# Patient Versus Provider Incentives in Long-Term Care[*]

Martin B. Hackmann[†]
UCLA, CESifo, and NBER

R. Vincent Pohl[‡]
Mathematica

Nicolas R. Ziebarth[§]
ZEW, University of Mannheim and Cornell University

May 3, 2023

**Abstract**

How do patient and provider incentives affect the provision of long-term care? Our analysis of 551 thousand nursing home stays yields three main insights. First, Medicaid-covered residents prolong their stays instead of transitioning to community-based care due to limited cost-sharing. Second, when facility capacity binds, nursing homes shorten Medicaid stays to admit more profitable out-of-pocket private payers. Third, providers react more elastically to financial incentives than patients. Thus, targeting provider incentives through alternative payment models, such as episode-based reimbursement, is more effective than increasing patient cost-sharing in facilitating transitions to community-based care and generating long-term care savings.

**Keywords:** Long-Term Care, Nursing Homes, Patient Incentives, Provider Incentives, Cost-Sharing, Episode-Based Reimbursement, Medicaid.

**JEL Codes:** H51, H75, I11, I13, I18, J14.

[*]We thank our discussants Scott Barkowski, Seth Freedman, Jason Hockenberry, Mark Pauly, Maria Polyakova, and Sally Stearns. We also thank John Asker, Moshe Buchinsky, Paul Grieco, Eli Liebman, Adriana Lleras-Muney, Volker Nocke, Edward Norton, Jonathan Skinner, Bob Town, Peter Zweifel, and seminar and conference participants at Aarhus University, Universitat Autonoma de Barcelona, Berlin Applied Micro Seminar, BU Questrom, Claremont McKenna College, University of Delaware, Duke University, George Washington University, University of Georgia, Georgia State University, Hamburg Center for Health Economics, University of Illinois at Chicago, Indiana University–Purdue University Indianapolis, LSE, NYU, Olin Business School, University of Maryland, University of Pennsylvania, University of Southern California, Pennsylvania State University, Queen's University, RAND, RWI, Simon Fraser University, Yale University, ASHEcon, EuHEA, iHEA, SHESG, TEAM-Fest, and Whistler for helpful comments. Jean Roth and Mohan Ramanujan provided invaluable help with the data. We thank Anna Wilkens for proofreading this paper very much. Funding from the National Institute on Aging grant #P01 AG005842-29 is gratefully acknowledged. Neither we nor our employers have relevant or material financial interests related to the research in this paper. We take responsibility for all remaining errors in and shortcomings of the paper.

[†]UCLA, Department of Economics and NBER, mbhackmann@gmail.com.

[‡]Mathematica, Division of Health Policy Assessment, vpohl@mathematica-mpr.com.

[§]ZEW Mannheim, University of Mannheim and Cornell University, nicolas.ziebarth@zew.edu. Nicolas Ziebarth is also affiliated with the Canadian Centre for Health Economics, the Health, Econometrics and Data Group (HEDG) at the University of York, the NBER, and IZA Bonn.

# 1 Introduction

Long-term care (LTC) expenditures are high and rising. In 2021, the United States spent $181 billion on nursing home care and another $125 billion on home health care. By 2050, long-term care expenditures are projected to double to 3% of GDP (Martin et al., 2023; Congressional Budget Office, 2013). Given this strong increase in projected spending, it is critical for public policy to align patient and provider incentives with social welfare objectives to ensure efficient use of LTC services. Because Medicaid covers more than half of all LTC expenditures in the U.S., many state Medicaid programs expand cost-effective home and community-based alternatives (Kaiser Family Foundation, 2015; Peebles et al., 2017). Ongoing state experimentation demonstrates that transitioning institutionalized patients to community settings such as homes, apartments, or group homes is of high policy relevance (Libersky et al., 2015). This includes the Money Follows The Person (MFP) Demonstration, funded by $4 billion in federal monies, to support Medicaid in transitioning nursing home patients to the community where funds can "follow the person" to the setting of her choice.[1] Fostering options for community-based care typically also aligns with patient preferences (Kane and Kane, 2001; Dixon et al., 2015).

Despite its significance for public policy, evidence on the link between financial incentives and LTC use remains limited and mixed. This paper develops an empirical framework to analyze the effects of patient and provider incentives on LTC provision. In general, nursing homes are run by private entities but largely funded through Medicare and in particular Medicaid. Thus, Medicaid policies can target patient and provider incentives through cost-sharing and alternative provider reimbursement models. To optimally design such policies, separating the roles of patient and provider incentives is key.

Motivated by the policy context, we study the substitution between nursing home and community-based care. Specifically, we investigate how patient and provider incentives affect the timing of patient discharges from nursing homes to the community. About half of all nursing home stays end with a community discharge, which illustrates that community-based care is a feasible alternative for many institutionalized residents (Arling et al., 2010, 2011; Holup et al., 2016; Hass et al., 2018). The precise timing of home discharges is largely at the discretion of nursing home discharge managers, patients, and their relatives. Thus, economic patient and provider incentives very likely affect home discharge decisions.

This paper exploits plausibly exogenous variation in patient and provider incentives in a unified frame-

[1] Congress authorized it as part of the Deficit Reduction Act of 2005 and then extended it through the Patient Protection and Affordable Care Act (ACA) of 2010.

work. On the patient side, we exploit the sharp decline in out-of-pocket costs when patients transition from paying the full private rate to Medicaid. On the provider side, the Medicaid transition also implies a drop in revenues from the higher private rate to the lower Medicaid reimbursement rate. To separate patient from provider incentives, we combine variation in Medicaid transitions with variation in nursing home occupancy rates. When nursing homes operate substantially below capacity, they profit from longer Medicaid patients stays if the Medicaid rate exceeds the marginal cost of care (which we validate empirically). However, when nursing homes operate at capacity, they profit from discharging Medicaid beneficiaries to admit more profitable new patients who pay the full private rate.

This research investigates these discharge incentives using administrative micro data from the Long-Term Care Minimum Data Set. We combine it with detailed Medicare and Medicaid claims data as well as survey data. Our database provides high-quality information on admissions, discharges, and health profiles for the universe of residents in Medicare and Medicaid approved nursing homes in California, New Jersey, Ohio, and Pennsylvania from 2000 to 2005. To identify our target population of interest, a machine learning algorithm identifies nursing home residents who could be integrated into community-based settings. As our empirical strategy exploits the transition to Medicaid, we drop Medicare-covered stays and focus on residents who *all* pay the private rate at beginning of their stay. This leaves us with about 552 thousand skilled nursing facility (SNF) stays. Private LTC insurance coverage is low across all wealth levels (Braun, Kopecky, and Koreshkova, 2019)—only four percent of total costs were covered by private policies at the time, see Congressional Budget Office (2004). Hence, residents effectively transition from paying the full private rate (set by the nursing home) to Medicaid coverage with little or no cost-sharing.

We use two approaches to assess the effect of patient and provider incentives on community discharges. Our first "fixed effects" approach compares discharge rates between payer types and occupancy rates conditional on SNF-year fixed effects and week-of-stay fixed effects. Our second approach exploits within-resident variation in Medicaid transitions at different occupancy levels in an event study approach. Reassuringly, both approaches yield very similar results. At low occupancy rates, when providers' financial incentives are muted, the weekly home discharge rate is 0.9 percentage points (30%) lower for Medicaid patients as compared to private payers, suggesting that patient incentives may affect the length of stay. At high occupancy rates, when providers' financial incentives are at work, the rate differential is much lower at 0.4 percentage points (12%), suggesting that provider incentives may also affect the length of stay.

To translate these effects into patient and provider elasticities, we then develop and estimate a structural model of nursing home discharges. The model allows us to quantify the relative importance of patient and provider incentives in different policy counterfactuals that either alter patient cost-sharing or alternative provider payment models. We consider a representative nursing home discharge manager and a patient who is either covered by Medicaid or who pays the private rate in a given week. Both the discharge manager and the patient can exercise costly effort to shorten the length of stay, for example, by finding alternative care options or preparing the resident for independent living arrangements. Providers trade off the profit from keeping a patient against the option value of admitting a more profitable patient who pays out of pocket. Patients trade off utility from nursing home care against community-based care.

To estimate the parameters governing the discharge process, we match the discharge profiles predicted by the model to those observed in the data. Using the estimated model parameters, we then simulate the patient and provider length-of-stay elasticities with respect to changes in out-of-pocket prices and Medicaid reimbursement rates. We estimate a robust patient elasticity of 0.2, consistent with the literature (Manning et al., 1987; Finkelstein et al., 2012; Shigeoka, 2014). In contrast, the provider elasticity is much larger at 1.2, suggesting that providers respond much more elastically to financial incentives.

Finally, we study patient and provider incentives in simulated policy counterfactuals. We find that increasing patient cost-sharing to 100%, combined with a compensating lump-sum (voucher) transfer to patients, reduces the length of Medicaid stays by 20% but increases Medicaid spending by 5.5%. In contrast, we find that policies targeting provider incentives can be effective in reducing the length of stay and spending, without lowering provider profits. For example, motivated by the Bundled Payments for Care Improvement (BPCI) initiative authorized by Centers for Medicare & Medicaid Services (CMS), we find that disbursing 10% of Medicaid per-diem reimbursements to an episode-based (up-front) reimbursement reduces the length of Medicaid stays by 17% and spending by 8.4%. However, we note the possibility of downsides to alternative payment models. Switching from inpatient to outpatient settings could disrupt patients' medical care, ADL support, and housing. It is beyond the scope of this paper to conduct a full welfare analysis.[2]

Our analysis contributes to the large literature on the relevance of financial incentives for health care utilization. Earlier studies have focused on patient incentives, see Aron-Dine, Einav, and Finkelstein (2013) for an overview, whereas a more recent literature has provided compelling evidence on the role

[2]Evidence from emergency departments in the United Kingdom suggest that early discharges can result in detrimental patient health outcomes (Hoe, 2022).

of provider incentives. This includes important work on provider responses to the introduction of the Inpatient Prospective Payment System in 1983 (Cutler, 1995; Cutler and Zeckhauser, 2000) and on how physicians and dialysis clinics react to financial incentives (Clemens and Gottlieb, 2014; Dickstein, 2014; Ho and Pakes, 2014; Grieco and McDevitt, 2017; Einav et al., 2020; Eliason et al., 2020). Closely related to our analysis are Eliason et al. (2018) and Einav, Finkelstein, and Mahoney (2018) who show that changing Medicare reimbursement to a lump-sum payment induces providers to discharge patients from long-term post-acute care hospitals. We contribute to this literature in three ways. First, we investigate patient and provider incentives in one unified framework, while the existing literature has largely studied their roles in isolation, see McGuire (2011) for an overview.[3] Second, our counterfactual analysis assesses the scope for episode-based or bundled payment models in a policy-relevant and economically significant setting. We find that bundled payment models, one of Medicare's leading alternative payment models (Finkelstein et al., 2018), are effective in shortening Medicaid stays by aligning provider discharge incentives more closely with the cost of care to the Medicaid program. Third, we study provider incentives exploiting variation in occupancy, thereby providing new evidence on the link between long-term care use and provider capacity, see Freedman (2016), Kleiner (2019) and Hoe (2022) for similar approaches in U.S. and U.K. acute care settings.

Naturally, our analysis contributes to the literature on financial incentives in long-term care, and in particular how they affect transitions from nursing home to community-based settings. A series of studies, known as the "Channeling demonstration," suggest very little substitutability between nursing home and community-based care (Rabiner, Stearns, and Mutran, 1994). Consistent with these results, McKnight (2006) and Grabowski and Gruber (2007) find that the decision to enter a nursing home is relatively inelastic with respect to Medicaid cost-sharing incentives. On the other hand, Konetzka et al. (2014) and Mommaerts (2018) find that private LTC insurance lowers, and Medicaid eligibility increases, the demand for nursing home care. As a distinct feature of our analysis, besides combining administrative data with novel identification strategies, it focuses on a specific and policy relevant margin: community discharges and the length of nursing home stays.

While the evidence on patient incentives in the LTC context remains mixed, there is an upswing in recent work on provider incentives. Ching, Hayashi, and Wang (2015) and Gandhi (2021) estimate

[3]A notable exception is Trottmann, Zweifel, and Beck (2012), who study the impact of demand and supply-side cost sharing on health care utilization in Switzerland. Also, Dickstein (2015) studies patient and physician incentives in the market for antidepressants and Xiang (2020) studies physician-patient interactions using health insurance claims data from China.

models of SNF admission practices and find evidence of discrimination against Medicaid patients. Others study the role of ownership for nursing home quality (Grabowski et al., 2013; Jones, Propper, and Smith, 2017; Gupta et al., 2021; Hackmann, Roja, and Ziebarth, 2022), the link between Medicaid rates, market structure, and SNF quality (Grabowski, 2001; Lin, 2015; Hackmann, 2019), SNF responses to the Medicare 20-day payment rule (Werner et al., 2019), public reporting (Grabowski and Town, 2011; Konetzka, Polsky, and Werner, 2013), and Medicaid bed-hold policies (Intrator et al., 2007). We contribute to the LTC provider incentive literature by quantifying effects on the length of nursing home stays in a unified empirical framework. We simulate counterfactual policies on alternative payment models, informing the debate on how Medicaid regulation may achieve cost savings.

# 2 Institutional Details

## 2.1 Medicaid Eligibility

Medicaid covers about two thirds of all nursing home days. About a quarter are funded privately. Medicare only covers post-acute care and thus solely ten percent of all days, see Table A.1 (Appendix A). Our analysis excludes Medicare-covered stays. Further it excludes Medicaid-covered stays since admission, in order to exploit within-in stay variation in the transition to Medicaid.

**Asset and Income Test:** To qualify for Medicaid, individuals' assets must fall below state-specific thresholds ranging between \$1,500 and \$4,000 in our sample period, see Table A.1.[4] Medicaid eligibility also requires an income test, where thresholds vary by state, over time, and are often tied to SSI eligibility (see Kaiser Family Foundation, 2019). However, under so-called "Medically Needy" programs, nursing home residents with incomes *above* the income limit can qualify for Medicaid. Nursing home residents who pass the asset test can deduct medical expenses, including SNF fees, from their incomes. Then they qualify for Medicaid if their *adjusted monthly income* falls below the state-specific limits of, at the time, between 51% FPL (\$367) in New Jersey and 83% FPL (\$600) in California[5], see Table A.1.[6]

In practice, the asset test is typically key to establishing Medicaid eligibility for nursing home residents.

[4]Some assets do not count toward the asset test; for example one vehicle and life insurance policies (Centers for Medicare & Medicaid Services, 2015). In some states, the homes of deceased former beneficiaries are used to repay Medicaid.

[5]Ohio did not have a Medically Needy program, but was a 209(b) state whose statues allowed individuals to spend their assets down to the comparable cash assistance level which was \$423 at the time (Table A.1).

[6]Similar asset and income rules apply to Home- and Community-Based Service (HCBS) waivers, which cover formal care for seniors living in the community, see Table A.1. In our sample period, these programs had tight enrollment caps and long waitlists (Kasper and O'Malley, 2006). As we exploit transitions to Medicaid and variation in occupancy rates, access to HCBS is unlikely to confound our estimates. Barczyk and Kredler (2018) show that community-based LTC is primarily comprised of *informal* care.

In the Health and Retirement Study (HRS), among seniors whose assets are below $4,000, only 1% have income levels that would disqualify them for Medicaid under a Medically Needy program. As seniors age and spend down their assets, Medicaid coverage becomes widespread (Borella, De Nardi, and French, 2018). Whereas income flows are typically very stable among nursing home residents (who rely mostly on social security payments, see Table B.1), asset spend-down is the primary factor in determining Medicaid coverage. Our identification strategy exploits such Medicaid transitions during nursing home stays.

**ADL and Medical Needs:** For Medicaid to cover SNF stays, beneficiaries must have medical long-term care needs or functional limitations. States have different level-of-care criteria; nurse or social worker evaluates patients' limitations in activities of daily living (ADL); for example, whether assistance for bathing, dressing or eating is needed, see Table A.1. In our sample, patients have about 12 ADLs, see Table 1.

### 2.2 Patient Cost Sharing and Provider Reimbursement

**Patient Cost-Sharing:** In our sample, everyone is a SNF resident and everyone pays the full private rate (set by the nursing home) initially. In Pennsylvania at the time, average private rates were $170 per day or $5100 per month. According to the HRS, private payers had net financial assets of $31,424 on average, see Hackmann and Pohl (2018). Consequently, nursing home residents who earn below the Medicaid income thresholds would typically spend down their assets and qualify for Medicaid within half a year after being admitted to a nursing home. Once residents transition to Medicaid, their out-of-pocket price for SNF care drops sharply. They contribute their income, net of an allowance of about $30 per month, towards the cost of nursing home care ("share of cost" see Pennsylvania Department of Human Services, 2020). Medicaid then covers the difference between this "patient liability amount" and the Medicaid reimbursement rate. In the NLTCS, Medicaid beneficiaries in SNFs have average monthly incomes of $819 (Table B.1), implying that monthly out-of-pocket prices drop by almost 90% from $5,100 to $819-$30=$789 as residents transition to Medicaid.

For simplicity, we discard private long-term care insurance coverage. Only four percent of total costs were covered by private policies at the time, see Congressional Budget Office (2004). Further, private insurance contracts commonly cover only about 50% of the overall rate, which implies that beneficiaries still pay the remaining 50% out-of-pocket (Hackmann, 2019). Section E.4 shows that our findings are robust to this simplification.

**Provider Reimbursement:** When patients transition to Medicaid, SNF reimbursement rates also change. Medicaid pays nursing homes a regulated, risk-adjusted, daily reimbursement rate. It is usually lower than the private rate. At the time, on average, Medicaid rates were 18% lower than the private rate in California and 15% lower in Pennsylvania, see Table A.1. Federal and state legislation, such as OBRA 1987, prohibit nursing homes from discriminating by payer type and offering lower quality of care to Medicaid patients. Research has generally confirmed this (Troyer, 2004; Grabowski, Gruber, and Angelelli, 2008). Thus, Medicaid residents are less profitable than private payers, conditional on LTC needs. However, Medicaid beneficiaries generally are profitable for nursing homes because reimbursement rates exceed the marginal cost of care (Hackmann, 2019).

