded subsample and can directly be compared with Table 1.

Comparing the patient populations between Tables D.1 and 1 indicates that the ML approach disproportionately excludes females, older patients, whites and the widowed. The also have more ADLs, cognitive impairments, and behavioral problems. These chronic conditions contribute to longer nursing home stays reducing the probability of a community discharge.

Table D.1: Summary Statistics of 10% with Lowest Discharge Potential at Resident-Week Level

| | Private | | Medicaid | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| **Panel A: Socio-Demographics** | | | | |
| Age | 85.6131 | (7.3722) | 85.2219 | (7.3957) |
| Female | 0.759 | (0.4277) | 0.8041 | (0.3969) |
| White | 0.9037 | (0.295) | 0.8904 | (0.3124) |
| Black | 0.0366 | (0.1877) | 0.0549 | (0.2278) |
| Hispanic | 0.0302 | (0.1711) | 0.027 | (0.1619) |
| Married | 0.2097 | (0.4071) | 0.1888 | (0.3914) |
| Widowed | 0.52 | (0.4996) | 0.5896 | (0.4919) |
| Divorced | 0.0423 | (0.2012) | 0.0593 | (0.2362) |
| **Panel B: Health Measures** | | | | |
| Case Mix Index (CMI) | 1.159 | (0.2659) | 1.1498 | (0.2682) |
| Number of ADLs | 14.2429 | (3.0964) | 14.1207 | (3.3434) |
| Clinically complex | 0.4628 | (0.4986) | 0.4407 | (0.4965) |
| Depression | 0.4752 | (0.4994) | 0.5313 | (0.499) |
| Weight Loss | 0.1067 | (0.3087) | 0.0872 | (0.2821) |
| Impaired Cognition | 0.9213 | (0.2692) | 0.9252 | (0.263) |
| Behavioral Problems | 0.1241 | (0.3296) | 0.1401 | (0.3471) |
| Observations | 1,175,169 | | 561,805 | |

Source: Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for CA, NJ, OH, PA from 2000 to 2005. The table shows summary statistics by payer source at the resident-week level for the 10% with the smallest discharge potential; these are excluded in the main sample. The Case Mix Index (CMI) is a summary measure of long-term care needs, calculated based on methodology 5.01, and normalized to 1. The remaining health measures are direct inputs to the CMI formula and provide more granular information on cognitive and physical disabilities. All health measures at taken at discharge. The summary statistic for the main sample is in Table 1.

Table D.2: Patient Summary Statistics by High-Low Occupancy and Insurance Status

| | Occupancy≤ 85% | | | | Occupancy>95% | | | |
|---|---|---|---|---|---|---|---|---|
| | Private | | Medicaid | | Private | | Medicaid | |
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| **Panel A: Socio-Demographics** | | | | | | | | |
| Age | 83.7174 | 7.9393 | 83.2767 | 8.0795 | 84.7545 | 7.6185 | 84.4062 | 7.7369 |
| Female | 0.673 | 0.4691 | 0.7171 | 0.4504 | 0.7230 | 0.4475 | 0.7666 | 0.423 |
| White | 0.877 | 0.3284 | 0.8388 | 0.3677 | 0.9093 | 0.2872 | 0.8672 | 0.3394 |
| Black | 0.0564 | 0.2307 | 0.1028 | 0.3037 | 0.0457 | 0.2088 | 0.0914 | 0.2882 |
| Hispanic | 0.0406 | 0.1973 | 0.0369 | 0.1886 | 0.0194 | 0.1379 | 0.0193 | 0.1376 |
| Married | 0.26 | 0.4386 | 0.1053 | 0.3069 | 0.2452 | 0.4302 | 0.2073 | 0.4054 |
| Widowed | 0.5076 | 0.4999 | 0.5259 | 0.4993 | 0.5564 | 0.4968 | 0.5818 | 0.4933 |
| Divorced | 0.0652 | 0.2469 | 0.0927 | 0.29 | 0.0473 | 0.2123 | 0.0711 | 0.257 |
| **Panel B: Health Measures** | | | | | | | | |
| Case Mix Index (CMI) Admission | 1.0808 | 0.4214 | 1.012 | 0.4045 | 1.0521 | 0.3733 | 0.9956 | 0.3791 |
| Case Mix Index (CMI) | 1.097 | 0.4004 | 1.0445 | 0.3819 | 1.0915 | 0.3543 | 1.0545 | 0.3553 |
| Number of ADL | 11.7687 | 4.2297 | 11.5281 | 4.53 | 12.1926 | 4.294 | 11.9616 | 4.6034 |
| Clinically complex | 0.5498 | 0.4975 | 0.4683 | 0.499 | 0.5218 | 0.4995 | 0.465 | 0.4988 |
| Depression | 0.4329 | 0.4955 | 0.5076 | 0.4999 | 0.5083 | 0.4999 | 0.5596 | 0.4964 |
| Weight Loss | 0.1201 | 0.3251 | 0.1041 | 0.3053 | 0.117 | 0.3214 | 0.1002 | 0.3002 |
| Impaired Cognition | 0.6057 | 0.4887 | 0.6408 | 0.4798 | 0.6132 | 0.487 | 0.6358 | 0.4812 |
| Behavioral Problems | 0.0857 | 0.2799 | 0.0998 | 0.2997 | 0.0886 | 0.2842 | 0.0925 | 0.2897 |
| Observations | 1,566,573 | | 1,189,075 | | 2,121,087 | | 1,868,735 | |

*Source:* Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for CA, NJ, OH, PA from 2000 to 2005. The table presents summary statistics by high and low occupancy rates at the resident-week level. The left columns show summary statistics for occupancy rates below 85%, and the right columns show summary statistics for occupancy rates between 95 and 100%. The Case Mix Index (CMI) is a summary measure of long term care needs, calculated based on methodology 5.01, and normalized to 1. The remaining health measures are direct inputs to the CMI formula and provide more granular information on cognitive and physical disabilities. Following Mor et al. (2007a), low ADL needs comprises patients who do not require physical assistance in any of the late-loss ADLs, bed mobility, transferring, using the toilet, and eating, and are not classified in either the "Special Rehab" or "Clinically Complex" Resource Utilization Group (RUG-III) group.

# E Additional Empirical Results and Robustness Checks

## A Discharge Patterns to Other Destinations and by Discharge Potential

Figure E.1 presents evidence on discharges to non-community destinations and patient mortality, building on the fixed effects model outlined in equation (2). The binary dependent variables equal one if a resident was discharged to a hospital (Figure E.1a), to a different nursing home (Figure E.1b), deceased (Figure E.1c), or discharged to any non-home destination (Figure E.1d). Note that provider incentives may affect discharges to other nursing homes or hospitals. In fact, while admissions to other hospitals are flat in occupancy, we do find small upward slopes in Figures E.1b, E.1c and E.1d. Below, we run various robustness checks but do not find that those pattern confound our main conclusions.

In particular, we find a small decline in the mortality gap between private payers and Medicaid patients as occupancy increases in Figure E.1c. We attribute this shirking gap to potential compositional changes in the patient population as providers likely first discharge healthier patients when occupancy increases. We note: First, observable patient health measures are quite balanced across the populations, Table D.2). Moreover, adding these as controls leaves the patterns intact (results are available upon request).

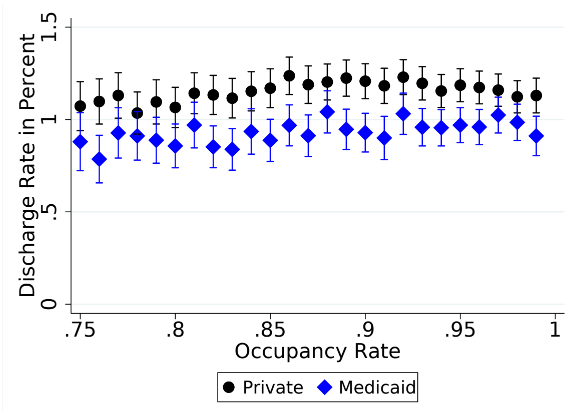
### A.1 Discharge Patterns by Discharge Potential

Second, we find that patients with a low discharge potential have a higher mortality risk. This may confound the analysis as the patient composition may shift towards those patients as the occupancy rate increases. Figure E.2 thus uses mortality rates as outcome but divides the sample into quartiles based on the patient's predicted home discharge potential at admission (using a machine learning approach as described in Section D). Each figure shows weekly mortality risk by payer type and occupancy.

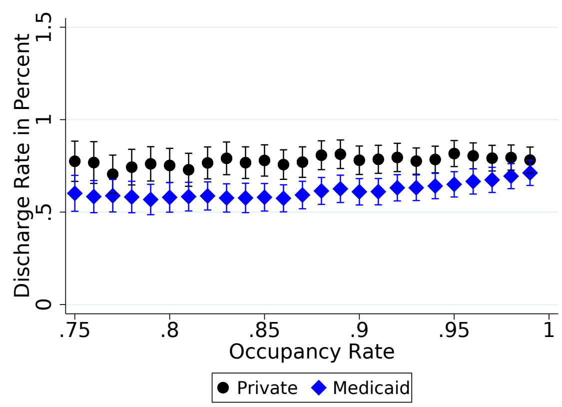
The top left figure shows the quartile of patients with the lowest home discharge potential. Here, the average mortality risk is the highest and we also see the largest differential increase in mortality risk for Medicaid patients in occupancy. Levels and convergence patterns are muted in the top right graph, which shows patterns for the second quartile. Finally, we find no evidence for increased Medicaid mortality rates in the bottom figures showing results for the third (bottom left) and fourth (bottom right) quartile.

