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Patient versus Provider Incentives in Long-Term Care†

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How do patient and provider incentives affect the provision of long-term care? Our analysis of 551,000 nursing home stays yields three main insights. First, due to limited cost-sharing, Medicaid-covered residents prolong their nursing home stays instead of transitioning to community-based care. Second, when facility capacity binds, nursing homes shorten Medicaid stays to admit more profitable out-of-pocket private payers. Third, providers react more elastically to financial incentives than patients. Thus, targeting provider incentives through alternative payment models, such as episode-based reimbursement, is more effective than increasing patient cost sharing in facilitating transitions to community-based care and generating long-term care savings. (*JEL* H51, H75, I11, I13, I18, I38, L84)

Long-term care (LTC) expenditures are high and rising. In 2021, the United States spent $181 billion on nursing home care and another $125 billion on home health care. By 2050, long-term care expenditures are projected to double to 3 percent of GDP (Martin et al. 2023; Congressional Budget Office 2013). Given this strong increase in projected spending, it is critical for public policy to align patient and provider incentives with social welfare objectives to ensure efficient use of LTC services. Because Medicaid covers more than half of all LTC expenditures in the United States, many state Medicaid programs expand cost-effective home and community-based alternatives (Ng et al. 2015; Peebles et al. 2017). Ongoing state experimentation demonstrates that transitioning institutionalized patients to community settings such

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as homes, apartments, or group homes is of high policy relevance (Libersky et al. 2015). This includes the Money Follows the Person Demonstration, funded by US$4 billion in federal monies, to support Medicaid in transitioning nursing home patients to the community where funds can "follow the person" to the setting of her choice.[1] Fostering options for community-based care typically also align with patient preferences (Kane and Kane 2001; Dixon et al. 2015).

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

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

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

This article investigates these discharge incentives using administrative microdata from the Minimum Data Set (MDS). We combine it with detailed Medicare and Medicaid claims data as well as survey data. Our database provides high-quality information on admissions, discharges, and health profiles for the universe of residents in Medicare and Medicaid approved nursing homes in California, New Jersey, Ohio, and Pennsylvania from 2000 to 2005. To identify our target population of interest, a machine learning (ML) algorithm identifies nursing home residents who could be integrated into community-based settings. As our empirical strategy exploits the

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

transition to Medicaid, we drop Medicare-covered stays and focus on residents who *all* pay the private rate at the beginning of their stays. This leaves us with about 551,000 skilled nursing facility (SNF) stays. Private LTC insurance coverage is low across all wealth levels (Braun, Kopecky, and Koreshkova 2019)—only 4 percent of total costs were covered by private policies at the time; see Congressional Budget Office (2004). Hence, residents effectively transition from paying the full private rate (set by the nursing home) to Medicaid coverage with little or no cost sharing.

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

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

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

Finally, we study patient and provider incentives in simulated policy counterfactuals. We find that increasing patient cost sharing to 100 percent, combined with a compensating lump-sum (voucher) transfer to patients, reduces the length of Medicaid stays by 20 percent but increases Medicaid spending by 5.5 percent. In contrast, policies targeting provider incentives can be effective in reducing the length of stay *and* spending, without lowering provider profits. For example, motivated by the Bundled Payments for Care Improvement (BPCI) initiative authorized by Centers for Medicare &

Medicaid Services (CMS), we find that disbursing 10 percent of Medicaid per diem reimbursements to an episode-based (up-front) reimbursement reduces the length of Medicaid stays by 17 percent and spending by 8.4 percent. However, we note the possibility of downsides to alternative payment models. Switching from inpatient to outpatient settings could disrupt patients' medical care, activities of daily living (ADL) support, and housing. It is beyond the scope of this paper to conduct a full welfare analysis.[2]

Our analysis contributes to the large literature on the relevance of financial incentives for health care utilization. Earlier studies have focused on patient incentives—see Aron-Dine, Einav, and Finkelstein (2013) for an overview—whereas a more recent literature has provided compelling evidence on the role of provider incentives. This includes important work on provider responses to the introduction of the Inpatient Prospective Payment System in 1983 (Cutler 1995; Cutler and Zeckhauser 2000) and on how physicians and dialysis clinics react to financial incentives (Clemens and Gottlieb 2014; Dickstein 2014; Ho and Pakes 2014; Grieco and McDevitt 2017; Einav et al. 2020; Eliason et al. 2020). Closely related to our analysis are Eliason et al. (2018) and Einav, Finkelstein, and Mahoney (2018), who show that changing Medicare reimbursement to a lump-sum payment induces providers to discharge patients from long-term care hospitals. We contribute to this literature in three ways. First, we investigate patient and provider incentives in one unified framework, while the existing literature has largely studied their roles in isolation; see McGuire (2011) for an overview.[3] Second, our counterfactual analysis assesses the scope for episode-based or bundled payment models in a policy-relevant and economically significant setting. We find that bundled payment models, one of Medicare's leading alternative payment models (Finkelstein et al. 2018), are effective in shortening Medicaid stays by aligning provider discharge incentives more closely with the cost of care to the Medicaid program. Third, we study provider incentives exploiting variation in occupancy, thereby providing new evidence on the link between long-term care use and provider capacity; see Freedman (2016), Kleiner (2019), and Hoe (2022) for similar approaches in US and UK acute care settings.