### 2.3 Nursing Home Discharges

**Discharge Destination:** Many nursing home patients return to the community. Hass et al. (2018) find that 43% of Medicaid patients above 65 return to the community within 90 days. In our sample, 39% of all nursing home stays end with a community discharge. Fourteen percent end because patients die, 21% end with hospital discharges, and 13% end with a discharge to a different nursing home, see Table B.2 (Appendix). Our analysis focuses on community discharges as the relevant policy margin of interest. We note that Medicaid reimburses nursing homes through "bed-hold" policies for keeping a bed vacant while a resident is hospitalized (Intrator et al., 2007). Our data allow us to distinguish between temporary and permanent discharges (our focus). As such, temporary hospital discharges do not affect our discharge or occupancy measures as nursing homes must keep the bed vacant.[7]

**Discharge Effort and Management:** Nursing homes regularly evaluate their residents' health; for example, to determine community discharges. After having relied on around-the-clock care in SNFs, community transitions may pose substantial challenges: The management of medical conditions, support from family members or other informal caregivers, and needs-specific housing accommodations need to be arranged (Meador et al., 2011). This requires time, money and planning by patients, their relatives, and nursing homes prior to community discharges. We model such arrangements as costly discharge effort below.

The precise timing of discharges, and costly discharge effort, is largely at the discretion of the nursing

[7] Specifically, the data indicate explicitly whether a return is anticipated or not. If anticipated, we assume an occupied bed until the patient returns. If we do not observe a patient return despite the initial assumption, we assume that the SNF keeps the bed occupied for either 50 days or—if we observe an admission to another SNF—half the days between the last health assessment and the new SNF admission date, whatever number is smaller.

home, the patient, and her relatives. According to discharge managers whom we interviewed, nursing homes usually do not have systematic protocols *for when specifically* to discharge a resident. For example, discharge decisions are not tied to a certain value of the case mix index (CMI) or other objective health outcomes (see Appendix Section B.3 for details on clinical health measures).

Although federal regulations, such as the Nursing Home Reform Law of 1987, prohibit involuntary discharges, residents may not be aware of their rights and nursing homes may stipulate the possibility of evictions in their admission agreements (Pipal, 2012; Siegel Bernard and Pear, 2018). One main objective of this paper is to assess whether and how economic provider and patient incentives affect community discharges among relatively healthy marginal residents.

# 3 Conceptual Framework

To guide the empirical analysis, this section formalizes how provider and patient incentives can affect nursing home discharges. We consider a single SNF and a single patient (the "focal" patient). The SNF maximizes profits. The patient trades off the utility of different care alternatives against their out-of-pocket prices. The model generates testable predictions, which we revisit in Sections 5 and 6. Finally, we estimate a quantitative version of the model in Section 7. This allows us to quantify the relative importance of patient and provider incentives in policy counterfactuals.

**Effort and Discharges:** To increase the probability of a discharge in any given week, the SNF and the patient have to exert costly effort, denoted by $e^{SNF} \geq 0$ and $e^{res} \geq 0$, respectively. The cost of effort, $c(e)$, is weakly positive and strictly increasing and convex in effort. As a result, agents only exert effort if they prefer a community discharge over a nursing home stay for an extra period.

The SNF and the resident choose their optimal effort levels simultaneously, $e^{SNF,*}(\cdot)$ and $e^{res,*}(\cdot)$, as a weakly increasing function of the financial discharge incentives, denoted by $\text{FinInc}^{SNF}$ and $\text{FinInc}^{res}$. Financial incentives then weakly increase the probability of a discharge:

$$Pr[D = 1|e^{SNF,*}, e^{res,*}] = F_\epsilon[\alpha \times e^{SNF,*}(\text{FinInc}^{SNF}(\tau, oc)) + \beta \times e^{res,*}(\text{FinInc}^{res}(\tau))] \qquad (1)$$

where $\tau = P, M$ denotes the payer type (private or Medicaid). Here, $\alpha \geq 0$ and $\beta \geq 0$ are scalars which capture the effect of financial incentives on nursing home discharges through nursing home's or patient's discharge efforts. If $\alpha = 0$, only the patient's financial incentives matter, whereas if $\beta = 0$, only the SNF's financial incentives matter. $oc$ is SNF's occupancy rate. We assume that residents do not observe the weekly occupancy rate and do not condition their optimal effort on it. Finally, $\epsilon \sim F_\epsilon$ captures other discharge factors.

**Provider Incentives:** Providers consider a dynamic tradeoff: If the focal bed is occupied, providers receive payer-type specific flow profits $\Pi^\tau$ with $\Pi^P > \Pi^M > 0$. If empty, with probability $\Phi(oc)$, a new private patient or Medicaid beneficiary will occupy it. Therefore, the tradeoff between the flow payoff and the option value of drawing a more profitable payer determines SNF's optimal discharge efforts. Because private payers are more profitable than Medicaid beneficiaries, SNFs do not exercise costly discharge efforts if a private payer occupies the focal bed. By contrast, if a Medicaid beneficiary occupies the focal bed, financial incentives and optimal discharge efforts are weakly increasing in *oc*. This is because the refill probability $\Phi(oc)$ is weakly increasing in the occupancy rate of the nursing home's *other* beds: $\frac{\partial \Phi(oc)}{\partial oc} \geq 0$. Intuitively, the next arriving patient will seek the focal bed with probability 1 if all other beds are taken. If multiple beds are vacant, however, the probability of filling the focal bed, conditional on a patient arrival, is $< 1$.

**Patient Incentives:** Patients consider the following static trade-off: Staying another week yields the utility of nursing home care minus the out-of-pocket health care costs. Leaving yields the utility of community care minus out-of-pocket costs in the community, including living costs. We assume that patients are myopic, an assumption that appears to be realistic in this setting as we show empirically below. Further, we assume that both Medicaid beneficiaries and private payers pay the full price of home care, but only private payers pay the full price for SNF care. Thus, conditional on the utilities from the two LTC options, private payers have larger financial incentives to leave nursing homes. Therefore they exert more discharge efforts than Medicaid beneficiaries, which results in longer nursing home stays for Medicaid beneficiaries.

**Graphical Discussion:** Figure 1 summarizes the model's predictions. It plots the per period discharge probability by payer type on the y-axis against the occupancy rate on the x-axis. Occupancy only affects the financial incentives of providers. As providers do not exercise effort to discharge private payers ($e^{SNF,*}(P, oc) = 0$ for all $oc$) their discharge rates are constant in occupancy, as indicated by the horizontal dashed line. This is not true for Medicaid beneficiaries. At low occupancy rates, providers do not exercise costly effort as the flow payoff from profitable Medicaid patients exceeds the option value of drawing a private payer (net of the cost of effort). The refill probability $\Phi(oc)$ is too small, such that the marginal benefit of effort is strictly smaller than the marginal cost of effort. Hence, the nursing home chooses the corner solution of no effort, $e^{SNF,*}(M, oc) = 0$ for $oc < oc^*$, which explains the horizontal profile in the solid blue line for $oc < oc^*$.

**[Insert Figure 1 about here]**

At low occupancy rates, the discharge probability is smaller for Medicaid beneficiaries. This is because private payers exercise greater discharge efforts as they pay the full rate: $e^{res,*}(P) > e^{res,*}(M)$. Hence, at $oc < oc^*$, the difference in discharge probabilities is purely driven by patient incentives—providers' optimal effort is zero for either payer type at low occupancy rates.

At $oc = oc^*$, provider's optimal discharge effort for Medicaid beneficiaries changes. Here, the marginal benefit of effort equals the marginal cost of effort at $e^{SNF} = 0$, providing an interior solution. As the marginal benefit of effort increases in occupancy, providers' optimal effort increases with $oc$—SNFs equate the marginal benefit and the marginal cost of effort. Hence, we have $e^{SNF,*}(M, oc) \geq 0$ and $\frac{\partial e^{SNF,*}(M,oc)}{\partial oc} > 0$ for $oc \geq oc^*$. Therefore, as shown in Figure 1, the discharge probability of Medicaid beneficiaries increases in the occupancy rate if $oc \geq oc^*$.[8]

Appendix Section C formally derives this relationship. An important assumption, and one that we maintain throughout our analysis, is that the occupancy rate only affects discharge rates through providers' discharge efforts. This rules out the possibility that crowding may disproportionately affect the quality of care for Medicaid patients, which could then affect home discharges through patient health or effort. In robustness exercises, for example in Figure E.8, we find no empirical evidence for such an operating channel.

# 4 Data

Our main dataset combines administrative micro data from the Long-Term Care Minimum Data Set (MDS) with Medicaid and Medicare SNF claims data as well as nursing home characteristics from annual surveys. The MDS contains the universe of SNF residents for all Medicaid or Medicare-certified nursing homes, which accounts for 98% of all nursing homes. Section B.3 (Appendix) provides further details on the various input datasets.

[8] We note that the Medicaid discharge rate profile may intersect with the private rate profile at high occupancy rates, depending on the significance of provider incentives.

## 4.1 Sample Construction and Selection

As a first step, we merge the MDS with the claims data. These administrative claims data allow us to record payment sources and Medicaid transitions at the weekly level. Next, we merge the weekly-stay data with facility information from the On-Line Survey, Certification, and Reporting system (OSCAR), accessed through Long-Term Care: Facts on Care in the U.S. (2020). Via the number of licensed beds in OSCAR we calculate weekly occupancy rates.[9] Appendix B.3 provides more details on all data sources and how we measure occupancy rates or payer transitions.

Our first empirical approach uses these uniquely compiled data for four states (California, New Jersey, Ohio, and Pennsylvania) from 2000 to 2005.[10] Moreover, we focus on patients above 65 who are private payers at the beginning of their SNF stay. We also exclude non-Medicaid certified SNFs.

## 4.2 Machine Learning and Community Discharge Potential

For some residents, discharges are extremely unlikely. Typically, these are residents with severe cognitive and physical disabilities and many ADLs who will stay in SNFs until death. Given our focus on marginal SNF residents who could potentially stay in the community or in a nursing home, we use a machine learning (ML) approach to identify and exclude patients with a very small probability of ever being discharged to the community. Similar to Einav, Finkelstein, and Mahoney (2019), we use a CART regression tree as our prediction algorithm, which is well-suited to capture the rich interactions between multiple disabilities and comorbidities that we observe in the MDS (Breiman, 1984; Mullainathan and Spiess, 2017; Athey and Imbens, 2019). As predictors we use 174 demographic and health characteristics from the resident's initial SNF health assessment at admission. 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, see Appendix Section D for more details. We exclude the ten percent of SNF stays with the smallest predicted probability of ever being discharged to the community.

[9] Within a facility, bed capacity varies only very little from year-to-year due to fixed investment costs and state regulations requiring Certificate of Needs (CON) to increase the number of beds.

[10] We use this data selection for several reasons: (a) when we started the project, we only had comprehensive MDS and Medicaid claims data access for these four states; (b) during this time period, Medicare Advantage plans were much less common and thus Medicare Fee-for-Service data more representative than today, (c) the MDS changed from MDS 2.0 to MDS 3.0 in 2010 which coincided with a Medicare reimbursement reform.

### 4.3 Summary Statistics

Our final sample consists of 551 thousand SNF stays and 13.3 million resident-week observations. Table 1 shows summary statistics, separately by payer type. The first column shows variable means for private payers and the second column shows variable means for Medicaid beneficiaries. The upper panels shows descriptives on socio-demographics such as resident's age (84.3 vs. 83.9 years), gender (70% vs. 74% female), race (89% vs. 85% white) or marital status (53% vs. 56% widowed), while the lower panel shows descriptives on a set of health measures. These include the Case Mix Index (1.1 vs. 1.1), the number of ADL (12.0 vs. 11.8), and the share of residents with impaired cognition (61% vs. 64%) or with behavioral problems (8.3% vs. 9.2%). Private payers and Medicaid beneficiaries are very similar in terms of socio-demographics and health.

**[Insert Table 1 about here]**

### 4.4 Occupancy Rates

Figure 2a summarizes the variation in occupancy rates over time (weeks) and between SNFs. The average occupancy rate is 89.3%, which translates into 13 empty beds in an average sized facility with 120 licensed beds, also see Figure B.1 (Appendix). Figure 2b displays within-SNF variation in the occupancy rate. Conditional on SNF-year fixed effects, the standard deviation in occupancy is 3.4 percentage points. To avoid a mechanical reverse relationship between the own discharge process and the occupancy rate, we exploit variation in the (one-week) lagged occupancy rate. The lagged rate isolates variation in other beds' occupancy once we exclude the first week of the stay, see Appendix Section B.3 for more details.

**[Insert Figure 2 about here]**

Admissions are a key driver of the within-SNF variation in occupancy rates. Figure 2c shows the frequency of new admissions divided by total number of beds, translating admissions into changes in occupancy rates. We observe substantial weekly variation in occupancy rates due to new admissions. Because a few new admissions can result in large variation in occupancy rates for very small nursing homes and introduce noise to our empirical models, we discard the bottom 2.5% of observations where occupancy rates are below 65%. However, our findings are robust to including these observations (available upon request).

Figure 2d displays the impulse-response function of occupancy rates to a three percentage point increase and decrease in occupancy relative to the sample average. Specifically, we construct an occupancy transition matrix from the data and simulate its profile over time. The response functions indicate that it takes 100 weeks (or two years) until the occupancy rate reaches its mean steady state again. However, it takes only 25 to 30 weeks until half of the effect has dissipated. This roughly coincides with the average length of stay of 25.7 weeks in our sample, as indicated by the vertical line in Figure 2d.

### 4.5 Monthly CA Sample for Event Study

Our second empirical approach leverages the panel dimension of our data. It exploits within-patient transitions to Medicaid in an event study and difference-in-differences framework. For this approach, we have to aggregate the data at the monthly level and focus on California. This is because we only observe Medicaid transitions *outside of nursing homes* at the monthly level for California.[11] Specifically, we use the so called administrative "buyin" indicator, which identifies dual beneficiaries at the monthly level (Rupp and Sears, 2000; Research Data Assistance Center, 2020). This indicator is measured without much error in California, as confirmed by data validity checks that map the official dual beneficiary rate with the rate identified by this indicator, see Appendix Section B.3.[12]

Note that the "buyin" indicator records Medicaid coverage with a delay of about three months. This delay captures the difference between the date of *filing* the Medicaid application and the date of *approval*. The application date marks the (retrospectively set) onset of Medicaid coverage for SNF care. It is the recorded coverage start in the Medicaid claims data used in our fixed effects approach. By contrast, in our event study approach, depending on how long approval takes, the buyin measure that we use here records Medicaid coverage with a delay. This is because states have up to 90 days to review and process a Medicaid application for long-term care; further, it also takes time to compile the extensive paperwork (American Counil on Aging, 2019). To account for this time gap and to maintain a consistent measure of Medicaid coverage, we lead the buyin indicator by three months and indicate the three month period from -1 to +2 as a transition period in the event studies. Figure B.4 (Appendix) illustrates and discusses this transition period. Otherwise, we maintain the same sample selection criteria as for the resident-week sample for the fixed effects approach, see Section 4.1. When aggregating the data at the

[11] For our event study model, it is essential to observe Medicaid transitions in the community because transitions represent our treatment and community discharges are our outcome measure.

[12] Specifically, the buyin variable, recorded in the Medicare claims data, indicates at the monthly level whether the state of residence of a Medicare beneficiary pays her monthly Medicare premium (because she is eligible for Medicaid), an action called "buying in."

monthly level and focusing on California, we obtain 1,158,557 patient-month observations; 15% of those are Medicaid-months after patients have transitioned.

# 5 Empirical Strategy

## 5.1 Fixed Effects Approach

Our first empirical approach employs rich sets of fixed effects and covariates.[13] The following regression model estimates equation (1) in the theoretical model when $\epsilon$ is uniformly distributed:

$$Y_{ijst} = \sum_{k=65}^{100} \gamma^k \times oc^k_{jt-1} + \sum_{k=65}^{100} \delta^k \times oc^k_{jt-1} \times Mcaid_{is} + \eta_s + \eta_{jy} + \eta_m + Z_i'\alpha + X_{it}'\beta + \epsilon_{ijst}. \qquad (2)$$

Here, $Y_{ijs}$ is an indicator equal to one if nursing home $j$ discharges resident $i$ to the community in week-of-stay $s$. $oc^k_{jt-1}$ is an indicator that turns on if the (rounded) one-week lagged occupancy rate equals $k = 65, \ldots, 100$ percent in nursing home $j$ in calendar week $t$. $Mcaid_{is}$ is an indicator for whether resident $i$ is covered by Medicaid in week $s$ of her stay.

The main coefficients of interest are $\gamma^k$ and $\gamma^k + \delta^k$. We interpret them as the effect of occupancy on weekly home discharge probabilities, where $\delta^k$ captures relevant differences between payer types. The estimates condition on SNF-year fixed effects $\eta_{jy}$, which control for differences in SNFs' management, quality of care, and private rates between nursing homes and over time. We also flexibly control for duration dependence within stays via week-of-stay fixed effects $\eta_s$. Moreover, to account for seasonal variation in discharges, we control for calendar month ($\eta_m$). Robust standard errors, $\epsilon_{ijst}$, control for within-resident correlation. We also correct for administratively assessed and time-varying differences in health ($X_{it}$) and time-invariant socio-demographics ($Z_i$), see Table 1.[14] We also estimate a "binned" version of equation (2). It replaces $oc^k$ with three occupancy *group* indicators than turn on for occupancies (i) below or equal 85%, (ii) between 85 and 95%, and (iii) at or above 95%.

This first approach uses rich fixed effects along with administrative data, but does not exploit within-patient transitions to Medicaid. For that purpose, we employ an event study approach detailed below (and similar to Dobkin et al. (2018)). Combined and benchmarked against each other, the two approaches

[13] To ease the computational burden, we estimate linear probability models.

[14] $Z_i$ includes the predicted length of stay (obtained by regressing length of stay on health at admission and predicting at the individual level.

allow us to assess the relevance of possible time-invariant unobservables at the patient level. By exploiting within-patient variation and plotting lead and lag event study coefficients, we assess the plausibility of important identifying assumptions, possible anticipation effects, and control for sample composition effects. The fixed effects approach, by contrast, has the advantage to rely on the full sample and is closely linked to Figure 1 and the theory. Moreover, homogenizing our sample and focusing on elderly SNF residents who *all* were initially private payers, further helps to minimize concerns that patient-level unobservables act as systematic confounding factors.