These pattern show that the increases in mortality rates are concentrated among patients with low discharge potential. Building on this insight, we conduct two robustness checks in which we exclude (i) patients from the bottom quartile and (ii) patients from the bottom two quartiles. We also consider a third

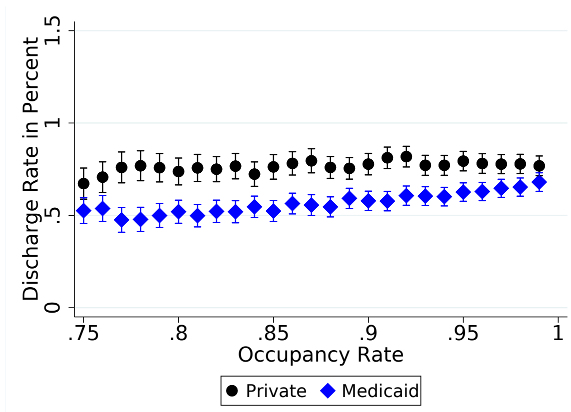
Figure E.1: Discharge Rates to Different Destinations by Occupancy and Payer Type



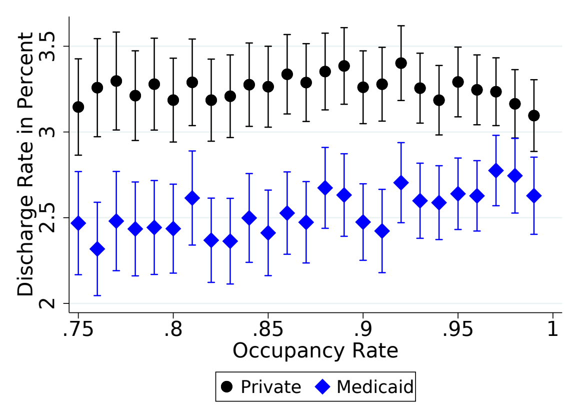

(a) Hospitalized




(b) Discharged to Another Nursing Home



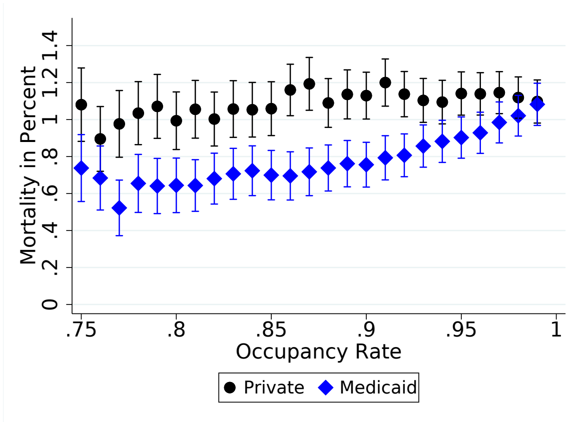

(c) Deceased



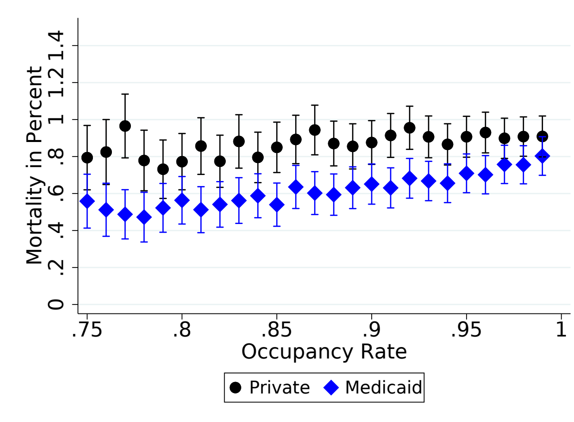

(d) Discharged to Other Destinations

**Notes:** See notes for Figure 3. This figure considers other discharge destinations, excluding home discharges. The binary dependent variables equal one if a resident was discharged to a hospital (Figure E.1a), to a different nursing home (Figure E.1b), deceased (Figure E.1c), or to any of the non-community destinations (Figure E.1d) in a given week. The vertical bars indicate 95% confidence intervals. We exclude estimates for 100% occupancy due to measurement error.

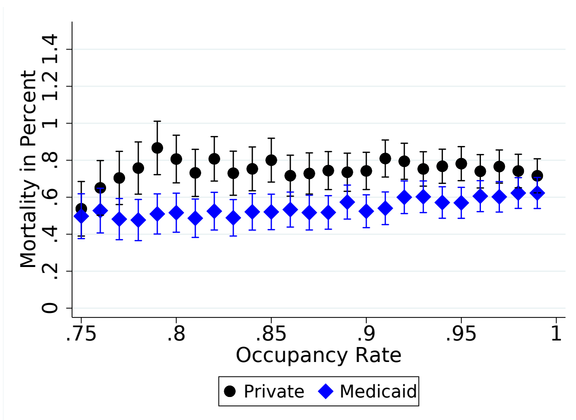
Figure E.2: Weekly Mortality Rate by Quartile of Predicted Home Discharge Potential



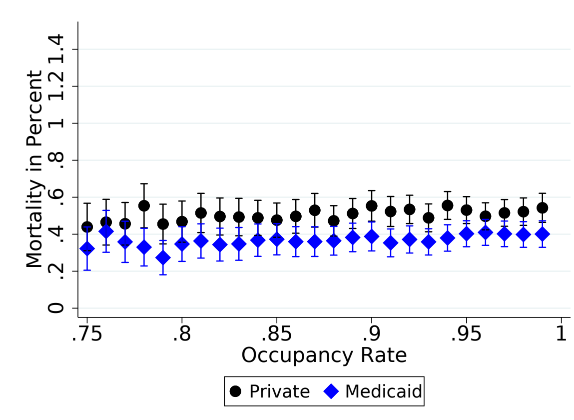

(a) First Quartile (lowest)




(b) Second Quartile




(c) Third Quartile




(d) Fourth Quartile (highest)

**Source:** Long-Term Care Minimum Data Set, Office of Statewide Health Planning and Development (2020). The figure presents the estimated weekly mortality rates, discharges due to death, by payer type and occupancy across four subpopulations, defined by the patient's predicted home/community discharge potential at admission, see Section B. Figure E.2a considers the bottom 25% of patients (1st quartile) with the lowest predicted home discharge potential. Figure E.2b considers patients in the second quartile. Figure E.2c considers patients in the third quartile and Figure E.2d considers patients in the fourth quartile. Otherwise the sample is the same as in Figure 3. The figure plots $\hat{\gamma}^k$ (private) and $\hat{\gamma}^k + \hat{\delta}^k$ (Medicaid) of equation (2) for the dependent variable "mortality" across occupancy rates $k$. The vertical bars indicate 95% confidence intervals.

robustness check using our baseline sample but allowing non-community discharges to vary exogenously in the occupancy rate.

Figure E.4 summarizes the estimated and predicted home discharge profiles for these robustness exercises. The top left graph shows again the patterns for our baseline sample, which excludes the 10% patients with the lowest discharge potential. The top right and the lower left graphs shows the same estimates for robustness exercises (i) and (ii). The corresponding structural parameter estimates along with the implied patient and provider elasticities are in Table E.1.

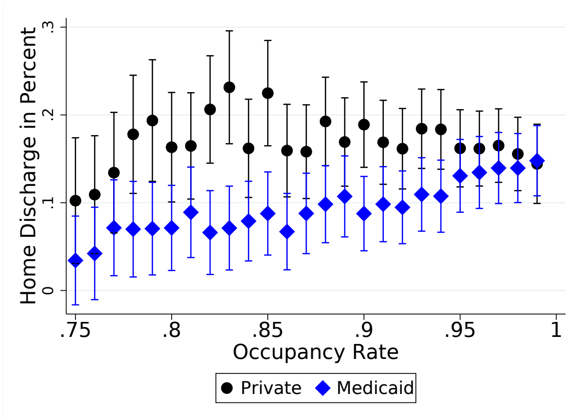
As seen in the bottom rows of Table E.1, the structural parameter estimates remain quite robust across

Table E.1: Structural Parameter Estimates—Robustness

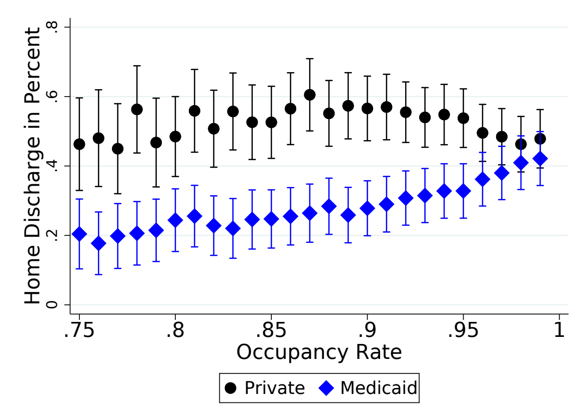
| | Baseline | (1) | (2) | (3) |
|---|---|---|---|---|
| Exclude Bottom x% of Home Discharge Potential | 10 | 25 | 50 | 10 |
| Discharges to Non-Home Destinations Varying in Occupancy | No | No | No | Yes |
| *A. Estimated Outside of Model* | | | | |
| Refill Probability | | See Figure E.11. | | |
| Occupancy Transition Matrix | | Estimated from weekly sample. | | |
| Pr[Payer Type Transition to Medicaid] | 1.1% | | | |
| Pr[Private Payer at Admission] | 78.0% | | | |
| Discharge Rate to Non-Home Destinations, Private | 3.19% | 3.31% | 3.75% | by occupancy |
| Discharge Rate to Non-Home Destinations, Medicaid | 1.46% | 1.48% | 1.54% | by occupancy |
| Daily Private Rate | \$258 | | | |
| Daily Medicaid Rate | \$214 | | | |
| *B. Calibrated* | | | | |
| Discount Factor | $0.95^{\frac{1}{52}}$ | | | |
| Cost of Effort Function | $e^2$ | | | |
| Utility of Nursing Home Care per day | 0.5 | | | |
| *C. Estimated Inside of Model* | | | | |
| SNF Effort Parameter | 0.021 | 0.022 | 0.026 | 0.023 |
| | [0.020, 0.026] | [0.021, 0.025] | 0.020, 0.035] | [0.020, 0.031] |
| Resident Effort Parameter | 0.177 | 0.183 | 0.226 | 0.177 |
| | [0.174, 0.184] | [0.180, 0.188] | [0.200, 0.2590] | [0.174, 0.188] |
| Resident Price Coefficient | 0.03 | 0.024 | 0.027 | 0.03 |
| | [0.027, 0.035] | [0.022, 0.028] | [0.02, 0.034] | [0.027, 0.041] |
| Marginal Cost of Care per Person and Day | 111.4 | 121.7 | 142.9 | 111.5 |
| | [111.1, 121.8] | [121.3, 122.4] | [107.1, 143.5] | [111.4, 121.7] |
| SNF Elasticity | 1.2 | 1 | 0.9 | 0.8 |
| Resident Elasticity | 0.2 | 0.2 | 0.3 | 0.2 |

