Patient Versus Provider Incentives in Long-Term Care*

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Abstract

How do patient and provider incentives affect the mode and cost of long-term care? In this paper, we develop a unified empirical and theoretical framework to separate the effects of patient and provider incentives on the timing of nursing home to community discharges. To estimate the model, we compile a unique database of half a million nursing home stays using administrative and survey data. Our analysis yields three main insights. First, Medicaid-covered residents reduce their efforts to transfer to the community due to limited cost-sharing. Second, nursing homes increase their efforts to discharge Medicaid beneficiaries when capacity binds to admit more profitable out-of-pocket payers. Third, providers react more elastically to financial incentives than patients. We find that targeting provider incentives through alternative payment models, such as episode-based reimbursement, is more effective than increasing patient cost-sharing in reducing the length of nursing home stays and in generating long-term care savings.

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

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1 Introduction

Long-term care (LTC) expenditures are high and rising. In 2018, the United States spent $169 billion on nursing home care and another $102 billion on home health care. By 2050, long-term care expenditures are projected to double to 3% of GDP (Hartman et al., 2020; Congressional Budget Office, 2013). Given this increased demand for LTC services, it is critical that public policies align patient and provider incentives with an efficient utilization of LTC. Because Medicaid covers more than 50% of LTC expenditures, developing and expanding cost-effective home and community alternatives to expensive nursing home care is of high policy priority for many state Medicaid programs (Kaiser Family Foundation, 2015). In particular, transitioning institutionalized patients to homes, apartments, or group homes is a topic of high policy relevance as demonstrated by extensive ongoing state experimentation (Libersky et al., 2015).[1]

Despite the significance for public policy, evidence on the link between financial incentives and LTC utilization remains limited and mixed. In this paper, we develop a unified empirical and theoretical framework to separate the effects of patient and provider incentives on the mode and cost of LTC. This setting is of particular interest because nursing home care is largely paid for using public funds but provided by private facilities. Medicaid policies can target patient and provider incentives through cost-sharing and alternative provider reimbursement models. To optimally design such policies and accurately assess them, separating the role 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. In our sample, more than 40% of nursing home stays end with a community discharge, illustrating that community-based care is a feasible alternative for many institutionalized residents. 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.

[1] This includes the Money Follows The Person (MFP) Demonstration, which was authorized by Congress as part of the Deficit Reduction Act of 2005 and then extended by the Patient Protection and Affordable Care Act of 2010. Under this demonstration, Congress authorized $4 billion in federal funds to support a twofold effort by state Medicaid programs to transition nursing home patients to the community and to change policies so that Medicaid funds for long-term care services and supports can "follow the person" to the setting of her choice.

We exploit two sources of plausibly exogenous variation in patient and provider incentives in a unified framework. On the patient side, we exploit the sharp decline in out-of-pocket costs when patients transition from being a private payer and paying the full private rate out-of-pocket to Medicaid during a stay. On the provider side, the Medicaid transition also implies a concurrent drop in flow revenues from the higher private rate to the lower regulated Medicaid reimbursement rate. This reduces the profitability of the patient stay as nursing homes have to offer the same quality of care, regardless of payer source (Grabowski, Gruber, and Angelelli, 2008). To separate patient from provider incentives, we combine the timing of Medicaid transitions with variation in nursing home occupancy rates. When nursing homes operate substantially below their capacity, they make a profit from keeping Medicaid patients longer, provided that the Medicaid rate exceeds the marginal cost of care, which we validate empirically. However, at high occupancy rates, when the capacity constraint is binding, nursing homes can benefit from discharging Medicaid beneficiaries to admit more profitable new residents who pay the full private rate.

We investigate these discharge incentives using administrative micro data from the Long-Term Care Minimum Data Set, combined with detailed Medicaid and Medicare claims data as well as survey data. Our database provides high-quality information on admissions, discharges, and health profiles for the universe of nursing home residents in California, New Jersey, Ohio, and Pennsylvania from 2000 to 2005. To identify our target population of interest, we employ a machine learning algorithm to identify nursing home residents who can be discharged and integrated into community-based long-term care settings. As our empirical strategy exploits within-resident variation in the transition to Medicaid during a nursing home stay, 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. In order to qualify for Medicaid, elderly patients have to first spend down their assets. We observe such transitions for about 10% of residents in our sample. Because private LTC insurance coverage is rare, these residents effectively transition from paying the full private rate (set by the nursing home) to Medicaid coverage with very little or no cost-sharing.

We start by estimating the effect of patient and provider incentives on community discharge decisions using two regression approaches. Our first "fixed effects" approach compares differences in discharge rates between payer types and occupancy rates conditional on SNF-year fixed effects—

which net out unobserved factors at the nursing home level—and week-of-stay fixed effects—which flexibly control for duration dependence. Our second approach exploits within-resident variation in the timing of Medicaid transitions (during a SNF stay) at different occupancy levels in an event study approach. Reassuringly, both approaches yield qualitatively and quantitatively highly similar results. At low occupancy rates, when providers' financial incentives are muted, we find that the weekly home discharge rate is 0.9 percentage points (30%) lower for Medicaid patients as compared to private payers, implying that patient incentives affect the length of stay. At high occupancy rates, provider incentives counteract patient incentives and we find a decline of only 0.4 percentage points (12%), implying that provider incentives also affect the length of stay.

To translate the effect of payer type transitions (by occupancy) on discharge rates into patient and provider elasticities with respect to financial incentives, we then develop and estimate a structural model of nursing home discharges. The purpose of the model is to quantify the relative importance of patient and provider incentives in a joint framework and to simulate policy counterfactuals that alter patient cost-sharing and consider 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 (and described above). 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 obtain a patient elasticity of 0.18, which is robust to alternative sources of patient cost-sharing variation. It is also consistent with existing evidence from other care settings, which center around 0.2 (Manning et al., 1987; Finkelstein et al., 2012; Shigeoka, 2014). In contrast, we find a provider elasticity of 1.3, suggesting that providers respond considerably more elastically to financial incentives. To lend further confidence in the implied provider behavior, we compare our model predictions to the evidence from a randomized experiment involving 36 nursing homes between 1980 and 1993 (Jones, 1986). The experimental design provided financial provider incentives to encourage nursing homes discharges to lower levels of care. Simulating the experiment within our model, we find a significant increase in the community discharge rate which accounts for 72% of the realized increase in the actual experiment (Norton, 1992).

Building on the estimated model, we study the role of patient and provider incentives in several simulated policy counterfactuals. Policies targeting patient incentives through increased cost-sharing, accompanied by a compensating lump-sum (voucher) transfer to patients, increase spending and provide mixed evidence on the length of stay. In contrast, policies targeting provider incentives are effective in reducing the length of stay and produce overall savings without harming provider profits. For example, and motivated by the Bundled Payments for Care Improvement (BPCI) initiative under the authorization of the Centers for Medicare & Medicaid Services (CMS), we find that disbursing 8% of current Medicaid per-diem reimbursements to an episode-based (up-front) reimbursement is as effective as increasing patient cost-sharing to 100% (through a voucher) in shortening the length of Medicaid stays, but yields substantially larger total cost savings.

Our analysis contributes to several literatures. First, we contribute to the large literature on the relevance of financial incentives for health care utilization. While most work focuses on patient incentives, see Aron-Dine, Einav, and Finkelstein (2013) for an overview, the role of provider incentives is largely unexplored. Previous work studies providers' responses to the introduction of the Inpatient Prospective Payment System in 1983 (Cutler, 1995; Cutler and Zeckhauser, 2000), while recent work investigates responses of physicians and dialysis clinics to financial incentives (Clemens and Gottlieb, 2014; Ho and Pakes, 2014; Grieco and McDevitt, 2017; Einav et al., 2020). More closely related to our analysis are Eliason et al. (2018) and Einav, Finkelstein, and Mahoney (2018) who show that a discrete change in Medicare reimbursement to a lump-sum payment induces providers to discharge patients from long-term (post-acute) care hospitals. Our main contribution to this strand of literature is that we investigate patient and provider incentives in one unified framework. While the implications for both market sides have been noted for a long time (Ellis and McGuire, 1993), the existing literature has largely studied their roles in isolation, see McGuire (2011) for an overview.[2] We exploit an alternative source of provider incentives stemming from variation in oc-

[2]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.

cupancy rates, which separates patient from provider incentives and provides new evidence on the link between health care utilization and provider capacity.[3] We find that excess capacity of nursing homes leads to extended Medicaid stays with substantial cost implications, providing an argument for Certificate of Need laws, which restrict entry and capacity investments. At the same time, we find that episode-based or bundled payment models, which have become one of the leading alternative payment models under Medicare (Finkelstein et al., 2018), are effective in shortening Medicaid stays by aligning provider discharge incentives more closely with the cost of care.

Second, we document the quantitative importance of financial patient and provider incentives in LTC, which is an important but understudied sector in economics. Existing work examines how demand and supply affect the allocation of patients and inputs between nursing homes.[4] Our paper is closely connected to work on financial incentives and the mode of LTC (e.g. nursing home vs. community based care). Existing evidence on patient incentives remains inconclusive. An earlier 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, we focus on a specific and policy relevant margin of substitution: community discharges and the length of nursing home stays.

While the evidence on patient incentives in the LTC context remains mixed, the evidence on provider evidence remains scant.[5] As mentioned, our findings are consistent with a randomized nursing home discharge experiment in 36 San Diego nursing homes between 1980 and 1983 (Jones, 1986).

[3]In a similar approach, Freedman (2016) exploits occupancy variation in neonatal intensive care units.

[4]See for example Ching, Hayashi, and Wang (2015), Lin (2015), Hackmann (2019), and Gandhi (2020). Notably, Ching, Hayashi, and Wang (2015) document an average nursing home occupancy of 89% using data from Wisconsin in 1999 and find that 20% of Medicaid patients were rationed out of their preferred nursing home. Related to this, Gandhi (2020) finds that nursing homes' selective admission practices harm Medicaid-eligible patients with lengthy anticipated stays. Finally Grabowski (2001) and Hackmann (2019) provide an overview of work on the link between Medicaid reimbursements and finds that 20% of the quality of nursing home care.

[5]Previous studies have investigated Medicaid bed-hold policies and *hospital discharges*, see Intrator et al. (2007). In two descriptive studies, Arling et al. (2011) and Holup et al. (2016) find that facilities with higher average occupancy rates are more likely to discharge residents to the community, but do not differentiate by payer type.

The experimental discharge incentives compensated providers for vacant bed costs and discharge effort, which we model explicitly in our analysis. We contribute to the literature by quantifying the effects of patient and provider incentives on the length of nursing home stays in a unified empirical framework, which also allows us to simulate several counterfactual policies on alternative payment models. Our findings inform the debate on how Medicaid regulation or managed care organizations (MCOs), which increasingly contract with state Medicaid agencies to provide long term care services, can achieve substantial cost savings.[6]

2 Institutional Details

2.1 Medicaid Eligibility

Nursing home care is largely financed by Medicaid, covering about 65% of all nursing home days. About 25% of all days are funded privately and the remaining 10% are covered by Medicare, which only covers post-acute care of up to 100 days after a qualifying hospital stay (see also Appendix Table A.1). We exclude Medicare patients from the analysis, who primarily require intensive rehabilitative post-acute care as opposed to LTC. To isolate within-stay variation from private pay to Medicaid transitions, we also exclude patients, who were covered by Medicaid from the beginning of their stay.

Asset and Income Test: To qualify for Medicaid, an individual's assets must fall below state-specific thresholds ranging between $1,500 and $4,000 in our sample period, see Table A.1.[7] Medicaid eligibility also requires an income test, where thresholds vary by state and 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 also qualify for Medicaid. Specifically, Medically Needy programs allow nursing home residents who pass the asset test to deduct medical expenses, including SNF fees, from their incomes. They then qualify for Medicaid if their *adjusted monthly income* falls below the state-specific limits of, at the time,

[6] The number of states contracting with MCOs over LTC services has increased to 24 states in 2018 up from 8 at the end of our sample period (AZ, FL, MA, MI, MN, NY, TX, and WI) (Medicaid and CHIP Payment and Access Commission, 2018). State agencies often provide MCOs with incentives to increase nursing home to community discharges through capitation payments and pay-for-performance contracts (Libersky et al., 2015). While little is known about how MCOs contract with LTC providers and if they pass these incentives on, survey evidence suggests that they negotiate nursing home reimbursements and networks in California (Graham et al., 2018).

[7] Some assets do not count toward the asset test; for example one vehicle and life insurance policies do not count if the total face value of all policies for the owner is $1,500 or less (Centers for Medicare & Medicaid Services, 2015). States also vary in how they assess home ownership; in some states the homes of deceased former beneficiaries are used to repay Medicaid. Finally, in some states, these thresholds are identical those for Social Security Income (SSI).

between 51% FPL ($367) in New Jersey and 83% FPL ($600) in California, see Table A.1.[8,9]

In practice, the asset test is typically the binding financial constraint to establish Medicaid eligibility for nursing home residents. Using data from the Health and Retirement Study (HRS), we find that among seniors whose assets are below $4,000, only 1% have income levels that would make them ineligible for Medicaid under a Medically Needy program. In the National Long Term Care Survey (NLTCS), which surveys specifically nursing home residents, Medicaid beneficiaries report average monthly incomes of $623, see Appendix B for details. Moreover, Borella, De Nardi, and French (2018) find that, in the middle income tercile, over a fifth becomes eligible for Medicaid as they age. Hence, Medicaid coverage becomes widespread as seniors age and spend down their assets. While income flows are typically very stable among nursing home residents (who rely mostly on social security payments), asset spend-down is the primary factor in determining the timing of 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, but typically a medical specialist (nurse or social worker) evaluates patients and their limitations in activities of daily living (ADL); for example, whether assistance for bathing, dressing or eating is needed, see Table A.1 for details. In our sample, the average number of ADLs is close to 10.5.

2.2 Patient Cost Sharing and Provider Reimbursement

Patient Incentives: 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 $218 per day or slightly more than $6000 per month. According to the HRS, private payers had net financial assets of just $27,845 (in 2000 dollars), see Appendix Table B.1. Consequently, nursing home residents who earn below the Medicaid income thresholds typically spend down their assets

[8] Ohio did not have a Medically Needy program, but was a 209(b) state whose statues allow individuals to spend down to the comparable cash assistance level which was $423 at the time, see Appendix Table A.1 for further details.

[9] Similar asset and income rules apply to the eligibility for home- and community-based service (HCBS) waivers, which cover formal care among for seniors living in the community, see Table A.1. These programs operated under tight enrollment caps in our sample period and waitlists have been a notorious problem (Kasper and O'Malley, 2006). Furthermore, access to HCBS requires an independent application and eligibility can typically only be established if the senior lives in the community. Hence, access to HCBS services was very limited and is very unlikely to serve as a confounder as we focus on within-SNF transitions into Medicaid and variation in occupancy rates. Related to this, Barczyk and Kredler (2018) show that community based LTC in the US is primarily comprised of *informal* care, with *formal* home care playing only a minor role.

and qualify for Medicaid within half a year of being admitted to a nursing home. Once residents become eligible for Medicaid, their daily out-of-pocket price for SNF care drops sharply. Medicaid beneficiaries contribute their income, net of a net allowance of about $30 per month, which varies by state, towards the cost of nursing home care ("share of cost" Pennsylvania Department of Human Services (see, e.g., 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 $623, implying that monthly out-of-pocket prices drop by 90% from $6,000 to $623-$30=$593 as residents transition into Medicaid.

For simplicity, we abstract away from private long term care insurance coverage, which affects only a very small patient population, as well as patient cost-sharing under Medicaid in our main analysis and assume that out-of-pocket prices drop to zero as patients transition into Medicaid.[10] We return to this assumption in Section 6.3, where we show that our findings are robust to this simplification.

Provider Reimbursement: As patients transition into Medicaid, SNF reimbursement rates change as well. Medicaid pays nursing homes a regulated, risk-adjusted, daily reimbursement rate that is usually lower than the out-of-pocket (private) rate. For example, Medicaid rates in California are 18% lower and, in Pennsylvania, they are 14% lower than the private rate, see Table A.1. At the same time, federal and state legislation, such as OBRA 1987, prohibits nursing homes from offering different quality of care levels by payer type. Grabowski, Gruber, and Angelelli (2008) find that nursing homes comply with this regulation indicating that nursing homes generate lower profits per Medicaid resident than per private payer conditional on LTC needs. Despite their structurally lower rates, Medicaid beneficiaries are generally profitable for nursing homes because reimbursement rates exceed the marginal cost of care (Hackmann, 2019), which we verify empirically in our setting.

[10]Only 2% of all nursing home days in Pennsylvania (or 4% nationwide), are covered by private long term care insurance, see Hackmann (2019). 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. The average maximum daily benefit of private insurance contracts equals $109 in 2000 (the modal benefit was $100), indicating substantial cost-sharing, see Hackmann (2019). This suggests that at most 4 out of the 25% of all private days in our data were partially insured. Accordingly, private payers pay on average at least $1 - 0.5 \times 4/25$=92% of the private rate out-of-pocket. This amounts to about $200 per day or about $6,000 per month.

2.3 Nursing Home Discharges

Discharge Destination: When discharged to the community, home health agencies or informal caregivers may support seniors for their ADL and/or provide long-term care. Residents can also be discharged to a hospital, to a different nursing home, to an assisted living facility or pass away.[11] In our data, about 40% of all nursing home stays end with a community discharge, whereas 20% end because residents pass away, 15% end with hospital discharges, and another 11% end with a discharge to a different nursing home, see Figure B.1a in Appendix B. In our main analysis, we focus on community discharges as the relevant policy margin of interest and treat "non-community" discharges as exogenous to financial incentives, which we support empirically.

Discharge Effort and Management: Nursing homes regularly evaluate their residents' health to determine whether they could be discharged to the community. For seniors who have spent some time in a nursing home, where they rely on around-the- clock care, transitioning into the community poses substantial challenges. Specifically, the management of complex medical conditions, support from family members or other informal caregivers, and housing that is adapted to the senior's medical conditions need to be arranged (see, for example, Meador et al., 2011). Nursing home residents, their relatives, as well as nursing homes therefore have to spend considerable time and resources, which we model as costly effort, before a discharge is possible.