### 5.2 Event Study Approach

Our second empirical approach leverages longitudinal within-patient variation and exploits the timing of transitions to Medicaid in an event-study approach. As mentioned in Section 4.5, for this approach, we have to aggregate the data at the monthly level and focus on California. We estimate:

$$Y_{ij\tau} = \sum_{\tau=-6}^{-2} \mu_\tau + \sum_{\tau=0}^{6} \mu_\tau + X_{it}'\beta + \eta_{mos} + \eta_m + \eta_i + \eta_{jt} + \epsilon_{ijst} \tag{3}$$

where $Y_{ij\tau}$ denotes the community discharge indicator as above along with rich fixed effects for the month-of-stay ($\eta_{mos}$), calendar month ($\eta_m$), patient ($\eta_i$) and SNF-year ($\eta_{jt}$). Event times to the Medicaid transition, $\mu_\tau$, are the key coefficients with $\mu_{-1}$ as reference category. Note that the period from $\mu_0 - \mu_2$ is the transition (or enrollment) period, see Section 4.5.

The 'lead' coefficients, $\tau < 0$, inform about potential pre-trends and the plausibility of the model assumptions. For example, a fully rational and forward-looking patient might start to reduce their discharge efforts in anticipation of an upcoming Medicaid transition, resulting a falling pre-trend. Conversely, the absence of pre-trends—usually a requirement for a clean causal effect elicitation—would be consistent with myopic patient behavior. The 'lag' coefficients, $\tau \geq 0$, capture the dynamic effect of the Medicaid transition on home discharges. To separate patient from provider incentives, we estimate equation (3) with full interactions between the event-time indicators and low (below 85%), medium (between 85 and 95%) and high occupancy indicators (above 95%).

The transition to Medicaid, triggered by the mechanical asset spend-down, represents the treatment. Ideally, private payers should be on identical spend-down schedules in inpatient and outpatient settings. While institutional details ensure similar eligibility thresholds for SNF and HCBS care (Section 2), private payers face higher cost-sharing for inpatient than outpatient care. However, as we show below, these differences only have a modest effect on our main estimates. Note that the transition to Medicaid causes a reduction in patient cost-sharing and also provider reimbursements.[15] We view it as a strength of this paper that we exploit the same price variation embedded in a coherent framework to estimate both patient and provider elasticities.

Again, we also estimate a "binned" version that pools the 'leads' and 'lags' into a pre- and post-transition period along with a transition period dummy included in $X_{it}$.

$$\begin{aligned} Y_{ij\tau} &= \mathbb{1}(occu < 85\%)_{jst-1} \times Mcaid_{\tau\geq 0} + \mathbb{1}(occu > 95\%)_{jst-1} \times Mcaid_{\tau\geq 0} \\ &+ \mathbb{1}(85\% < occu \leq 95\%)_{jst-1} \times Mcaid_{\tau\geq 0} + \mathbb{1}(occu < 85\%)_{jst-1} + \mathbb{1}(occu > 95\%)_{jst-1} \\ &+ X_{it}'\beta + \eta_{mos} + \eta_m + \eta_i + \eta_{jt} + \epsilon_{ijst} \end{aligned} \tag{4}$$

Equation (4) is a two-way fixed effects model. A recent literature discusses possible biases associated with heterogeneous treatment effects in such models (de Chaisemartin and D'Haultfuille, 2020; Goodman-Bacon, 2021). Below, we implement the Gardener correction as robustness check (Gardner, 2021).

# 6 Empirical Results

## 6.1 Results from Fixed Effects Approach

We begin with the Fixed Effects Approach. Figure 3 is the empirical analogue to Figure 1. It plots weekly community discharge probabilities by payer type on the y-axis against SNF occupancy on the x-axis, see equation (2). The estimates correspond to the mean-adjusted coefficients for private payers, $\hat{\gamma}$, and for Medicaid beneficiaries, $\hat{\gamma} + \hat{\delta}$, along with their 95% confidence intervals. These estimates are conditional on SNF-year, month, and week-of-stay fixed effects and resident characteristics.

**Patient Incentives:** Figure 3 shows that private payers have weekly community discharge rates of around 2.6% across the entire range of occupancies. In contrast, Medicaid beneficiaries have discharge rates of about 1.5% at low occupancy rates below 85%. This lower discharge rate for Medicaid beneficiaries is consistent with differences in resident cost-sharing. As SNFs do not have financial incentives to discharge residents of either payer type at low occupancies, see Section 3, it suggests that patient incentives affect

[15] Pre-transition, we do not rely on variation in daily private SNF rates and, post-transition, the prices for both parties, patients and providers do not vary either.

the length of stay.

**[Insert Figure 3 about here]**

Table 2 quantifies this difference showing results from the binned version of equation (2). Each column in the upper panel stands for one regression model. Consistent with Figure 3, we find a one percentage point (ppt) difference between Medicaid and private payers, see column (4) in panel "Patient Incentives." As shown in columns (1) to (3), this difference is fairly robust to adding SNF-year fixed effects (column (2)), month and year fixed effects (columns (3)) as well as socio-demographic controls (column (4)). Relative to the private payer discharge rate at 85 to 95% occupancy (2.8%), the difference corresponds to a 29 to 36% lower home discharge rate for Medicaid beneficiaries.

When relating the home discharge differential to the overall SNF discharge rate of private payers to any destination (5.9% at medium occupancy), a 0.97ppt lower home discharge rate (column 4) translates into a 16% reduction in the overall discharge rate. Considering the almost 100% out-of-pocket price difference between private payers and Medicaid beneficiaries, we obtain a price elasticity of demand of around 0.2, in line with the standard health care demand elasticity estimates (Aron-Dine, Einav, and Finkelstein, 2013). We return to a more formal calculation in Section 7.

**[Insert Table 2 about here]**

**Provider Incentives:** Figure 3 also shows that community discharge rates for Medicaid beneficiaries start to increase at around 90% occupancy, first slowly, and then faster above 95% occupancy once SNFs approach full capacity. Discharge rates for private payers remain largely constant across occupancy rates and, if anything, decrease slightly at high occupancy rates. Table 2 quantifies this change in the discharge rate differential in the panel "Provider Incentives." Subtracting the discharge differentials between private payers and Medicaid beneficiaries at occupancy rates above 95% and below 85%, respectively, home discharge rates converge by 0.33ppt between these occupancy bins (column (4)).

Interpreted through the lens of the theoretical model, nursing homes start to exert positive discharge efforts at high occupancies when benefits exceed the cost of effort, see Section 3. At low occupancies, SNFs benefit from extended Medicaid stays as long as Medicaid rates exceed the marginal cost of care. At higher occupancies, this incentive is muted because nursing homes prefer to occupy their scarce beds with more profitable private payers. Consistent with the theoretical predictions of Section 3, the increase in Medicaid discharge rates in Figure 3 suggest that provider incentives affect discharges as well.

Relating the 0.33ppt change in the home discharge differential to the overall discharge rate of 5.9%, we find a 6% higher discharge rate for Medicaid patients. However, provider reimbursement increases by only about 15 to 18% (Section 2.2) when substituting a Medicaid patient with a private payer, implying a provider elasticity of about 0.4, twice as large as the patient elasticity. Note, however, that this provider elasticity estimate is a lower bound because (i) not all new arriving patients are private patients, (ii) about ten percent of private patients transition to Medicaid before discharge, and (iii) it takes time to fill an empty bed, during which the nursing home forgoes Medicaid revenue. We use the structural model in Section 7 to quantify the role of these components. Indeed, we find a much larger provider elasticity of around 1.

**Robustness:** Appendix Section B.3 shows robust results when we use an alternative occupancy measure from bed counts in California (Figure B.2), and correct for measurement errors using an Instrumental Variable (IV) approach, see Table B.3.

Moreover, Appendix Section E.3 uses unique pricing data at the SNF-year level from Pennsylvania and California (see Section B.5) to stratify the total discharge differentials by private rates and by the mark-up of private rates over Medicaid rates. Figure E.9a shows larger discharge differentials in facilities who charge higher private rates, and Figure E.9b shows that the relative probability (to private payers and low occupancies) that Medicaid beneficiaries get discharged when SNFs operate at capacity is larger, the larger the private rate mark-ups.

Figure E.1 shows that discharge rates to other nursing homes (Figures E.1b) but also patient mortality (Figure E.1c) might be elevated when SNFs operate at capacity. We attribute the pattern in Figure E.1c to potential compositional changes in the patient population. At higher occupancy, providers likely discharge healthier patients first. Appendix Section E.1 provides an in-depth analysis and extensive robustness tests. First, we investigate differences in patient health by payer type and occupancy. As observable patient health measures are quite balanced across the populations, see Table D.1, the pattern remains robust when adding them as controls. Second, we document that changes in mortality are concentrated among patients with the lowest discharge potential as estimated by our ML approach, see Section D; Figure E.2 shows the results. Excluding those and re-running the entire structural analysis leaves the patient and provider elasticities largely unchanged. Appendix E provides details.

Finally, note that our implicit assumption of SNFs providing equal quality of care independent of payer type represents federal and state law (see Section 2.2). If SNFs (illegally) provide lower quality of care to Medicaid patients, then Figure 3's discharge differential overstates the role of patient incentives. A more nuanced version of this concern is that providers may lower the (service) quality of care for Medicaid patients at higher occupancies, for example, spent less time with patients. While this could be interpreted as a form of provider discharge effort through the lens of our model, we find no evidence for differential changes in patient health at higher occupancy rates, see Figure E.8. We return to this point in the next section.

### 6.2 Results from Event Study Approach

We continue with the event study approach. Figure 4 shows event coefficients, $\hat{\mu_\tau}$ with their 95% confidence intervals, based on equation (3), separately for low (below 85%) and high (above 95%) occupancy environments. Here we use data from California at the monthly level, but otherwise maintain the same sample selection. That is, we focus on relatively healthy marginal SNF residents who are all private payers at the beginning of their stay. The y-axis shows changes in home discharge rates, and the x-axis shows event time in months since the transition to Medicaid. We illustrate the transition period with a gray shaded area, see Section B.4 for details.

**[Insert Figure 4 about here]**

**Patient Incentives:** We start with the low occupancy environment ($\leq$85%) where capacity constraints are not binding. Here, provider incentives are muted but patient incentives are at play. Figure 4 shows no evidence for anticipatory behavior during the pre-transition period. This corroborates our research design and provides evidence against a model of a rational, fully forward-looking patient who would reduce her discharge efforts in anticipation of a future drop in out-of-pocket prices (Dalton, Gowrisankaran, and Town, 2020). The point estimates are close to zero and all confidence bands overlap with the zero line on the y-axis. We then observe a gradual decline in discharge rates over the transition period, which we attribute to the timing of the Medicaid application and its approval. As seen, relative discharge rates then gradually increase again over the post-transition period. The pattern suggest that some patients (or their relatives) reduce discharge efforts for a few months, possibly to make outpatient care arrangements. For example, Medicaid coverage for HCBS care required an additional application and HCBS applicants were waitlisted at the time (and are still today). The effect sizes remain negative and statistically significant throughout the post-transition period, indicating that patients reduce their discharge efforts as their out-of-pocket prices drop from the full private rate to near zero. Even at $\tau = +6$, in the low occupancy environment, discharge rates are about two percentage points lower than before the transition, representing patient incentives at lower marginal prices.

**[Insert Table 3 about here]**

Table 3 presents the differences-in-differences (DD) analogue for Figure 4, binning occupancy environments into three categories: (i) below or equal 85%, (ii) between 85 and 95%, and (iii) at or above 95%. As above, each column in the upper panel represents a DD model where we add sets of control variables stepwise from column (1) to (4). The model in column (3) mirrors our preferred model in column (4) Table 2. It shows an average post-transition decline in monthly discharge rates of 2.9ppt or -22.4% due to patient incentives. The estimates are again robust to adding patient fixed effects, SNF-year, and month fixed effects (column (2)), socio-demographic controls (column (3)) as well as the Gardner (2021) correction and a two-stage difference-in-differences model (column (4)). Finally, note that the monthly coefficient estimates carry three to four times the effect sizes of the weekly estimates, as expected.

**Provider Incentives:** Next, we study the high occupancy environment (>95%) where capacity constraints are binding. As seen in Figure 4, we find no evidence for a pre-trend in the months leading up to the Medicaid transition. Moreover, the estimates are very similar to those above, where nursing homes operate below capacity (≤85%). In the first months after the Medicaid transition, community discharge rates decrease. At high occupancy rates, after residents become Medicaid beneficiaries, the decline is significantly smaller and fades out half a year after the transition. Note that the difference in high vs. low occupancy discharge rates remains remarkably stable over the entire post transition period. Figure E.7 (Appendix) also confirms very stable home discharge rates for $\tau$=6 through $\tau$=12. Interpreted though the lens of the theoretical model, this reinforces that provider counteract patient incentives. The lower panel of Table 3 summarizes the identified provider incentives—the differential decline in discharge rates at high vs low occupancies. At high occupancies, provider incentives increase the community discharge rates by 1.4 ppt, see column (3), naturally exceeding the estimated effect size on weekly discharge rates (0.33 ppt, see Table 2) by a factor of 4.2.

**Robustness:** As discussed, one concern is that private payers may be on different asset spend-down schedules in inpatient and outpatient settings. Our calculations for California, also see Section 8.1, suggest a price tag for SNF care of \$5400 per month but only \$1956 per month for community LTC settings (in \$2005 dollars). To assess the robustness of our findings to differences in spend-down schedules, we rescale the time to Medicaid transitions. Specifically, we revisit the event study under a threefold faster spend-down rate in the community. Intuitively, if we observe a patient transitioning to Medicaid six months after discharge, we rescale that time to 6/3=2 months. Figure E.5 (Appendix) shows qualitatively and quantitatively very similar results.

We also test for changes in patient health around the time of Medicaid transitions (Figure E.8a to d). The purpose is twofold. First, it allows us to test if the Medicaid transition could be confounded by health shocks or may be a reaction to those. Second, it allows us to (imperfectly) test for health effects after Medicaid transitions in high and low occupancy environments. It also tests the key assumption that quality of care does not decrease after patients transition to Medicaid. Pressure ulcers are an accepted quality of care outcome measure. As seen in Figure E.8, the pre-transition and post-transition trends of all four health outcomes (CMI, depression, pressure ulcers stage 3 and 4) are relatively flat and show no trend.

Finally, we revisit the responsiveness of patient to financial incentives among Medicaid patients, who occur some cost-sharing during the first days of a month. Plotting discharge probabilities by the day-of-the month shows clear bunching for Medicaid beneficiaries, but not for private payers (Figure E.10). To map the bunching evidence into a patient elasticity, we estimate a stylized patient discharge model that captures (potential) forward-looking behavior by a discount factor. We find that a static model provides the best fit to the observed bunching behavior and estimate a patient elasticity of less than 0.2 across specifications, see Appendix E.4.

**Discussion:** The fixed effects and the event study approach both provide consistent and quantitatively similar evidence that patient and provider incentives affect home discharge rates. Henceforth, we focus on the fixed effects approach. First, it uses a larger patient and provider population spread across four states. Second, it summarizes differences in discharge patterns across granular occupancy rates. As such, it exploits high-frequency variation at the weekly level. Finally, the discharge patterns in Figure 3 connect closely to theoretical counterpart in Figure 1, thereby providing a natural set empirical moments for the structural estimation.

# 7 Structural Model of Discharges

This section develops and estimates a stylized model of community discharges. It incorporates financial discharge incentives for a representative nursing home and a representative patient. In a given week, the patient is either covered by Medicaid or pays out-of-pocket. To estimate the model, we use a simulated methods of moments estimator (SMM) which matches the model predictions to the discharge profile in Figure 3. Intuitively, the fixed effects model in equation (2) purges the raw data from patient and provider heterogeneity (by controlling for patient demographics, length of stay, time, and provider fixed effects). In doing so, it isolates aggregate discharge patterns that we seek to explain through the lens of the model. We then use the model to quantify the relative importance of patient and provider incentives and to evaluate counterfactual policies.

### 7.1 The Empirical Model

**Discharge Probabilities:** Consistent with our fixed effects empirical model, 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:

$$\Pr[D = 1|e^{SNF}, e^{res}] = D^{other,\tau} + \alpha \times e^{SNF}[\text{FinInc}^{SNF}(\tau, oc)] + \beta \times e^{res}[\text{FinInc}^{res}(\tau)]. \tag{5}$$

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.[16]

**Resident's Effort Choice:** The resident's benefit from a discharge is captured by the indirect conditional utility:

$$W(\tau, D, \eta) = \begin{cases} \eta^{home} & \text{if } D = 1 \\ u - \kappa p^{\tau} + \eta^{SNF} & \text{if } D = 0 \end{cases} \tag{6}$$

where $u$ is the resident's gross utility from a period of nursing home care relative to the gross utility of discharge, which we normalize to zero. The out-of-pocket price $p^{\tau}$ enters utility negatively and is scaled by the price coefficient $\kappa$, which is the marginal utility of income. $\eta^{SNF}$ and $\eta^{home}$ are type I extreme value taste shocks that are observed by the resident before choosing the effort level, but unobserved by the

[16] Equation (5) assumes constant marginal effects of discharge efforts. A true relationship that is inherently nonlinear violates this assumption, and predicted discharge probabilities may exceed 100% when $D^{other,\tau}$ is large. In our setting, weekly discharge probabilities range between three and eight percent alleviating these concerns. While our model could be viewed as a linear approximation of a potentially nonlinear relationship between effort and discharges, we note that our counterfactual predictions will be biased if this exercise extrapolates a misspecified linear relationship out-of-sample.

SNF. To simplify, we set the utility from a discharge equal to the utility from a home discharge, $\eta^{home}$.[17] Residents choose the optimal discharge effort given by:

$$e^{res,*} = \arg\max_{e^{res}\geq 0} \Big\{ \Pr[D=1|\cdot, e^{res}] \times W(\tau, D=1, \eta) \\ + (1-\Pr[D=1|\cdot, e^{res}]) \times W(\tau, D=0, \eta) - \kappa \times c(e^{res}) \Big\}. \quad (7)$$

$c(e)$ is the cost of effort, measured in dollars and scaled by $\kappa$ to be denoted in units of utility. Note that the discharge probability depends on $D^{other,\tau}$ and resident's expectations about $e^{SNF}$, captured by "$\cdot$", but the optimal discharge effort does *not*, see Appendix C.