Panel A summarizes the parameters that we estimate outside of the model. The discharge rates to non-home destinations in columns 1-2 denote the sample average weekly discharge rate to other (non-home) destinations by payer type. Panel B summarizes the calibrated parameters. Panel C summarizes the parameters that we estimate inside the model along with their 95% bootstrap confidence intervals. The estimated private and Medicaid rates as well as the marginal costs are presented as daily rates (per patient and day). We conduct inference via bootstrapping. Column (1) shows results for the sample without the bottom quartile of patients in terms of their discharge potential; column (2) omits the two bottom quartiles and column (3) allows the non-community discharge rates to vary in occupancy. See main text for details.

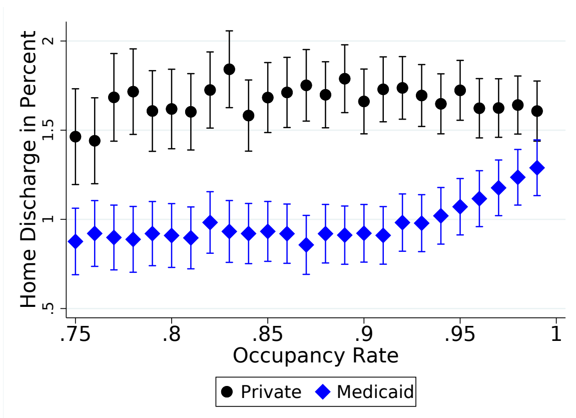
Figure E.3: Replication of Figure 3 by Quartile of Predicted Home Discharge Potential



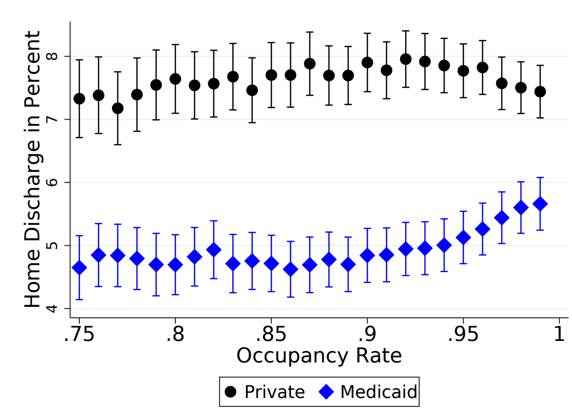

(a) First Quartile (lowest)




(b) Second Quartile




(c) Third Quartile

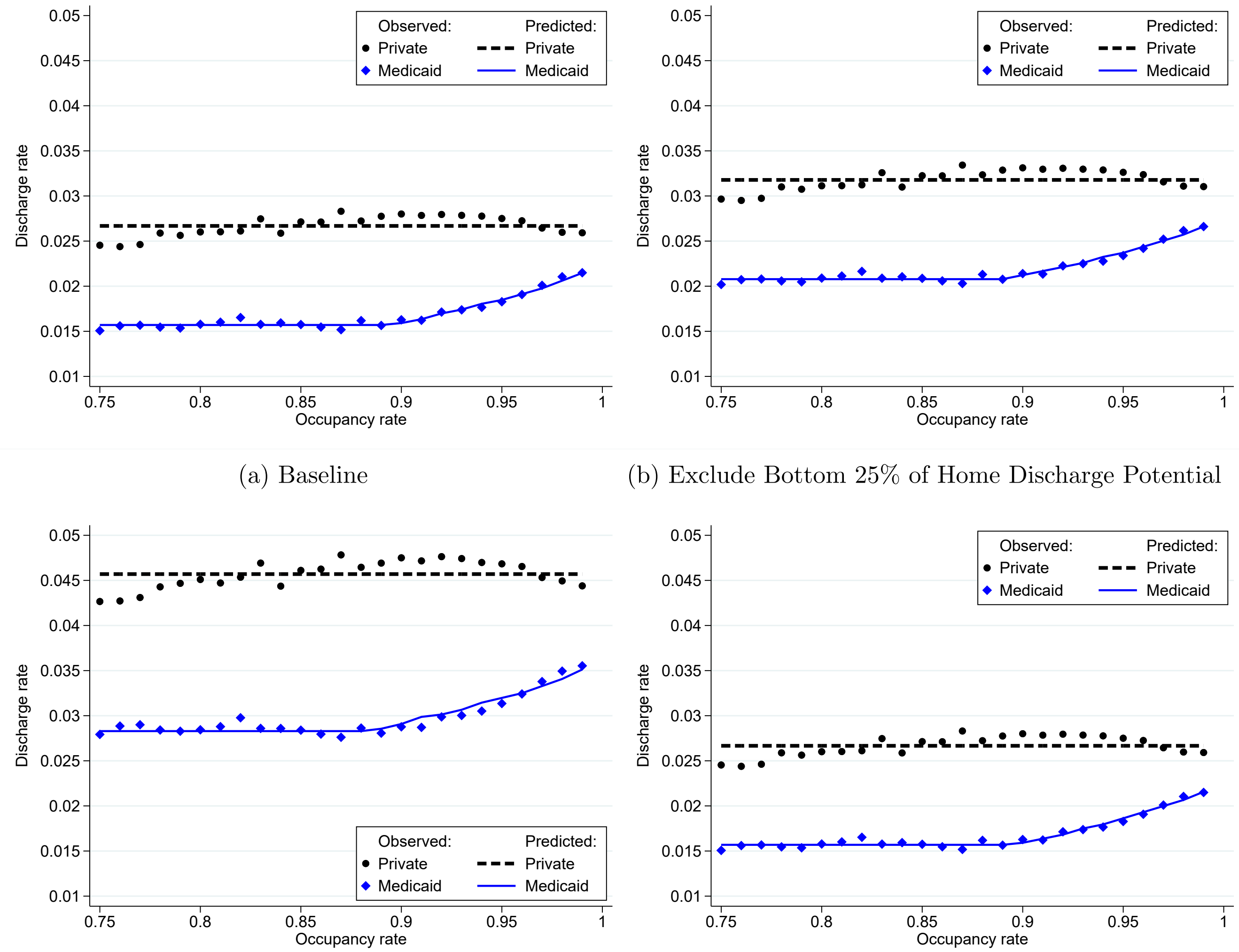



(d) Fourth Quartile (highest)

**Source:** Long-Term Care Minimum Data Set, Office of Statewide Health Planning and Development (2020). The figure presents the estimated weekly home discharge rates by payer type and occupancy across four subpopulations, defined by the patient's predicted home/community discharge potential at admission, see Section B. Figure E.3a considers the bottom 25% of patients (1st quartile) with the lowest predicted home discharge potential. Figure E.3b considers patients in the second quartile. Figure E.3c considers patients in the third quartile and Figure E.3d considers patients in the fourth quartile. Otherwise the sample is the same as in Figure 3. The figure plots $\hat{\gamma}^k$ (private) and $\hat{\gamma}^k + \hat{\delta}^k$ (Medicaid) of equation (2) for the dependent variable "home discharge" across occupancy rates $k$. The vertical bars indicate 95% confidence intervals.

the first three specifications. Going from left to right, we estimate larger patient effort parameters, which can account for the increase in the home discharge rate for Medicaid patients at low discharge rates, see the top graphs and the bottom left graph in Figure E.4. The estimated resident price coefficients remain relatively constant across these specifications. Most importantly, the implied patient elasticities remain at 0.2 across columns. Turning to providers, and again going from left to right, we estimate larger marginal costs and larger SNF effort parameters that account for differences in the kink point location and the slope of the Medicaid discharge profile at higher occupancy rates. Importantly, the implied provider elasticities change relatively little, ranging between 0.9 and 1.2. Overall, these results indicate that the

Figure E.4: Simulated Home Discharge Rates: Robustness




(a) Baseline

(b) Exclude Bottom 25% of Home Discharge Potential

(c) Excludes Bottom 50% of Home Discharge Potential

(d) Non-Home Discharges Varying by Occupancy

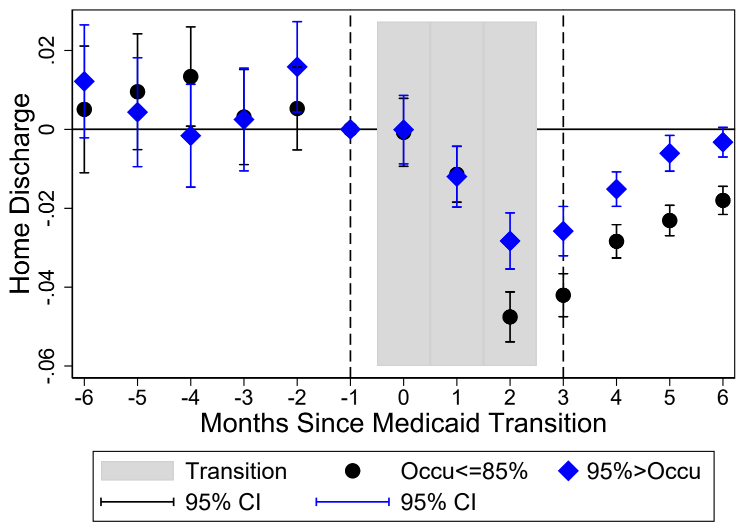
**Source:** Long-Term Care Minimum Data Set, Office of Statewide Health Planning and Development (2020). The figures show the estimated home discharge rates for private payers and Medicaid beneficiaries from Figure 3, denoted by dots (private) and diamonds (Medicaid), along with the corresponding model predictions captured by the dashed line (private) and the solid line (Medicaid). Figure E.4a presents the baseline home discharge patterns, see also Figure 5, and excludes the 10% of patients with the lowest home discharge potential at admission, see Section B. Figure E.4b excludes the bottom 25% of patients based on their home discharge potential at admission and Figure E.4c excludes the bottom 50% of patients. Finally, Figure E.4d considers the baseline population but allows non-community discharges to vary in occupancy. The figure plots $\hat{\gamma}^k$ (private) and $\hat{\gamma}^k + \hat{\delta}^k$ (Medicaid) of equation (2) for the dependent variable "home discharge" across occupancy rates $k$. The vertical bars indicate 95% confidence intervals.

slight occupancy-mortality gradient does not confound our main analysis and conclusions. To increase sample size and cover a broader and more representative patient population, we therefore maintain our baseline sample definition.