The precise timing of discharges (and costly discharge efforts) is largely at the discretion of the nursing home discharge manager and the patient (or 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.2 for details on the clinical health measures). The lack of formal requirements suggests that economic patient and provider incentives may affect home discharge decisions at least to some extent.[12] Recent media

[11] Medicaid reimburses nursing homes through "bed-hold" policies for keeping a bed vacant while a resident is hospitalized; thus nursing homes may have financial incentives to temporarily discharge Medicaid residents to a hospital (Intrator et al., 2007). Our data allow us to distinguish between temporary and permanent discharges (our focus), where a return is not anticipated. As such, temporary hospital discharges do not affect our measurement of discharges or occupancy as nursing homes must keep the bed vacant.

[12] Although federal regulations such as the Nursing Home Reform Law of 1987 prohibit involuntary discharges from nursing homes, Pipal (2012) argues that residents may not be aware of their rights and that nursing homes may stipulate the possibility of evictions in their admission agreements.

coverage has cast a spotlight on nursing homes that discharge residents whose Medicare coverage runs out (Siegel Bernard and Pear, 2018). One main objective of this paper is to empirically assess whether economic provider and patient incentives affect discharge decisions to the community for relatively healthy marginal residents.

3 A Theoretical Model of Nursing Home Discharges

Building on the institutional discussion, this section formalizes how provider and patient incentives can affect the timing of nursing home discharges in a theoretical framework. Our model considers a single SNF and a single resident (the "focal" resident). The nursing home maximizes profits and the resident trades off the utility of different care alternatives against their out-of-pocket prices.

Effort and Discharges. To increase the probability of a discharge in any given week, the SNF and the resident have to exert costly effort, denoted by $e^{SNF} \geq 0$ and $e^{res} \geq 0$, respectively. We assume that the cost of effort for each agent, $c(e)$, is weakly positive and strictly increasing and convex in effort. As a result, the SNF and the resident 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, $e^{SNF,*}(\cdot)$ and $e^{res,*}(\cdot)$, as a weakly increasing function of the financial discharge incentives, denoted by FinInc^{SNF} and FinInc^{res}. Financial incentives then weakly increase the probability of a discharge:

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

where $\tau = P, M$ denotes the focal resident's payer type (private or Medicaid), and oc is the SNF's occupancy rate in beds other than the focal resident's. The occupancy rate is defined over other beds to avoid a mechanical reverse relationship between the discharge of the focal patient and occupancy.[13] We assume that the resident's financial discharge incentive and hence her effort are independent of oc.[14] $\epsilon \sim F_{\epsilon}$ captures other discharge factors.

[13] To simplify the estimation we also assume that the focal resident's discharge manager does not internalize her indirect impact on the occupancy in other beds. We return to this assumption in Section 7.

[14] We also abstract away from possible strategic free-riding of residents assuming asymmetric information over the weekly occupancy rate. We assume that residents and relatives cannot perfectly observe the weekly occupancy rate and hence do not condition their effort on occupancy. Mechanically, in the empirical analysis, we assume a constant

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 resident's discharge efforts. If $\alpha = 0$, only the resident's financial incentives matter, whereas if $\beta = 0$, only the SNF's financial incentives matter.

Provider Incentives and Discharges: Providers consider the following dynamic tradeoffs: If the focal bed is occupied, providers receive payer-type specific flow profits Π^τ with $\Pi^P > \Pi^M > 0$. If the patient is discharged, the bed can remain empty, in which case the nursing home forgoes the flow payoff. However, with probability $\Phi(oc)$, the bed is filled with a new patient who may be a private payer or a Medicaid beneficiary. Therefore, the nursing home's optimal discharge effort is determined by the tradeoff between the flow payoff and the option value of drawing a more profitable payer type in the future. Because private payers are more profitable than Medicaid beneficiaries, a nursing home will not exercise costly discharge efforts if a private payer occupies the focal bed. By contrast, if the focal bed is filled with a Medicaid beneficiary, 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 resident will seek the focal bed with probability one if all other beds are taken. If multiple beds are vacant, however, the probability of filling the focal bed, conditional on patient arrival, is < 1.

Patient Incentives and Discharges: Patients consider the following static trade-off: Staying another week in the nursing home yields the utility of nursing home care minus the out-of-pocket price. If the resident leaves the nursing home, she obtains the utility of home-based care minus home care costs, including other costs of living. Both Medicaid beneficiaries and private payers pay for home care in full, but only private payers pay for nursing home 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.

[Insert Figure 1 about here]

return to resident effort, which shuts down resident incentives to free-ride. Importantly, we note that free-riding, if present, would work against finding an effect of provider incentives on discharge rates.

Graphical Discussion: We summarize the model's predictions in Figure 1, which plots the per period discharge probability by payer type on the vertical axis against the nursing home's occupancy rate on the horizontal axis. The occupancy rate only affects the nursing home's financial incentive. As the nursing home does 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 black line. This is not true for Medicaid beneficiaries. At low occupancy rates, nursing homes are not willing to exercise costly effort as the flow payoff exceeds the option value of drawing a private payer (net of the cost of effort) in the future. 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 $oc < oc^*$.

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—the nursing home's optimal effort is zero for either payer type at low occupancy rates.

At $oc = oc^*$, the nursing home's optimal discharge effort for Medicaid beneficiaries starts to change. 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 continues to increase in the occupancy rate, the nursing home raises its optimal effort with increasing oc—it equates the marginal benefit and the marginal cost of effort. Cost of effort increases in effort due to the convex nature of the 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 $oc \geq oc^*$.[15] Appendix Section C formally derives this relationship under simplifying assumptions.

4 Data

The dataset in this paper 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-

[15] 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.

certified nursing homes, about 98% of all nursing homes. Section B.2 (Appendix) provides further details.

4.1 Sample Construction and Selection

In a first step, we merge the MDS with the Medicaid and Medicare SNF claims data at the weekly SNF-stay level. These administrative claims data allow us to record payment sources at the weekly level and to identify transitions from being private payers to becoming Medicaid beneficiaries. Next, we merge the weekly SNF-stay data with facility information from the On-Line Survey, Certification, and Reporting system (OSCAR), which we access through LTCfocus.[16] This includes the number of licensed beds, which allows us to calculate weekly occupancy rates. In our first empirical approach, we use these uniquely compiled data for four states (California, New Jersey, Ohio, and Pennsylvania) and the years 2000 to 2005.

Moreover, we focus on residents above 65 and who are private payers at the beginning of their stay. Hence, we exclude stays which were covered by Medicaid from the first week. This also implies that we exclude all Medicare-covered stays, that is, post-acute stays following "qualified" hospitalizations (see Table A.1). We also exclude nursing homes that are not Medicaid certified. In other words, because we leverage the transition to Medicaid as source of variation, we focus on cases where elderly patients enter a Medicaid-certified nursing home as private payers.

4.2 Machine Learning and Community Discharge Potential

For some residents, it is extremely unlikely that they will ever be discharged again. Typically these are residents with severe cognitive and physical disabilities and many LTC needs. These long stay patients are not the relevant target group for our research question given our primary 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

[16] Shaping Long Term Care in America Project at Brown University funded in part by the National Institute on Aging (1P01AG027296).

174 demographic and health characteristics, which are pre-determined at the resident's first SNF health assessment. 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. Finally, we exclude the 10% of SNF stays with the smallest predicted probability of ever being discharged to the community. These excluded patients struggle with significantly more ADLs and are more likely to have a cognitive impairments, see Appendix Table D.1 for a comparison.

4.3 Summary Statistics

Our final sample consists of 552 thousand SNF stays and 13.8 million resident-week observations. Table 1 shows summary statistics for our main sample at the resident-week level, 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 (84.2 vs. 83.9 years), gender (70% vs. 74% female), race (89% vs. 85% white) or marital status (29% vs. 30% widowed), while the lower panel shows descriptives on a set of health measures. These include the Case Mix Index (1.04 vs. 0.98), the number of ADL (10.5 vs. 10.5), and the share of residents with impaired cognition (44% vs. 47%) or with behavioral problems (8% vs. 9%). Together, this suggests that private payers and Medicaid beneficiaries in our sample are similar in terms of several socio-demographic and health measures.

[Insert Table 1 about here]

4.4 Occupancy Rates

To construct the occupancy rate at the weekly level, we combine the universe of admission and discharge dates from the MDS with capacity information (number of licensed beds) contained in OSCAR.[17] We note that bed capacity varies only very little from year-to-year within a facility due to fixed investment costs, but also due to state regulations requiring Certificate of Needs (CON) in order to increase the number of beds. To avoid a mechanical reverse relationship between the own

[17] In our second identification approach, we aggregate the data at the monthly level and focus on California (see Section 4.5). In this approach we use an alternative measure for the number of licensed beds from the Long-Term Care Facility Integrated Disclosure and Medi-Cal Cost Reports as a robustness check (Long-Term Care: Facts on Care in the U.S., 2020; Office of Statewide Health Planning and Development, 2020), see Appendix B.2 and Figure B.3 for more details.

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 once we exclude the first week of the stay.[18]

[**Insert Figure 2 about here**]

Figure 2a summarizes the variation in occupancy rates over time (weeks) and between SNFs. The average occupancy rate is 91%, which translates into 11 empty beds in an average sized facility with 120 licensed beds, also see Figure B.2 in Appendix B. Figure 2b displays within-SNF variation in the occupancy rate, which is considerable. Within nursing homes, conditional on SNF-year fixed effects, the standard deviation in occupancy is 3.4 percentage points (about 63% of the standard deviation in SNF fixed effects).

The volatility in new admissions is an important driver of the intertemporal variation in occupancy rates. Figure 2c shows the frequency of new admissions divided by total number of beds. This translates admissions into changes in occupancy rates. As seen, the relative number of arrivals varies substantially from week to week leading to (unexpected) variation in occupancy at the SNF level. Because a few new admissions can result in large occupancy rate changes for very small nursing homes and introduce noise to our empirical models, in our main specification, 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).

To assess the persistence of occupancy shocks, Figure 2d displays the impulse response function of occupancy rates to a sudden 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 the occupancy rate 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.

[18]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.

4.5 Monthly CA Sample for Event Study

Our second empirical approach leverages the panel dimension of our data and focuses on within-resident transitions to Medicaid in event study and difference-in-differences models. For this approach, we have to aggregate the data at the monthly level and focus on California. The reason is simply that we only observe Medicaid transitions *outside of nursing homes* at the monthly level for California.[19] Specifically, we use the so called administrative "buyin" indicator which allows us to identify dual beneficiaries at the monthly level (Rupp and Sears, 2000; Research Data Assistance Center, 2020). While this indicator does not identify all dual beneficiaries in some states, it is measured without error in California. Data validity checks to map the official dual beneficiary rate with the rate identified by this indicator confirms this, see Appendix Section B.2 for more details.[20]

Otherwise, we maintain exactly the same sample selection criteria as for our resident-week sample, described above in Section 4.1. That is, we focus on SNF residents who were private payers at the beginning of their SNF stay. Some transition to Medicaid during the stay (or after being discharged) and other remain private payers over the entire period from 2000 to 2005. Moreover, as above, we also employ our ML approach to identify and omit the 10% of residents who are the least likely to ever be discharged. When aggregating the data at the monthly level and focusing on California, we obtain a sample with 239,353 patient-month observations.

5 Empirical Strategy

5.1 Fixed Effects Approach

Our first empirical approach employs rich sets of fixed effects and covariates.[21] Specifically, we estimate the following reduced-form regression model for equation (1) in the theoretical model,

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

[20]Specifically, the buyin indicator indicates at the monthly level whether the state of residence of a Medicare beneficiary pays her monthly Part B premium (because she is eligible for Medicaid), an action called "buying in." However, one disadvantage of this indicator is that it only records the Medicaid status from the month when beneficiaries officially enroll, whereas the claims data provide a retrospectively cleaned version of the status. Because states have up to 90 days to review and process a Medicaid application for long-term care, and it also takes time to compile the extensive paperwork required for the application (American Counil on Aging, 2019), the official enrollment status lags the initiation of the enrollment process by about three months, in some cases more. To correct this enrollment lag, we lag the indicator by three months as well.

[21]To ease the computational burden of the large number of observations and fixed effects, we estimate a series of linear probability models.

which expresses financial incentives as flexible functions of occupancy and payer type:

$$Y_{ijst} = \sum_{k=65}^{100} \gamma^k \times oc_{jt-1}^k + \sum_{k=65}^{100} \delta^k \times oc_{jt-1}^k \times Mcaid_{is} + \eta_s + \eta_{jy} + \eta_c + X_i'\beta + \epsilon_{ijst}. \tag{2}$$

Here, Y_{ijst} denotes an indicator variable that equals one if nursing home j discharges resident i to the community in week-of-stay s. oc_{jt}^k is an indicator variable that turns on if the (rounded) 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 γ^k and $\gamma^k + \delta^k$. These can be interpreted as the effect of occupancy on weekly home discharge probabilities, where δ^k captures relevant differences between payer types. The estimates condition on SNF-year fixed effects η_{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 η_s. Moreover, to account for seasonal variation in discharges, we control for calendar month fixed effects, η_c. Robust standard errors, ϵ_{ijst}, control for within-resident correlation, and we also correct for administratively assessed differences in health at admission as well as socio-demographics through X_i.[22]

To ease the comparison between the fixed effects approach and the event study approach below, we also estimate a "binned" version of equation (2). The binned version replaces the occupancy rate indicators oc^k with three occupancy *group* indicators than turn on for low, medium, and high occupancy rates. Motivated by the empirical evidence produced by equation (2), we define these occupancy groups as (i) below 85%, (ii) between 85 and 95%, and (iii) at or above 95%.

This first empirical approach uses rich sets of fixed effects along with administrative data, but does not exploit the timing of within-resident 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 allow us to assess the relevance of possible time-invariant unobservables at the resident level. By exploiting within-resident variation, employing resident fixed effects, and plotting lead and lag event study coefficients, we are able to revisit the plausibility of important identifying assumptions, possible anticipation effects, and sample compo-

[22]These health measures include the individual case mix index, as well as the predicted length of stay. We construct the latter by regressing length of stay on a rich set of disability and health measures and obtaining the predicted outcome for each resident.

sition effects. The fixed effects approach, by contrast, has the advantage to rely on the full sample and be closely linked to Figure 1 and our theory. Moreover, homogenizing our sample and focusing on elderly SNF residents who *all* were private payers at the beginning of their stay, further helps to minimize concerns that resident-level unobservables act as systematic confounding factors. The remaining conditional differences in discharge rates between payer types and across occupancies could then be interpreted as primarily driven by financial incentives.

5.2 Event Study Approach

Our second empirical approach leverages the longitudinal within-resident 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 only. We estimate the following econometric model:

$$Y_{ijst\tau} = \sum_{\mu=-6}^{-2} \mu_\tau + \sum_{\tau=0}^{6} \mu_\tau + \eta_s + \eta_c + \eta_i + \eta_{jt} + X_i'\beta + \epsilon_{ijst} \tag{3}$$

where $Y_{ijst\tau}$ denotes our community discharge indicator as above, and η_s, η_c, η_i and η_{jt} are month-of-stay, calendar month, patient, and SNF-year fixed effects. X_i denotes patient health and socio-demographics at admission.

The key coefficients of interest are indicators for months relative to the Medicaid transition, μ_τ, where μ_{-1} is the reference category. This event study approach allows for a graphical inspection of potential pre-trends and dynamics of the Medicaid effects over time (Schmidheiny and Siegloch, 2019). Specifically, the 'lead' coefficients, $\tau < 0$, are informative about potential pre-trends across patients. The 'lag' coefficients, $\tau \geq 0$, capture the dynamic effect of the payer type change on home discharges. To separate patient from provider incentives, we estimate equation (3) separately for low (below 85%) and high occupancy rates (above 95%).

The transition to Medicaid triggered by the mechanical asset spend down represents the treatment. The main identification assumption is the (conditional) common time trends assumption which requires the absence of systematic pre-trends which would indicate that changes in the outcome are driven by correlated unobservables rather than the transition to Medicaid (Goodman-Bacon, 2018).

As we exploit within-resident variation over time, we will be able to control for sample composition effects through our resident fixed effects and also check for whether anticipation effects might play a role.

Analogous to the fixed effects approach, we also estimate a "binned" version that pools the 'leads' and 'lags' into a pre- and post-transition period. Specifically, we estimate

$$Y_{ijst} = \mu_{post} + \eta_s + \eta_c + \eta_i + \eta_{jt} + X_i'\beta + \epsilon_{ijst} \tag{4}$$

where μ_{post} is the indicator for the post-transition period, $\tau \geq 0$, in this difference-in-differences model. As with the event study model, we estimate equation (4) separately for low (below 85%) and high (above 95%) occupancy rates representing environments where either financial provider incentives are muted or not. Conceptually, and leaving the differences in the unit of time aside, μ_{post} corresponds to the δ coefficients from equation (2), conditional on the occupancy rate.

6 Empirical Results

6.1 Results from Fixed Effects Approach

We begin by presenting results from the fixed effects approach, outlined in equation (2). Figure 3 is the empirical analogue to Figure 1 and plots weekly community discharge probabilities by payer type on the vertical axis against nursing home occupancy on the horizontal axis. The depicted estimates correspond to the mean-adjusted coefficients for private payers, $\hat{\gamma}$, and for Medicaid beneficiaries, $\hat{\gamma}+\hat{\delta}$, along with their 90% confidence intervals. These estimates are conditional on SNF-year, month, and week-of-stay fixed effects and resident characteristics including health at admission; therefore they indicate the link between occupancy rates and payer type specific discharge rates.

[Insert Figure 3 about here]

Patient Incentives: Figure 3 shows that private payers have weekly community discharge rates of about three percent across the entire range of occupancies. In contrast, at low occupancy rates below 85%, Medicaid beneficiaries have discharge rates of about two percent. A smaller discharge rate for Medicaid beneficiaries is consistent with differences in resident cost-sharing, as discussed in Section 3. As SNFs do not have financial incentives to discharge residents of either payer type at low occupancies, the estimated difference suggests that patient incentives do affect the length of stay. We quantify this difference in Table 2, which presents the regression results from the binned version of equation (2), which bins occupancy rates into low, medium, and high. Each column in the upper panel stands for one regression model. Consistent with the graphical evidence, we find a difference of 0.95 percentage points between Medicaid and private payers, see column (4) in panel "Patient Incentives." As shown in columns (1) to (3), this difference is robust across alternative specifications. Specifically, the coefficient estimates barely change when we add SNF-year fixed effects (column (2)), month and year fixed effects (columns (3)) as well as socio-demographic controls (column (4)). Relative to the baseline discharge rate, the difference corresponds to a 26 to 30 percent lower home discharge rate for Medicaid beneficiaries, relative to private payers.