**Provider's Effort Choice:** The SNF observes the payer type and forms expectations over residents' optimal effort levels. By contrast, resident's taste shocks, $\eta^{SNF}$ and $\eta^{home}$, and their discharge effort, $e^{res}$ are unobservable for the nursing home.[18] To derive the optimal provider effort, $e^{SNF,*}$ we impose that, during the period, providers choose $e^{SNF}$ and realize the weekly flow payoff:

$$\Pi^{\tau} = \begin{cases} -c(e^{SNF}) & \text{if bed is empty: } \tau = 0 \\ r^{\tau} - mc - c(e^{SNF}) & \text{otherwise} \end{cases},$$

where $r^{\tau}$ is the private or the Medicaid reimbursement rate, $mc$ is the marginal cost of providing care, and $c(e^{SNF})$ is the cost of effort. We assume that $c(\cdot)$ is convex in effort. This implies that optimal effort is continuous and (weakly) increasing in financial incentives which helps to explain the Medicaid discharge profile in Figure 3. At the same time, and as discussed in Section 3, optimal provider effort increases discontinuously from $e^{SNF}=0$ to $e^{SNF}>0$ as patients transition into Medicaid (if $oc > oc*$).

Discharges, arrivals, and Medicaid transitions are random events, realized at the *end* of the period. Arrivals and Medicaid transitions are exogenous. The weekly refill probability $\Phi(oc)$ and the per-period Medicaid transition probability $\psi$ determines them.[19] Discharges, by contrast, depend on endogenous

[17] Since $\epsilon$ is uniformly distributed, discharges to other destinations are "additively" separable from home discharges. As a result, the utility from other discharge destinations affects patient welfare but not the optimal discharge effort, see also Appendix C.

[18] We assume that SNFs maximize over effort under the following belief $\Pr[D=1|e^{SNF}, \tau] = D^{other,\tau} + \alpha \times e^{SNF} + \beta \times E_{\eta}[e^{res,*}|\tau]$.

[19] We do not model private information by providers about patients' future Medicaid transition date. This could provide incentives to frontload provider effort to the periods just before the Medicaid transition at high occupancy. We find no evidence for anticipation effects in our event studies and therefore consider a fixed weekly Medicaid transition probability, $\psi$, in the nursing home's optimization problem as detailed below.

discharge efforts; together with arrivals, they determine the occupancy rate in the other beds $oc$.

To simplify, we assume that discharge managers do not coordinate their discharge efforts between residents and do not internalize the effect of their "focal" discharge decision on the occupancy rate and discharges in other beds, which are both endogenous equilibrium objects. Instead, we assume that, in equilibrium, the discharge manager takes the time series process of the occupancy rate in other beds as given and chooses the discharge effort in the focal bed optimally. We model occupancy rate transitions as a Markov process, which is characterized by a period-to-period transition matrix, $\Theta$. This transition matrix denotes the conditional probability mass function over next week's occupancy rate, $oc'$, conditional on today's occupancy rate, $oc$: $\Theta(oc, oc') = \Pr[oc'|oc]$.

We can now express the SNF's optimal discharge efforts through the following Bellman equation:

$$V(\tau, oc) = \max_{e^{SNF} \geq 0} \left\{ \Pi^{\tau} - c(e^{SNF}) + \delta E\left[V(\tau', oc')\middle|\tau, oc, e^{SNF}\right]\right\} \quad , \tag{8}$$

where $\delta$ is a discount factor and

$$\begin{aligned}
E\left[V\middle|0, oc, e^{SNF}\right] &= \sum_{oc'} \Theta(oc, oc') \times \Big[(1 - \Phi(oc')) \times V(0, oc') \\
&\quad + \Phi(oc') \times \Big(\rho V(P, oc') + (1-\rho)V(M, oc')\Big)\Big] \qquad (9) \\
E\left[V\middle|M, oc, e^{SNF}\right] &= \sum_{oc'} \Theta(oc, oc') \times \Big[\Big(1 - \Pr[D = 1|e^{SNF}, M]\Big) \times V(M, oc') \\
&\quad + \Pr[D = 1|e^{SNF}, M] \times \Big((1 - \Phi(oc')) \times V(0, oc') \\
&\quad + \Phi(oc') \times \Big(\rho V(P, oc') + (1-\rho)V(M, oc')\Big)\Big)\Big] \qquad (10) \\
E\left[V\middle|P, oc, e^{SNF}\right] &= \sum_{oc'} \Theta(oc, oc') \times \Big[\Big(1 - \Pr[D = 1|e^{SNF}, P]\Big) \times \Big((1-\psi)V(P, oc') \\
&\quad + \psi V(M, oc')\Big) + \Pr[D = 1|e^{SNF}, P] \times \Big((1 - \Phi(oc')) \times V(0, oc') \\
&\quad + \Phi(oc') \times \Big(\rho V(P, oc') + (1-\rho)V(M, oc')\Big)\Big)\Big]. \qquad (11)
\end{aligned}$$

The value function combines the flow profit, net of the cost of effort, and a continuation value. The continuation value of an empty bed, as indicated in equation (9), is given by the probability of drawing a new resident, and captured by the refill probability vector $\Phi(oc')$, multiplied by the payer type probability at admission. For example, the new resident is a private payer with probability $\rho$ delivering a payoff vector of $V(P, oc')$. Furthermore, expectations are taken over next week's occupancy rate as indicated by the transition matrix $\Theta(oc, oc')$. The continuation value of a bed filled with a Medicaid beneficiary, see equation (10), adds the possibility that the focal resident may be discharged, which depends on the efforts of the nursing home and the resident. Finally, the continuation value of a bed filled with a private payer, see equation (11), adds to this a payer type transition to Medicaid, which happens with probability $\psi$.

**Discussion of Assumptions.** For reasons of tractability, we abstract from differences in gross utilities between payer types, see equation (6), assuming that our rich fixed effects purge the raw data off heterogeneity in patient preferences between payer types. We thus assume that the timing variation in Medicaid transitions affects $p^\tau$ but it is independent of $u$. Likewise, we do not model (payer-type specific) non-pecuniary motives in provider efforts. The analogue assumption is that the variation in Medicaid transitions affects $\pi(\tau)$ but it is independent of non-pecuniary motives.[20]

We also assume that occupancy only affects discharge efforts through the bed refill probability $\Phi$ and not, for instance, via potential congestion effects. That said, we find no conclusive evidence for changes in patient health at higher occupancy, which could be indicative of congestion effects, see Appendix E.1. Relatedly, we do not model quality of care decisions or how private rates are set. Both are determined over longer planning horizons, largely invariant when the period of analysis becomes sufficiently short, and hence potentially absorbed by nursing home-year fixed effects in the fixed effects regressions. However, optimal pricing or staffing may vary in our counterfactual analysis, see below.

We also acknowledge that our analysis abstains from cream-skimming of private payers at admission (Ching, Hayashi, and Wang, 2015; Gandhi, 2021). As our empirical discharge moments focus on private payers at admission and as our event study approach controls for changes in the patient composition, this omission is likely less concerning for estimation. In our simulations, provider-targeted policies slightly raise the profitability of Medicaid stays and result in slightly lower occupancy, muting the incentive to cream-skim private patients. If incorporated, this might increase occupancy and thereby reinforce the increase in provider efforts (at higher occupancies).

Finally, we deliberately focus on a static model where patients react to spot prices. While the literature has provided evidence for both, behavior consistent with rational forward-looking agents as well as myopic behavior focusing on spot prices (Aron-Dine et al., 2015; Einav, Finkelstein, and Schrimpf, 2015; Brot-Goldberg et al., 2017; Dalton, Gowrisankaran, and Town, 2020), our modeling choice is motivated by

[20]We note that non-pecuniary motives that are invariant to payer types can be captured by our marginal cost estimate (Lakdawalla and Philipson, 1998).

the empirical evidence and institutional context. Specifically, consistent with spot prices, we find no empirical evidence that vulnerable nursing home patients respond strategically in anticipation of their Medicaid transition. In additional robustness exercises exploiting cost-sharing variation among Medicaid patients, we also find that a myopic model of patient behavior provides the best fit for the observed timing of discharges, see Appendix Section E.4. Turning to the institutional context, we note that our analysis focuses on a very old vulnerable population where two thirds have impaired cognition and more than half have depression. On average, residents are in their 80s with a short and highly uncertain live expectancy (Table D.1, Appendix).

### 7.2 Estimation Strategy

**Parameters Estimated Outside the Model:** Panel A of Table 4 lists parameters estimated outside of the structural model. A period is one week. We then estimate the weekly refill probabilities $\Phi$, see Appendix E.5, and use the empirical week-to-week occupancy transition matrix $\Theta(oc, oc')$ for estimation.[21] We estimate payer type transitions from private to Medicaid from observed week-to-week changes (in 1.1%). We estimate that 78% of newly admitted residents initially pay out-of-pocket after excluding Medicare beneficiaries. To calculate $D^{other,\tau}$, we measure the average discharge rate by payer type to any non-home destinations by payer type by summing over the various discharge destinations in Figure E.1. Finally, the out-of-pocket rate and the Medicaid reimbursement rate correspond to the average rates in Pennsylvania and California in the sample period. We convert these rates to 2022 dollars using the consumer price index (CPI).

**[Insert Table 4 about here]**

**Calibrated Parameters:** Panel B of Table 4 lists all calibrated parameters. We set the weekly discount factor to $\delta = 0.95^{1/52}$. Note that we require a scale normalization on either the cost of effort or the return on effort as, naturally, we cannot separately identify them in our data. In the baseline analysis, we assume $c(e) = e^2$ and thereby load differences in cost functions between payer types onto differences in the returns to effort (Appendix Section C). Finally, we normalize the utility from nursing home care (0.5 per day) as we can only identify utility up to scale. This is because utility affects discharges through effort, which is again scaled by the factor $\beta$.

[21] For counterfactuals, we endogenize the transition matrix to allow for changes in discharge efforts affecting occupancy transitions, which in turn feed back into optimal effort choices.

**Parameters Estimated Within the Model:** As key structural parameters, we estimate the daily marginal cost of nursing home care per resident, $mc$, the price coefficient, $\kappa$, and the effort parameters $\alpha$ and $\beta$. We estimate the parameters using a nested fixed point procedure and conduct inference via bootstrapping, see Appendix C.3. To estimate the parameters, we match the model predictions to the empirical discharge profiles in Figure 3. Specifically, 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 $\hat{D}_{\tau,oc}$:

$$\hat{\theta} = \arg\min_{\theta} \sum_{\tau=P,M} \sum_{oc=65}^{99} \left( D_{\tau,oc}(\theta) - \hat{D}_{\tau,oc} \right)^2. \tag{12}$$

Intuitively, the occupancy rate where the Medicaid discharge rate starts to increase, $oc^*$ in Figure 1, is informative about $mc$. At $oc^*$, the marginal benefit of effort to discharge a Medicaid beneficiary equals the marginal cost of effort at $e^{SNF} = 0 = mc_e(0)$. Hence, the marginal benefit must be zero as well. This trades off the Medicaid flow profit $\pi(M)$ against the option value of drawing a new resident in the next period. The option value increases in the refill probability. Intuitively, we can pin down the marginal cost that equates $\pi(M)$ with the option value when evaluated at $oc^*$.

Next, we rely on discharge rates at low occupancy rates, $oc < oc^*$, to recover the resident coefficients, $\beta$ and $\kappa$.[22] Then, to quantify the provider coefficient $\alpha$, we build on the increase in discharge rates for Medicaid beneficiaries at higher occupancy rates, $oc \geq oc^*$.

### 7.3 Results

First of all, the model provides a very good fit to the observed community discharge rates in Figure 5. Panel C of Table 4 lists the estimated model parameters. Patients dislike paying higher out-of-pocket prices, $\hat{\kappa} > 0$. Both discharge effort parameters are positive, $\hat{\alpha} > 0$ and $\hat{\beta} > 0$, implying that provider and resident discharge efforts increase the discharge probability. Finally, we estimate a marginal cost of \$111 per day, which is considerably smaller than the marginal cost estimate of \$212 in Hackmann (2019) (in 2022 dollars). The main reason for the cost difference is likely the different time horizons between the two settings. Hackmann (2019) studies the optimal pricing and nurse staffing decisions over the course of a *full* calendar year. Our setting explores high-frequency variation in occupancy rates on a week-to-week basis. While nursing homes can employ some staff on a short-term notice, due to contracts, labor market

[22] Appendix Section C.1 provides more discussion on the identification of $\beta$ and $\kappa$.

rigidities and shortages, SNFs cannot easily adjust most labor input in response to short-term fluctuations in the patient composition. For these reasons, we expect lower marginal (variable) costs in our setting.

**[Insert Figure 5 about here]**

**Patient and Provider Elasticities:** To assess the relative importance of provider and patient incentives, we simulate the effect of a 1% change in financial incentives on the length of stay—holding discharge efforts of the opposite market side fixed. Starting with private payers, we find that increasing the private rate by 1% reduces the expected length of stay by 0.2%. This suggests a patient elasticity of 0.2, which is close to the literature that also centers around 0.2 (Manning et al., 1987; Finkelstein et al., 2012; Shigeoka, 2014).[23] Turning to providers, we find that a 1% increase in the Medicaid reimbursement rate increases the expected length of stay of Medicaid patients by 1.2%. This suggests a provider elasticity of 1.2, which exceeds the patient elasticity by a factor of six.[24]

**Validation With a Randomized Experiment:** To validate the provider elasticity, we revisit a unique randomized experiment in 36 Medicaid-certified SNFs in San Diego between November 1980 and April 1983 (Jones, 1986). It provided discharge incentives reflecting vacant bed costs as well as staff discharge effort. These are also the two key cost elements that nursing homes trade off in our framework, making our model well-suited to use the experiment as a validation exercise, see Appendix F. Specifically, we simulate the effects of the experimental financial incentives and find a community discharge rate of 0.96%, which is reasonably close to the 0.7% reported in Jones (1986). We view this as a successful validation exercise. However, the experiment happened 40 years ago and provided various additional incentives.

# 8 Policy Implications

## 8.1 Potential Cost Savings

Before turning to the policy counterfactuals, we assess the scope for cost savings. We compare Medicaid spending on nursing home care (including room and board) to community health care and living expenses

[23] Our calculation considers patients who pay out-of-pocket throughout their stays but we also find a patient elasticity of 0.2 when considering Medicaid transitions.

[24] Note that the calculated elasticities are not perfectly comparable as the patient elasticity considers variation in private rates in a static model, whereas the provider elasticity considers variation in Medicaid rates in a dynamic model. That said, we find that allowing for potential Medicaid transitions during the simulated patient stays leaves the implied patient elasticity at 0.2. Furthermore, considering an alternative source of financial incentives among Medicaid patients yields an even smaller patient elasticity, see Appendix E.4. Considering forward looking consumer behavior in this robustness exercise yields a larger implied patient elasticity (compared to the static robustness exercise) but the implied elasticity still falls below 0.2.

that would accrue if the nursing home patient would live in the community instead. As Medicaid only covers a fraction of these community expenditures, our cost savings represent overall LTC savings and are a lower bound on Medicaid savings from shortened nursing home stays.

Using data from the Medical Expenditure Panel Survey (MEPS) and the Consumer Expenditure Survey (CEX) on individuals aged 80 and older, we find mean annual expenditures of \$1,741 for formal home health care (provided by professional caregivers) and of \$22,061 for all other medical care and cost of living expenditures including housing, food (all in 2022 dollars). Adding the opportunity costs of informal care provided by family members to these expenses (Skira, 2015; Barczyk and Kredler, 2018), we obtain $\$1{,}741 + \$22{,}061 + \$11{,}784 = \$35{,}592$ per year or \$98 per person and day. This is considerably lower than the daily Medicaid rate of \$214 used in our model. Hence, Medicaid spending could be lowered by $(\$214 - \$98) \times 7$ days $\times\, \Delta^{weeks} = \$812 \times \Delta^{weeks}$ if the resident's nursing home stay was shortened by $\Delta^{weeks}$ weeks.

### 8.2 Policy Counterfactuals

Building on the estimated model, we evaluate three policy counterfactuals that change the discharge incentives for patients and providers. When simulating their effects on the length of stay and Medicaid spending, we account for endogenous changes in occupancy rates, which in turn affect provider discharge efforts.[25] In the counterfactual simulations, we add an outer loop to the optimization problem that searches for a fixed point in the discharge profiles, see Appendix G for details.

**[Insert Figure 6 about here]**

**Voucher Program:** Our first policy is a voucher program that requires Medicaid beneficiaries to pay the full private rate out-of-pocket. The program compensates Medicaid beneficiaries for their expected outlays through a lump-sum transfer, which equals the expected length of stay, 24.2 weeks, times the weekly private rate of \$1,806. This amounts to a lump-sum of \$43,723 per Medicaid stay.[26] The program affects resident and provider incentives in opposite directions. Medicaid beneficiaries have an incentive to shorten their stays. Providers are indifferent between private and Medicaid residents as they generate identical

[25] To this end, we divide the nursing home into two "wings." The "additional wing" incorporates admissions and discharges among residents that we excluded from the estimation sample but also affect overall occupancy. We treat these admissions and discharges as exogenous. For the "nursing home wing", we take observed weekly admissions as exogenous and use our structural model to predict discharge rates under alternative policy regimes. Combining admission and discharge profiles between wings allows us to incorporate the effect of policy changes on occupancy rates.

[26] For patients who transition into Medicaid during their stay, this payment is made at the time of transition covering their expected "remaining" length of stay, which also equals 24.2 weeks.

weekly profits. Therefore, nursing homes will minimize their discharge effort for Medicaid beneficiaries.

Figure 6a shows that private payers and Medicaid beneficiaries have the same community discharge rate profile under the voucher program. As indicated in the second column in Table 5, Medicaid beneficiaries' length of stay would decrease by 6.1 weeks, which reduces occupancy to 86.4%. Medicaid saves the baseline 30.3 weeks of Medicaid reimbursement worth \$1,498 each or \$1,498*30.3=\$45,434 in total, but provides transfers (to beneficiaries) worth \$43,723 under this policy. The costs for the additional 6.1 weeks spent in the community are 6.1 weeks $\times$ 7 days $\times$ \$98 = \$4,198 per reduced Medicaid stay. Hence, overall expenditures increase by \$43,723 + \$4,198$-\$45,434 = \$2,487$ per Medicaid stay, or about \$2,487/\$45,434=5.5%.[27]

**[Insert Table 5 about here]**

**Discharge Bonus:** Motivated by the randomized discharge experiment of Norton (1992), our second policy considers a bonus payment counterfactual. It rewards nursing homes for successful community discharges, independent of the underlying patient or provider effort.[28] Figure 6b shows an increase in provider efforts at high occupancies. This reduces the length of stay by 0.4 weeks, which reduces Medicaid spending by $0.4 \times 7 \times (\$214 - \$98) = \$357$ per stay (Table 5). Considering that Medicaid would pay nursing homes the bonus of \$986 for 38% of all stays (that end in a community discharge), suggests only a very small cost increase of $0.38 \times \$986 - \$357 = \$17$ per stay, 1.7% of the bonus amount or 0.04% of Medicaid spending per stay.