In a last check, we consider a model in which non-community discharges vary by payer source and occupancy. Instead of using the average non-home discharge rates as in the baseline model, in Figure E.1, we use any non-community discharges by occupancy (Figure E.1d) in the structural estimation. While we do not formally endogenize the link between occupancy and non-community discharges in our model, we view this exercise as a feasible middle ground between our baseline approach and very rich model that fully endogenizes discharges along other dimensions. Reassuringly, we find again very similar parameter estimates and elasticities in this approach, see column (4) of Table E.1.

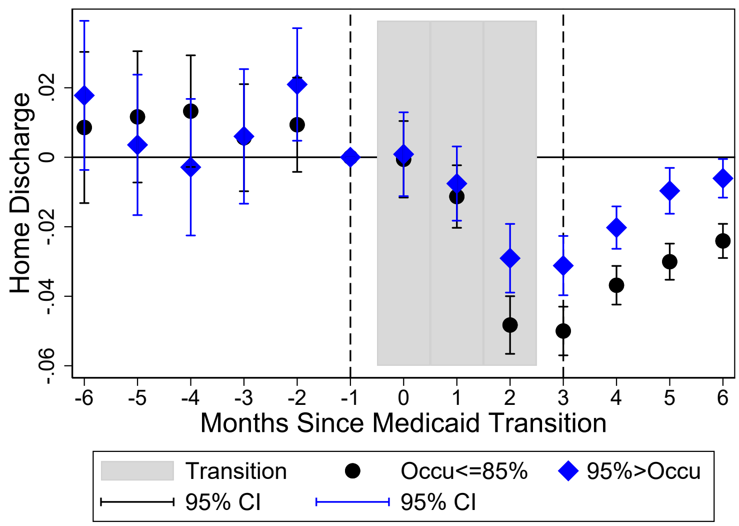
# B Additional Robustness Checks for Event Study Approach

Figure E.5: Robustness of Figure 3—Rescaled Community Transitions



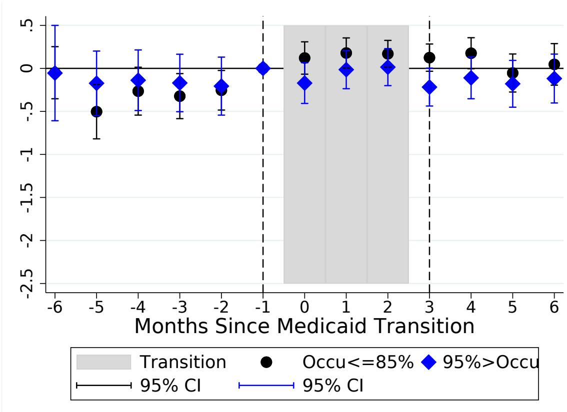

**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section E. The figure plots $\sum_{\iota=-6}^{-2} \mu_t$ and $\sum_{\tau=0}^{6} \mu_t$ of equation (3). This robustness check uses a rescaled time-to-Medicaid transition spend-down schedule for patients discharged to the community. The rescaled spend-down rate is three times faster than the factual (observed) spend-down rate among patients in HCBS. The vertical bars indicate 95% confidence intervals.

Figure E.6: Robustness of Figure 3—Omitting Ongoing Stays

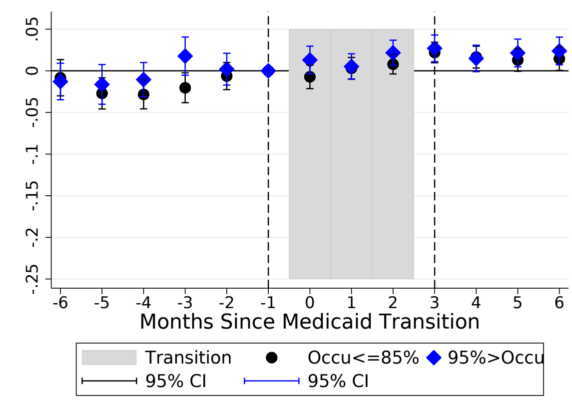



**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section E. The figure plots $\sum_{\iota=-6}^{-2} \mu_t$ and $\sum_{\tau=0}^{6} \mu_t$ of equation (3). This robustness check omits ongoing stays. The vertical bars indicate 95% confidence intervals.

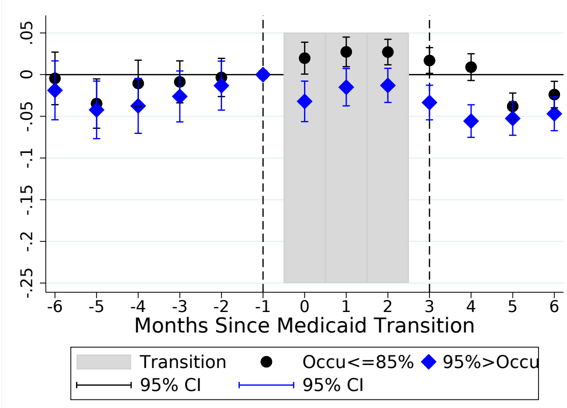
Figure E.7: Robustness of Figure 3: Health as Potential Confounder and Outcome



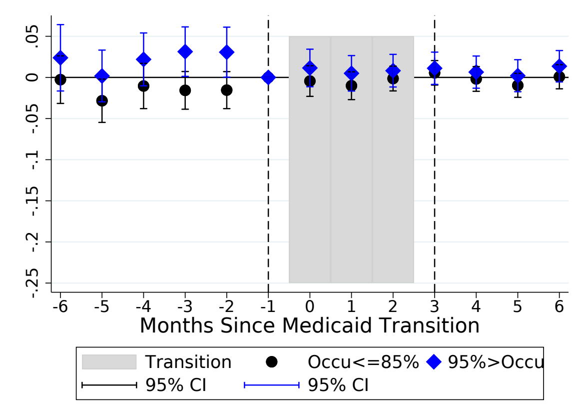

(a) Total ADLs




(b) Weight Loss

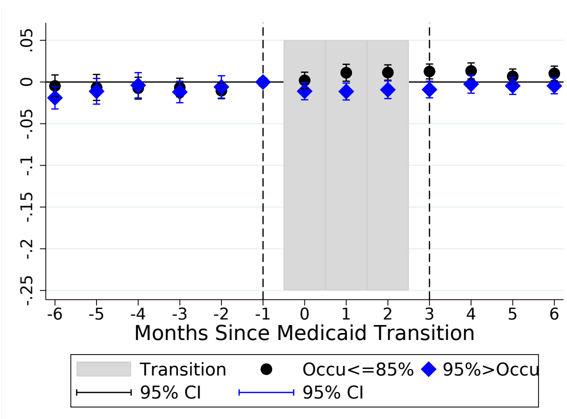



(c) Impaired Cognition

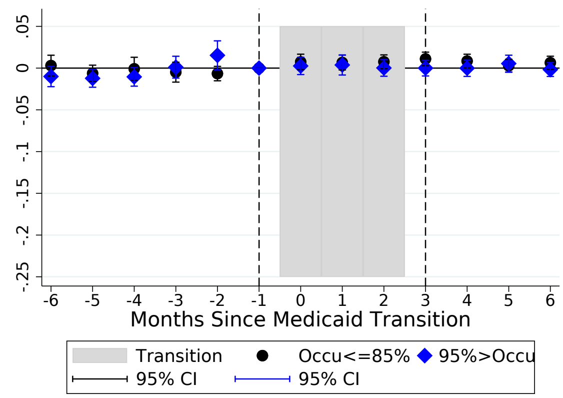



(d) Depression

**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section E. The figure plots $\sum_{\iota=-6}^{-2} \mu_t$ and $\sum_{\tau=0}^{6} \mu_t$ of equation (3). The dependent variables are the time-varying health measures as indicated by the subheadings. The vertical bars indicate 95% confidence intervals.




(e) Stage-3 Pressure Ulcers




(f) Stage-4 Pressure Ulcers

**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section E. The figure plots $\sum_{\iota=-6}^{-2} \mu_t$ and $\sum_{\tau=0}^{6} \mu_t$ of equation (3). The dependent variables are all time-varying health measures as indicated by the subheadings. The vertical bars indicate 95% confidence intervals.