To put the difference in discharge rates into perspective, we complement home discharges with other discharges (hospital, death, etc.) and find that the 0.95 ppt reduction now translates into a 20 percent reduction in the overall discharge rate in our preferred specification (column 4). Considering the 100% patient out-of-pocket price difference between private payers and Medicaid beneficiaries, we obtain a price elasticity of demand of 0.2. 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 differential increase in discharge rates in the panel "Provider Incentives." Subtracting the discharge differentials between private payers and Medicaid beneficiaries at occupancy rates above 95% and below 85%, respectively, we find that the home discharge rates converge by 0.38 percentage points between these occupancy bins, see column (4).

Interpreted through the lens of the theoretical model, nursing homes start to exert positive discharge efforts at high occupancies when their benefit exceeds 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. However, 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 systematic increase in Medicaid discharge rates in Figure 3 suggest that provider incentives affect discharge decisions as well. Complementing this evidence, Appendix Section E.1 shows that discharges to a hospital, another nursing home or due to the resident's death do not vary with occupancy rates to the same extent.[23]

Note that the direct evidence presented here does not allow us to calculate supply side elasticities, which requires a supply side model. While the convergence in discharge rates is smaller than the level difference at low occupancy rates, we note that this does not imply that providers respond less elastically as the magnitude of the financial benefits may be substantially larger for patients. We will return to this point and a formal calculation in Section 7.3.

Robustness: We revisit the evidence from the fixed effects approach in numerous robustness exercises to corroborate our quantitative conclusions. For example, in the Appendix Section B.2, we document robustness to alternative occupancy measures based on alternative bed data, rebutting potential concerns over measurement issues in occupancy. Moreover, in the Appendix, we present qualitatively and quantitatively consistent evidence on the link between patient and provider incentives and community discharges when we exploit cross-sectional variation in private and Medicaid SNF reimbursement rates, see Figure E.3b.

6.2 Results from Event Study Approach

Turning to the event study approach, Figure 4 presents the estimated event coefficients, $\hat{\mu_\tau}$, with their 90% confidence intervals, based on equation (3). We show the estimates separately for low (below 85%) and high (above 95%) occupancy rates. As mentioned, this analysis is aggregated to the month-of-stay level and uses data from California only but otherwise keeps 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 vertical axis shows changes in the home discharge rates and the horizontal axis shows the event time in months leading up to and since the transition onto Medicaid.

[23]We attribute small changes along these other discharge margins to changes in the health composition of residents as a result of endogenous changes of relatively healthy patients in home discharges. We therefore conclude that financial patient and provider incentives operate primarily through the home discharge margin.

[Insert Figure 4 about here]

Patient Incentives: We start with a low occupancy rate environment where capacity constraints are not binding. Here provider incentives are muted but patient incentives are at play. Reassuringly, Figure 4 does not show much trending in the discharge rate during the months leading up to the transition, suggesting the absence of systematic time-variant links between discharges and transitioning to Medicaid such as anticipation effects. The point estimates are close to zero and all confidence bands overlap with the zero line on the y-axis. After patients transition to Medicaid, we note a significant reduction in the community discharge rate. The decline is most pronounced two months after the transition and then converges to a two percentage point lower monthly community discharge rate in the subsequent months.

To summarize the effect of the Medicaid transition, Table 3 presents difference-in-differences regression results, as outlined in equation (4). The structure of the table follows Table 2; each column in the upper panel represents on regression model where we add sets of control variables stepwise from column (1) to (4). Our preferred model in column (4) shows an overall decline in monthly discharge rates of 3.75 percentage points relative to the rate for private payers of 14.7%. It is noteworthy that the point estimates are again very robust to adding patient fixed effects (column (2), SNF-year, month and year fixed effects (column (3)) as well as socio-demographic controls (column (4)).

To relate the event study findings to the fixed effects analysis, we translate the weekly results from the fixed effects analysis to the monthly level in the middle panel of Table 3. To this end, we assume that each month has 4.5 weeks and that the weekly discharge shocks ϵ_{ijst} from equation (2) are i.i.d. between weeks.[24] The results are remarkably similar. Based on the fixed effects approach, we would predict a decline in the monthly community discharge rate of 3.2 to 3.7 percentage points. Accordingly, the event study coefficients imply a quantitatively comparable patient elasticity.

[Insert Table 3 about here]

[24] We aggregate the evidence from the week-of-stay level as follows:

$$Pr[D^{month}_{home}] = \sum_{t=1}^{4} Pr[D^{week}_{home}] \times \Big[1 - Pr[D^{week}_{any}]\Big]^{t-1} + \frac{Pr[D^{week}_{home}]}{2} \times \Big[1 - Pr[D^{week}_{any}]\Big]^{4} \quad (5)$$

, where $Pr[D^{month}_{home}]$ denotes the monthly community discharge rate and $Pr[D^{week}_{home}]$ and $Pr[D^{week}_{any}]$ denote the weekly community and overall discharge rates, respectively. We divide the last summand by 2 to account for the last half week of the month.

Provider Incentives: Next, we turn to how Medicaid transitions affect home discharges in a high occupancy environment when nursing homes operate close to capacity. As seen in Figure 4, importantly, we again find no evidence for a home discharge pre-trend in the months leading up to the Medicaid transition. Moreover, the coefficient estimates as almost identical to those above, where nursing homes operate below capacity. In the first two months after the Medicaid transition, community discharge rates decrease. However, and consistent with the fixed effects approach, we observe statistically significant differences in the trends for low vs. high occupancy environments. At high occupancy rates, when residents become Medicaid beneficiaries and their out-of-pocket costs substantially decrease along with provider reimbursement rates, the decline is significantly smaller and fades out entirely five months after the transition. Interpreted though the lenses of the theoretical model, this reinforces that provider incentives counteract the patient incentives.

The lower panel of Table 3 summarizes the identified provider incentives in the context of our difference-in-differences model, see equation (4). Again, we calculate the differential decline in community discharge rates at high occupancies relative to low occupancies. At high occupancies, provider incentives increase the community discharge rates by between 1.2 and 1.4 percentage points or between 8.4 and 9.5% relative to the mean. To relate these findings to the fixed approach, we repeat the week-to-month conversion discussed above. The estimates from the fixed effects approach are again very similar ranging between 1.3 and 1.5 percentage points, see Table 3.

Discussion: The fixed effects and the event study approach provide clear evidence that patient and provider incentives affect home discharge rates and thus the length of nursing home stays. While the event study approach leverages within-resident variation and the panel nature of the data, the fixed effects approach allows us to assess the impact across a wider patient population at the weekly level. As both approaches yield quantitatively very similar point estimates, we focus on the fixed effects approach in the reminder of this analysis.

6.3 Interlude—Financial Patient and Provider Incentives

Financial Patient Incentives: As a robustness exercise on patient incentives, we now explore an alternative source of variation in Medicaid cost-sharing.[25] Specifically, we return to the "share of

[25] This addresses some concerns regarding the role of private LTC insurance that we abstract away from in our main analysis, see Section 2.2.

cost", see Section 2, which Medicaid beneficiaries must pay during the first days of a month before Medicaid covers all costs for the rest of the month. For example, the average Medicaid beneficiary has a monthly income of $623 (Table B.2), which requires the beneficiary to pay the first $623/$188=3.3 days of the month out-of-pocket, considering a daily Medicaid rate of $188 in Pennsylvania, where we are most familiar with the specifics of the share of cost regulations. Once Medicaid patients have contributed their share of cost, the daily co-pay drops to zero for the rest of month. As this within-month variation in cost-sharing only affects patients with a high discharge potential, we first identify patients with high monthly discharge potential (more than 25%), again using our ML approach in Section 4.2.

[**Insert Figure 5a about here**]

Figure 5a plots a histogram of the day of the month on which patients were discharged to the community.[26] As seen, for Medicaid beneficiaries, we find discharge rate bunching on the last two and the first two days of the month. In contrast, we find no bunching for private payers, who pay the private rate on any day of the month. Reassuringly, we also find no evidence for Medicaid bunching for the other discharge destinations. To quantify a patient's sensitivity to prices, we invert the relationship and present discharge probabilities based on the current day of the month. Figure 5b aggregates these discharge probabilities to the week of the month.[27] Now we observe modest bunching in the focal week 0. Compared to the neighboring weeks, discharge probabilities increase by 1.8 percentage points or 17%.

Implied Patient Elasticity: To map the bunching evidence into a patient elasticity, we build on our theoretical framework and specify a static model in which patients compare the flow payoffs between nursing home care and community-based care and assume that co-pays are concentrated in week 0. Comparing relative changes in copay to relative changes in discharge rates (or simulated length of stay), we find again a patient elasticity of 0.2, see Appendix Section E.4.

We revisit this calculation in a dynamic model assuming a rational dynamically-optimizing agent,

[26] In Figure 5a we plot Pr[Day of month at Discharge|Discharged to Community]. For this exercise we focus on the years 2000 to 2005, but only rely on Pennsylvania. At the time, this state definitely applied the share of costs as described above, leading to the sharp variation in spot prices over the course of a month.

[27] In Figure 5b we plot Pr[Discharged to Community|Week of the Month]. 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.

see Appendix Section E.4. Given the compelling evidence on behavioral biases especially among older people in the health care context (Dalton, Gowrisankaran, and Town, 2020), we view the results from the perfectly forward-looking dynamically-optimizing agent as an upper bound.[28] Even under these strong assumptions, we still find an inelastic patient demand (elasticity of 0.8).[29]

Financial Provider Incentives: As a robustness exercise on provider incentives, we now study the bed refill probability, $\Phi(oc)$, which 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, see Section E.5 in the Appendix for details.

[**Insert Figure 6 about here**]

Figure 6 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).

7 Structural Model of Discharges

In this section, we develop and estimate a structural model of community discharges which builds on the theoretical model discussed in Section 3. We 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: We start from the theoretical discharge equation (1) and assume that, consistent with the linear probability model outlined in Section 6.1, exogenous discharge factors ϵ

[28]Specifically, the evidence in Dalton, Gowrisankaran, and Town (2020) suggests that Medicare Part D enrollees do not take future coverage gap prices into account in their choices of prescription drugs. Translated to our setting, that might suggest that the static model provides a more realistic characterization of patient behavior.

[29]The elasticity is now larger because the underlying financial incentive in the focal week is muted over a longer time horizon (Einav, Finkelstein, and Schrimpf, 2017).

are uniformly distributed. This allows us to express the discharge probability per period as:

$$\Pr[D = 1|e^{SNF}, e^{res}] = D^{other,\tau} + \alpha \times e^{SNF}[\text{FinInc}^{SNF}(\tau, oc)] + \beta \times e^{res}[\text{FinInc}^{res}(\tau)]. \quad (6)$$

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 in the exogenous discharge rate $D^{other,\tau}$. We extend our model of community discharges to overall discharges to capture the profit motives of nursing homes more accurately. While consumer payoffs depend on the discharge destination, we show below that the marginal benefit of resident effort remains unchanged in this extended framework. We define a period to be one week.

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

$$W(\tau, D, \eta) = \begin{cases} \eta^{home} & \text{if } D = 1 \\ u - \kappa p^{\tau} + \eta^{SNF} & \text{if } D = 0 \end{cases} \quad (7)$$

where u is the resident's gross utility from a week of nursing home care where we normalize utility from home health care to zero. To simplify notation, we set the utility from discharge equal to the utility from home discharge, η^{home}. Utility differences between discharge reasons will not affect optimal effort choices as discussed below. κ is a price coefficient, which maps the per period out-of-pocket price, p^{τ}, into utility. η^{SNF} and η^{home} are type I extreme value taste shocks that are observed by the resident before choosing the effort level, but unobserved by the SNF. Residents choose the optimal discharge effort given by:

$$e^{res,*} = \arg\max_{e^{res} \geq 0} \Big\{ \Pr[D = 1|\cdot, e^{res}] \times W(\tau, D = 1, \eta) + (1 - \Pr[D = 1|\cdot, e^{res}]) \times W(\tau, D = 0, \eta) - \kappa \times c(e^{res}) \Big\}, \quad (8)$$

where $c(e)$ denotes the cost of effort, measured in dollars. To translate the cost of effort back into utility, we multiply the cost by the price coefficient κ. The discharge probability is conditional on $D^{other,\tau}$ and the resident's beliefs 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 ϵ, see equation (1), shutting down potential free-riding incentives, Appendix Section C.1 for more details.

Provider's Effort Choice: The nursing home observes the payer type of the focal resident and forms expectations over her optimal effort level. By contrast, resident's taste shocks, η^{SNF} and η^{home}, and discharge effort, e^{res} is unobservable for the nursing home. We assume that SNFs maximize over effort under the following belief:

$$\Pr[D = 1|e^{SNF}, \tau] = D^{other,\tau} + \alpha \times e^{SNF} + \beta \times E_{\eta}[e^{res,*}|\tau] \ . \tag{9}$$

To derive the optimal provider effort, $e^{SNF,*}$, we impose the following timing of events. During the period (week), providers choose their discharge effort level 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^{τ} is the private rate or the Medicaid reimbursement rate, respectively, mc is the weekly marginal cost of providing LTC, and $c(e^{SNF})$ is the cost of effort measured in dollars. Discharges, arrivals, and payer type transitions are random events, realized at the *end* of the period. Arrivals and payer type transitions are exogenous and characterized by the weekly refill probability Φ, see equation (E.2) and the per-period Medicaid transition probability ψ. Discharges, in contrast, depend on endogenous discharge efforts as outlined in equation (9); together with arrivals, they determine the occupancy rate in other beds oc.

To simplify the analysis, we assume that discharge managers do not coordinate their discharge efforts between residents. In other words, discharge managers 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. To reduce the state space, we model occupancy rate transitions as a Markov process, which is characterized by a week-to-week transition matrix, Θ. This transition matrix denotes the conditional probability mass function over next week's occupancy rate in other beds, oc', conditional on today's occupancy rate on other beds, oc: $\Theta(oc, oc') = \Pr[oc'|oc]$.[30]

Combining the timing assumptions with the assumptions on arrivals, discharges, and payer type transitions, we can express the SNF's optimal discharge efforts through the following Bellman equation:

$$V(\tau, oc) = \max_{e^{SNF} \geq 0} \left\{ \pi(\tau) - c(e^{SNF}) + \delta E\Big[V(\tau', oc')\Big|\tau, oc, e^{SNF}\Big] \right\} \quad , \tag{10}$$

where δ is a discount factor and

$$\begin{aligned}
E\Big[V\Big|0, oc, e^{SNF}\Big] &= \sum_{oc'} \Theta(oc, oc') \times \Big[(1 - \Phi(oc')) \times V(0, oc') \\
&\quad + \Phi(oc') \times \Big(\rho V(P, oc') + (1-\rho) V(M, oc')\Big)\Big] \qquad (11) \\
E\Big[V\Big|M, oc, e^{SNF}\Big] &= \sum_{oc'} \Theta(oc, oc') \times \Big[\Big(1 - \Pr[D = 1|e^{SNF}, M]\Big) \times V(M, oc') \\
&\quad + \Pr[D = 1|e^{SNF}, M] \times \Big((1 - \Phi(oc')) \times V(0, oc') \\
&\quad + \Phi(oc') \times \Big(\rho V(P, oc') + (1-\rho) V(M, oc')\Big)\Big)\Big] \qquad (12) \\
E\Big[V\Big|P, oc, e^{SNF}\Big] &= \sum_{oc'} \Theta(oc, oc') \times \Big[\Big(1 - \Pr[D = 1|e^{SNF}, P]\Big) \times \Big((1-\psi) V(P, oc') \\
&\quad + \psi V(M, oc')\Big) + \Pr[D = 1|e^{SNF}, P] \times \Big((1 - \Phi(oc')) \times V(0, oc') \\
&\quad + \Phi(oc') \times \Big(\rho V(P, oc') + (1-\rho) V(M, oc')\Big)\Big)\Big]. \qquad (13)
\end{aligned}$$

In words, the value function combines the flow profit net of the cost of effort and a continuation value, see equation (10). The continuation value of an empty bed, as indicated in equation (11), 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 ρ delivering a payoff vector of $V(P, oc')$. Furthermore, expectations

[30] Conceptually, oc refers to the occupancy in other beds. In practice, we approximate oc by the overall occupancy rate in the structural estimation. We also assume that discharge managers form beliefs over next week's occupancy rate based on the current occupancy rate only. That simplification implies that the discharge manager does not condition on the payer type distribution nor the payer type in the focal bed.

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 (12), 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 (13), adds to this a payer type transition to Medicaid, which happens with probability ψ.

Discussion: Before turning to the estimation strategy, we briefly discuss some of our modeling decisions. For tractability reasons, our analysis of patient incentives abstracts away from differences in gross utilities, u, between payer types, see equation (7). The implicit assumption behind this simplification is that the timing variation in Medicaid transitions affects p^τ but it is independent of u. However, idiosyncratic variation in u is captured by η.[31] Related to this point, our model also abstracts away from non-pecuniary motives in provider discharge efforts. The analogues assumption behind this simplification is that the timing variation in Medicaid transitions affects $\pi(\tau)$ but it is independent of non-pecuniary motives.[32,33] We also assume that the week-to-week variation in occupancy, captured by Θ, only affects discharge efforts through Φ and not through marginal costs. Most inputs into nursing home production are fixed over a significantly longer time window, e.g. annual nurse contracts, suggesting that the marginal cost structure is largely invariant on a week-to-week basis. Finally, the present analysis does not consider potential cream-skimming of private payers at admission (Ching, Hayashi, and Wang, 2015). We believe that this simplification is less concerning for the estimation, as our empirical discharge moments focus on private payers at admission only and because our event study approach controls for changes in the patient composition. In regards to the counterfactual analysis, we note that Einav et al. (2020) find no evidence for cream-skimming (or quality shirking) in hospitals following the introduction of bundled payments. We also note that in our simulations, provider-targeted policies slightly raise the profitability of Medicaid stays and result in slightly lower occupancy, muting the incentive cream-skim against Medicaid patients. If incorporated, this might increase occupancy and thereby reinforce the striking increase in provider

[31] A potential extension of the model can accommodate persistent heterogeneity in gross utility through the patient's (observed) health state, which would then also enter the state space of the SNF's value function.