**Episode-Based Reimbursements:** Our final policy shifts from per-diem to episode-based reimbursement. In the counterfactual simulation, we reduce the daily Medicaid reimbursement rate by 2% but compensate providers for the forgone Medicaid revenues with an up-front payment. Specifically, the provider receives an up-front compensation of 2% of the expected baseline Medicaid revenues per stay (2% $\times$ 30.3 $\times$ 7 $\times$ \$214) whenever a new Medicaid beneficiary arrives or a private payer transitions into Medicaid.[29] This compensation maintains the profitability of Medicaid beneficiaries and mutes providers' incentives to respond along unintended margins, such as reducing the quality of care for all residents, see

[27]Equating Medicaid and private rates increases the profitability of Medicaid patients. This provides nursing homes incentives to respond along other dimensions not considered here. This is also true for the second counterfactual. We also note that the prospect of a lump-sum payment upon a Medicaid transition may encourage some rational forward-looking private payers with little assets to extend their stay until after they transition to Medicaid. Such behavior would increase the cost to the Medicaid program further by increasing the number of Medicaid stays. We do not model this potential effect.

[28]We consider a payments for discharges after 30 days of \$986 and simply add the term $(\Pr[D = 1|e^{SNF}, M] - D^{other,M}) \times$ \$986 to equation (10), where the first factor subtracts exogenous discharges to other destinations and thereby isolates the home discharge probability.

[29]We replace $V(M, oc')$ by $V(M, oc') + \Delta$ in equations (9) and (11), where $\Delta$ denotes the up-front payment.

Hackmann (2019). We also note that provider profits must weakly increase in this counterfactual as they can always maintain their baseline discharge efforts leaving revenues, costs, and hence profits unchanged.

The simulated discharge rates in Figure 6c point to an increase in provider discharge efforts. The new kink point $oc^*$ is now at around 86%. As seen in Table 5, the length of stay decreases by 0.7 weeks as does occupancy to 89%. The change in Medicaid spending per stay is simply the difference between marginal SNF and community care spending, scaled by the change in the length of stay. This implies savings of about $(0.98 \times \$214 - \$98) \times 7$ days $\times$ 0.7 weeks = \$565 or 1.2% per stay. Transitioning 10% of per-diem payments to an upfront episode-based reimbursement is about as effective as the voucher program in reducing the average length of a Medicaid stay, see last column of Table 5. However, the implied cost savings are substantially larger. We find cost savings of \$3,829 per stay or 8.4%.

### 8.3 Discussion

We find that targeting provider incentives is more cost effective than increasing patient cost-sharing in shortening the length of Medicaid SNF stays. However, note that this paper does not explicitly quantify patient welfare. While targeting provider incentives maintains financial risk protection for patients, a comprehensive assessment of patient welfare would require a quantification of the causal effects on patient health and well-being. Such an analysis is beyond the scope of this paper and inherently difficult to carry out, even with high-quality administrative data. For example, to label incremental use of long-term care as "waste", in our view, researchers require time-varying and high-quality comprehensive physical and mental health care measures as well as quality-of-life measures. However, especially the latter are usually based on self-reports and inherently difficult to collect among very old long-term care patients with cognitive challenges. Nevertheless, several pieces of evidence mitigate concerns over the potentially detrimental health effects from earlier SNF discharges under alternative payment models.

First, only four percent of Medicaid community discharges are readmitted to a nursing home within 30 days, consistent with the literature (Mor et al., 2007a) and the policy goal of promoting community-based care over institutional care. Second, patients who are discharged at high occupancy rates, triggered by provider incentives, have an identical readmission rate than patients discharged at low occupancy rates.[30] Third, pairing bonus payments inversely to the readmission rate and requiring explicit discharge protocols are likely useful measures to further improve discharge outcomes (cf. Jones, 1986). Finally, in complementary analyses, we find no evidence that shorter nursing home stays (on the margin) lead to

[30] The exact difference is 0.04ppt with a standard deviation of 0.2ppt.

increases in hospitalization or mortality rates or a worse health at discharge, see Appendix Section D.4. in Hackmann and Pohl (2018).

## 9 Conclusion

We develop an empirical framework to separate the effects of patient and provider incentives on nursing home discharges to the community. Using administrative claims data on half a million nursing home stays in the U.S., we find that providers respond significantly more elastically to financial incentives than patients. We estimate a patient elasticity of 0.2, consistent with the literature, and a provider elasticity of around one.

Our counterfactual analysis assesses the scope of alternative payment models (APMs) in promoting community discharges. APMs are increasingly used in hospital reimbursement (Dummit et al., 2018; Norton et al., 2018). However, they have received, perhaps surprisingly, rather little attention despite promising early experimental evidence (Norton, 1992). Our simulations show that introducing discharge bonus payments or partially transitioning from a per-diem to an episode-based provider reimbursement reduces nursing home stays in a meaningful manner. Importantly, it generates cost savings without reducing provider profits or exposing patients to substantial financial risk.

Our findings inform future policies on how to contain long-term care spending. Given its large and growing fiscal consequences, containing LTC spending is of high policy relevance to state Medicaid programs. Hence, states continue to experiment with a variety of Medicaid waiver programs to contain spending, illustrating how little is known on how to best align patient and provider incentives with the costs of long term care to the Medicaid program. Currently, the 52 state-level Medicaid systems provide the only permanent public insurance coverage for long-term care in the U.S., resulting in a patchwork of policy proposals without systematic randomization and evaluation (Finkelstein, 2020). One possible pathway to harness cost savings would be through the growing number Medicaid managed care organizations (MCOs) that contract with providers on behalf of state agencies and Medicaid beneficiaries (Graham et al., 2018; Medicaid and CHIP Payment and Access Commission, 2022). Our findings suggests that targeting provider incentives through alternative payment models may be more effective than targeting patient incentives in promoting community discharges.

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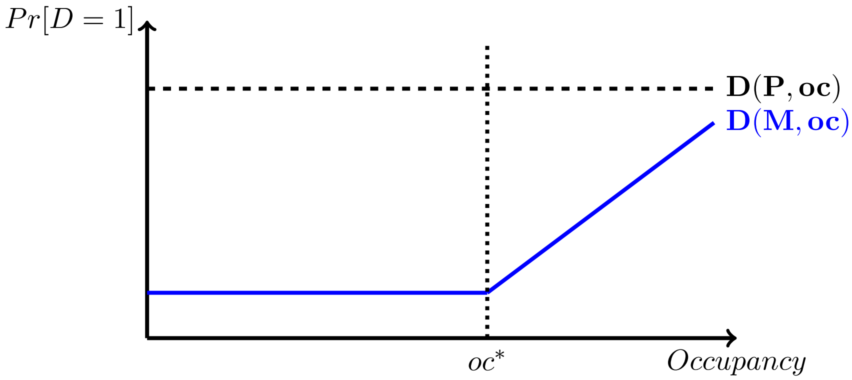
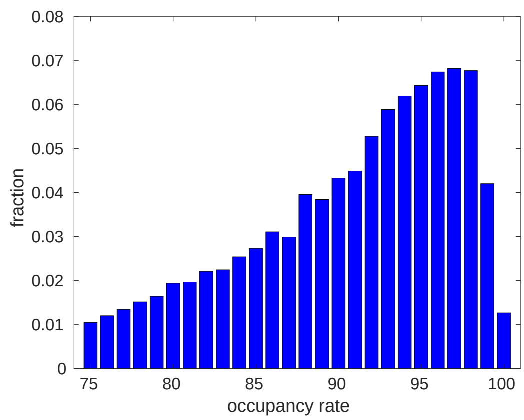
# Figures and Tables

Figure 1: Predicted Discharge Profiles by Payer Type and Across Occupancies

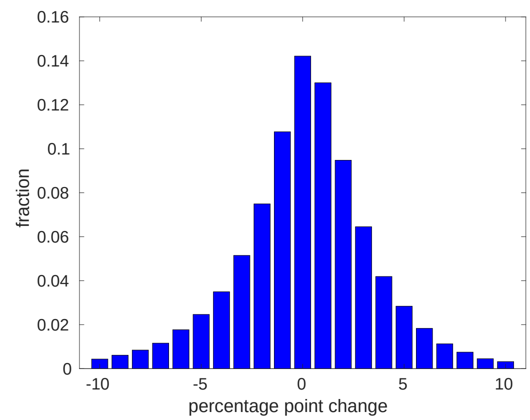



**Notes:** On the y-axis, the figure shows discharge probabilities for Medicaid beneficiaries (solid line) vs. private payers (dashed horizontal line) by SNF occupancy. $oc^*$ indicates when nursing homes start to exercise positive discharge efforts for Medicaid beneficiaries (see Section 3).

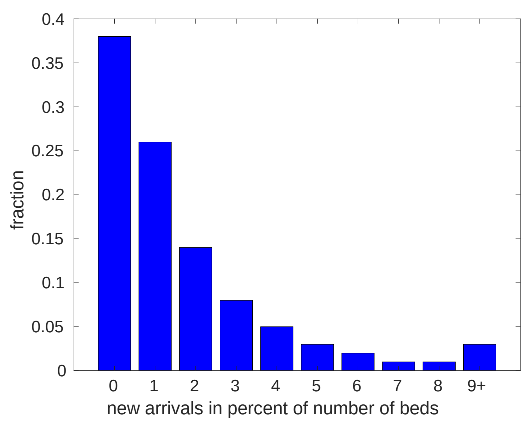
Figure 2: Variation in Occupancy Rates and New Arrivals by SNF and Week



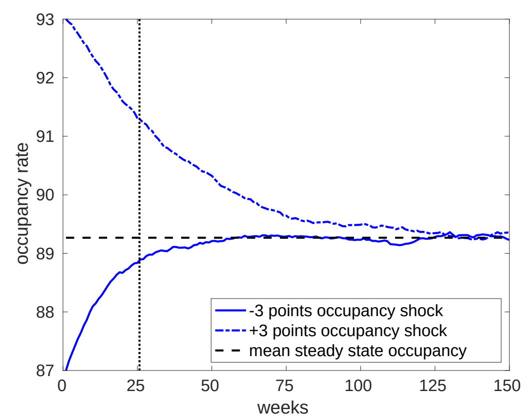

(a) Occupancy Rate Distribution




(b) Occupancy Variation Within SNF and Year



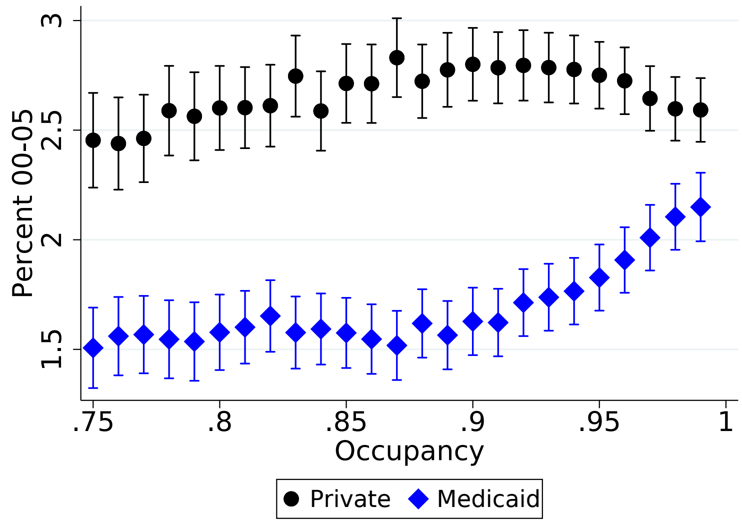

(c) New Arrivals Relative to Number of Beds




(d) Impulse Response to Change in Occupancy

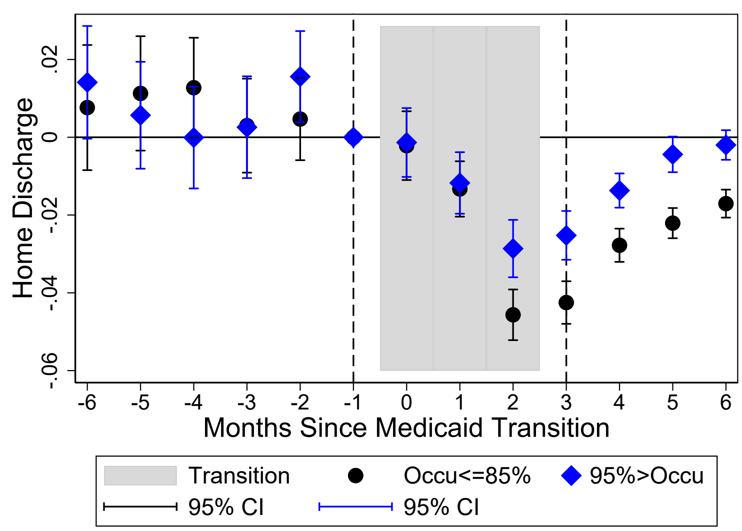
**Notes:** The unit of observation for Figures 2a, 2b, and 2c is the SNF-week level. Figure 2a shows variation in occupancy rates. Figure 2b shows the *residual* variation conditional on SNF-year fixed effects. Figure 2c summarizes the frequency of weekly arrivals, divided by the number of licensed beds. Figure 2d presents two impulse response functions, which document the mean reversion of an initial deviation of $\pm 3$ percentage points. The vertical line marks the average length of a nursing home stay.

Figure 3: Home Discharge Rates by Payer Type and Occupancy Rate



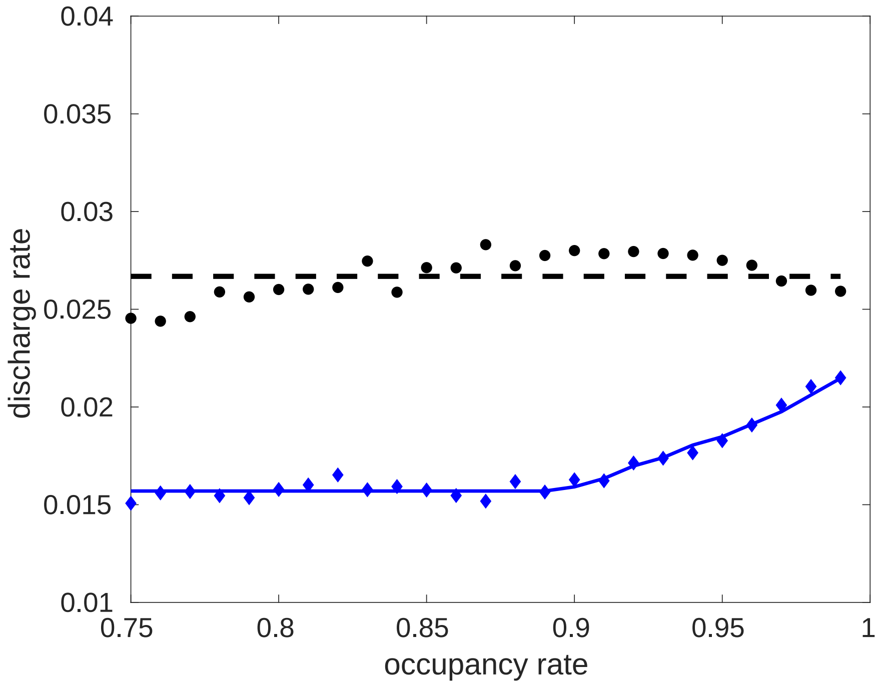

**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for CA, NJ, OH, PA from 2000 to 2005. The figure plots $\hat{\gamma}^k$ (private) and $\hat{\gamma}^k + \hat{\delta}^k$ (Medicaid) of equation (2) for the dependent variable "home discharge" across occupancy rates $k$. The vertical bars indicate 90% confidence intervals. Figure 3 is the empirical analogue to Figure 1. We exclude estimates for 100% occupancy due to measurement error, which biases the point estimate towards the sample mean.

Figure 4: Event Study: Medicaid Transition at Low and High Occupancies



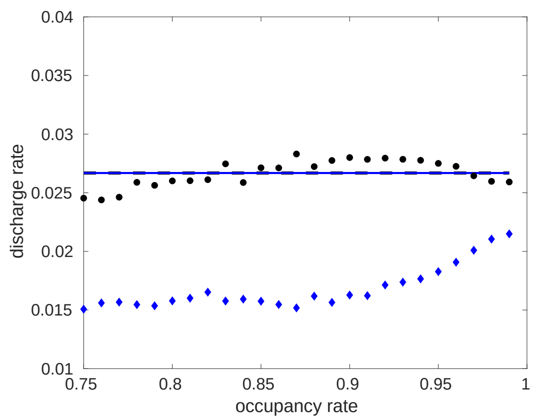

**Notes:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section 4.5. The figure plots $\sum_{\iota=-6}^{-2} \mu_\tau$ and $\sum_{\tau=0}^{6} \mu_\tau$ of equation (3), separately for the low occupancy environment ($\leq$ 85%) where solely patient incentives operate and the high occupancy environment (>95%) where patient and provider incentives are at work. The vertical bars indicate 95% confidence intervals.