## C Total Discharge Differentials by Private Payer Prices and Mark-Ups

The following robustness check stratifies the total discharge differentials in Table 2 by private nursing home rates and the mark-up of private rates over Medicaid rates. Using unique pricing data from Pennsylvania and California, we estimate the following variant of equation (2):

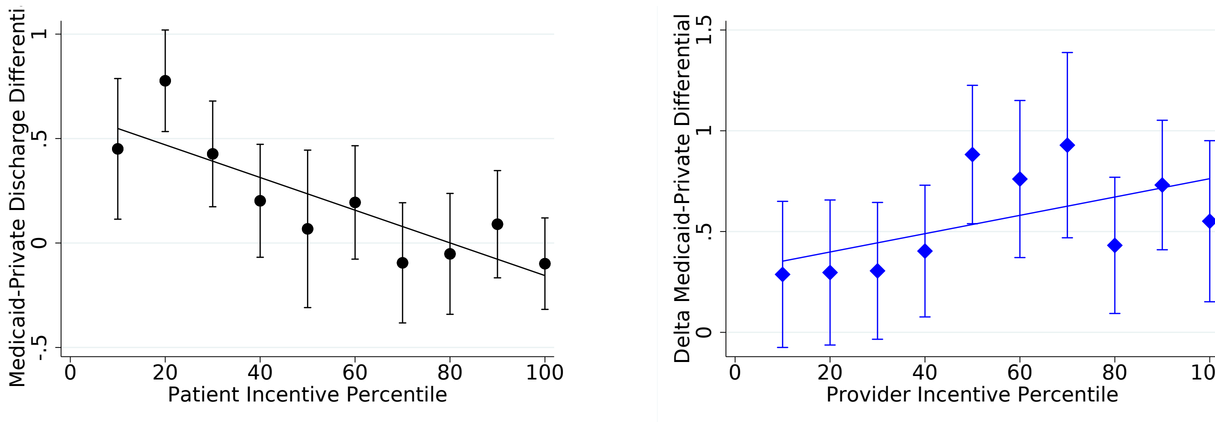
$$\begin{aligned} Y_{ijst} &= \mathbf{1}\{oc_{jt-1} < 85\%\} Mcaid_{is} \times \sum_{\tau=1}^{10} \delta_\tau^l \mathbf{1}\{r_{jt}^P \in PI^\tau\} \\ &+ \mathbf{1}\{oc_{jt-1} > 95\%\} Mcaid_{is} \times \sum_{\tau=1}^{10} \delta_\tau^h \mathbf{1}\{r_{jt}^P \in PI^\tau\} + \delta Mcaid_{is} \\ &+ \sum_{k=65}^{100} \gamma^k oc_{jt-1}^k + \eta_s + \eta_{jy} + \eta_c + X_{it}'\beta + \epsilon_{ijst}, \end{aligned} \tag{E.1}$$

where the first two rows replace $\sum_{k=65}^{100} \delta^k occ_{jt-1}^k Mcaid_{is}$ from equation (2). Specifically, $\mathbf{1}\{oc_{jt-1} < 85\%\}$ stands for an environment with low (less than 85%) and $\mathbf{1}\{oc_{jt-1} > 95\%\}$ stands for an environment with high (more than 95%) occupancy rates. We then interact those binary variables with series of indicator variables, $\mathbf{1}\{r_{jt}^P \in PI^\tau\}$, that turn on if the nursing home's private rate falls into one of ten price deciles in the state of that year.

The key parameters of interest are $\delta_\tau^l$. They govern differences in discharge rates between Medicaid and private payers at low occupancy rates for different private rate deciles. Figure E.8a plots the ten $\delta_\tau^l$ point estimates along with 95% confidence intervals for nursing homes below full capacity. The y-axis shows $\delta$, the total discharge differential, and the x-axis shows the price percentile, where 90-100$^{th}$ indicates the strongest patient incentives and the highest private rates. As seen, at low occupancy rates, the statistically significant downward slope indicates larger discharge differentials between Medicaid and private residents in facilities who charge higher private rates.

Figure E.8b tests for differences in total discharge differentials. It stratifies by the strength of provider incentives. Specifically, we replace $\mathbf{1}\{r_{jt}^P \in PI^\tau\}$ with $\mathbf{1}\{\mu_{jt} \in MU^\tau\}$, which turns on if the nursing home's private rate *markup* falls into one of ten markup deciles. The key parameters of interest represent now $\delta^{oc>oc^*} = \alpha + \zeta_{SNF}$, which is $\delta_\tau^h - \delta_\tau^l$—analogous to the lower panel of Table 2. The y-axis represents this difference. Figure E.8b again presents point estimates for all ten percentiles on the x-axis, along with 95% confidence intervals. Here, the statistically significant *upward* slope indicates that the relative probability that Medicaid beneficiaries get discharged when SNFs operate at capacity (relative to private

Figure E.8: Discharge Differentials by Private Payer Mark-Ups and Occupancy Rates




(a) Patient Incentives

(b) Provider Incentives

**Notes:** Figure E.8a plots $\delta^l_\tau$ of equation (E.1), that is, the discharge differential when nursing homes operate below full capacity with $\alpha = 0$ as in Figure 1. The x-axis indicates the size of the private nursing home rate in that state and year, where 90-100$^{th}$ indicates the highest private rates. Figure E.8b replaces $\mathbf{1}\{r^P_{jt} \in PI^\tau\}$ in equation (E.1) with $\mathbf{1}\{\mu_{jt} \in MU^\tau\}$, which indicates private rate markup deciles over Medicaid rates when nursing homes operate at full capacity with $\beta = 0$ and exert effort to substitute private payers for Medicaid beneficiaries. The y-axis plots $\delta^h_\tau - \delta^l_\tau$ of equation (E.1). The vertical bars indicate 90% confidence intervals.

payers and low occupancies) increases with higher private rate mark-ups. These findings corroborate the baseline evidence on provider incentives.

## D Patient Incentives: Bunching and the Share of Cost

This section exploits an alternative source of patient cost-sharing to revisit the patient elasticity with respect to financial incentives. One main purpose is to compare the performance of a myopic static model and a stylized dynamic model of a rational forward-looking agent in fitting the observed patient behavior. Specifically, we exploit within-month cost-sharing variation among Medicaid beneficiaries through the "share of cost". The share of cost corresponds to a monthly deductible. Every month, Medicaid beneficiaries must pay the Medicaid reimbursement rate for the first days of the month until they have exhausted their own income (net of a small personal allowance). Once their monthly income is depleted, Medicaid starts paying the daily Medicaid reimbursement rate for the rest of the month. We focus the analysis on the state of Pennsylvania, where we are most familiar with the share of cost regulations during our sample period, see e.g. Section 468.3 in Pennsylvania Department of Human Services (2020) and 55 Pa.Code § 181.453.

This section proceeds as follows. First, we present descriptive evidence on how the timing of Medicaid home discharges responds to the non-linear variation in patient cost-sharing over the course of the month.

Second, we develop a stylized dynamic model of patient behavior, which nests a fully myopic model with a discount factor of 0 and a model of rational forward-looking agent with a discount factor of 0.95. We calibrate the model to the observed data, assess the implied patient elasticities with respect to financial incentives, and compare the model fit.

### D.1 Descriptive Evidence

Figure E.9a illustrates the daily SNF consumer prices for private payers and Medicaid beneficiaries on the y-axis against the day-of-the-month on the x-axis. The graph relies on income data among Medicaid SNF residents from 1999 and 2004 in the NLTCS, see Table B.1, and price data from Pennsylvania. Net of a personal allowance of $30 per month it shows daily cost-sharing by day of the month. As seen, already on the first day of the month, *average* cost-sharing falls short of the average Medicaid rate of $159, indicating that some beneficiaries have monthly net incomes below $159. Cost-sharing then falls sharply after the first three days of the month. By contrast, private payers pay the constant private rate over the course of the month.

Next, in Figure E.9b, we study the relationship between cost-sharing and SNF home discharges. As in our main approach, we identify patients with a monthly discharge probability of more than 10% using our machine learning approach, see Section D. Figure E.9b plots the frequency of community discharges against the day-of-the-month, among patients from Pennsylvania that were discharged to the community. Mathematically, we plot $Pr[\text{Day of month at Discharge}|\text{Discharged to Community}]$. Among Medicaid patients, we observe bunching at the end of a month as evidenced by a more than twofold increase in the discharge frequency (the last day of the month is normalized to zero), consistent with a positive patient demand elasticity.

Figure E.9c aggregates the discharge probabilities to the week-of-the-month, which we use in subsequent structural analysis detailed below.[31] and shows again bunching in the focal week 0. Compared to the neighboring weeks, weekly discharge probabilities increase by 4-5 percentage points or 24-34%.

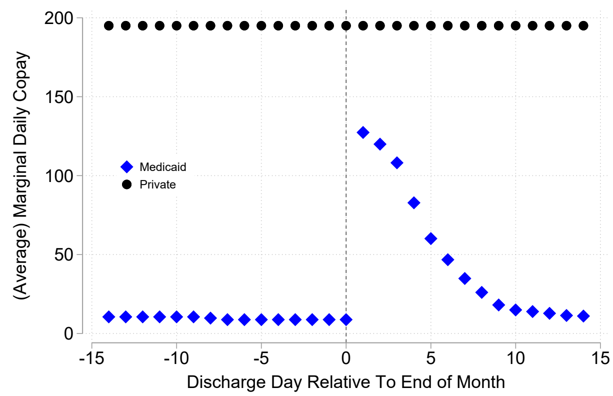
### D.2 Implied Patient Elasticity

To translate the bunching evidence in Figure E.9 into a patient price elasticity and to conduct an empirical horse race between a static myopic model and a dynamic forward-looking model of patient behavior, we next specify a parsimonious patient discharge model. In contrast to our baseline model, we do not model

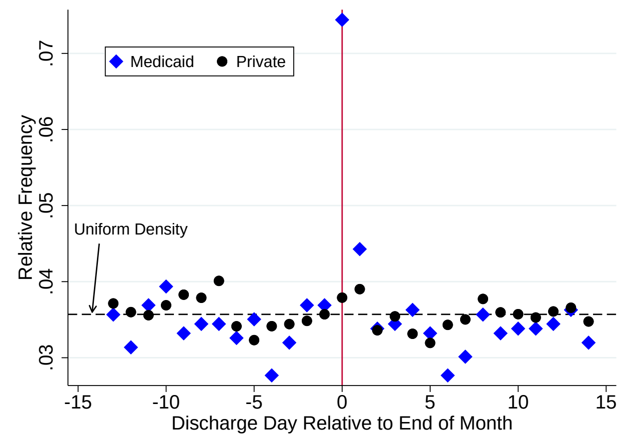
[31] To capture the symmetric bunching around the end of the month, we define our focal bunching week 0 to include the days -3 to +3. Week 1 captures days 4 to 10, week -1 captures days -10 to -4 and week 2 the rest normalized to seven days.