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

[33] Technically, we exploit variation in discharge patterns by payer types and occupancy from the fixed effects approach to recover the patient parameters (u, β, κ), which does not isolate the timing variation in Medicaid transitions. However, the event study approach, which does isolate the timing variation, yields qualitatively and quantitatively very similar discharge profiles as discussed in Section 6.2.

efforts (at now higher occupancies).[34]

7.2 Estimation Strategy

Parameters Estimated Outside the Model: Panel A of Table 4 lists parameters estimated outside of the structural model. For example, we estimate the weekly refill probabilities Φ according to equation (E.2), see Figure 6. The week-to-week occupancy transition matrix Θ is an endogenous equilibrium object. For the purpose of estimation, we use the empirical transition matrix. An excerpt is provided in Table B.3 (Appendix B). In the counterfactual exercises, we endogenize the transition matrix to allow for changes in discharge efforts affecting occupancy transitions, which in turn feed back into optimal effort choices.

[Insert Table 4 about here]

We also estimate the probability of a payer type transition from private to Medicaid from observed week-to-week changes, which happens in 1.1% of all cases. To calculate $D^{other,\tau}$, we sum over the average discharge rates to non-community destinations, see Figure E.1 (Appendix 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.

Calibrated Parameters: Next, we set the weekly discount factor to $\delta = 0.95^{1/52}$, as indicated in Panel B of Table 4. 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, see Appendix Section C.1 for more details. Finally, we normalize the utility from nursing home care u as we can only identify utility up to scale. This is because utility affects discharges through effort in our specification, which is again scaled by the factor β.

Parameters Estimated Within the Model: The key structural parameters that we estimate using the model include the daily marginal cost of nursing home care per resident mc, the price coefficient κ, and the effort parameters α and β. To estimate the parameters, we leverage the variation in the estimated discharge profiles in Figure 3, which is the empirical (observable) analogue

[34] Nevertheless, we note that a feasible extension can model the share of private payers among admission as a function of occupancy, $\rho(oc)$, or even as a function of financial incentives provided by $V(0, oc) - V(M, oc)$.

of equation (6) after replacing discharge efforts by flexible functions of payer type and occupancy.

Specifically, the occupancy threshold oc^*, that is, the occupancy rate where the Medicaid discharge rate starts to increase, see Figure 1, is informative about mc. At oc^*, the marginal benefit of effort to discharge a Medicaid beneficiary equals the marginal cost of effort when evaluated at $e^{SNF} = 0 = mc_e(0)$. Hence, the marginal benefit must be zero as well, which trades off the Medicaid flow profit $\pi(M)$ against the option value of drawing a new resident tomorrow. 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, β and κ. Finally, to quantify the provider coefficient α, we build on the increase in discharge rates for Medicaid beneficiaries at higher occupancy rates, $oc \geq oc^*$.

By minimizing the sum of squared differences between discharge rates predicted by the model and observed home discharge rates, we estimate the parameters $\theta = (\alpha, \beta, \kappa, mc)$:

$$\hat{\theta} = \arg\min_{\theta} \sum_{\tau=P,M} \sum_{oc=65}^{99} \left(D_{\tau,oc}(\theta) - \hat{D}_{\tau,oc} \right)^2, \tag{14}$$

where $\hat{D}_{\tau,oc}$ denotes the estimated home discharge rates by payer type and occupancy shown in Figure 3. The estimation algorithm proceeds as follows: First, for an initial parameter guess θ_0, we solve the provider value function given by equations (10) to (13) 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 equation (9). We then update the parameter vector and iterate until the least squares criterion in equation (14) 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, Σ, 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, α, β and κ, 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.

7.3 Results

Model Fit: Figure 7 combines the estimated discharge rates from Figure 3 with the model predictions for private payers and Medicaid beneficiaries. As seen, the model provides a very good fit to the observed community discharge rates and estimates the model parameters as listed in Panel C of Table 4. Panel C shows marginal cost estimates mc per resident and day of \$77.[35] Moreover, both discharge effort parameters are positive, $\hat{\alpha} > 0$ and $\hat{\beta} > 0$, implying that provider and resident discharge efforts increase the discharge probability.

[Insert Figure 7 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 patients, we quantify the effect of a 1% increase in private rates on the discharge probability for private payers, and then simulate the change in the expected length of stay, holding the supply side fixed. We find a patient elasticity of 0.18, which is very close to the seminal estimate from the RAND Health Insurance experiment, which centers around 0.2 (Manning et al., 1987) as well as more recent estimates, for example Shigeoka (2014) for elderly people in Japan. Turning to providers, we quantify the effect of a 1% increase in the Medicaid reimbursement rate on provider discharge efforts and the length of stay of Medicaid beneficiaries, holding the demand side fixed. We find a provider elasticity of 1.3, which exceeds the patient elasticity by a factor of seven.

We illustrate the sensitivity of providers to financial incentives in an alternative thought experiment. Using the estimated model, we consider the counterfactual provider effort if a focal bed occupied by a Medicaid patient could be refilled immediately with a private payer. This would result in a 20% increase in daily revenues from the Medicaid rate of \$159 to the private rate of \$194. To quantify the counterfactual provider effort, we adjust the refill probability to $\Phi(oc) = 100\%$, $\forall oc$,

[35] This estimate is smaller than marginal cost estimates for the entire SNF population. For example, Hackmann (2019) estimates an average marginal cost of \$159 using data from Pennsylvania over the entire resident population. However, we focus on a healthier marginal population of nursing home residents who could be discharged to the community; hence, this smaller marginal cost estimate is plausible.

assume that all new admissions are private payers, $\rho = 100\%$, and abstract away from Medicaid transitions during a stay, $\psi = 0\%$. We find a Medicaid discharge rate of 4.1% for all occupancy rates, which now exceeds the private pay discharge rate by 1 percentage point (ppt). As discussed earlier, the decrease in patient effort alone (as they transition to Medicaid) decreases the discharge rate by 0.95 ppt. Combined with the overall net increase of 1 ppt, this suggests that the increase in provider effort alone increases the discharge rate by 1ppt+0.95ppt=1.95ppt, more than offsetting the decline in patient effort. Considered in isolation, a 20% change in provider revenues triggers twice the effect on discharge rates than a 100% change in patient out-of-pocket prices.

Validation With a Randomized Experiment: To validate our provider elasticity, we revisit a unique randomized experiment designed to encourage nursing homes to appropriately discharging residents by providing them with financial incentives. The experiment was conducted in 36 Medicaid-certified nursing homes in the San Diego Metropolitan Statistical Area between November 1980 and April 1983 (Jones, 1986). The discharge incentive payments were paid upon a successful discharge to a lower level of care setting; they were established to reflect vacant bed costs and staff (discharge) effort. These are also the two key cost elements that nursing homes trade off in our conceptual framework, making our model well-suited to revisit the evidence from the experiment. Translated into current dollars, the payments ranged from $2,800 (17.6 times the daily Medicaid rate) if the patient was discharged within 5 days to $730 (4.6 times the daily Medicaid rate) if the patient was discharged after 30 days. Consistent with a high provider elasticity, Norton (1992) finds a substantial increase in the biweekly community discharge rate from 0.38 to 0.7%.

We revisit the experiment through the lens of our model and increase the Medicaid patient utility parameter from $u = 5$ to $u = 7.4$ and the exogenous discharge rate from 1.3% to 2.72% to match the longer length of stay (and the smaller community discharge rate) of patients in the control group, see Appendix F for details. We then simulate the effects of the financial incentives provided by the experiment. We find that the community discharge rate increases to 0.61%, which accounts for 72% of the increase reported in the experiment. Hence, our structural model produces outcomes very close to the experimental evidence and suggests that our analysis might even understate providers' responsiveness to financial 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 that would accrue if the nursing home patient lived in the community instead. As Medicaid will only cover a fraction of these community expenditures, our cost savings represent overall LTC savings and are a lower bound on Medicaid savings.

Using data from the Medical Expenditure Panel Survey and the Consumer Expenditure Survey on individuals aged 80 and older, we find mean annual expenditures of \$1,018 for formal home health care and of \$12,903 for all other medical care and cost of living expenditures including housing, food, etc. Adding the opportunity costs of informal care provided by family members to these expenses (Skira, 2015; Barczyk and Kredler, 2018), we obtain $\$1{,}018 + \$12{,}903 + \$6{,}552 = \$20{,}473$ per year or \$56 per person and day.[36] This is considerably lower than the daily Medicaid rate of \$159 used in our model. Hence, Medicaid spending could be lowered by $(\$159 - \$56) \times 7$ days $= \$721$ if a resident was discharged one week earlier.

8.2 Policy Counterfactuals

Building on the estimated model, we evaluate four 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. To this end, we divide the nursing home into two "wings." The additional wing allows us to incorporate admissions and discharges among residents that were excluded from the estimation sample but also affect overall occupancy. We treat these admissions and discharges as exogenous. For the study population of interest (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

[36] According to the HRS, and average individual receives 39 hours of informal care per month. We then translate median weekly earnings from the Bureau of Labor Statistics for men and women for the years 2000 to 2005 to an average hourly wage of \$14, assuming a 40-hour work week and using the fact that 71% of informal caregivers of HRS respondents are women. This implies an annual monetary value of informal care of $\$14 \times 39 \times 12 = \$6{,}552$.

effect of policy changes on occupancy rates. 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 8 about here]

Voucher Program: Our first policy is a voucher program 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, 23.2 weeks, times the weekly private rate of $1,358. This amounts to a lump-sum of $31,519 per Medicaid stay. The program affects resident and provider incentives in opposite directions. On the one hand, Medicaid beneficiaries now have a larger incentive to shorten their stays. On the other hand, providers are now indifferent between private and Medicaid residents because they generate identical weekly profits. Therefore, nursing homes will reduce their discharge effort for Medicaid beneficiaries to zero.

Figure 8a 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 to 23.2 weeks, which also reduces the average occupancy rate to 88.1%. Medicaid saves 29.42 weeks of nursing home payments worth $32,744 but provides transfers (to beneficiaries) worth $31,533 under this policy. We also consider the costs for the additional 6.2 weeks spent in the community, worth 6.2 weeks $\times$ 7 days $\times$ \$56 $=$ \$2,430 per reduced Medicaid stay. Hence, the overall expenditures increase by \$31,533 $+$ \$2,430 $-$ \$32,744 $=$ \$1,219 per Medicaid stay, or about 3.7%.

[Insert Table 5 about here]

Top-Up Program: The second policy charges Medicaid patients the difference between the private rate and the Medicaid reimbursement rate as an out-of-pocket rate.[37] This is paid in addition to the Medicaid rate. Such a policy also equates the revenues among payer types and affects provider and patient incentives again in opposing directions, as discussed in the voucher counterfactual. Because of residents' increased discharge incentives, home discharge rates among Medicaid residents at low

[37]This counterfactual is motivated by the German LTC reform from 1995, which provides a generous voucher but requires beneficiaries to pay the difference between the voucher amount and nursing home rate out-of-pocket.

occupancies are slightly higher than under current policies (Figure 8b vs. 7). However, as both payer types are now equally profitable for nursing homes, Medicaid discharges do not increase at high occupancies. In sum, the incentive effects for providers outweigh the incentive effects for patients, leading to a small increase in the length of stay by 0.3 weeks (third column in Table 5). Spending per stay increase by 22.7% due to a longer stay but mostly because Medicaid (as a public insurance program) eventually has to reimburse beneficiaries for the cumulated top-up payment, worth $7,274 alone.

Discharge Bonus: Motivated by the randomized discharge experiment of Norton (1992), our third policy considers a bonus payment counterfactual which rewards nursing homes for successful community discharges, independent of the underlying patient or provider effort. We consider the payments for discharges after 30 days of $730 and simply add the term $(\Pr[D = 1|e^{SNF}, M] - D^{other,M}) \times \$730$ to equation (12), where the first factor subtracts exogenous discharges to other destinations and thereby isolates the home discharge probability.

Figure 8c shows an increase in provider efforts at high occupancies. Quantitatively, the increase in provider effort reduces the length of stay by 1.12 weeks, see the fourth column of Table 5, which reduces Medicaid spending by $1.12 \times 7 \times (\$159 - \$56) = \$808$ per stay. Considering that Medicaid would pay nursing homes the bonus payment of $730 for 62% of all stays (that end in a community discharge), suggests cost savings of $\$808 - 0.62 \times \$730 = \$355$ per stay (49% of the bonus amount) or 1.1% 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 ($2\% \times 29.42 \times 7 \times \$159$) whenever a new Medicaid beneficiary arrives or a private payer transitions into Medicaid.[38] 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 Hackmann (2019).

The simulated discharge rates in Figure 8d point to an increase in provider discharge efforts.

[38]We replace $V(M, oc')$ by $V(M, oc') + \Delta$ in equations (11) and (13), where Δ denotes the up-front payment.

The new kink point oc^* is now at around 88%. As seen in Table 5, we find that the length of stay decreases by 1.3 weeks and a corresponding decline in average occupancy to 90.3%. 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 change implies per stay savings of about $(0.98 \times \$159 - \$56) \times 7$ days $\times$ 1.3 weeks = \$919 or 2.8%.

Finally, the last column of Table 5 shows that 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. However, the implied cost savings are substantially larger. We find cost savings worth \$4,282 per stay or 13.0%.

8.3 Discussion

Our evidence suggests that targeting provider incentives via discharge bonus payments or by transitioning to an episode-based reimbursement model is more effective than increasing resident cost-sharing in shortening the length of Medicaid stays and in reducing LTC spending. We note, however, that this analysis cannot speak to the overall welfare implications of these policies as we do not quantify the effects on patient welfare. While targeting provider incentives would maintain financial risk protection for patients, a comprehensive assessment of patient welfare would also need to quantify the causal effects on patient health and well-being, which is left for future work. Nevertheless, several pieces of evidence mitigate concerns over the potentially detrimental health effects from early discharges caused by moving to alternative payment models.

First, we find that only 3.9% of Medicaid patients discharged to the community are readmitted to any nursing home within 30 days from the discharge date.[39] This suggests that the vast majority of patients discharged to the community are appropriately placed there, which is consistent with evidence from the literature (Mor et al., 2007) as well as the stated policy goals to promote community-based care over institutional care. Second, we find no evidence that providers are more likely to encourage inappropriate community discharges. Patients discharged at high occupancy rates, increasingly triggered by provider incentives, have readmission rate of 3.9%, which exceeds the rate for low occupancy discharges by only 0.04 percentage points (standard deviation of 0.2 per-

[39]Our 30-day nursing home readmission measure excludes Medicare-covered post-acute stays that are typically triggered by acute adverse heath shocks such as heart attacks, which also occur inside nursing homes.

centage points). Third, we note that pairing bonus payments inversely to the readmission rate and requiring an explicit discharge protocol with detailed instructions on how to prepare and follow up on a community discharge, as done in the nursing home experiment mentioned earlier (Jones, 1986), may prove effective in improving discharge outcomes.

9 Conclusion

We develop a unified empirical and theoretical framework to separate the effects of patient and provider incentives on the timing of nursing home discharges to the community. Using administrative claims data on over half a million U.S. nursing home stays, we find that providers respond significantly more elastically to financial incentives than patients. We estimate a patient elasticity of 0.18, which is consistent with the existing literature, and a provider elasticity of 1.3.

These findings suggest that targeting provider incentives through alternative payment models may prove effective in increasing the efficiency of LTC. Alternative payment models are increasingly used in hospital reimbursement (Dummit et al., 2018; Norton et al., 2018) but have received, perhaps surprisingly, rather little attention in nursing homes despite promising early experimental evidence (Norton, 1992). In counterfactual simulations, we find that introducing discharge bonus payments or partially transitioning from a per-diem to an episode-based provider reimbursement results in meaningful reductions in the length of nursing home stays as well as substantial cost savings without reducing provider profits or exposing patients to substantial financial risk.

Our findings are informative for future policies on how to contain LTC spending, which is a topic of highest policy relevance to state Medicaid programs, given its large and growing fiscal burden. States continue to experiment with a variety of Medicaid waiver programs to contain LTC spending, showing that little is known on how to best align patient and provider incentives with efficient LTC use. Currently, the 52 state-level Medicaid systems provide the only public insurance coverage for LTC, resulting in a patchwork of policy proposals and initiatives but lacking a systematic randomization and evaluation (Finkelstein, 2020). One pathway to harness these cost savings is through the growing number Medicaid managed care organizations, which may contract with LTC providers on behalf of state agencies and Medicaid beneficiaries (Graham et al., 2018).