Figure 5: Observed Discharge Pattern and Model Fit

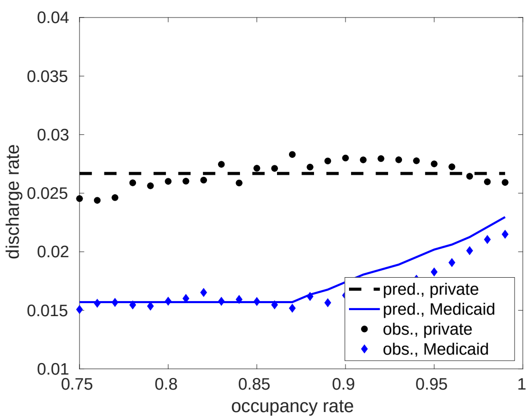



**Notes:** This figure plots the observe discharge pattern against the model predictions, see main text for details.

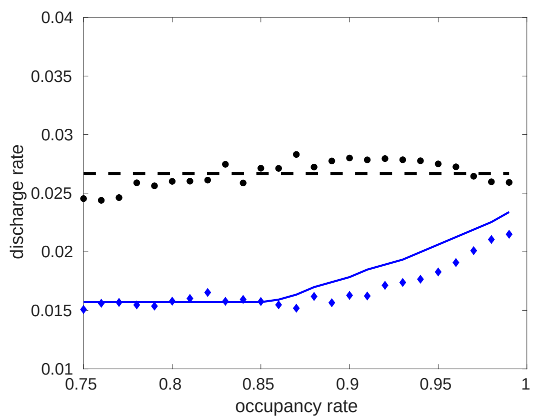
Figure 6: Simulated Discharge Rates Under Different Policies




(a) Medicaid Voucher




(b) Discharge Bonus




(c) Front-Loaded Medicaid Reimbursement

**Notes:** The figures show the estimated home discharge rates for private payers and Medicaid beneficiaries from Figure 3 along with the corresponding model predictions. Figure 6a shows model predictions under a voucher policy, and Figure 6b under a provider bonus payment for community discharges within 30 days. Figure 6c shows model predictions under prospective front-loaded Medicaid payments where we reduce the Medicaid rate by 2% and compensate providers by an up-front payment as described in the text.

Table 1: Summary Statistics at Resident-Week Level

| | Private | | Medicaid | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| **Panel A: Socio-Demographics** | | | | |
| Age | 84.2732 | (7.7942) | 83.9177 | (7.8916) |
| Female | 0.7030 | (0.457) | 0.7442 | (0.4363) |
| White | 0.89 | (0.3129) | 0.8484 | (0.3586) |
| Black | 0.0515 | (0.2209) | 0.0967 | (0.2955) |
| Hispanic | 0.0316 | (0.1751) | 0.031 | (0.1734) |
| Married | 0.2538 | (0.4352) | 0.2179 | (0.4128) |
| Widowed | 0.5334 | (0.4989) | 0.5556 | (0.4969) |
| Divorced | 0.0559 | (0.2296) | 0.0818 | (0.274) |
| **Panel B: Health Measures** | | | | |
| Case Mix Index (CMI) | 1.0971 | (0.378) | 1.0523 | (0.3669) |
| Number of ADL | 12.0068 | (4.2134) | 11.778 | (4.5409) |
| Low ADL Needs | 0.133 | (0.332) | 0.123 | (0.324) |
| Depression | 0.4651 | (0.4988) | 0.5285 | (0.4992) |
| Weight Loss | 0.1188 | (0.3235) | 0.1017 | (0.3022) |
| Impaired Cognition | 0.6083 | (0.4881) | 0.6407 | (0.4798) |
| Behavioral Problems | 0.0831 | (0.276) | 0.0922 | (0.2892) |
| **Panel C: Occupancy Rates** | | | | |
| Occupancy $\leq$ 85% | 0.2135 | (0.4098) | 0.1982 | (0.3987) |
| Occupancy $>$ 85% & $\leq$ 95% | 0.4973 | (0.5) | 0.4902 | (0.4999) |
| Occupancy $>$ 95% | 0.2892 | (0.4534) | 0.3116 | (0.4631) |
| Observations | 7,330,679 | | 5,994,994 | |

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. 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. SD stands for standard deviation.

Table 2: Fixed Effects Approach: Home Discharges by Payer Type and Occupancy Rate

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Medicaid×Occupancy≤ 85% | -0.0078*** | -0.0078*** | -0.0079*** | -0.0097*** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Medicaid×Occupancy>85% & ≤95% | -0.0092*** | -0.0093*** | -0.0094*** | -0.0109*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0003) |
| Medicaid×Occupancy>95% | -0.0050*** | -0.0051*** | -0.0051*** | -0.0064*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| **Patient Incentives:** | | | | |
| Medicaid× Occupancy ≤ 85% | -0.0078*** | -0.0078*** | -0.0079*** | -0.0097*** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Discharge Rate Private Payers: | *0.0272* | | | |
| (at 85% < Occupancy ≤ 95%) | | | | |
| Change in percent: | -28.7% | -28.7% | -29% | -35.7% |
| **Provider Incentives:** | | | | |
| (Medicaid×Occupancy>95%) – | 0.0029*** | 0.0027*** | 0.0028*** | 0.0033*** |
| (Medicaid×Occupancy≤85%) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Discharge Rate Private Payers: | *0.0272* | | | |
| (at 85% < Occupancy ≤ 95%) | | | | |
| Change in percent: | 10.7% | 9.9% | 10.3% | 12.1% |
| LOS-week FE | X | X | X | X |
| SNF-year FE | | X | X | X |
| Month FE | | | X | X |
| Socio-dem. controls | | | | X |
| Observations | 13,325,673 | 13,325,673 | 13,325,673 | 13,325,673 |
| R-squared | 0.0575 | 0.0512 | 0.0512 | 0.0572 |

Source: Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for CA, NJ, OH, PA from 2000 to 2005. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table summarizes empirical evidence from the fixed effects approach when aggregating occupancy into low (≤85%), medium, (85-95%), and high (>95%) occupancy rates. Each column in the upper panel is one regression model with different sets of fixed effects, described in the bottom panel.

Table 3: Transition to Medicaid: Disentangling Financial Patient from Provider Incentives

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Medicaid×Occupancy ≤ 85% | -0.0369*** | -0.0422*** | -0.0312*** | -0.0292*** |
| | (0.0027) | (0.0026) | (0.0025) | (0.0011) |
| Medicaid×Occupancy>85% & ≤ 95% | -0.0699*** | -0.0465*** | -0.0258*** | 0.0066*** |
| | (0.0015) | (0.0017) | (0.0016) | (0.0004) |
| Medicaid×Occupancy>95% | -0.0254*** | -0.0266*** | -0.0171*** | 0.0086*** |
| | (0.0026) | (0.0024) | (0.0023) | (0.002) |
| **Patient Incentives:** | | | | |
| Medicaid×Occupancy≤ 85% | -0.0369*** | -0.0422*** | -0.0312*** | -0.0292*** |
| | (0.0027) | (0.0026) | (0.0025) | (0.0011) |
| Pre-transition discharge rate: | *0.1306* | | | |
| Change in percent: | -28.2% | -32.3% | -23.9% | -22.4% |
| **Provider Incentives:** | | | | |
| (Medicaid×Occupancy>95%) – (Medicaid×Occupancy≤85%) | 0.0115*** | 0.0156*** | 0.0141*** | 0.0379*** |
| | (0.0036) | (0.0034) | (0.0033) | (0.0023) |
| Change in percent: | 8.8% | 11.9% | 10.8% | 29.0% |
| LOS-month FE | X | X | X | X |
| Patient FE | | X | X | X |
| SNF-year control | | X | X | X |
| Month FE | | X | X | X |
| Socio-dem. controls | | | X | |
| Gardner (2001) correction | | | | X |
| Observations | | 1,158,557 | 1,158,557 | 1,158,557 |
| R-squared | 0.0944 | 0.1277 | 0.1587 | |

Source: Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for CA only from 2000 to 2005. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table summarizes empirical evidence from the fixed effects approach when aggregating occupancy into low (≤85%), medium, (85-95%), and high (>95%) occupancy rates. Each column in the upper panel is one difference-in-differences regression model as in equation (4) with different sets of controls, as shown in the bottom panel. Column (4) reports results from the Gardner (2021) correction and runs a two-stage difference-in-differences model.

Table 4: Structural Parameter Estimates

| | |
|---|---|
| *A. Estimated Outside Model* | |
| Refill probability $\Phi$ | See Figure E.12. |
| Occupancy transition matrix $\Theta$ | Estimated from weekly sample. |
| Pr(transition to Medicaid) $\psi$ | 1.1% |
| Pr(private at admission) $\rho$ | 78.0% |
| Discharge rate, private $D^{other,P}$ | 3.2% |
| Discharge rate, Medicaid $D^{other,M}$ | 1.5% |
| Daily private rate $r^P/7$ | $258 |
| Daily Medicaid rate $r^M/7$ | $214 |
| *B. Calibrated* | |
| Discount Factor $\delta$ | $0.95^{\frac{1}{52}}$ |
| Cost of Effort $c(e)$ | $e^2$ |
| Utility SNF Care per Day $u$ | 0.5 |
| *C. Estimated Inside Model* | |
| SNF Effort $\alpha$ | 0.021 |
| | [0.020, 0.026] |
| Resident Effort $\beta$ | 0.177 |
| | [0.174, 0.184] |
| Resident Price $\kappa$ | 0.030 |
| | [0.027, 0.035] |
| Daily marginal cost of care $mc/7$ | 111.4 |
| | [111.1, 121.8] |
| SNF Elasticity $\epsilon^{SNF}$ | 1.2 |
| Resident Elasticity $\epsilon^{res}$ | 0.2 |

Notes: Panel A summarizes the parameters that we estimate outside of the model. 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) to facilitate the interpretation. We conduct inference via bootstrapping. All estimates are for the full sample. See main text for details.

Table 5: Simulated Length of Stay and Cost Savings Under Policy Counterfactuals

| | Actual | Voucher | Bonus | 2% Front | 10% Front |
|---|---|---|---|---|---|
| Medicaid LOS | 30.33 | 24.21 | 29.89 | 29.62 | 25.09 |
| Average Occupancy | 89.7% | 86.4% | 89.3% | 89.2% | 87.2% |
| $\Delta$ Medicaid LOS (vs. "actual") | | −6.12 | −0.44 | −0.72 | −5.25 |
| $\Delta$ Medicaid spending per stay in $ | | 2,487 | 17 | −565 | −3,829 |
| $\Delta$ Medicaid spending per stay in % | | 5.5% | 0.04% | −1.2% | −8.4% |

**Notes:** The table summarizes the length of stay (LOS) in weeks, average occupancy rates, Medicaid savings per stay, and national Medicaid savings for the counterfactual policy experiments.

# Online Appendix

## 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 B.3. 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

## B.1 Creation of Main Datasets

For the main analysis, we compile a unique dataset. In our first "fixed-effects" approach, in Section 6.1, we use it at the week-stay level for four states from 2000 to 2005. In our second "event study" approach, in Section 6.2, we aggregate this dataset to the month-stay level and focus on California, see Section 4.5 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 B.3 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 B.3 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.2 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).

## B.3 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 to 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.

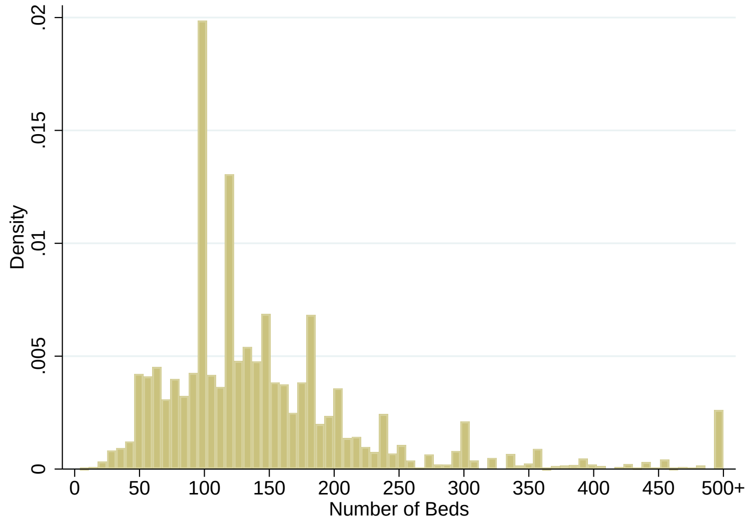
**Health Assessments:** The MDS provides information on residents' health assessments, which typically take place at admission, then on a quarterly basis, and then at discharge. The MDS data include several clinical health measures on a variety of cognitive, physical functional, behavioral, communication, 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).

To avoid a mechanical reverse relationship between the own discharge process and the 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.

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 cross-validate the OSCAR survey data, we benchmark the number of licensed beds with another administrative data sources 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-

Figure B.1: Number of Licensed Beds



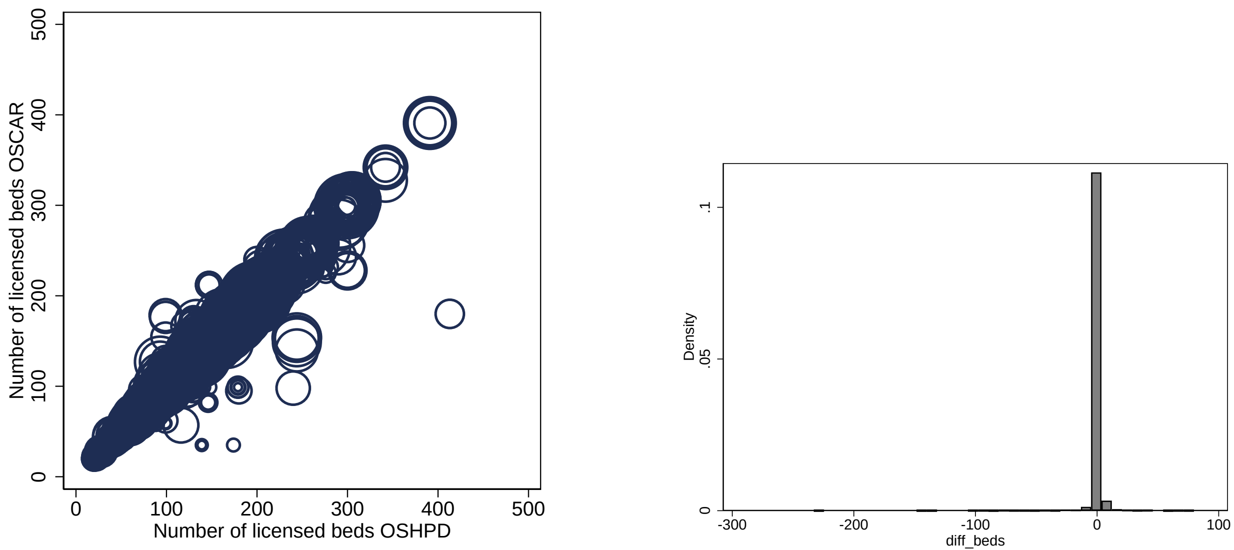

**Source:** Administrative data from Long-Term Care: Facts on Care in the U.S. (2020) linked to MDS data. The figure presents a histogram of the overall number of licensed beds. The unit of observation is the week of the nursing home stay.

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 B.2a correlates the number of reported beds by SNF and year between the two data soures: OSCAR vs. OSHPD. The size of the scatters represent the size of the SNF. As seen, while we can observe some deviations between both data sources, (a) the deviations appear symmetric, and (b) the large majority of all values are identical and line up on the 45 degree line in Figure B.2a. Plotting the histogram of bed size deviations, Figure B.2b corroborates this conclusion. As seen, the overwhelming majority of reported beds are identical between the two data sources.

Finally, we 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 measures are correlated as shown 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:

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




**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.

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

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 note that classical measurement error in occupancy would bias the provider elasticity estimates downward. However, the evidence from Table B.3 suggests that in our setting, the potential

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

| | (1) | (2) |
|---|---|---|
| Medicaid × Occupancy $\leq$ 85% | -0.0168*** | -0.0170*** |
| | (0.0005) | (0.0004) |
| Medicaid × Occupancy $>$ 85% & $\leq$ 95% | -0.0188*** | -0.0187*** |
| | (0.0003) | (0.0002) |
| Medicaid × Occupancy $>$ 95% | -0.0128*** | -0.0130*** |
| | (0.0008) | (0.0004) |
| Occupancy $\leq$ 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.

measurement error in occupancy has only a relatively small effect on the estimated relationship between occupancy and Medicaid home discharges, and hence the implied provider elasticity.

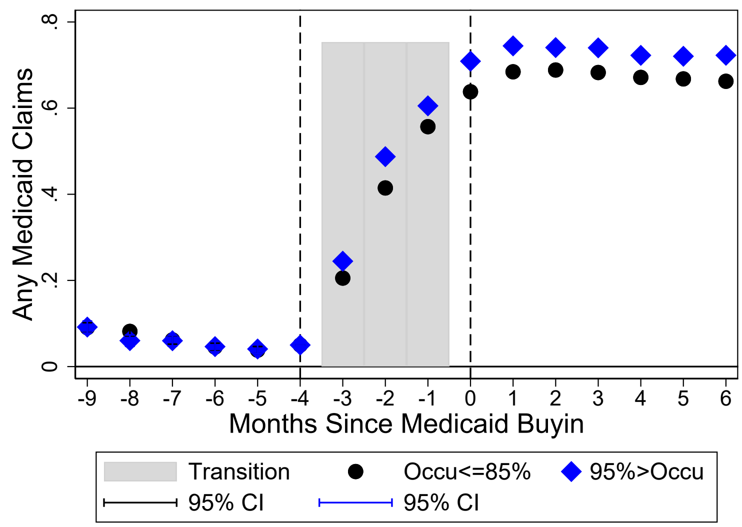
## B.4 Payer Types and Transition to Medicaid

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 4.5. 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.[31] 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.

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 4.5. 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 $\mu_0$).

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

[31]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%.

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.

### B.5 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.

## C.1 Optimal Resident Effort

As stated in the main text, 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 of the uniform distribution of $\epsilon$, see equation (1), shutting down potential free-riding incentives as shown by the first order condition:

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

where $c_e^{-1}(\cdot)$ is the inverse marginal cost of effort function.

**Scale Normalizations:** Identification of the model requires a scale normalization on either the cost of effort, $c(e)$, or the return on effort, $\beta$, as we cannot separately identify them from overall discharge rates. We assume $c(e) = e^2$ and thereby load differences in cost functions between payer types onto differences in the returns to effort. To see this, consider the resident's optimal effort choice in equation (C.1). We observe the private rate $p^P$ as well as the discharge rates. Suppose we generalize the costs $c(e) = \gamma e^2$. Then we have $\partial Pr[D=1]/\partial p^P = \beta \times \partial e^{res,*}/\partial p^P = \beta^{2*}/2\gamma$. Hence, scaling up the costs would simply scale up $\beta$.[32]

Likewise, we require a scale normalization on either utility, $u$, or the return on effort, $\beta$, as only the product of the two determines optimal effort. To see this, note that $W(\tau, D=1,\eta) - W(\tau, D=0,\eta) = \eta^{home} - u + \kappa p^\tau - \eta^{SNF}$ in equation (C.1). We assume $u$ =0.5 per day.