Figure E.9: Daily Cost-Sharing and Community Discharges—Bunching Analysis

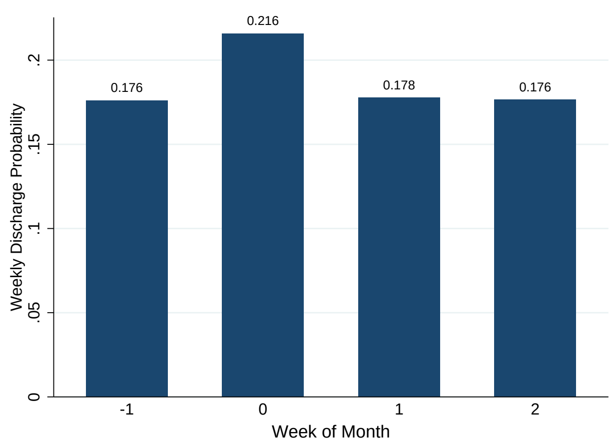
(a) Simulated Cost-Sharing by Day-of-Month




(b) Community Discharges by Day-of-Month




(c) Medicaid Discharge by Week-of-Month




**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for PA from 2000 to 2005, NLTCS from 1999 and 2004. Figure E.9a presents average daily cost-sharing amounts for private payers and Medicaid beneficiaries by the day-of-the-month. Figure E.9b plots the frequencies of the discharge day of the month for private payers and Medicaid beneficiaries that were discharged to the community, $Pr[\text{Day of month at Discharge}|\text{Discharged to Community}]$. We normalize the average discharge rate to 1/28 to match a month of 4 weeks (28 days). The horizontal line presents this average discharge rate. In Figures E.9a and E.9b the last day of the month is normalized to zero. Figure E.9c aggregates the discharge frequencies for Medicaid patients in Figure E.9b to the week of the month. Week -1, 0, and 2 capture the days [-10,-4], [-3,3], and [4,10], respectively. Week 2 captures the remaining days normalized to seven days.

the patient's discharge effort explicitly. The goal of this exercise is not to compare the effort function or the returns on effort between specifications. Instead, we care about the implied patient elasticity of financial incentives on the length of stay. As such, we choose a simplified model which implicitly captures the parameters governing the cost of effort function and the returns to effort in the preference parameters.

We model the discharge process at the weekly level and assume that the month is comprised of four weeks. We define patient flow utilities in week $\tau$ as follows:

$$\begin{aligned} u_s(\tau) &= \delta - \alpha \times Price(\tau) + \epsilon_s \\ u_o(\tau) &= \epsilon_o \end{aligned}$$

where $\epsilon$ is an i.i.d. extreme value shock. $\delta$ denotes the relative utility of nursing home care (relative to the outside option, denoted by $o$). $Price(\tau)$ denotes the out-of-pocket price for Medicaid patients in week $\tau$ and $\alpha > 0$ captures the disutility of prices. Next we consider a weekly discount factor of $\beta$ and specify the patient's Bellman equation as

$$V(\tau) = E_\epsilon\Big[max\{\delta - \alpha \times Price(\tau) + \epsilon_s + \beta \times V(\tau'), \epsilon_o\}\Big] \quad .$$

**Estimation Strategy:** We consider a static model with a discount factor $\beta = 0$ and a dynamic model with $\beta = 0.95^{1/52}$. The remaining structural parameters of interest are then $\theta = (\delta, \alpha)$. We estimate $\theta$ using a nested fixed point algorithm. For a given guess of $\theta$, we solve the Bellman equation and predict the discharge probability as

$$\hat{Pr}(\theta, \tau) = \frac{1}{1 + exp(\delta - \alpha \times Price(\tau) + \beta \times V(\tau', \theta))}$$

Finally, we choose the parameter vector that minimizes the squared difference between observed and predicted discharge probabilities. Specifically, we match the predicted discharge probabilities for week -1 and week 0 to their observed empirical counterparts, denoted simply by $Pr(\tau)$, and then use evidence from week 1 and week 2 for model validation. We choose week 0 as a data moment as we require price variation between weeks to recover the price coefficient $\alpha$. As detailed below, one of our pricing models assumes that prices are 0 in weeks -1,1, and 2 and 1 in week 0. Hence, we need to target week 0 in the estimation. We also use week -1 as a data moment in order to match potential anticipation effects (reduced discharge rates) that one would expect among forward looking consumers. Our estimator solves

$$\hat{\theta} = arg \min_\theta \Big[(Pr(\tau = -1) - \hat{Pr}(\theta, \tau = -1))^2 + (Pr(\tau = 0) - \hat{Pr}(\theta, \tau = 0))^2\Big] \; .$$

To estimate the model, we also need to specify the corresponding empirical discharge probabilities and the weekly out-of-pocket prices. Starting with the former, we note that the discharge frequencies displayed in Figure E.9c are conditional on home discharges: $Pr[week\ of\ month|Home\ Discharge]$. Instead the model makes predictions about $Pr[Home\ Discharge|week\ of\ month]$. Using Bayes rule, we have

$$Pr[Home\ Discharge|week\ of\ month] = Pr[week\ of\ month|Home\ Discharge] \times \frac{Pr[Home\ Discharge]}{Pr[week\ of\ month]}.$$

We approximate $Pr[week\ of\ month]$ by 1/4, considering four weeks of the month and abstracting from the effects of bunching on the unconditional distribution of calendar weeks. We consider an average weekly home discharge rates for Medicaid patients of 1.7%, which corresponds to our baseline estimates at lower occupancy rates, see Figure 3. With these estimates at hand, we calculate $Pr[Home\ Discharge|week\ of\ month]$ for Medicaid patients. Finally, we add the weekly probability of non-home discharges for Medicaid patients (1.5%) to each of the four weeks. The first column in Table E.2 presents the corresponding discharge probabilities in rows 6 to 10.

We consider three alternative specifications. The first model assumes that cost-sharing is charged at the end of the week. If a person is discharged in a given week, she will not be charged for that week. To provide a conservative upper bound on patient incentives, we assume that discharges in week 0 are motivated to circumvent daily charges for the first 7 days of the month. Since week 0 encompasses days $[-3, +3]$, this approach interprets discharges in the first three days of the month as discharges towards the end of the previous month, thereby avoiding all charges in the current month. Then we use Figure E.9a and construct the cumulative cost-sharing over the relevant 7-day window, which we refer to as $Price(\tau)$.[32] Finally, we normalize charges in week 0 to 100%. We present these estimates under $Price(\tau)$ in rows 2 to 5 of columns (2) and (5) in Table E.2.

Second, we consider a model where cost-sharing is entirely concentrated in the bunching week, see rows 2 to 5 of column (3) and (6). Here charges equal 100% in week 0 and 0% otherwise. Finally, we consider a model of concurrent charges, where discharges in week $\tau$ are motivated to avoid charges for the days falling precisely into the defined time window.[33] We present these estimates under $Price(\tau)$ in rows 2 to 5 of columns (4) and (7) in Table E.2. The difference between the first and third set of prices is that in columns (2) and (5), we assume that residents are not charged for the week when they are discharged

[32] As mentioned, we use a four-day lag in charges, whereby Figure E.9a's charges for days 1 to 7 correspond to week 0, charges for days 8 to 14 to week 1, charges for the days -13 to -7 to week 2, and charges for the days -6 to 0 for week -1.

[33] Specifically, charges for days -3 to 3 correspond to week 0, charges for days 4 to 10 to week 1, charges for the days 11 to 17 to week 2, and charges for the days -10 to -4 for week -1.

whereas they are charged in columns (4) and (7).

Building on these assumptions and the estimated structural parameters, we calculate the weekly discharge probabilities and the implied (simulated) length of stay. We repeat that exercise after increasing the weekly prices by 10% and construct the implied patient elasticity by diving the relative change in the length of stay by the relative change in weekly out-of-pocket prices (10%).

**Results:** We start with our first static model in the second column. The second panel presents the predicted discharge rates by week of the month. For weeks -1 and 0, targeted in the estimation, we almost perfectly fit the observed rates (3.1% and 3.47%). We then simulate the length of stay under different price schedules and find an elasticity of only 0.08. The static model in the second column assumes that cost-sharing is concentrated in week 0. We again fit discharge rates almost perfectly in weeks -1 and 0, and the mean squared error (MSE) is even slightly lower than the MSE for the first model. We find a similar elasticity of 0.06. The static model in the third column assumes that charges occur concurrently, which yields a worse fit of the data. The model predicts almost the same discharge rate in weeks 0 and 1, which is inconsistent with the data. Nevertheless, we find a similar elasticity of 0.05.