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Figures and Tables

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

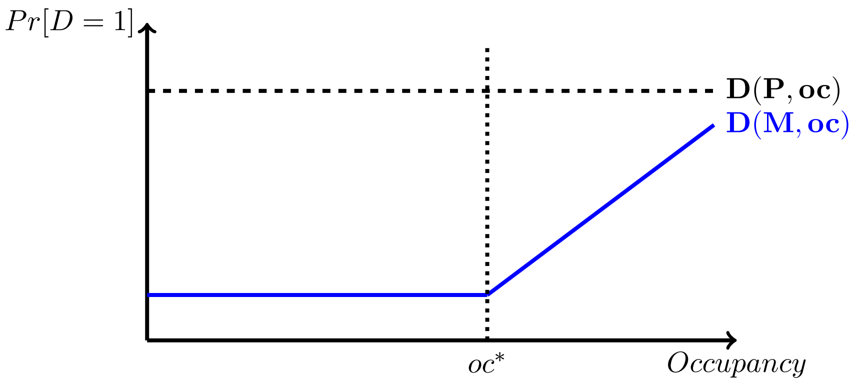
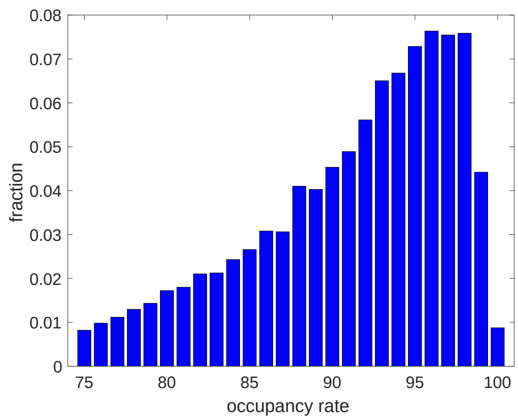
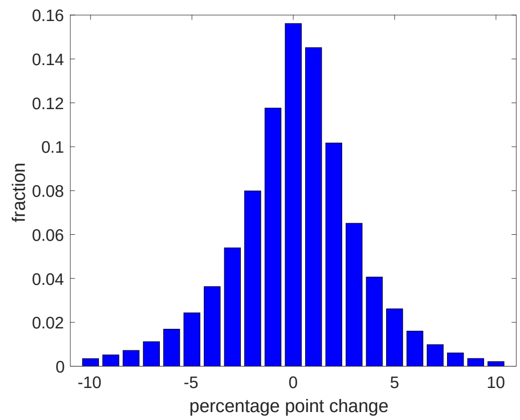


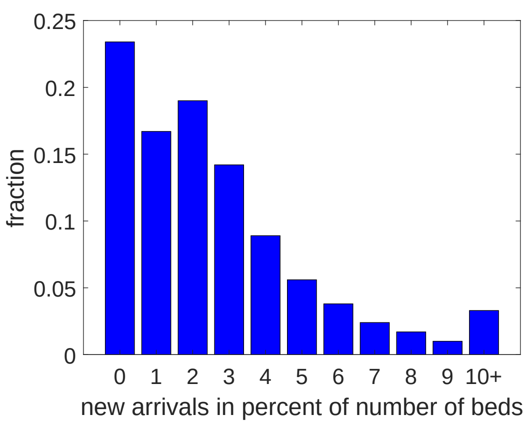
Figure 2: Variation in Occupancy Rates and New Arrivals by SNF and Week



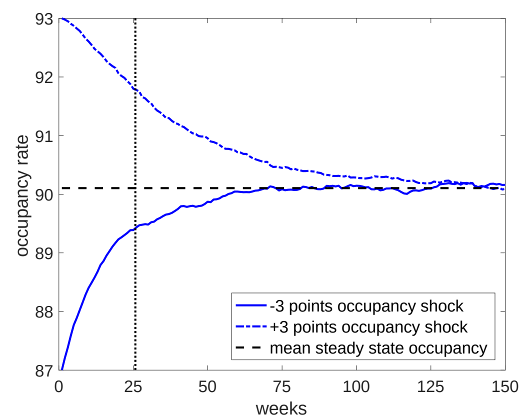
(a) Occupancy Rate Distribution



(b) Occupancy Variation Within SNF and Year



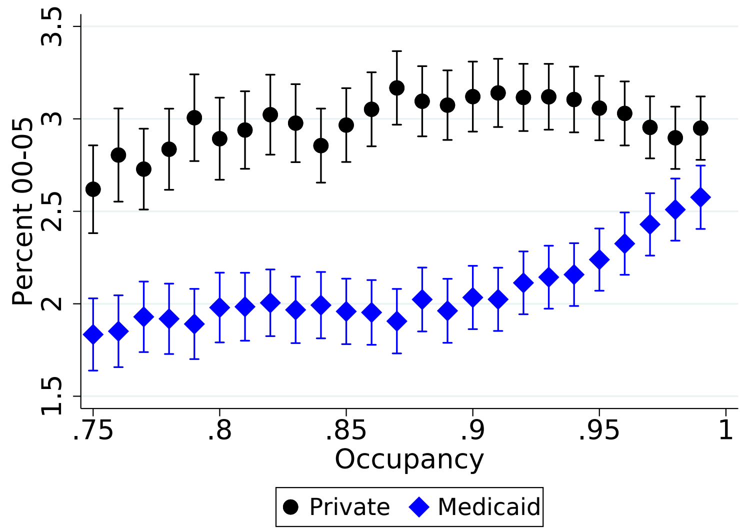
(c) New Arrivals Relative to Number of Beds



(d) Impulse Response to Change in Occupancy

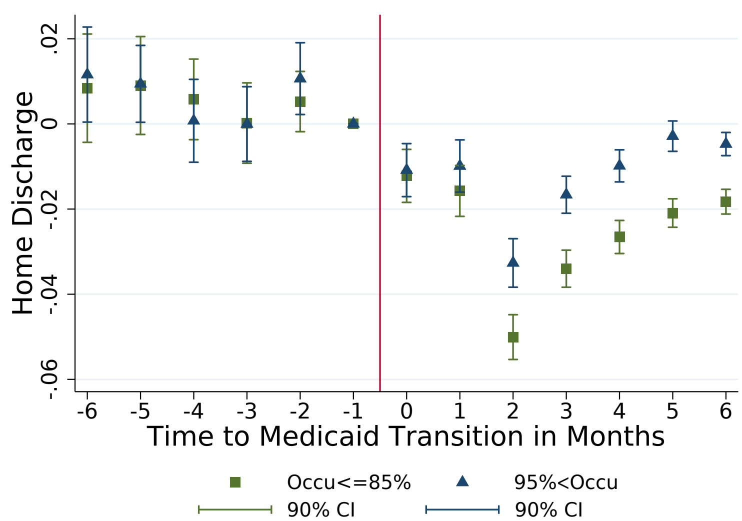
Notes: The unit of observation for Figures 2a, 2b, and 2c is the SNF-week level. Figure 2a shows variation in occupancy rates. Figure 2b shows the *residual* variation conditional on SNF-year fixed effects. Figure 2c summarizes the frequency of weekly arrivals, divided by the number of licensed beds. Figure 2d presents two impulse response functions, which document the mean reversion of an initial deviation of ±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.

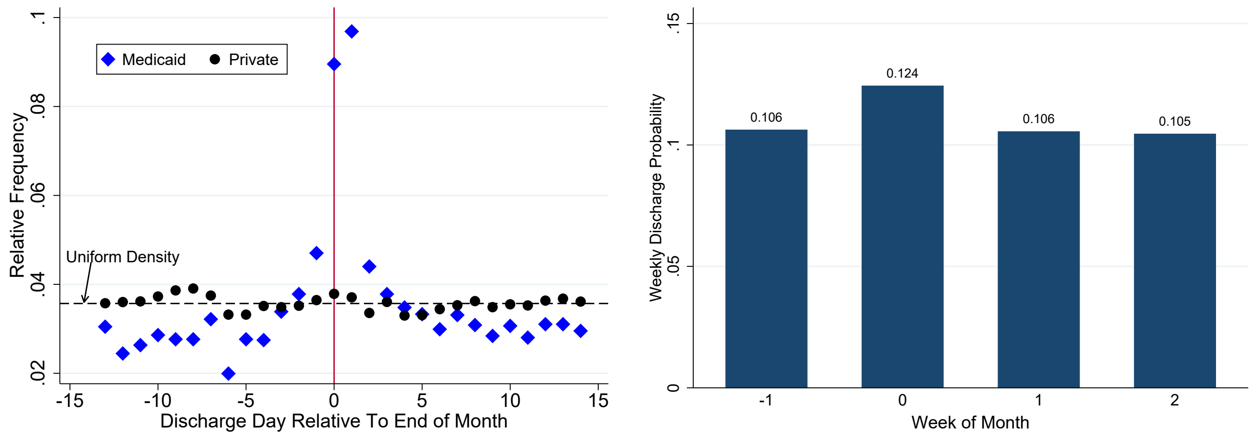
Figure 4: Medicaid Transition at Low and High Occupancies



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 $\sum_{\iota=-6}^{-2} Mcaid_{im}$ and $\sum_{\tau=0}^{6} Mcaid_{im}$ of equation (3). The vertical bars indicate 90% confidence intervals.

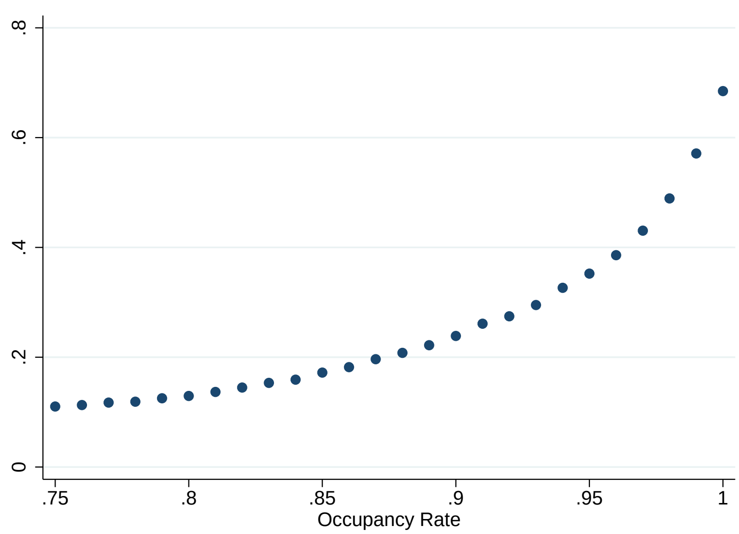
Figure 5: Community Discharges and Medicaid Cost Sharing

(a) Day-of-Month at Community Discharge (b) Probability of Discharge by Week-of-Month



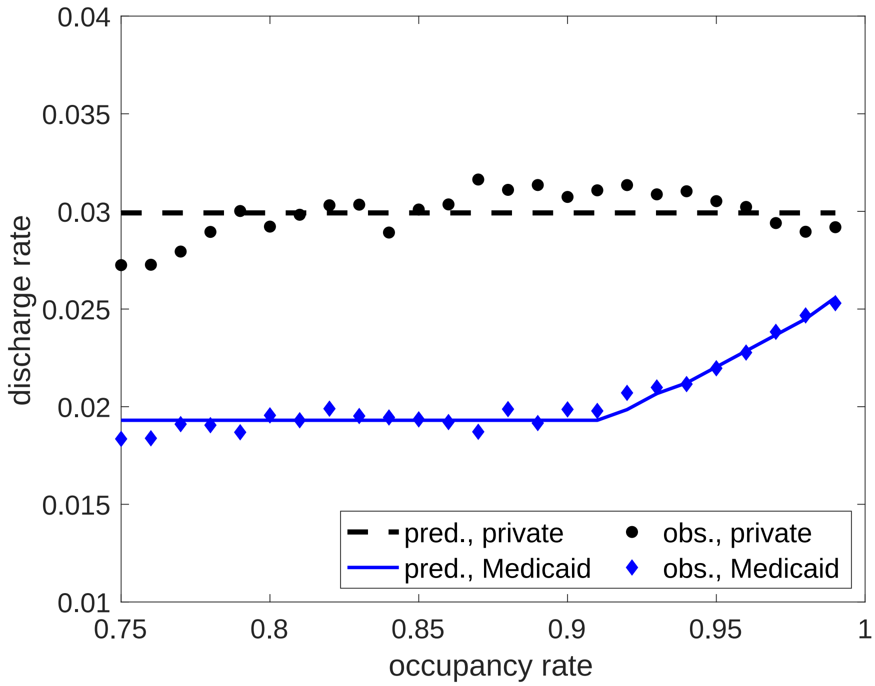
Notes: Long-Term Care Minimum Data Set, Medicare and Medicaid claims data for PA from 2000 to 2005. Figure 5a plots a histogram of the day-of-month on which patients are discharged to the community. Days are measured relative to the end of the month. Figure 5b displays the weekly discharge probability by week-of-month for patients with monthly discharge probability of more than 25%. 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.

Figure 6: Weekly Refill Probability by Occupancy Rate



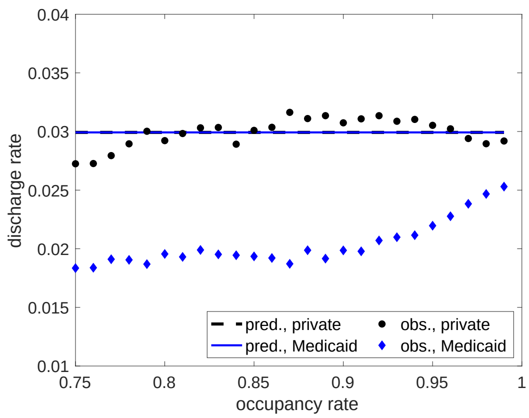
Notes: This figure plots the average weekly refill probability of an empty bed against the facility's occupancy rate, see equation (E.2) (Appendix) for details.

Figure 7: Observed Discharge Pattern and Model Fit

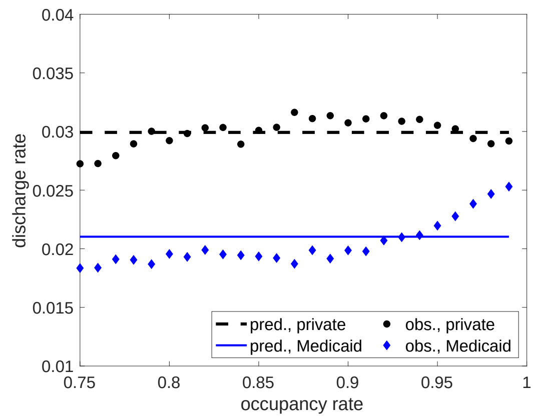


Notes: This figure plots the observe discharge pattern against the model predictions, see text for details.

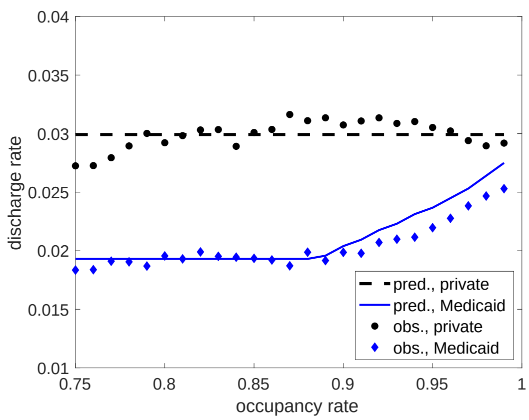
Figure 8: Simulated Discharge Rates Under Different Policies



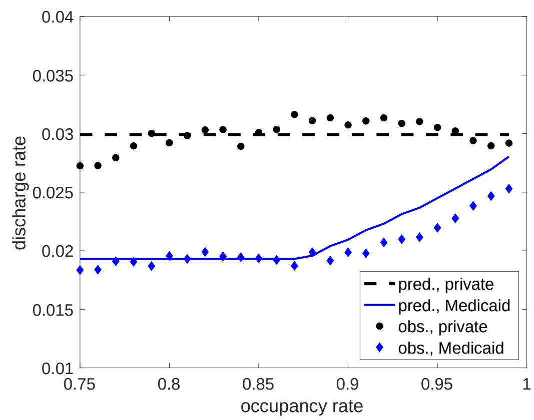
(a) Medicaid Voucher



(b) Top-Up Payment



(c) Discharge Bonus



(d) Front-Loaded Medicaid Reimbursement

Notes: The figures present the estimated home discharge rates for private payers and Medicaid beneficiaries from Figure 3 along with the corresponding model predictions. Figure 8a shows model predictions under a voucher policy. Figure 8b shows the case of top-up payments, where Medicaid beneficiaries pay the difference between the private and the Medicaid rate out-of-pocket. Figure 8c shows model predictions under on a bonus payment to providers for community discharges within 30 days. Figure 8d shows the case of 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	84.234	(7.796)	83.910	(7.887)
Female	0.702	(0.458)	0.744	(0.436)
White	0.890	(0.312)	0.848	(0.360)
Black	0.052	(0.222)	0.097	(0.296)
Hispanic	0.032	(0.175)	0.032	(0.176)
Married	0.128	(0.334)	0.100	(0.300)
Widowed	0.292	(0.454)	0.299	(0.458)
Divorced	0.028	(0.165)	0.041	(0.199)
Panel B: Health Measures				
Case Mix Index (CMI)	1.040	(0.458)	0.977	(0.412)
Number of ADL	10.534	(4.613)	10.493	(4.788)
Low ADL Needs	0.133	(0.332)	0.123	(0.324)
Depression	0.357	(0.477)	0.429	(0.493)
Weight Loss	0.112	(0.315)	0.093	(0.290)
Impaired Cognition	0.441	(0.494)	0.471	(0.498)
Behavioral Problems	0.078	(0.268)	0.092	(0.288)
Panel C: Occupancy Rates				
Occupancy $\leq$ 85%	0.214	(0.410)	0.198	(0.399)
Occupancy > 85% & $\leq$ 95%	0.497	(0.500)	0.491	(0.500)
Occupancy > 95%	0.289	(0.453)	0.312	(0.463)
Observations	7,484,442		6,014,006	

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 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. (2007), 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.

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

	(1)	(2)	(3)	(4)
Medicaid×Occupancy>95%	-0.0049***	-0.0050***	-0.0050***	-0.0058***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Medicaid×Occupancy>85% & ≤95%	-0.0095***	-0.0095***	-0.0096***	-0.0106***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Medicaid×Occupancy≤ 85%	-0.0083***	-0.0083***	-0.0083***	-0.0095***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Occupancy>95%	-0.0016***	-0.0015***	-0.0015***	-0.0016***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Occupancy≤85%	-0.0017***	-0.0020***	-0.0020***	-0.0018***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Patient Incentives:				
Medicaid× Occupancy≤85%	-0.0083***	-0.0083***	-0.0083***	-0.0095***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Discharge Rate Private Payers:	*0.0313*			
(at Occupancy >85% & ≤ 95%)				
Change in percent:	-26.5%	-26.5%	-26.5%	-30.4%
Provider Incentives:				
(Medicaid×Occupancy>95%) −	0.0034***	0.0033***	0.0033***	0.0038***
(Medicaid×Occupancy≤85%)	(0.0006)	(0.0006)	(0.0006)	(0.00057)
Discharge Rate Private Payers:	*0.0313*			
(at Occupancy >85% & ≤ 95%)				
Change in percent:	10.9%	10.5%	10.5%	12.1%
LOS-week FE	X	X	X	X
SNF-year FE		X	X	X
Month FE			X	X
Year FE			X	X
Socio-dem. controls				X
Observations	13,465,006	13,465,006	13,465,006	13,455,387
R-squared	0.0575	0.0575	0.0576	0.0628

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>95%	-0.0195***	-0.0224***	-0.0245***	-0.0245***
	(0.0026)	(0.0023)	(0.0023)	(0.0023)
Medicaid×Occupancy>85% & ≤ 95%	-0.0270***	-0.0322***	-0.0332***	-0.0334***
	(0.0016)	(0.0018)	(0.0017)	(0.0017)
Medicaid×Occupancy ≤ 85%	-0.0318***	-0.0365***	-0.0375***	-0.0375***
	(0.0026)	(0.0027)	(0.0026)	(0.0026)
Occupancy>95%	-0.0076**	-0.0102***	-0.0113***	-0.0114***
	(0.0031)	(0.0027)	(0.0025)	(0.0025)
Occupancy≤85%	0.0024	0.0050	0.0036	0.0036
	(0.0032)	(0.0034)	(0.0029)	(0.0029)
Patient Incentives:				
Medicaid×Occupancy≤ 85%	-0.0318***	-0.0365***	-0.0375***	-0.0375***
	(0.0026)	(0.0027)	(0.0026)	(0.0026)
Pre-transition discharge rate:	*0.1471*			
Change in percent:	-21.6%	-24.8%	-25.5%	-25.5%
Monthly Fixed Effects Results:				
Medicaid×Occupancy≤ 85%	-0.0318	-0.0318	-0.0318	-0.0365
Pre-transition discharge rate:	*0.125*			
Provider Incentives:				
(Medicaid×Occupancy>95%) – (Medicaid×Occupancy≤85%)	0.0123***	0.0140***	0.0129***	0.0129***
	(0.0035)	(0.0033)	(0.0032)	(0.0032)
Change in percent:	8.4%	9.5%	8.8%	8.8%
Monthly Fixed Effects Results:				
(Medicaid×Occupancy>95%) – (Medicaid×Occupancy≤85%)	-0.0131	-0.0128	-0.0128	-0.0147
LOS-month FE	X	X	X	X
Patient FE		X	X	X
SNF-year control			X	X
Month FE			X	X
Year FE			X	X
Socio-dem. controls				X
Observations	1,014,698	1,014,698	1,011,647	1,011,647
R-squared	0.0007	0.1311	0.1570	0.1576

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 regression model with different sets of fixed effects, described in the bottom panel. The middle panels add results from Table 2 aggregated to the month-of-stay.