Building on these normalizations, 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:

[32]In an alternative attempt, we define effort as a change in the probability of discharge by normalizing $\alpha = \beta = 1$. Here, we allow for linear quadratic cost functions of effort, $c(e) = \gamma_1 e + \gamma_2 e^2$ and estimate separate cost parameters for patients and providers. This approach yields qualitatively similar results, see Hackmann and Pohl (2018).

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

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

$$Pr[D=1|\tau=P,oc=low]=\frac{\beta^2}{2\times\kappa}\times E_\eta[\max\{\eta^{home}-u+\kappa p^\tau-\eta^{SNF},0\}] \ . \quad (C.3)$$

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

## C.2 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.3 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):

$$\hat{\theta} = \arg\min_{\theta} \sum_{\tau=P,M} \sum_{oc=65}^{99} \left(D_{\tau,oc}(\theta) - \hat{D}_{\tau,oc}\right)^2. \tag{C.4}$$

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.4) 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.

Comparing the patient populations 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 (detailed results available upon request).

Table D.1: 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

## E.1 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.1). Moreover, adding these as controls leaves the patterns intact (results are available upon request).

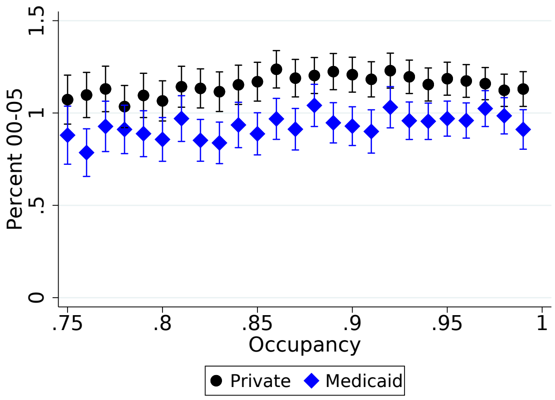
### E.1.1 Discharge Patterns by Discharge Potential

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.

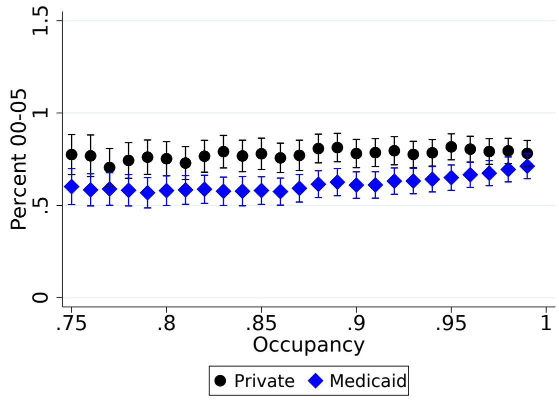
The top left figure shows the quartile of patients with the lowest home discharge potential. Here, the average mortality risk is the highest and we also see the largest differential increase in mortality risk for Medicaid patients in occupancy. Levels and convergence patterns are muted in the top right 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

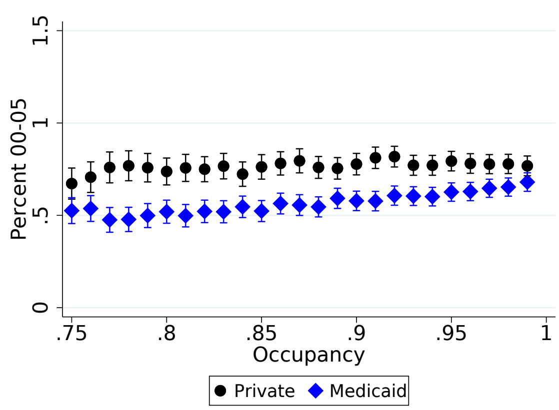
Figure E.1: Discharge Rates to Different Destinations by Occupancy and Payer Type



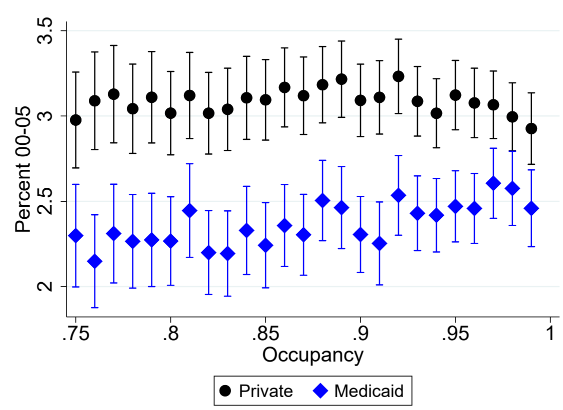

(a) Hospitalized




(b) Discharged to Another Nursing Home



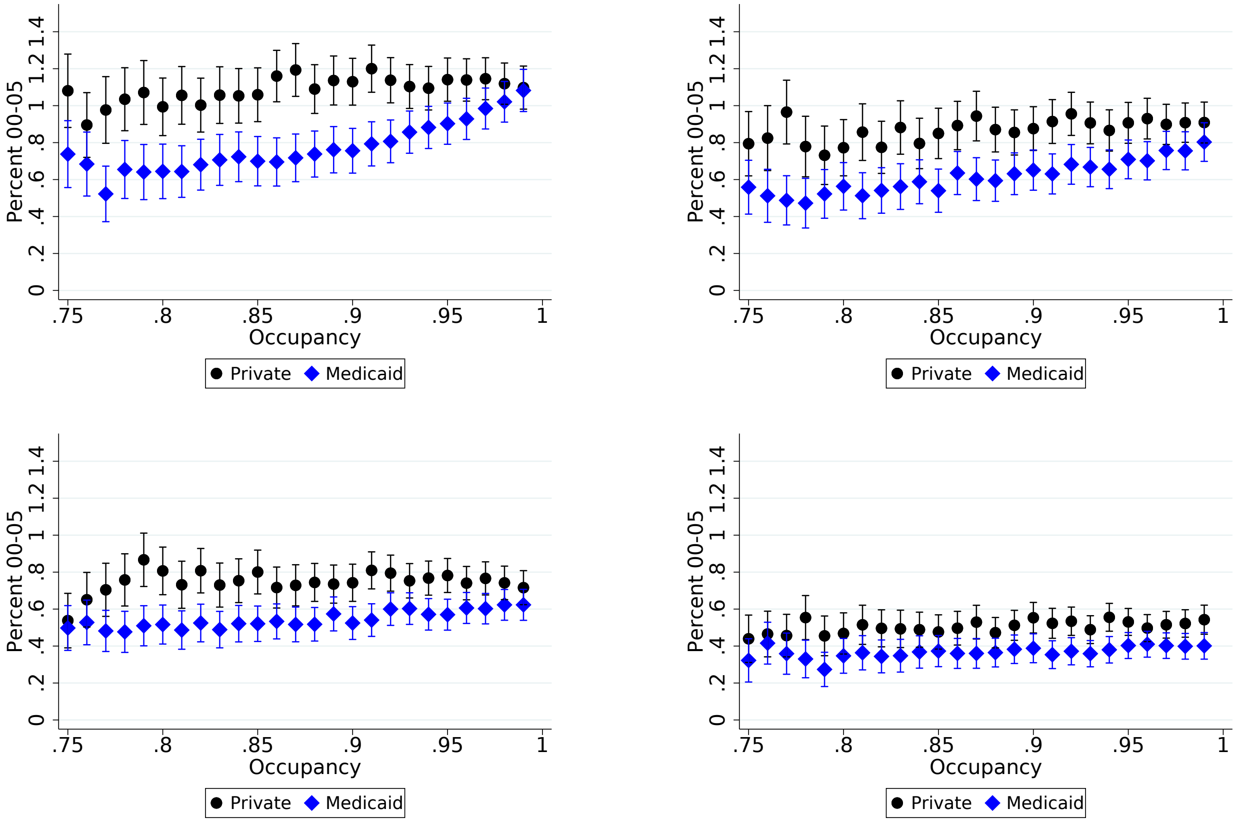

(c) Deceased




(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: Discharges Due to Death by Quartiles of Discharge Potential




**Source:** Long-Term Care Minimum Data Set, Office of Statewide Health Planning and Development (2020). The upper left figure is solely based on the bottom quartile of discharge potential, the upper right on the second quartile, the lower left on the third, and the lower right on the fourth quartile of discharge probability. 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.3 shows our the baseline sample, which excludes the 10% patients with the lowest discharge potential, in the top left graph. 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.

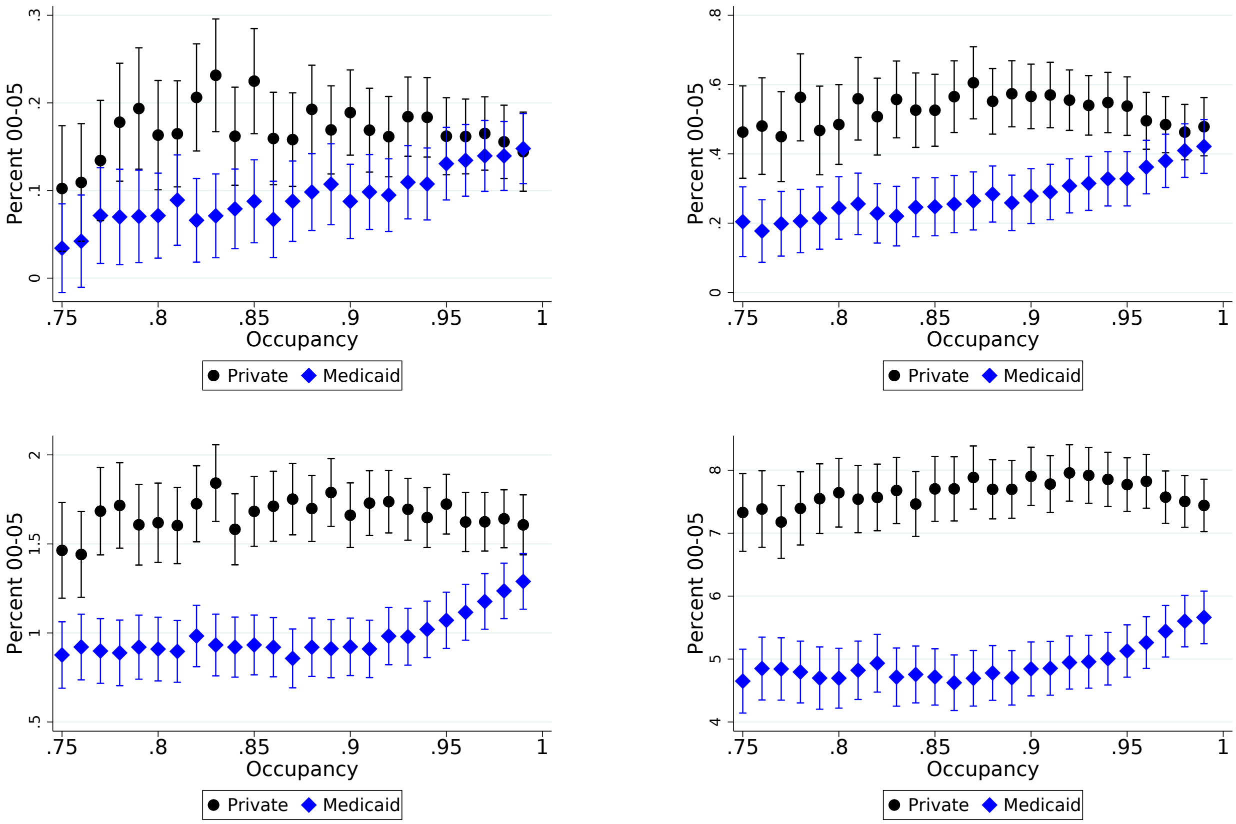
As seen in the bottom rows of Table E.1, the structural parameter estimates remain quite robust across the first three specifications. This is also true for provider elasticities, which range between 0.9 and 1.1. The patient elasticities remain at 0.2 and are consistently lower than the provider elasticities. This indicates that the 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

Table E.1: Structural Parameter Estimates—Robustness

| | Baseline | (1) | (2) | (3) |
|---|---|---|---|---|
| Exclude Bottom x% of Home Discharge Potential | 10 | 25 | 50 | 10 |
| Non-Home Discharges Varying in Occupancy | No | No | No | Yes |
| *A. Estimated Outside of Model* | | | | |
| Refill Probability | | | See Figure E.12. | |
| Occupancy Transition Matrix | | | Estimated from weekly sample. | |
| Pr[Payer Type Transition to Medicaid] | 1.1% | | | |
| Pr[Private Payer at Admission] | 78.0% | | | |
| Discharge Rate, private | 3.2% | 3.30% | 3.70% | by occupancy |
| Discharge Rate, Medicaid | 1.5% | 1.50% | 1.50% | 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. 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 Quartiles of Discharge Potential

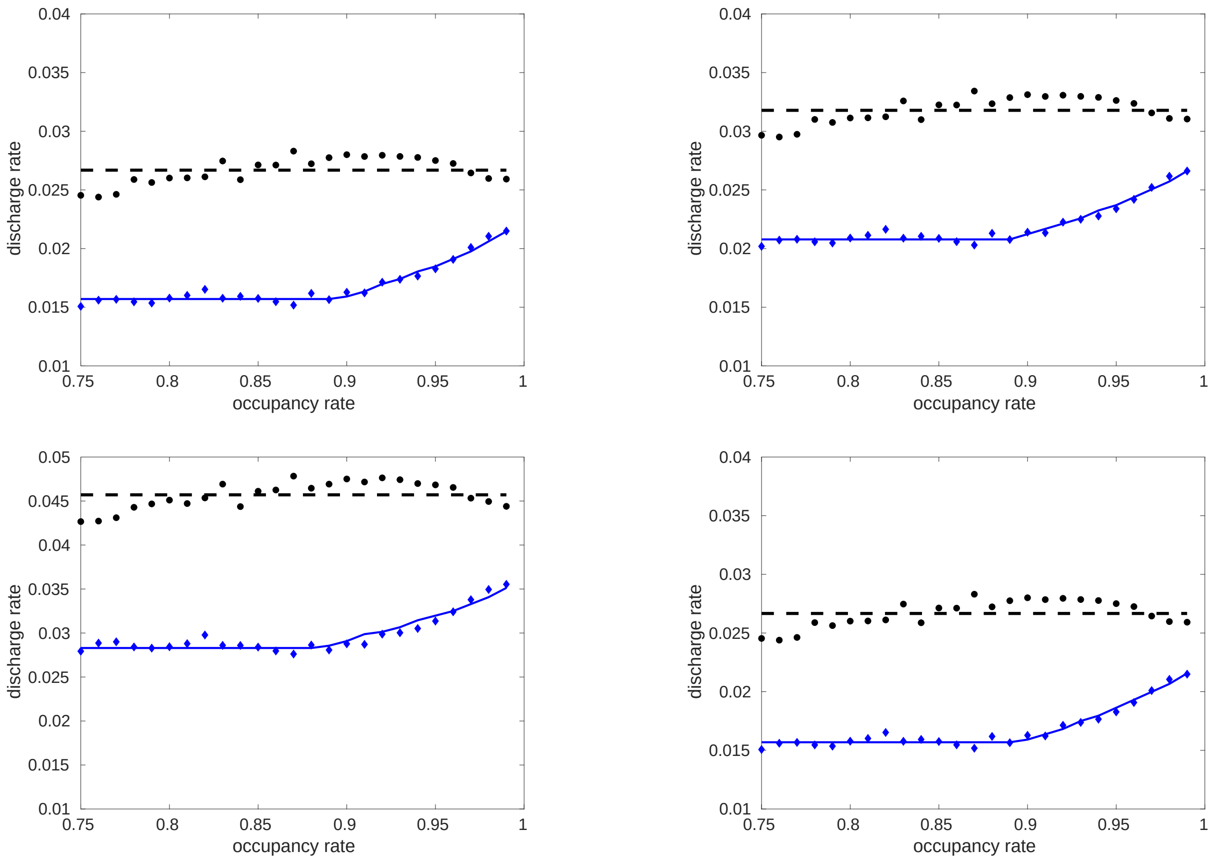



**Source:** Long-Term Care Minimum Data Set, Office of Statewide Health Planning and Development (2020). The upper left figure is solely based on the bottom quartile of discharge potential, the upper right on the second quartile, the lower left on the third, and the lower right on the fourth quartile of discharge probability. 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.

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.

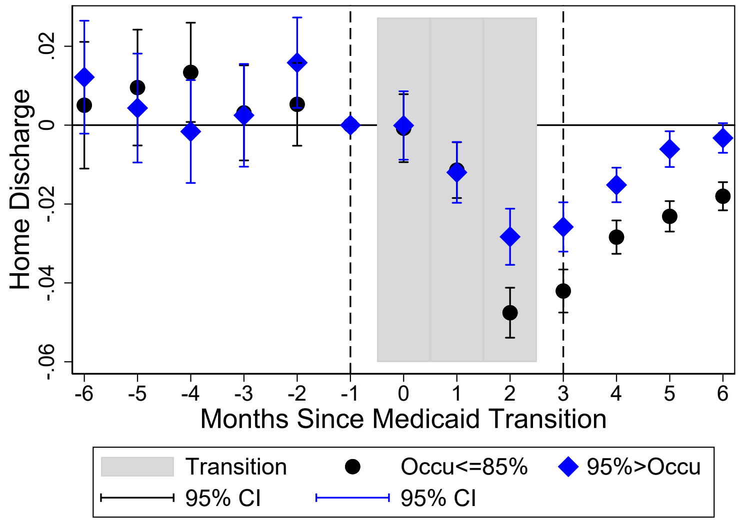
Figure E.4: Simulated Discharge Rates: Robustness




**Source:** Long-Term Care Minimum Data Set, Office of Statewide Health Planning and Development (2020). The upper left figure presents the baseline home discharge patterns and excludes the bottom 10% of patients with lowest discharge potential, the top right graph excludes patients in bottom quartile of home discharge potential, and the lower left excludes patients from the first on and second quartile of home discharge potential. Finally, the lower right graph 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.