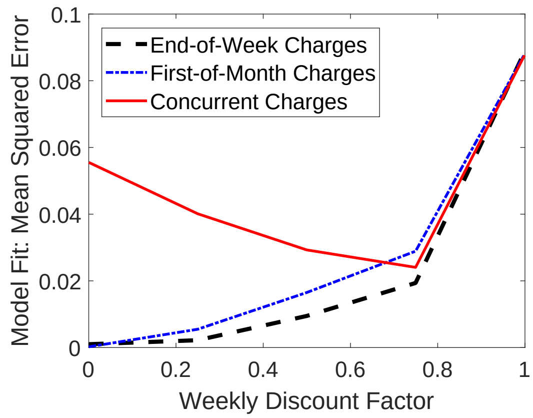
Turning to the dynamic models, columns (5) to (7) revisit the static specifications but set $\beta = 0.95^{1/52}$. We find slightly larger elasticities of up to 0.11. This is expected as the long-term horizon mutes the short term incentives provided by the week-to-week variation (Einav, Finkelstein, and Schrimpf, 2017). We note, however, that this dynamic calculation assumes rational dynamically-optimizing agents, which is not particularly plausible in our setting, given the evidence on behavioral biases and sub-optimal behavior among the elderly (Dalton, Gowrisankaran, and Town, 2020). The dynamic model also provides a poor fit of the data and cannot reconcile the observed degree of bunching in week 0. The predicted discharge rates increase from 0.032 to only 0.322 between weeks -1 and 0. More generally, we find that the first two static models provide the best fit of the data (lowest MSE) for $\beta = 0$, see Figure E.10. The models contained in columns (2) and (3) of Table E.2, referred to as "End-of-Week Charges" and "First-of-Month Charges" in the figure, achieve a near-perfect fit at a discount factor of $\beta = 0$. We conclude that a static model provides the best fit for the observed bunching evidence. All models indicate a patient elasticity of at most 0.11, which is somewhat smaller than our baseline patient elasticity estimate of 0.2.

Table E.2: Patient Elasticity—Evidence from Week of the Month Bunching

| | Data | Static Model | | | Dynamic Model | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\beta$ | | 0 | 0 | 0 | $0.95^{1/52}$ | $0.95^{1/52}$ | $0.95^{1/52}$ |
| $Price(\tau=-1)$ | | 0.14 | 0.00 | 0.23 | 0.14 | 0.00 | 0.23 |
| $Price(\tau=0)$ | | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| $Price(\tau=1)$ | | 0.28 | 0.00 | 0.95 | 0.28 | 0.00 | 0.95 |
| $Price(\tau=2)$ | | 0.16 | 0.00 | 0.31 | 0.16 | 0.00 | 0.31 |
| $\hat{Pr}[D\|\tau=-1]$ | 0.0310 | 0.0309 | 0.0311 | 0.0309 | 0.0320 | 0.0320 | 0.0320 |
| $\hat{Pr}[D\|\tau=0]$ | 0.0347 | 0.0347 | 0.0347 | 0.0331 | 0.0321 | 0.0321 | 0.0322 |
| $\hat{Pr}[D\|\tau=1]$ | 0.0312 | 0.0315 | 0.0311 | 0.0329 | 0.0319 | 0.0319 | 0.0320 |
| $\hat{Pr}[D\|\tau=2]$ | 0.0310 | 0.0310 | 0.0311 | 0.0311 | 0.0320 | 0.0319 | 0.0319 |
| MSE: $\sum_\tau (Pr[D\|\tau]-\hat{Pr}[D\|\tau])^2 \times 10k$ | | 0.0010 | 0.0002 | 0.0555 | 0.0886 | 0.0880 | 0.0876 |
| Patient Elasticity | | 0.0766 | 0.0630 | 0.0482 | 0.0666 | 0.0430 | 0.1061 |

**Source:** This table summarizes the implied patient elasticities for Medicaid patients, presented in the last row, under different model specifications that all leverage the bunching evidence presented in Figure E.9. Column 1 summarizes the implied weekly discharge rates conditional on the week of the month. Columns 2-4 consider a static model with different Medicaid cost-sharing amounts by week of the month, which are presented in rows 2-5. Rows 6-9 in the second panel present the discharge probabilities predicted by the model, which intend to match the observed discharge rates presented in Figure E.9c Differences between model fit and data are summarized in row 10. Columns (5) to (7) present analogues results for dynamic models, as evidenced by the discount factor summarized in the first row.

Figure E.10: Model Fit of Bunching Evidence




**Source:** This figure presents the goodness of fit, defined as the mean squared error between predicted and actual weekly discharge rates for Medicaid patients, based on the bunching evidence outlined in Figure E.9. The x-axis shows weekly discount factors ranging from 0 to 1. The "end-of-week charges" graph considers spot prices defined in column (2) of Table E.2. The "first-of-month" and "concurrent charges" graphs consider spot prices defined in column (3) and (4) of Table E.2, respectively.

## E Provider Incentives: Weekly Refill Probabilities

This section presents a robustness check on provider incentives via the bed refill probability, $\Phi(oc)$. It determines the option value of an empty bed in our framework. To measure the weekly refill probability of an empty bed, we combine the observed number of vacant beds with the realized admissions.

Consider a nursing home with $a \geq 0$ incoming residents per week. Assume that the nursing home randomly assigns these incoming residents to $v$ vacant beds. If $a > v$, demand exceeds capacity and the nursing home must turn away $a - v$ of the newly arriving seniors. The probability that a focal bed remains empty in a given week equals:

$$\Pr[\text{Not Refilled}] = \begin{cases} \frac{v-1}{v} \times \frac{v-2}{v-1} \times \cdots \times \frac{v-a}{v-a+1} = \frac{v-a}{v} & \text{if } a < v \\ 0 & \text{otherwise}. \end{cases}$$

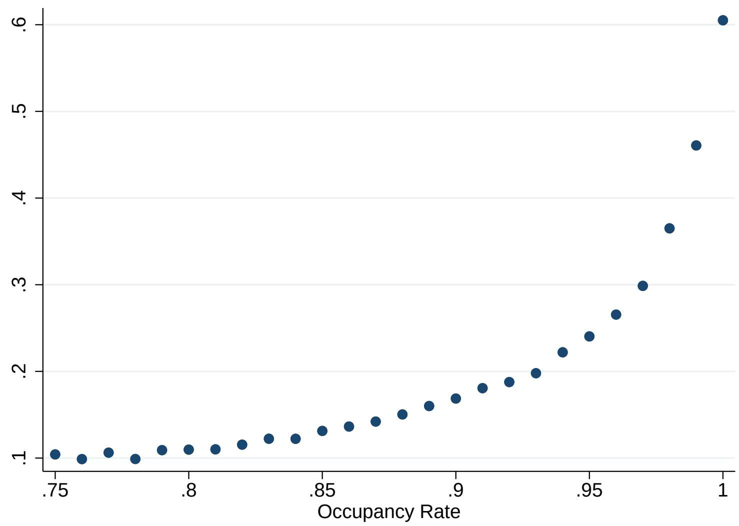
Hence, the probability that the bed is refilled is simply:

$$\Phi = \Pr[\text{Refilled}] = 1 - \Pr[\text{Not Refilled}] = 1 - \max\left\{\frac{v-a}{v}, 0\right\}. \tag{E.2}$$

We measure $\Phi$ at the facility-week level and construct its conditional mean by weekly occupancy.

Figure E.11 plots the weekly refill probability by SNF occupancy rates.

Figure E.11: Weekly Refill Probability by Occupancy Rate




**Notes:** This figure plots the average weekly refill probability of an empty bed against the facility's occupancy rate, see equation (E.2) (Appendix) for details.

Figure E.11 plots the average weekly refill probability of an empty bed on the vertical axis against the weekly occupancy rate on the horizontal axis. The figure documents a highly convex relationship and highlights the strongly increasing option value of an empty bed at occupancies exceeding 95%. The refill probability increases only slightly from 10% to 18% between 75% and 90% occupancy. Between 90% and 100% occupancy, however, the refill rate increases drastically from 18% to 60%. Considering that the large majority of newly-admitted (non-Medicare) residents pay out-of-pocket at the beginning of their stay, this exercise illustrates the strong incentives to discharge Medicaid beneficiaries at high occupancies and replace them with private payers (Figure 3).

# F Nursing Home Discharge Experiment

This section discusses the nursing home discharge experiment in Jones (1986). Norton (1992) provided several elasticities for the robustness exercise.

## A The Experiment

Between November 1980 and April 1983, the National Center for Health Services Research and Health Care Technology Assessment (NCHSR) carried out a demonstration project in cooperation with the Health Care Financing Administration cooperation. The idea was to investigate incentive payments to alter discharge patterns for Medicaid patients in nursing homes. The discharge incentives of the experiment were part of a larger study.

The experiment was conducted in 36 Medicaid-certified skilled nursing homes in the San Diego Metropolitan Statistical Area (SMSA). The aim was to improve placements of nursing home residents in lower level care settings through incentive payments. Lower levels of care included intermediate care facilities (ICF), board and care facilities, private homes, and other community settings.

The discharge incentive payments covered two cost components: vacant bed costs and staff effort cost. Payments varied by facility size (more vs. less than 60 beds) and time to discharge. We focus on payments for nursing homes with more than 60 beds. Payments were largest if a person was discharged within 5 days. In that case, payments amounted to 10 days of regular reimbursements to cover vacant bed costs and staff effort. Payments declined gradually in the time to discharge, dropping to about 25% for discharges after 1 month. Table F.1 below presents Exhibit 1 in Jones (1986) for nursing homes with 60-299 beds.

**Discharge Process:** For each patient, staff members completed a form whether the patient could be provided with services in a lower level of care setting to adequately meet their needs. The facility also developed a discharge plan which was reviewed by a research team to approve the discharge. Further, the placements and addresses were noted for follow-up visits and a discharge coordinator was assigned for weekly follow-up visits during the first month, and biweekly vists thereafter.

In addition, a nurse belonging to the research team visited the resident after 30, 60, and 90 days. The research nurse could authorize additional payments to the facility, depending on the status of the implementation and additional services that were required. Full payments were only granted if the patient stayed in the lower level setting for 90 days, in which case the discharge was considered successful.