Table 4: Structural Parameter Estimates

A. Estimated Outside Model	
Refill probability Φ	See Figure 6.
Occupancy transition matrix Θ	See Tab. B.3.
Pr(transition to Medicaid) ψ	1.1%
Pr(private at admission) ρ	78.2%
Discharge rate, private $D^{other,P}$	3.6%
Discharge rate, Medicaid $D^{other,M}$	1.6%
Daily private rate r^P	\$194
Daily Medicaid rate r^M	\$159
B. Calibrated	
Discount Factor δ	$0.95^{\frac{1}{52}}$
Cost of Effort $c(e)$	e^2
Utility SNF Care u	5
C. Estimated Inside Model	
SNF Effort α	0.0273
	[0.0042, 0.0295]
Resident Effort β	0.416
	[0.3470, 0.4224]
Resident Price κ	0.0358
	[0.0129, 0.0378]
Margina Care Cost mc	74.33
	[73.71, 75.75]
SNF Elasticity ϵ^{SNF}	1.316
Resident Elasticity ϵ^{res}	0.175

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. 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	Top-up	Bonus	2% Front	10% Front
Medicaid LOS	29.42	23.22	29.69	28.31	28.12	23.36
Average Occupancy	90.8%	88.1%	91.1%	89.7	90.3%	88.4%
Δ Medicaid LOS (vs. "actual")		−6.20	0.27	−1.12	−1.30	−6.06
Δ Medicaid spending per stay in $		1,219	7,490	−355	−919	−4,282
Δ Medicaid spending per stay in %		3.7%	22.7%	−1.1%	−2.8%	−13.0%

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: One vehicle through which states can reform the delivery of long-term care services are Section 1115 Demonstrations. States commonly use these demonstrations to implement Managed Long Term Services and Supports (MLTSS) programs aimed at reducing long-term care expenditures through managed care and, whenever possible, placing Medicaid beneficiaries into community-base care. Depending on beneficiaries' long-term care needs, MLTSS also provide nursing home care. In this case, nursing homes are typically paid on a episode or capitation basis. The number of states that have MLTSS programs increased from 8 in 2004 to 23 in 2018 (Libersky et al., 2018). None of the states in our sample had a mandatory MLTSS program during our study period.

HCBS Waivers: Nursing home stays are expensive for states' Medicaid programs. Moreover, patients with LTC needs typically prefer community-based care settings over nursing homes and being institutionalized. Hence, states have developed and expanded home- and community-based services (HCBS) under their Medicaid programs. In 1991, 86% of Medicaid spending for LTC was for institutional care and only 14% for HCBS. By 2001, the latter share had more than doubled to 29%, see Milne, Chang, and Mollica (2004). A driving force of this HCBS expansion has been HCBS waivers that states can apply for—and which were authorized under section 1915(c) of the Social Security Act as part of the Omnibus Budget Reconciliation Act (OBRA) of 1987.

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), automatic enrollment, federal single payer system	Asset test: CA ($2000), PA ($2400), NJ ($4000), OH ($1500) "Medically Needy" (MN) income limits: 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 hospital stays of at least three days.	ADL and/or medical condition requiring 24 hour supervision: CA and PA (both), NJ and OH (one of two) Needs allowance: CA ($35), PA ($30), NJ ($35), OH ($40)
Eligibility HCBS	prescribed by physician, for home-bound patients	All states w/ HCBS waivers under Section 1915(c) of the Social Security Act. Idea is to provide Medicaid HCBS to patients who would be eligible for Medicaid in SNF. Asset test: CA ($2000), PA ($2000), NJ ($2000), OH ($1500) Income limits: CA (MN =$600); PA, NJ, OH: (300% SSI or $1635 in 2002) Needs allowance: CA ($600), PA ($521), NJ ($1482), OH ($964)
Panel B: Patient Incentives		
Price SNF	After first 100 days, private rate. Per day: CA ($168); PA ($219); NJ (n/a); OH ($148)	Except for allowance, income applied to costs, e.g. ($623-$30)/($219×30 days)=9% of private rate for PA; 13% of private rate for CA and OH
Price HCBS	Part-time home health aide by Medicare -certified agency covered. Physical, speech, occupational therapy: no cost-sharing. No coverage of personal (assistance w/ ADL) or household services. 20% coins. for durable equipment (walkers,...).	Home health aides, nursing services, medical equipment generally covered. $1/visit in CA, no copay in other states. 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: $168 (CA); $219 (PA); NJ (n/a); $148 (OH)	Medicaid rates per day: CA ($137), PA ($188), NJ ($142), OH ($144). All states pay per diem. PA used case-mix index; OH and NJ based on cost; CA by size, location, level of care.
Reimbursement HCBS	see above, limited home health care.	Depends on service provided. 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). Because of high nursing home costs, 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.2 in the Appendix. 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. Private SNF rates for PA and CA are in our data and for OH they are from Mehdizadeh and Applebaum (2003). Information of Medicare coverage is from Komisar and Feder (1998) and Centers for Medicare & Medicaid Services (2019). 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

To investigate the impact of patient and provider incentives on nursing home community discharges, we compile a unique dataset. Specifically, we combine administrative micro data from the Long-Term Care Minimum Data Set (MDS) with Medicaid and Medicare claims data from skilled nursing facilities (SNF) as well as information on nursing home characteristics from annual surveys. The MDS contains the universe of SNF residents for all Medicaid or Medicare-certified nursing homes, about 98% of all nursing homes. The data contain the exact admission and discharge dates as well as the the discharge destination. We also observe residents' long-term care needs and clinical health assessments, see Section 4 and below for details.

B.1 Financial Characterization of Nursing Home Residents Using the HRS and NLTCS

To provide further background information on nursing home residents, we supplement our analysis with representative auxiliary data from two surveys. First, we use data from the Health and Retirement Study (HRS) between 1998 and 2010. We select HRS respondents who spent at least one night in a nursing home in the two years prior to the HRS interview. Table B.1 shows summary statistics by payer type. A striking and expected difference between payer types is that Medicaid beneficiaries have net financial assets of $5,500, whereas private payers have net financial assets of almost $28,000.

Second, we use data from the National Long Term Care Survey(NLTCS) between 1999 and 2004. In contrast to the HRS, the NLTCS samples individuals who are *currently* residing in nursing homes. Moreover, the NLTCS contains information on the payer type at admission and at the time of the interview, which allows us to observe payer type switches. Table B.2 shows nursing home residents' average income and assets by payer type. This includes residents who switch from private to Medicaid during their nursing home stays. As we drop residents who were Medicaid beneficiaries already at admission in our main analysis, columns (2) and (3) provide the relevant information on income and wealth. Permanent Medicaid beneficiaries report average incomes of $623, those who transition to Medicaid incomes of $792, and those who remain private payers incomes of $1,117 as evidenced by the first row. In contrast to the relatively comparable income levels, we again find substantial differences in assets as evidenced by the last two rows.

Table B.1: Summary Statistics: Income, and Asset (HRS)

	Medicaid		Private	
	Mean	SD	Mean	SD
Social security income	7,018	(4,346)	5,881	(3,837)
Total household income	11,934	(11,235)	19,214	(10,292)
Net financial assets	5,495	(51,800)	27,846	(45,702)
Home ownership	0.274	(0.446)	0.597	(0.491)
Total wealth	32,990	(119,989)	130,946	(142,363)
Observations	1,693		526	

Note: Health and Retirement Study 1998 to 2010. All income and asset amounts are in 2000 dollars. The sample conditions on HRS respondents who spent at least one night in a nursing home in the two years prior to the interview. We define them as Medicaid beneficiaries if they report being covered by a Medicaid plan. We define them as private payers if they report that their nursing home stay was not covered by a government plan or if they hold private long term care insurance.

Table B.2: Summary Statistics: Monthly Income and Assets (NLTCS)

	(1) Mcd/Mcd		(2) Prv/Mcd		(3) Prv/Prv		(4)
	Mean	SD	Mean	SD	Mean	SD	p-value
Total income	622.6	(582.6)	792.2	(585.7)	1117.3	(1516.3)	0.0518
Social Security benefits	620.8	(367.3)	770.7	(319.6)	872.0	(545.1)	0.1190
Other retirement income	60.33	(203.1)	153.0	(361.0)	337.9	(875.8)	0.0636
SSI	10.94	(125.7)	0	(0)	10.88	(101.0)	0.4396
Home ownership	0.0819	(0.280)	0.0899	(0.295)	0.160	(0.376)	0.2933
Net home value	5264.2	(25189.0)	3995.2	(18530.6)	23287.9	(115402.0)	0.2368
Observations	203		48		266		

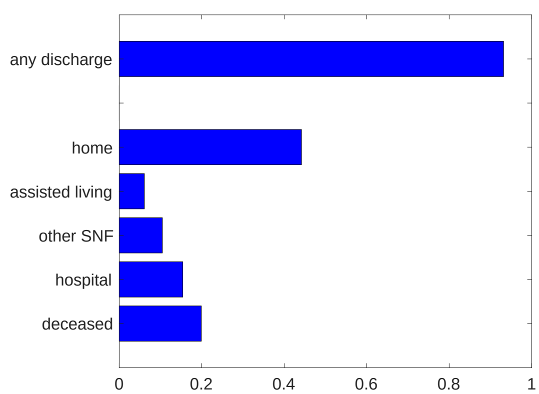
Notes: National Long Term Care Survey 1999 to 2004. p-value from the F-test of the null hypothesis $H_0 : \beta_P = \beta_M$ in the regression $Y_i = \beta_0 + \beta_P Prv_i + \beta_M Mcd_i + \sum_t \delta_t \mathbf{1}\{LOS_i = t\} + \epsilon_i$, where Prv_i and Mcd_i are indicators for payer type at the interview, given that payer type at admission is private (excluded category is Medicaid at admission). All amounts are in 2004 dollars.

B.2 Discharge Destination, Occupancy Rates and Health Assessments

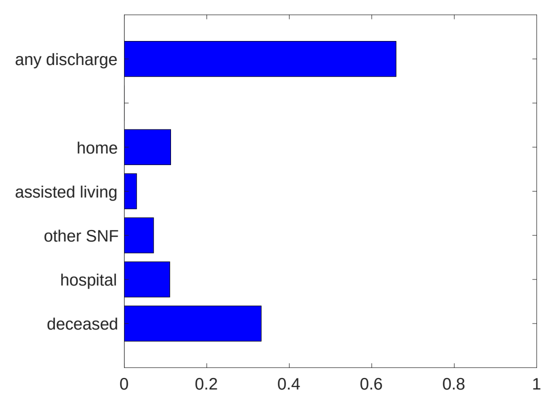
Discharge Destination: The MDS indicates the admission and discharge dates for each resident. This information allows us to construct the exact length of each nursing home stay. Moreover, we observe a discharge code, which provides information on the reason of discharge and the discharge destination. Figure B.1a (a) displays overall and destination-specific stay-level discharge probabilities. In our sample, 93% of skilled nursing facility (SNF) residents are discharged by the end of the sample period. Almost half of them return to the community, 20% of residents pass away in the nursing home, and the remaining residents enter an assisted living facility, another nursing home, or a hospital upon being discharged.

We note that residents who are discharged to the community have shorter stays on average. Hence, the fraction of present residents (present in the SNF at a given point in time) that are eventually discharged to the community will be smaller since the composition of present residents is skewed towards longer stay patients. To see this we weight nursing home stays by length of stay and show the corresponding breakdown of discharge destinations in Figure B.1b (b). As expected, we now find that fewer SNF stays end in a home discharge (11%) and more stays end through the resident's death (33%).

Figure B.1: Discharge Probabilities by Destination



(a) Discharge Probabilities at the Stay Level

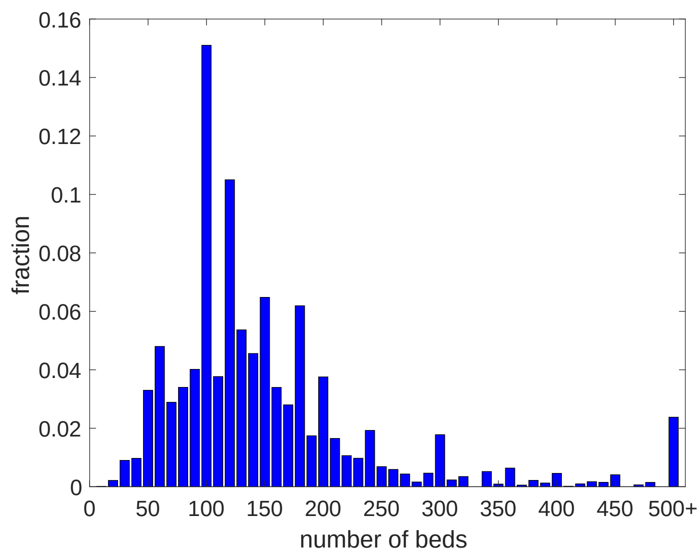


(b) Discharge Probabilities Weighted by LOS

Notes: The figure summarizes the propensity for different discharge reasons. *Any discharge* is an indicator that turns on if the stay ends with a discharge. *Home*, *Assisted Living*, *Other SNF*, *Hospital*, and *Deceased* are indicator variables that turn on if the stay ends with a discharge to the community, to an assisted living facility, a different SNF, a hospitals or if the resident deceased, respectively. The figures shows the fraction of stays that end accordingly. In the left figure, the unit of observation is the nursing home stay. In the right figure, the unit of observation is week of the nursing home stay. LOS stands for length of stay.

Occupancy Rates: To quantify the occupancy rate of each nursing home at any point in time, 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 once every 15 months (Long-Term Care: Facts on Care in the U.S., 2020). Figure B.2 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.

Figure B.2: 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.

Table B.3 summarizes within nursing home week-to-week variation in the occupancy rate. The cells document the relative frequency compared to any transition between 90% and 100% occupancy. The cells on the main diagonal sum to 58% illustrating that occupancy rates change from week-to-week in 42% of all cases.

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 by the state of California. Each year SNFs have to submit Long-Term Care Facility Integrated Disclosure and Medi-Cal Cost Reports (FIDCR). These report include key indicators about the facility such as the number of licensed beds.

Table B.3: Week-to-Week Transitions in Occupancy 90%-100%

	90%	91%	92%	93%	94%	95%	96%	97%	98%	99%	100%
90%	3.51%	0.93%	0.63%	0.36%	0.16%	0.08%	0.04%	0.02%	0.01%	0.00%	0.00%
91%	0.77%	3.75%	1.05%	0.73%	0.37%	0.18%	0.07%	0.03%	0.01%	0.00%	0.00%
92%	0.49%	0.83%	4.55%	1.24%	0.71%	0.40%	0.17%	0.08%	0.03%	0.01%	0.00%
93%	0.31%	0.57%	1.02%	5.48%	1.32%	0.86%	0.39%	0.19%	0.06%	0.02%	0.00%
94%	0.17%	0.34%	0.59%	1.08%	5.66%	1.46%	0.84%	0.36%	0.14%	0.03%	0.01%
95%	0.11%	0.19%	0.35%	0.70%	1.22%	6.35%	1.55%	0.89%	0.34%	0.08%	0.02%
96%	0.05%	0.09%	0.18%	0.36%	0.70%	1.33%	7.18%	1.54%	0.79%	0.21%	0.03%
97%	0.03%	0.04%	0.09%	0.21%	0.37%	0.74%	1.29%	7.47%	1.61%	0.47%	0.07%
98%	0.02%	0.02%	0.05%	0.10%	0.17%	0.34%	0.72%	1.35%	8.45%	1.13%	0.14%
99%	0.00%	0.01%	0.01%	0.03%	0.04%	0.10%	0.22%	0.46%	1.03%	5.14%	0.28%
100%	0.00%	0.00%	0.00%	0.01%	0.01%	0.02%	0.04%	0.06%	0.14%	0.26%	0.87%

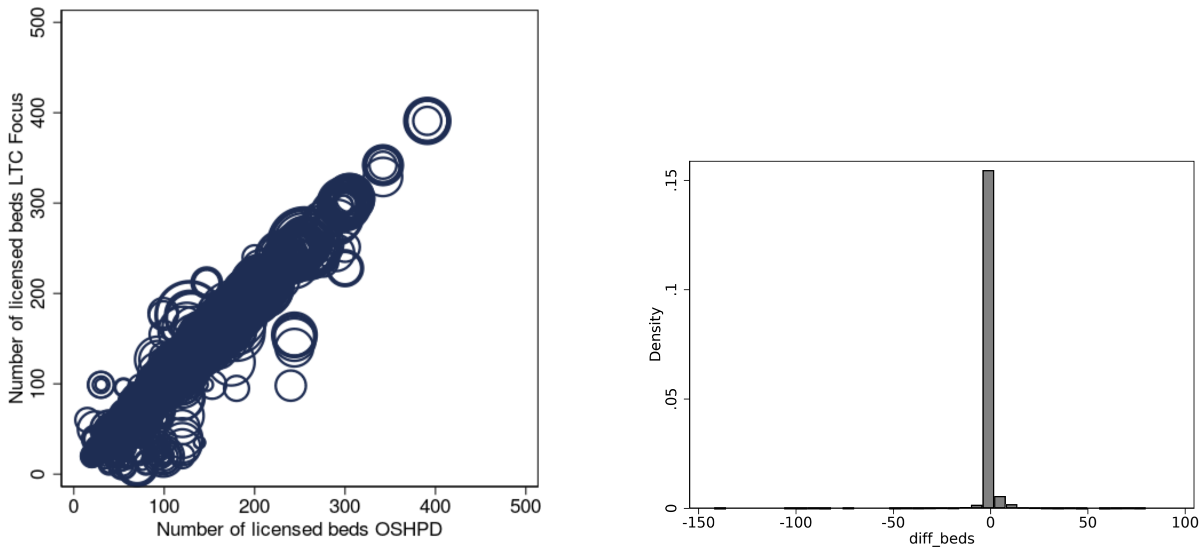
Notes: The table summarizes within nursing home week-to-week variation in the occupancy rate. Current and next week's occupancy rate are displayed in rows and columns, respectively. Each cell documents the relative frequency, compared to any transition between 90 and 100% occupancy. For expositional reasons, occupancy variation is only shown between 90% and 100%.