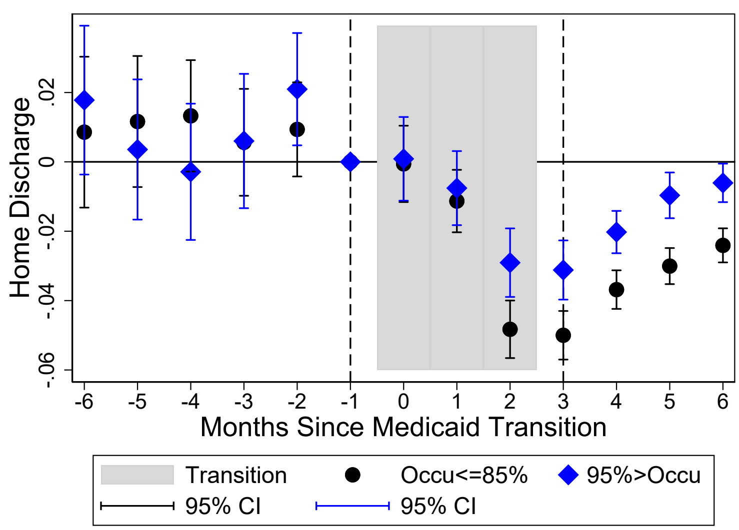
## E.2 Additional Robustness Checks for Event Study Approach

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



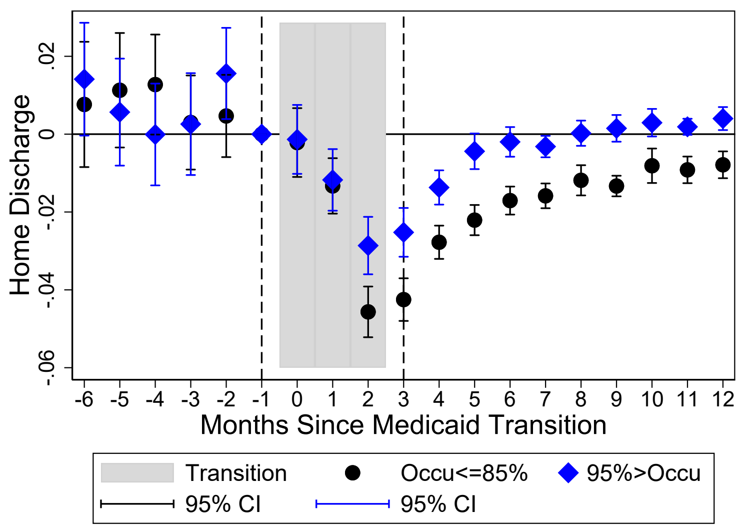

**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section 4.5. The figure plots $\sum_{\iota=-6}^{-2} \mu_t$ and $\sum_{\tau=0}^{6} \mu_t$ of equation (3). This robustness check uses a rescaled time-to-Medicaid transition 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



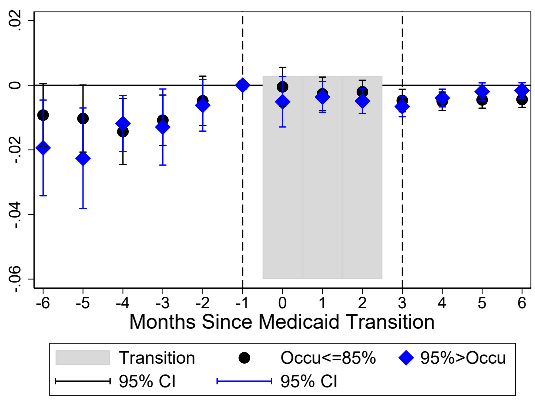

**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section 4.5. The figure plots $\sum_{\iota=-6}^{-2} \mu_t$ and $\sum_{\tau=0}^{6} \mu_t$ of equation (3). This robustness check omits ongoing stays. The vertical bars indicate 95% confidence intervals.

Figure E.7: Robustness of Figure 3: Medium-Term Effects

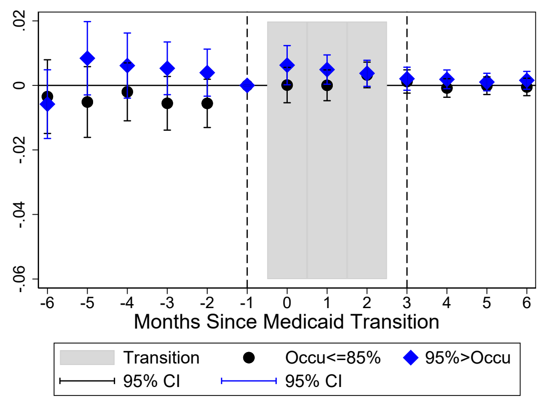



**Source:** Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for California at the monthly level from 2000 to 2005, see Section 4.5. The figure plots $\sum_{\iota=-6}^{-2} \mu_t$ and $\sum_{\tau=0}^{12} \mu_t$ of equation (3). The vertical bars indicate 95% confidence intervals.

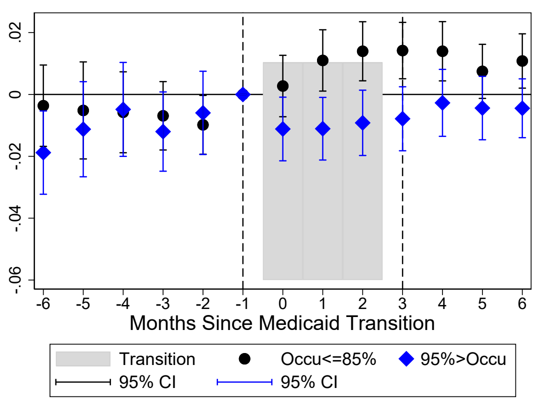
Figure E.8: Robustness of Figure 3: Health as Potential Confounder and Outcome



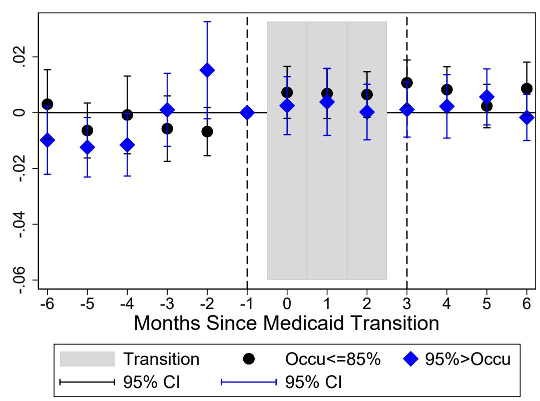

(a) CMI




(b) Depression




(c) Stage-3 Pressure Ulcers




(d) 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 4.5. 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.

## E.3 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):

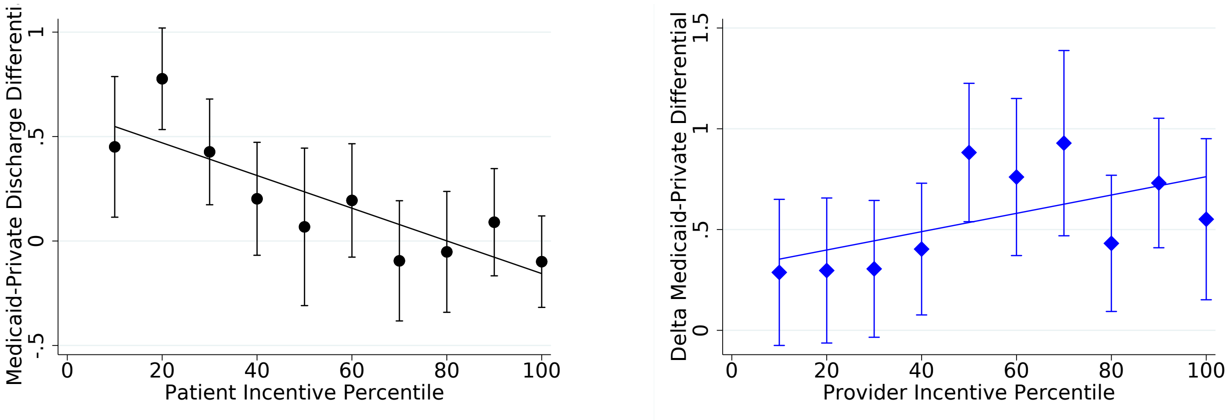
$$\begin{aligned} Y_{ijst} &= \mathbf{1}\{oc_{jt-1} < 85\%\}Mcaid_{is} \times \sum_{\tau=1}^{10} \delta_{\tau}^{l}\mathbf{1}\{r_{jt}^{P} \in PI^{\tau}\} \\ &+ \mathbf{1}\{oc_{jt-1} > 95\%\}Mcaid_{is} \times \sum_{\tau=1}^{10} \delta_{\tau}^{h}\mathbf{1}\{r_{jt}^{P} \in PI^{\tau}\} + \delta Mcaid_{is}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

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.9a 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.9b 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.9b 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.9: Discharge Differentials by Private Payer Mark-Ups and Occupancy Rates




(a) Patient Incentives

(b) Provider Incentives

**Notes:** Figure E.9a plots $\delta_\tau^l$ 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.9b replaces $\mathbf{1}\{r_{jt}^P \in PI^\tau\}$ 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 $\delta_\tau^h - \delta_\tau^l$ 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.

## E.4 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.

### E.4.1 Descriptive Evidence

Figure E.10a 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.10b, 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.10b 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 $Pr$[Day of month at Discharge|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.10c aggregates the discharge probabilities to the week-of-the-month, which we use in subsequent structural analysis detailed below.[33] 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%.

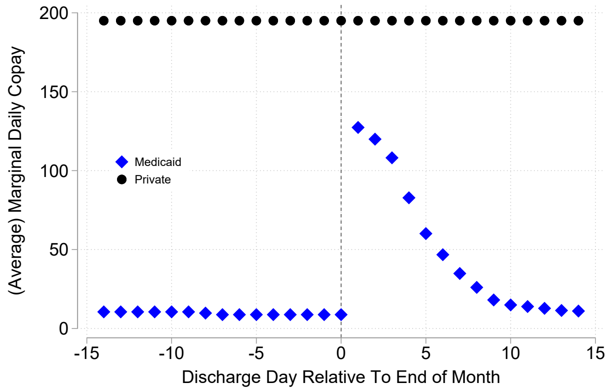
### E.4.2 Implied Patient Elasticity

To translate the bunching evidence in Figure E.10 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,

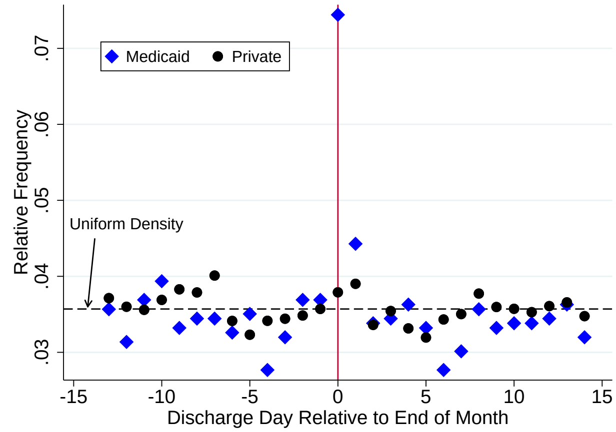
[33]To capture the symmetric bunching around the end of the month, we define our focal bunching week 0 to include the days -3 to +3. Week 1 captures days 4 to 10, week -1 captures days -10 to -4 and week 2 the rest normalized to seven days.

Figure E.10: Daily Cost-Sharing and Community Discharges—Bunching Analysis

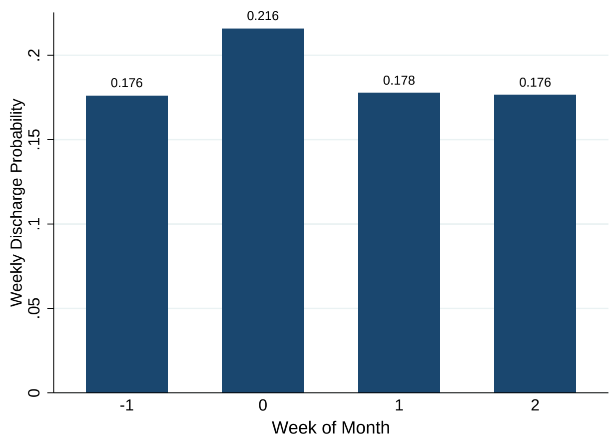
(a) Simulated Cost-Sharing by Day-of-Month




(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.10a presents average daily cost-sharing amounts for private payers and Medicaid beneficiaries by the day-of-the-month. Figure E.10b 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.10a and E.10b the last day of the month is normalized to zero. Figure E.10c aggregates the discharge frequencies for Medicaid patients in Figure E.10b 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.

we do not model 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

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

**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.10c 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.10a and construct the cumulative cost-sharing over the relevant 7-day window, which we refer to as $Price(\tau)$.[34] 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.[35] We present these estimates under $Price(\tau)$ in rows

[34] As mentioned, we use a four-day lag in charges, whereby Figure E.10a'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.

[35] 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.

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 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 perfectly fit the rates (3.1% and 3.47%). We then simulate the length of stay under different price schedules and find an elasticity of only 0.03. The static model in the second column assumes that cost-sharing is concentrated in week 0. We again fit discharge rates 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 0.02. 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.

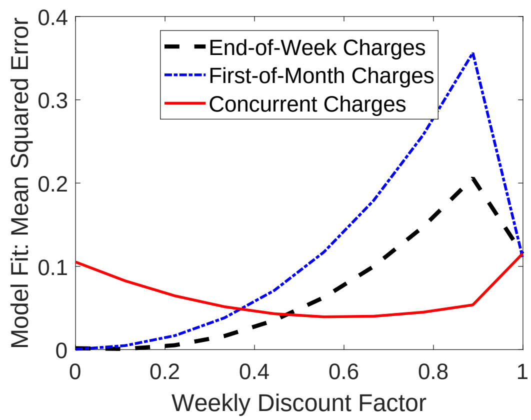
Turning to the dynamic models, columns (5) to (7) revisit the static specifications but set $\beta = 0.95^{1/52}$. We find slightly larger elasticities of up to 0.11. This is expected as the long-term horizon mutes the short term incentives provided by the week-to-week variation (Einav, Finkelstein, 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 0.0328 to only 0.33 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.11. 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 |
| $\hat{Pr}[D\vert\tau=-1]$ | 0.0310 | 0.0310 | 0.0310 | 0.0310 | 0.0328 | 0.0328 | 0.0328 |
| $\hat{Pr}[D\vert\tau=0]$ | 0.0347 | 0.0347 | 0.0347 | 0.0347 | 0.0329 | 0.0329 | 0.0330 |
| $\hat{Pr}[D\vert\tau=1]$ | 0.0312 | 0.0316 | 0.0310 | 0.0345 | 0.0327 | 0.0326 | 0.0328 |
| $\hat{Pr}[D\vert\tau=2]$ | 0.0310 | 0.0311 | 0.0310 | 0.0314 | 0.0328 | 0.0327 | 0.0327 |
| MSE: $\sum_\tau (Pr[D\vert\tau]-\hat{Pr}[D\vert\tau])^2 \times 10k$ | | 0.0017 | 0.0003 | 0.1052 | 0.1146 | 0.1109 | 0.1148 |
| Patient Elasticity | | 0.0268 | 0.0152 | 0.0493 | 0.0652 | 0.0419 | 0.1058 |

**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.10. 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.10c 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.11: 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.10. 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.5 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:

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

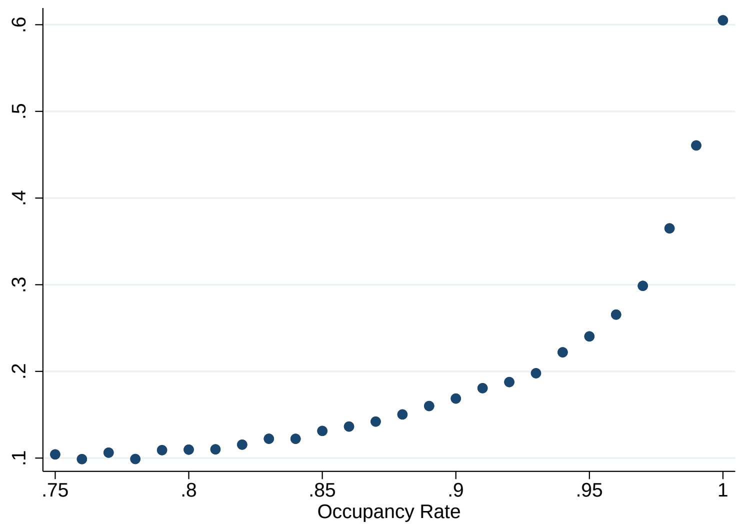
Hence, the probability that the bed is refilled is simply:

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

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

Figure E.12 plots the weekly refill probability by SNF occupancy rates.

Figure E.12: 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.12 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.

## F.1 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.

## F.2 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

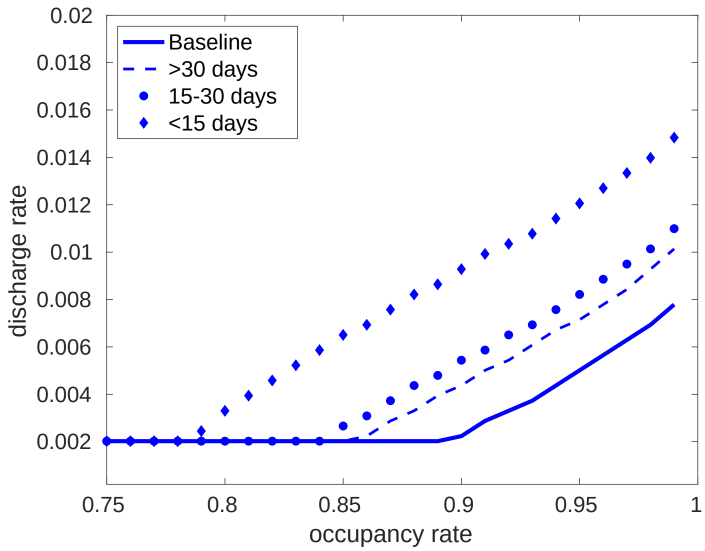
| | Experiment (Exhibit 1 (Jones, 1986)) | | | Current Prices ($\times$ 214/36) | Two Week Avg |
|---|---|---|---|---|---|
| Discharged: | Vacant Bed Cost | Staff Effort Cost | Total Cost | Total Cost | Total Cost |
| Within 5 days | 352.6 | 288.4 | 641 | 3810.4 | 3114.0 |
| Within 15 days | 176.3 | 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 7 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.