## B Experimental Outcomes through the Lenses of the Model

To calibrate our model to the experimental environment, we undertook the following adjustments. First, we identified a target population in the experiment that most closely resembles our empirical setting. Patients in the experiment were classified into five states of health. Given our focus on patients with a decent discharge potential, we focus on the next healthiest patient group B, which require help with 1 to 4 activities of daily living see Norton (1992).

Second, we use our model to match the length of stay of group B patients in the control group. These patients have an average length of stay of 33 fortnights (or 66 weeks), see Table 2 in Norton (1992) and Table F.1. To match this, we assume that a period in our model corresponds to 2 weeks (as opposed to one week in our baseline analysis). This suggests that Medicaid patients have an average length of stay of 30.3 fortnights, which is already close to group B patients in the control group. We then adjust the flow utility parameter $u$ for Medicaid patients as well as the exogenous discharge rate to match the length of stay and the biweekly community discharge rate in the experiment.

We match these moments perfectly when increasing the daily flow utility parameter of nursing home care from $u = 0.5$ to $u = 7.4$ and the exogenous discharge rate from 1.3% to 2.7%. Figure F.1 presents the resulting Medicaid home discharge rates by occupancy for the control group (baseline).

Finally, we average the incentive payments to the two-week level to match the timing of the revised model. Specifically, we construct a bonus of (\$641+\$407)/2 if a person was discharged home within 2 weeks, and a bonus of (\$407+\$236)/2 if a person was discharged home after 2 weeks but within 4 weeks. Finally, we consider a bonus of \$166 if a person was discharged after 4 weeks. To adjust these bonus payments for inflation, we divide them by the Medicaid reimbursement rate in the experiment environment of \$36 and then multiply by the average Medicaid rate in our setting—\$214 per day.

Building on the calibrated model, we simulate the schedule of bonus payments via backward induction. We first consider patients that were not discharged within 4 weeks and simulate the effort function based on the smallest bonus payment, which is paid if the person was ever discharged home. Figure F.1 shows the corresponding discharge profile (>30 days). We then update the continuation value accordingly factoring in the optimal effort response to the bonus incentive. The calculation is considerate of the fact that the bonus payments only apply to select patients who were identified for the discharge goal. Specifically, the bonus payments do not apply to new incoming patients or patients that transition from private pay to Medicaid. In the simulation, we only consider the incentives for patients that are already on Medicaid.

Table F.1: Incentive Payments and Length of Stay in Discharge Experiment

Panel A: Schedule of Discharge Incentive Payments in $ for nursing homes with bed size 60-299

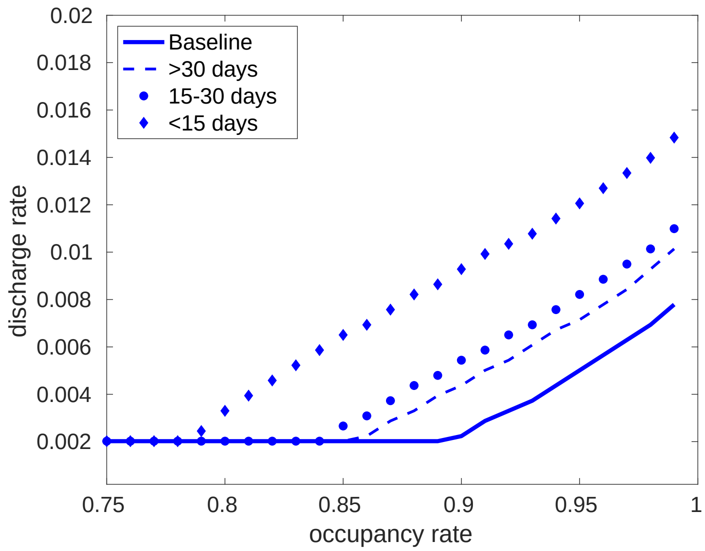
| | Experiment (Exhibit 1 (Jones, 1986)) | | | Current Prices (× 214/36) | Two Week Avg |
|---|---|---|---|---|---|
| Discharged: | Vacant Bed Cost | Staff Effort Cost | Total Cost | Total Cost | Total Cost |
| Within 5 days | 352.6 | 288.4 | 641 | 3810.4 | 3114.0 |
| Within 15 days | 176.3 | 230.4 | 406.7 | 2417.6 | 3114.0 |
| Within 30 days | 70.62 | 165.83 | 236.35 | 1405.0 | 1911.3 |
| More than 30 days | 0 | 165.83 | 165.83 | 985.8 | 985.8 |

Panel B: (Biweekly) Community Discharge Rate (Patient Group B, Norton (1992)):

| | Experiment | Model |
|---|---|---|
| Control Group | 0.38% | 0.38% |
| Treatment Group | 0.7% | 0.96% |

**Notes:** Panel A summarizes the discharge bonus payments from the nursing home experiment. The first three columns are excerpts from Exhibit 1 in Jones (1986). Column 4 translates total payments into current dollars. We divide by the Medicaid rate in the experiment environment and multiply by the average Medicaid rate in our sample population. Column 5 aggregates payments into two week averages. Panel B presents the community discharge rate for patients in group B of the experiment, who require help with 1 to 4 activities of daily living. The first column presents the discharge rate in the treatment and the control group as calculated in Norton (1992). The second column presents the predictions of our model.

Figure F.1: Discharge Effort by Bonus Payments




Building on the calculated continuation value, we then move two weeks ahead and consider the incentive payments for home discharges within 2 and 4 weeks, considering the continuation value of patients that are not discharged and may still generate bonus payments if home discharged at any future time during their stay. Given the larger incentives, we now find a steeper discharge profile as illustrated in Figure F.1 (15-30 days). Finally, we move another two weeks ahead and repeat the case for potential discharges in the first two weeks. Again we find an even steeper discharge profile (<15 days).

Building on these profiles, we simulate the average community discharge rate, factoring in different effort profiles as outlined in Figure F.1. We find that the community discharge rate increases from 0.38 to 0.96%. For comparison, Norton (1992) reports that the community discharge rate increases to only 0.7% (Table 3 in Norton (1992)), suggesting that our model predicts a larger increase in community discharge rates, (0.96%-0.38%)/(0.7%-0.38%)-1=81%, when evaluated at current prices that exceed the prices in the experiment by a factor of \$214/\$36=5.9.

# G Structural Analysis: Endogenous Occupancy

In the counterfactual analysis, we take endogenous changes in occupancy rates into account, which in turn affect provider discharge efforts. To this end, we divide the nursing home into two wings. The additional (external) wing allows us to incorporate admissions and discharges among residents that were not explicitly modeled in Section VI but also affect overall occupancy. These include the nursing home stays who were initially covered by Medicare. We treat these admissions and discharges as exogenous to the counterfactual policy changes. For the study population (nursing home wing) of interest, we take observed weekly admissions as exogenous, and use our structural model to predict discharge rates under alternative policy regimes.

We calibrate admissions and discharges in the external wing to match observed changes in occupancy rates conditional on observed admissions and the estimated discharge strategies in the focal wing of interest. Specifically, we consider a nursing home of $b$ beds and simulate occupancy changes in the focal wing of interest. To this end, we draw a sequence of shocks, $\epsilon^s = \left\{\epsilon^s_{occ}, \epsilon^s_{arr}, \epsilon^s_{\phi}, \epsilon^s_{\rho}, \epsilon^s_{dis}\right\}$ for each simulation iteration $s \in 1, ..., S$. The first shock $\epsilon^s_{occ}$ determines the change in occupancy rate for the entire nursing home. In combination with the occupancy transition matrix $\Theta(oc, oc')$, this shock specifies the occupancy for the next simulation draw (or next week) $oc^{s+1}$ conditional on today's occupancy rate, $oc^s$.

The remaining shocks govern admissions, payer type changes, and discharges in the focal wing of interest. $\epsilon^s_{arr}$, in conjunction with the arrival process outlined in Figure 2c, determines the number of new arrivals. $\epsilon^s_{\phi}$ and $\epsilon^s_{\rho}$ specify, in combination with $\phi$ and $\rho$ in Table 4, the payer type composition of new and previously admitted residents. Finally, $\epsilon^s_{dis}$, in combination with discharge probabilities by occupancy rate and payer type (Figure 6), specify the number of discharged residents.

Finally, we calibrate net changes in the number of residents in the external wing to match the overall change in the occupancy rate as a result of shock $\epsilon^s_{occ}$. For instance, suppose we start out with 90 occupied beds at time $s$ in the entire nursing home and that $\epsilon^s_{occ}$ implies a net increase to 92 occupied beds by $s+1$. Furthermore, suppose that the remaining shocks imply that the number of occupied bed in the focal wing of interest decreases from 38 to 37. Then we would assume a net increase of $\Delta^s_{ext} = 3$ seniors in the external wing to reconcile to overall increase from 90 to 92. This procedure generates a sequence of resident changes in the external wing $\{\Delta^s_{ext}\}$ for $s \in 1, ..., S$.

In the counterfactual analysis, we hold fixed the sequence of shocks to the focal wing and resident changes in the external wing, $\epsilon^s = \left\{\epsilon^s_{arr}, \epsilon^s_{\phi}, \epsilon^s_{\rho}, \epsilon^s_{dis}, \Delta^s_{ext}\right\}$ for $s \in 1, ..., S$. Importantly, we can now ignore the sequence of occupancy shocks, $\epsilon^s_{occ}$. Absent any policy changes, we can replicate the overall occupancy rate changes by inverting the strategy discussed in the previous paragraph which identified the sequence $\Delta^s_{ext}$. In the counterfactual analysis in Figure 6, we document changes in the discharge policies, which we use to simulated a new sequence of overall occupancy rates. The third row of Table 5 summarizes the mean occupancy rates over the simulation draws.