Figure B.3a correlates the number of reported beds by SNF and year. The size of the scatters represent the size of the SNF. As seen, while we can observe some deviations between both data sources, it is important to note that (a) the deviations do not appear to be symmetric, (c) the large majority of all values are identical and line up nicely on the 45 degree line in Figure B.3a.

Plotting the histogram of bed size deviations, Figure B.3b corroborates this conclusion. As we can see, the overwhelming majority of reported available beds are identical between the two data sources. The negative and positive deviations appear small and not systematic in either direction.

Payer Types and Transition to Medicaid: To investigate differences in discharge patterns between residents with different payer sources, we combine the MDS with administrative Medicare and Medicaid claims data from the MedPAR and MAX databases. We link the information at the nursing home-stay level and are thus able to quantify the days of each stay covered by Medicare and Medicaid. We assume that the remaining days are paid out-of-pocket, given that very few residents

Figure B.3: 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 LTC Focus 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.

have private LTC insurance. Importantly, we observe the exact transition date between private payment and Medicaid eligibility, which is key for our empirical analysis. However, it should be noted that we only see payer sources reliably for payments made to the SNFs, while patients are residing in nursing homes.

However, our second empirical approach, the event study analysis, leverages within-patient variation in the time to and since they transitioned to Medicaid. This analysis requires that we observe transitions to Medicaid also outside of SNFs. For this purpose, we exploit the so called "buyin" indicator which is an administrative Medicare indicator that identifies dual beneficiaries (Rupp and Sears, 2000; Research Data Assistance Center, 2020). However, the 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 information and the monthly buyin indicator information, using just the population in nursing homes. These cross validation checks provided reliable information that both measures consistently identify Medicaid beneficiaries for California. Specifically, we find that 99% of dual beneficiaries also have buyin information. For 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%. However, 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%.

Private and Medicaid SNF Rates: To collect private and Medicaid rates that OSCAR does not include, we use information from two distinct nursing home surveys from California and Pennsylvania, (for details, see Hackmann, 2019).[40] 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 rate amounts to $219 for Pennsylvania and $168 for California. The Medicaid rates are $188 for Pennsylvania and $137 for California (also see Table A.1).

SNF Residents' 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 that are 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.

[40] The Pennsylvania survey data were provided by the Bureau of Health Statistics and Research of the Pennsylvania Department of Health. California data come from the Office of Statewide Health Planning and Development (see http://www.oshpd.ca.gov/HID/Products/LTC/AnnFinanclData/PivotProfls/default.asp).

C Details for Theoretical Discussion

This section describes the key predictions of our model in greater detail. See Section 3 for the model set-up. We start from the theoretical discharge equation (1) and assume that exogenous discharge factors ϵ are uniformly distributed. This allows us to express the discharge probability per period as:

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

Here, D denotes any discharge, which includes endogenous community discharges (our focus) but also discharges to a hospital, a different nursing home, or death—all captured in the exogenous discharge rate D^{exog}. We extend our model of community discharges to overall discharges to capture the profit motives of nursing homes more accurately. While consumer payoffs depend on the discharge destination, we show below that the marginal benefit of resident effort remains unchanged in this extended framework. We define a period to be one week.

C.1 Resident Effort

Residents trade off the utility from staying an additional week in the nursing home versus returning to the community. We assume the following indirect conditional utility:

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

where u is the resident's gross utility from nursing home care and we normalize utility from home health care to zero. κ is a price coefficient and p^{τ} is the per-period price paid by the resident where $\tau = P, M$ denotes the focal resident's payer type (private or Medicaid with $p^P > p^M$). η^{SNF} and η^{home} are type I extreme value taste shocks. If $u - \kappa p^{\tau} \leq \eta^{home} - \eta^{SNF}$, residents prefer to be discharged and exert strictly positive discharge effort.

C.1.1 Optimal Resident Effort

Residents choose the optimal discharge effort given by:

$$e^{res,*} = \arg\max_{e^{res}\geq 0} \Big\{ \Pr[D=1|\cdot, e^{res}] \times W(\tau, D=1, \eta) + (1 - \Pr[D=1|\cdot, e^{res}]) \\ \times W(\tau, D=0, \eta) - \kappa \times c(e^{res}) \Big\}, \quad \text{(C.2)}$$

where $c(e)$ denotes the cost of effort, measured in dollars. To translate the cost of effort back into utility, we multiply the cost by the price coefficient κ. The discharge probability is conditional on D^{exog} and the resident's beliefs 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 ϵ, see equation (1), shutting down potential free-riding incentives as shown by the first order condition:

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

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

Note on estimation: To estimate the model from observed discharge rates by payer type and occupancy, 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. To see this, consider the resident's optimal effort choice in equation (C.3). 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 β. 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) for details.

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 δ 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 $oc \geq oc^*$.

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

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

Finally, we exclude the 10% of SNF stays with the smallest predicted probability of ever being discharged to the community. We summarize select predictors in Table D.1 based on the underlying discharge potential. The left columns revisit the evidence for our baseline population with a discharge potential of more than 10%. The right columns present analogues evidence for patients with a discharge potential of less than 10%, which are excluded from the main analysis. The comparison of the patient populations indicates that the ML approach disproportionately excludes females, that are on average slightly older, and slightly more likely to be white and widowed. Turning to the health measures, patients with a small community discharge potential struggles with more ADLs on average and are more likely to have a cognitive impairment or behavioral problems. These chronic conditions contribute to longer nursing home stays reducing the probability of a community discharge.

Table D.1: Patient Summary Statistics by Community Discharge Potential

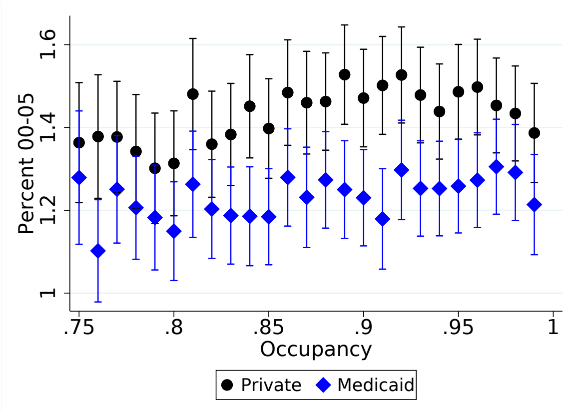
	Baseline Sample Population				Small Discharge Potential			
	Private		Medicaid		Private		Medicaid	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Socio-Demographics								
Age	84.234	(7.796)	83.910	(7.887)	85.593	(7.369)	85.226	(7.386)
Female	0.702	(0.458)	0.744	(0.436)	0.757	(0.429)	0.804	(0.397)
White	0.890	(0.312)	0.848	(0.360)	0.903	(0.297)	0.890	(0.313)
Black	0.052	(0.222)	0.097	(0.296)	0.037	(0.189)	0.055	(0.228)
Hispanic	0.032	(0.175)	0.032	(0.176)	0.031	(0.174)	0.028	(0.164)
Married	0.128	(0.334)	0.100	(0.300)	0.111	(0.314)	0.094	(0.291)
Widowed	0.292	(0.454)	0.299	(0.458)	0.294	(0.456)	0.328	(0.469)
Divorced	0.028	(0.165)	0.041	(0.199)	0.023	(0.151)	0.029	(0.169)
Panel B: Health Measures								
Case Mix Index (CMI)	1.040	(0.458)	0.977	(0.412)	1.079	(0.331)	1.086	(0.327)
Number of ADL	10.534	(4.613)	10.493	(4.788)	12.999	(4.063)	13.104	(4.154)
Low Care Needs	0.133	(0.332)	0.123	(0.324)	0.043	(0.196)	0.039	(0.188)
Depression	0.357	(0.477)	0.429	(0.493)	0.361	(0.479)	0.423	(0.493)
Weight Loss	0.112	(0.315)	0.093	(0.290)	0.098	(0.297)	0.083	(0.275)
Impaired Cognition	0.441	(0.494)	0.471	(0.498)	0.633	(0.480)	0.671	(0.468)
Behavioral Problems	0.078	(0.268)	0.092	(0.288)	0.130	(0.336)	0.151	(0.358)
Observations	7,484,442		6,014,006		1,184,192		561,317	

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 payer source at the resident-week level by community discharge potential. The left columns revisit the baseline sample population. The right columns present analogues statistics for the 10% of stays with the lowest predicted probability of ever being discharged to the community. 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. (2007), 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.

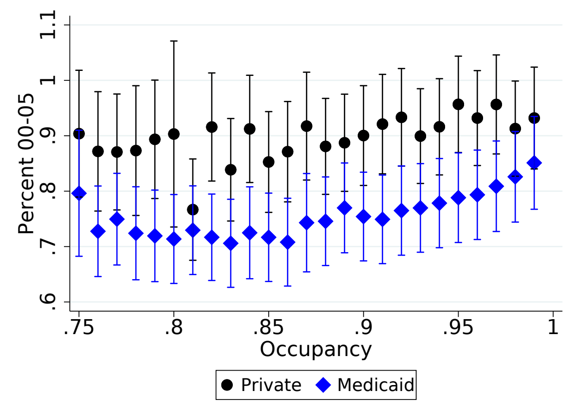
E Robustness and Additional Empirical Results

E.1 Discharge Patterns to Other Destinations

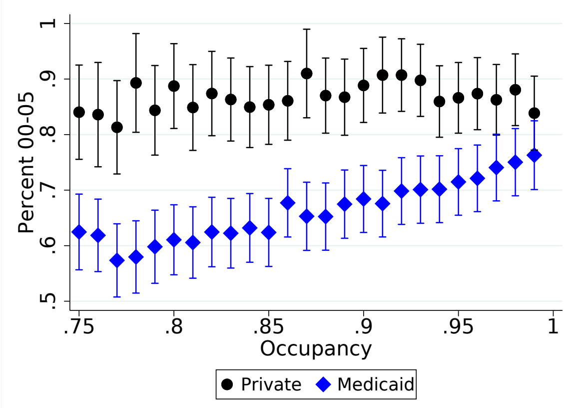
Figure E.1: Discharge Rates to Different Destinations by Occupancy and Payer Type



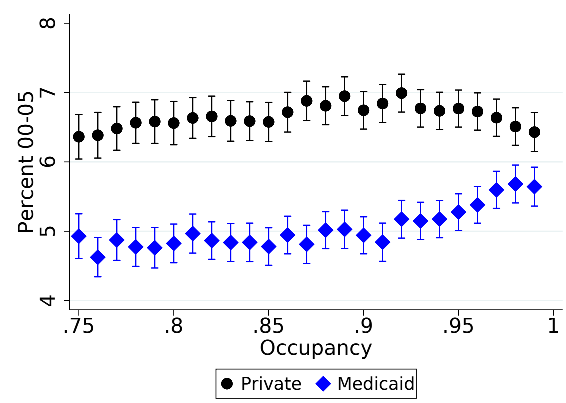
(a) Hospitalized



(b) Discharged to Another Nursing Home



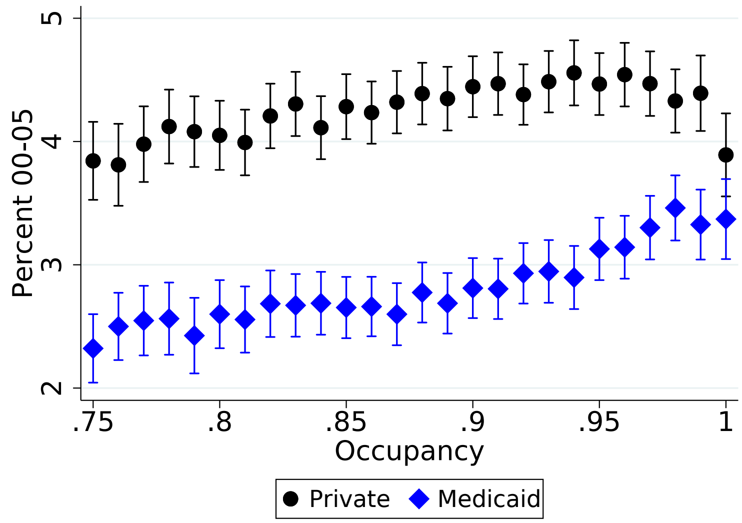
(c) Deceased



(d) Discharged to Any Destination

Notes: See notes for Figure 3. The dependent variables are indicator variables that 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 destination (Figure E.1d) in a given week. The vertical bars indicate 90% confidence intervals. We exclude estimates for 100% occupancy due to measurement error, which biases the point estimate towards the sample mean.

Figure E.2: Replication of Figure 3 Using Californian FIDCR Data



Source: Long-Term Care Minimum Data Set, Office of Statewide Health Planning and Development (2020). The figure uses an alternative data source for the number of licensed beds to calculate occupancy rates at the resident-week level. These data from come Office of Statewide Health Planning and Development (2020) and are solely available for California. Moreover, the sample is not pre-selected based on the Machine Learning approach described in Section 4.2. Otherwise the sample selection 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 90% confidence intervals.

E.2 Discharge Differential in California

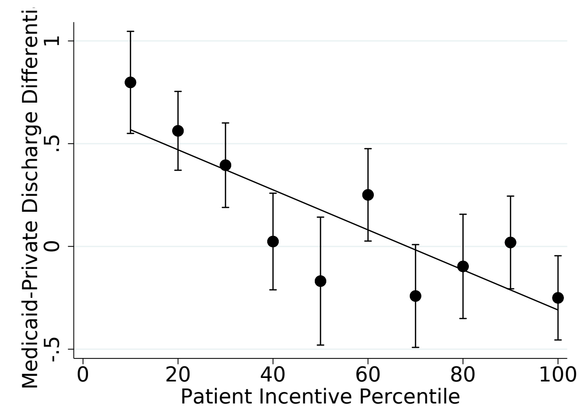
E.3 Total Discharge Differentials by Exact Private Payer Prices and Mark-Ups

The following robustness check stratifies the total discharge differentials as identified 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):

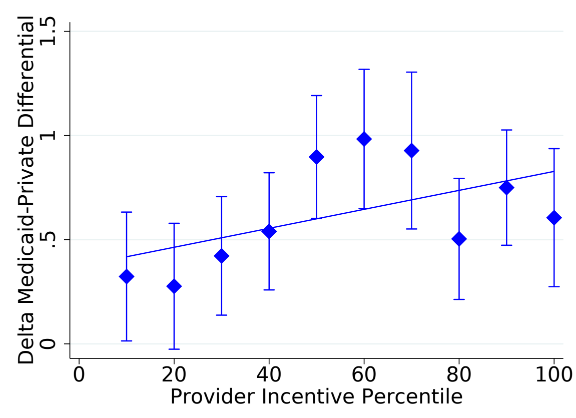
$$
\begin{aligned}
Y_{ijst} \;=\;& \mathbf{1}\{oc_{jt-1} < 85\%\} Mcaid_{is} \times \sum_{\tau=1}^{10} \delta^l_\tau \mathbf{1}\{r^P_{jt} \in PI^\tau\} \\
+\;& \mathbf{1}\{oc_{jt-1} > 95\%\} Mcaid_{is} \times \sum_{\tau=1}^{10} \delta^h_\tau \mathbf{1}\{r^P_{jt} \in PI^\tau\} + \delta Mcaid_{is} \\
+\;& \sum_{k=65}^{100} \gamma^k oc^k_{jt-1} + \eta_s + \eta_{jy} + \eta_c + X'_{it}\beta + \epsilon_{ijst},
\end{aligned}
\tag{E.1}
$$

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 occupancy rates (more than 95%). 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.

Figure E.3: Discharge Differentials by Private Payer Mark-Ups and Occupancy Rates



(a) Patient Incentives



(b) Provider Incentives

Notes: Figure E.3a plots δ_τ^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 90-100th indicates the highest private rates. Figure E.3b 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.

The key parameters of interest are δ_τ^l, which govern differences in discharge rates between Medicaid and private payers at low occupancy rates for different private rate deciles. Figure E.3a plots the ten δ_τ^l point estimates along with 90% confidence intervals for nursing homes below full capacity; the y-axis shows δ, the total discharge differential, and the x-axis shows the price percentile, where 90-100th 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.3b tests for differences in total discharge differentials by stratifying 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 $\delta^h_\tau - \delta^l_\tau$ analogous to the lower panel of Table 2. The y-axis represents this difference. Figure E.3b again presents point estimates for all ten percentiles on the x-axis, along with 90% 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 payers and low occupancies) increases with higher private rate mark-ups, which corroborates the baseline evidence on provider incentives.

E.4 Bunching Analysis

This section presents further details about the bunching analysis in Section 6.3. In this exercise, we exploit cost-sharing variation among Medicaid beneficiaries through the "share cost", which 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.

Figure E.4a plots the marginal daily SNF consumer prices for both private payers and Medicaid beneficiaries on the y-axis against the day-of-the-month on the x-axis. The graph uses data on the income distribution (net of a personal allowance of $30 per month) among Medicaid nursing home residents from 1999 and 2004 in the NLTCS, see Table B.2, and constructs average daily co-pays by day of the month. The co-pays start below the average Medicaid rate of $159 even on day 1 indicating that some individuals have net monthly incomes of less than $159. It then starts to fall off sharply after 3 days. After one week, average daily co-pays is $50 or about 24% of the corrresponding private rate. At the end of the month, average co-pays are at $12.5, indicating that $12.5/$159=8% of beneficiaries can afford the Medicaid rate throughout the entire month. Finally, we benchmark Medicaid co-pays to the out-of-pocket payments for private payers that do not differ over the course of the month.

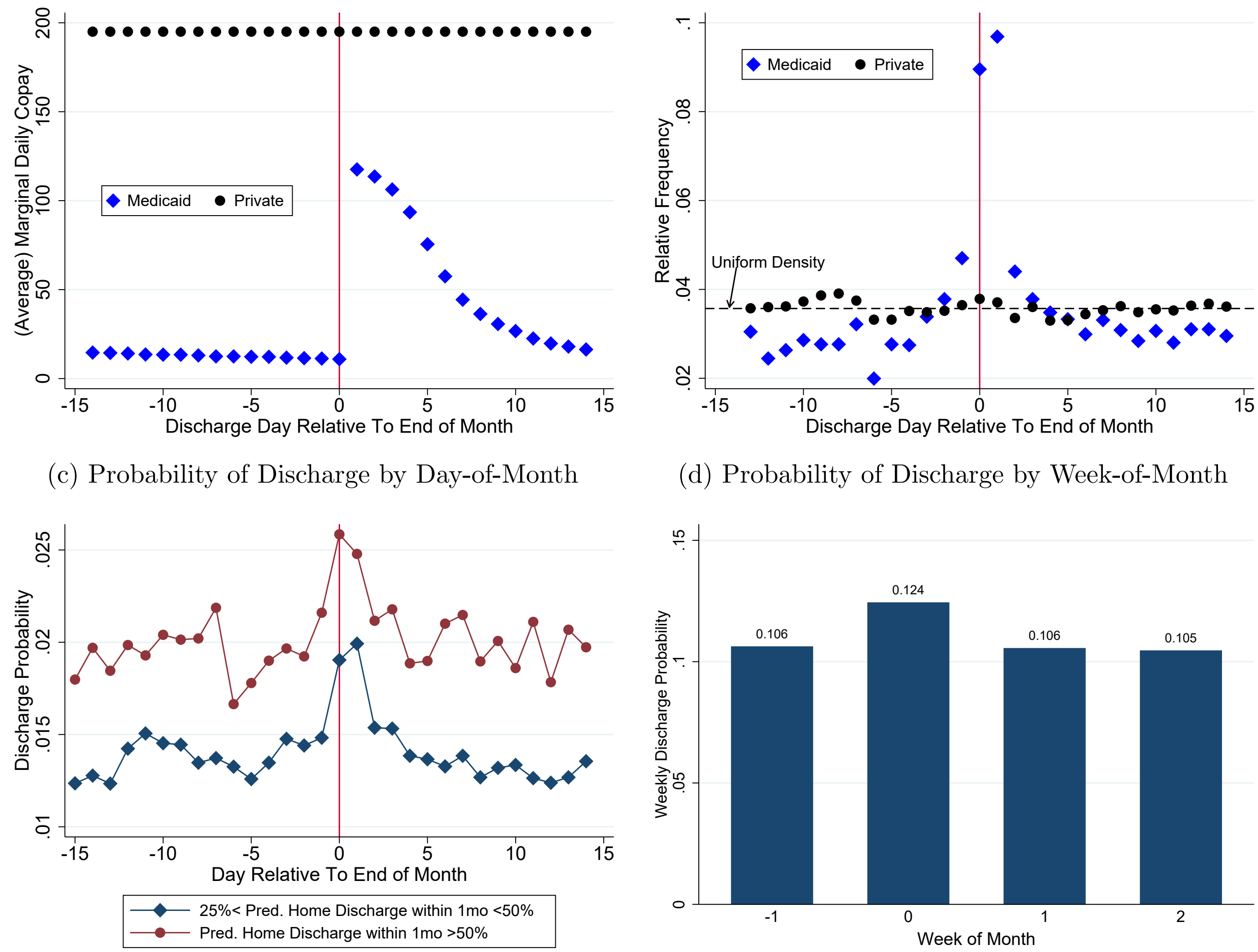
Next, we turn to the link between the non-linear cost-sharing and the timing of community discharges. Of course, the within month variation in cost-sharing will only affect patients with a high discharge potential to a meaningful degree. Therefore, we use our machine learning approach, outlined in Section 4.2, to identify patients with high discharge probabilities. Specifically, we focus on patients with a monthly discharge probability of more than 25%. Figure E.4b is equivalent to

Figure 5a from the main text and plots again a histogram of the day of the month on which patients were discharged to the community.[41]

Figure E.4: Daily Cost-Sharing and Community Discharges: Bunching Analysis

(a) Simulated Cost-Sharing by Day-of-Month (b) Community Discharges by Day-of-Month

(c) Probability of Discharge by Day-of-Month (d) Probability of 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.4a presents average daily cost-sharing amounts for private payers and Medicaid beneficiaries by the day-of-the-month. Figure E.4b plots the frequencies of different days of the month being the day of a community discharge for private payers and Medicaid beneficiaries. Figure E.4c plots the discharge probability by day-of-month for Medicaid beneficiaries with high predicted community discharge rates. In Figures E.4a,E.4b and E.4c, the last day of the month is normalized to zero. Figure E.4d aggregated Figure E.4c across both patient types and by 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.

To quantify a patient's sensitivity to prices, we invert the relationship and turn to discharge probabilities based on the current day of the month. Figure E.4c presents the overall discharge

[41] In Figure 5a we plot Pr[Day of month at Discharge|Discharged to Community]. For this exercise we focus on the years 2000 to 2005, but only rely on Pennsylvania. At the time, this state definitely applied the share of costs as described above, leading to the sharp variation in spot prices over the course of a month.

probabilities by the day of the month for patients with a predicted home discharge probability of 25-50% and more than 50% over the course of the month. Consistent with the evidence from Figure E.4b, we continue to find evidence for bunching around the end of the month. To simplify the exposition and the quantitative analysis, we aggregate discharge probabilities across both risk types and to the week of the month. 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.4d is the same as Figure 5b in the main text and presents again the corresponding average weekly discharge probabilities, which points to modest bunching in the focal week 0. Compared to the neighboring weeks, we see an increase of 1.8 percentage points or 17%.

E.4.1 Implied Patient Elasticity

We model the discharge process at the weekly level and assume that the month is comprised of four weeks. We define weeks based on the bunching evidence presented in Figure E.4d. Hence, week $\tau = 0$ corresponds to the bunching week comprising the days [-3,+3]. $\tau \in (-1, 1, 2)$ are again the week prior to bunching and the two weeks after bunching as indicated in Figure E.4d.

Medicaid cost-sharing differs between weeks, which we assume to be charged at the end of the week. Hence, 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, days 1-7, as opposed to the days -3 to 3 included in the bunching window. Intuitively we interpret 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. Specifically, we build on Figure E.4a and construct the cumulative average co-pays over the relevant 7-day window, which we refer to as $Price(\tau)$. As mentioned, we use a four-day lag in charges, whereby charges for the days 1 to 7 correspond to week 0, charges for the days 8 to 14 correspond to week 1, charges for the days -13 to -7 to week 2, and charges for the days -6 to 0 for week -1. Finally, we normalize charges in week 0 to 100%. We present these estimates under $Price(\tau)$ in rows 2-5 of column 1 in Table E.1. However, we also consider a model of concurrent charges, where discharges in week τ are motivated to avoid charges for the days falling precisely into that time window. Rows 2-5 of column (3) present the analogues charges. Finally, we

Table E.1: Patient Elasticity: Evidence from Week of the Month Bunching

	Static Model			Dynamic Model		
	(1)	(2)	(3)	(4)	(5)	(6)
β	0	0	0	$0.95^{1/52}$	$0.95^{1/52}$	$0.95^{1/52}$
$Price(\tau = -1)$	0.14	0.00	0.23	0.14	0.00	0.23
$Price(\tau = 0)$	1.00	1.00	1.00	1.00	1.00	1.00
$Price(\tau = 1)$	0.28	0.00	0.95	0.28	0.00	0.95
$Price(\tau = 2)$	0.16	0.00	0.31	0.16	0.00	0.31
$\hat{Pr}[D\|\tau = -1]$	0.105	0.105	0.103	0.113	0.114	0.113
$\hat{Pr}[D\|\tau = 0]$	0.124	0.124	0.124	0.124	0.124	0.124
$\hat{Pr}[D\|\tau = 1]$	0.108	0.105	0.123	0.102	0.098	0.114
$\hat{Pr}[D\|\tau = 2]$	0.105	0.105	0.105	0.105	0.105	0.105
Error: $\sum_\tau \lvert Pr[D\lvert\tau] - \hat{Pr}[D\lvert\tau]\rvert \times 100$	0.305	0.200	1.954	1.116	1.568	1.459
Patient Elasticity	0.193	0.163	0.235	0.806	0.691	0.936

Notes: This model 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.4. Columns 1-3 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.4d Differences between model fit and data are summarized in row 10. Columns (4) to (6) present analogues results for dynamic models, as evidenced by the discount factor summarized in the first row.

consider a model where co-pay is entirely concentrated in the bunching week, see rows 2-5 of column (2).

Building on the co-pay structure, we define patient flow utilities as follows:

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

where ϵ is an i.i.d. extreme value shock. δ denotes the relative utility of nursing home care (relative to the outside option). And $\alpha > 0$ captures the disutility of prices.

Next we consider a weekly discount factor of β and specify the patient's Bellman equation as

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

Evidently, we simplify the analysis here as 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.

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 θ using a nested fixed point algorithm. For a given guess of θ, we solve the Bellman equation and predict the discharge probability as

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

Finally, we choose the parameter vector that minimizes the squared difference between observed and predicted discharge probabilities. Specifically, we intend to match the discharge probabilities for week 0 and week 2, displayed in Figure E.4d, and then use evidence from week -1 and week 1 for model validation. Our estimator solves

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

Results: Table E.1 shows the results. We start with our preferred static model outlined in the first column. The second panel presents the predicted discharge rates by week of the month. For weeks 0 and 2, which were targeted in the estimation, we fit the observed discharge rates presented in Figure E.4d perfectly. The sum of absolute differences for week -1 and 1 equals only 0.3 percentage points. We then simulate the length of stay under different price schedules and find an elasticity of 0.2.

The static model in column (2) assumes that co-pays are concentrated in week 0. Here the fit is even slightly better. We find a similar elasticity of 0.16. The static model in column 3 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 0.24.

Turning to the dynamic models, specifications 4-6 in Table E.1 revisit the analogue static specifications when setting $\beta = 0.95^{1/52}$. We find larger elasticities of about 0.8, which is expected since 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 a rational dynamically-optimizing agents, which is not particularly plausible here given the evidence on sub-optimal behavior resulting from mistakes or non-neoclassical biases among the elderly in the literature (Dalton, Gowrisankaran, and Town, 2020). Consistent with that, we find that the static model provides a better fit of the observed discharge rates. As such, we view the dynamic elasticity as a conservative upper bound.

E.5 Weekly Refill Probabilities and Provider Incentives

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

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

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

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

We measure Φ at the facility-week level and construct its conditional mean by weekly occupancy. Figure 6 plots the weekly refill probability by SNF occupancy rates.

F Nursing Home Discharge Experiment

This section discusses key components of the nursing home discharge experiment. The institutional discussion briefly summarizes the detailed description in Jones (1986). Several key elasticities for the robustness exercise are taken from Norton (1992).

F.1 Details on the Experiment

Between November 1980 and April 1983, the National Center for Health Services Research and Health Care Technology Assessment (NCHSR) undertook a demonstration project, in cooperation with the of the Health Care Financing Administration cooperation, to investigate the consequences of using incentive payments to change discharge patterns for Medicaid patients in nursing homes. The discharge incentives of the experiment were part of a larger study that also considered incentive payments to change admissions and outcome patterns.

The discharge experiment was conducted in 36 Medicaid certified skilled nursing homes in the San Diego Metropolitan Statistical Area (SMSA) and intended to promote appropriate placement 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 where necessary care is provided. The experiment excluded patients who appeared to be dischargeable within 90 days, as well as those dischargeable under Medicaid criteria, but who had to overcome social, psychological, financial, or functional barriers before their placement in a lower level of care environment could be made.

The discharge incentive payments cover two cost components, vacant bed costs and staff effort cost. The incentive payments differed by facility size (more or less than 60) beds and the time of 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 about 10 days of reimbursements to cover vacant costs as well as similar amount to cover staff effort, see Table F.1 below, which presents the evidence from Exhibit 1 in Jones (1986) for nursing homes with 60-299 beds. The incentive payments declined gradually in the time to discharge, dropping to about 25% for discharges after 1 month. The payments only applied to Medicaid patients who agreed to be part of the experiment and were nominated by the facility (nursing home) for the discharge goal.

Discharge Process: For each of these patients, a form was completed by staff members that intended to evaluate whether the patient could be linked with services in a lower level of care setting which would adequately meet his or her needs. The facility also developed a discharge plan for the patient, which (together with the form) was reviewed by a research team, that ultimately had to approve discharge. Before the research team could approve the discharge, the facility had to arrange for all of the requisite services prior to the date of discharge, and to document the date services would begin, including the agency's or caregivers' names and telephone numbers. Furthermore, the facility had to specify the type of placement and the address, so that the research team could conduct follow-up visits after the resident's discharge. The facility would also assign a discharge coordinator, who was required conduct follow-up visits to conduct follow-up visits each week during the first month, and biweekly visits during the second and third months.

In addition, and following discharge, a research team nurse visited the resident in his or her discharge setting after 30, 60, and 90 days to assess whether the discharge plan was being implemented as prescribed. Depending on whether the plan was being implemented and whether the resident would not require additional services, the research nurse could authorize additional payments to the facility. Full payments as outlined above were only granted if the patent stayed in the lower level setting for 90 days, in which case the discharge was considered as successful.

F.2 Experimental Outcomes through the Lenses of the Model

To calibrate our model to the experimental environment, we undertake the following adjustments. First, we identify a target population in the experiment that most closely resembles our empirical setting. Patients in the experiment are classified into five states of health, depending on their need for help with activities of daily living. Patient group A comprises the healthiest patients. These patients were excluded from the incentive payments as they were considered to be discharged anyways within 90 days, regardless of incentives. Given our focus on patients with a decent discharge potential, we focus on the next healthiest patient group B, which comprises 22% of the entire patient population. Group B patients 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

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 ($\times$ 159/36)	Two Week Avg
Discharged:	Vacant Bed Cost	Staff Effort Cost	Total Cost	Total Cost	Total Cost
Within 5 days	352.6	288.4	641	2831.1	2313.7
Within 15 days	176.3	230.4	406.7	1796.3	2313.7
Within 30 days	70.62	165.83	236.35	1043.9	1420.1
More than 30 days	0	165.83	165.83	732.4	732.4

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

	Experiment	Model
Control Group	0.38%	0.38%
Treatment Group	0.7%	0.61%

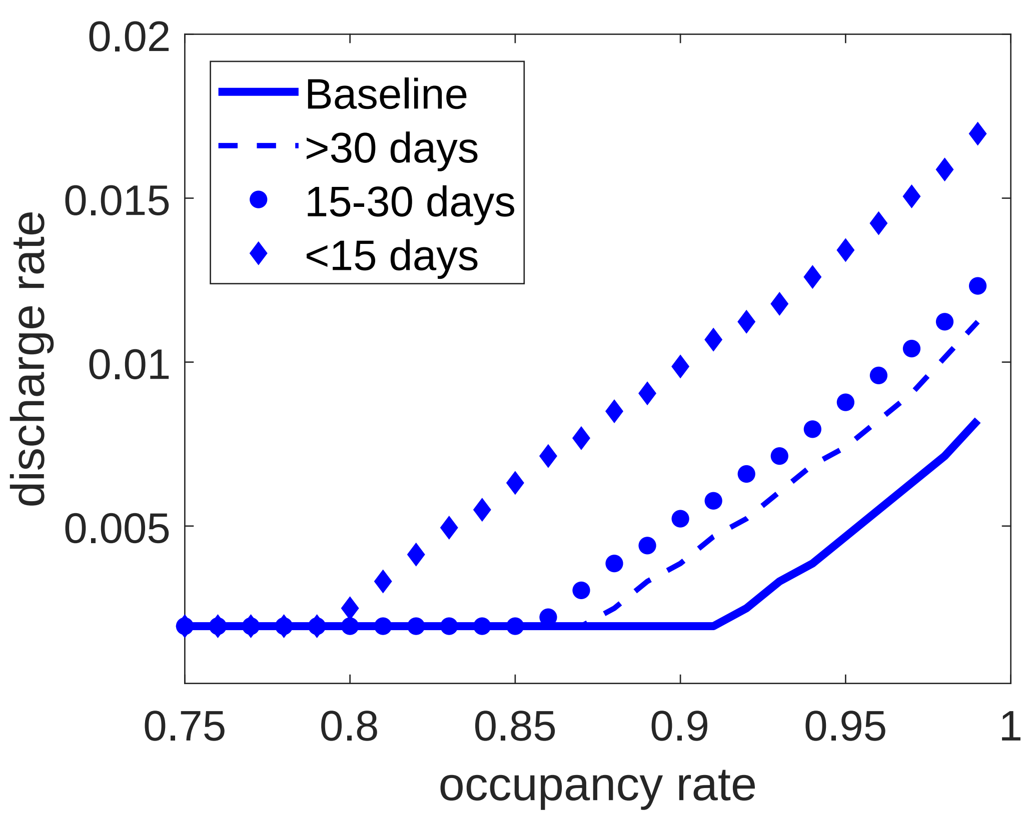
Notes: Panel A summarizes the discharge bonus payments from the nursing home experiment. The first three columns are excerpts from Exhibit 1 in Jones (1986). Column 4 translates total payments into current dollars. We divide by the Medicaid rate in the experiment environment and multiply by the average 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.

(as opposed to one week in our baseline analysis), which suggests that Medicaid patients have an average length of stay of 29.4 fortnights, which is already quite close to the average among 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 as well as the biweekly community discharge rate in the experiment. We match these moments perfectly when increasing the flow utility parameter of nursing home care from $u = 5$ to $u = 7.4$ and the exogenous discharge rate from 1.3% to 2.72%. 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—\$159 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.

Figure F.1: Discharge Effort by Bonus Payments



Source: .

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 0.61%. For comparison, Norton (1992) reports that the community discharge rate increases to 0.7% (Table 3 in Norton (1992)). This suggests that our model can account for (0.61-0.38)/(0.7-0.38)=72% of the actual increase in the home discharge rate.

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 excluded from the estimation sample but also affect overall occupancy. These include the 22% of nursing home stays, who were initially covered by Medicare, and an additional 22% of stays that were initially covered by Medicaid. 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 ϵ^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. ϵ^s_{arr}, in conjunction with the arrival process outlined in Figure 2c, determines the number of new arrivals. ϵ^s_{ϕ} and ϵ^s_{ρ} specify, in combination with ϕ and ρ in Table 4, the payer type composition of new and previously admitted residents. Finally, ϵ^s_{dis}, in combination with discharge probabilities by occupancy rate and payer type (Figure 8), 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 ϵ^s_{occ}. For instance, suppose we start out with 90 occupied beds at time s in the entire nursing home and that ϵ^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, ϵ^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 Δ^s_{ext}. In the counterfactual analysis in Figure 8, 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.