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

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

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

for nursing home care. As a distinct feature of our analysis, besides combining administrative data with novel identification strategies, it focuses on a specific and policy relevant margin: community discharges and the length of nursing home stays.

While the evidence on patient incentives in the LTC context remains mixed, there is an upswing in recent work on provider incentives. Ching, Hayashi, and Wang (2015) and Gandhi (2021) estimate models of SNF admission practices and find evidence of discrimination against Medicaid patients. Others study the role of ownership for nursing home quality (Grabowski et al. 2013; Jones, Propper, and Smith 2017; Gandhi, Song, and Upadrashta 2020; Gupta et al. 2021; Hackmann, Rojas, and Ziebarth 2024), the link between Medicaid rates, market structure, and SNF quality (Grabowski 2001; Lin 2015; Hackmann 2019), SNF responses to the Medicare 20-day payment rule (Werner et al. 2019), public reporting (Grabowski and Town 2011; Konetzka, Polsky, and Werner 2013), and Medicaid bed-hold policies (Intrator et al. 2007). We contribute to the LTC provider incentive literature by quantifying effects on the length of nursing home stays in a unified empirical framework. Further, we simulate counterfactual policies on alternative payment models, informing the debate on how Medicaid regulation may achieve cost savings.

I. Institutional Details

A *Medicaid Eligibility*

Medicaid covers about two-thirds of all nursing home days. About a quarter are funded privately. Medicare only covers postacute care and thus solely 10 percent of all days; see online Appendix Table A.1. Our analysis excludes Medicare-covered stays. Further, it excludes Medicaid-covered stays since admission, in order to exploit within-in stay variation in the *transition* to Medicaid.

Asset and Income Test.— To qualify for Medicaid, individuals' assets must fall below state-specific thresholds ranging between US$1,500 and US$4,000 in our sample period; see online Appendix Table A.1.[4] 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: nursing home residents who pass the asset test can deduct medical expenses, including SNF fees, from their incomes. Then they qualify for Medicaid if their *adjusted monthly income* falls below the

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

state-specific limits of, at the time, between 51 percent FPL (US$367) in New Jersey and 83 percent FPL (US$600) in California;[5] see online Appendix Table A.1.[6]

In practice, the asset test is typically key to establishing Medicaid eligibility for nursing home residents. In the Health and Retirement Study (HRS)—see RAND (2023a); RAND (2023b)—among seniors whose assets are below US$4,000, only 1 percent have income levels that would disqualify them for Medicaid under a Medically Needy program. As seniors age and spend down their assets, Medicaid coverage becomes widespread (Borella, De Nardi, and French 2018). Whereas income flows are typically very stable among nursing home residents (who rely mostly on social security payments; see online Appendix Table B.1), asset spend down is the primary factor in determining Medicaid coverage. Our identification strategy exploits such Medicaid transitions during nursing home stays.

ADL and Medical Needs.— For Medicaid to cover SNF stays, beneficiaries must have medical long-term care needs or functional limitations. States have different level-of-care criteria. Nurses or social workers evaluate patients' limitations in ADL. For example, they assess whether they require assistance for bathing, dressing, or eating (online Appendix Table A.1). In our sample, patients have about 12 ADLs; see Table 1.

B. *Patient Cost Sharing and Provider Reimbursement*

Patient Cost Sharing.— In our sample, everyone is a SNF resident and everyone pays the full private rate (set by the nursing home) initially. In Pennsylvania at the time, average private rates were US$170 per day or US$5,100 per month. According to the HRS, private payers had net financial assets of US$31,424 on average; see Hackmann and Pohl (2018). Consequently, nursing home residents who earn below the Medicaid income thresholds would typically spend down their assets and qualify for Medicaid within half a year after being admitted to a nursing home. Once residents transition to Medicaid, their out-of-pocket price for SNF care drops sharply. They contribute their income, net of an allowance of about US$30 per month, toward the cost of nursing home care ("share of cost"; see Pennsylvania Department of Human Services 2020). Medicaid then covers the difference between this "patient liability amount" and the Medicaid reimbursement rate. In the National Long Term Care Survey (NLTCS)—see Manton (2023)—Medicaid beneficiaries in SNFs have average monthly incomes of US$819 (online Appendix Table B.1), implying that monthly out-of-pocket prices drop by almost 90 percent from US$5,100 to US$819–$30=$789 as residents transition to Medicaid.

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

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

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

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

C. *Nursing Home Discharges*

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

Discharge Effort and Management.— Nursing homes regularly evaluate their residents’ health—for example, to determine community discharges. After having relied on around-the-clock care in SNFs, community transitions may pose substantial challenges: The management of medical conditions, support from family members or other informal caregivers, and needs-specific housing accommodations need to be arranged (Meador et al. 2011). This requires time, money, and planning

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

by patients, their relatives, and nursing homes prior to community discharges. We model such arrangements as costly discharge effort below.

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

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

II. Conceptual Framework

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

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

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

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

where $\tau = P, M$ denotes the payer type (private or Medicaid). Here, $\alpha \geq 0$ and $\beta \geq 0$ are scalars that capture the effect of financial incentives on nursing home discharges through nursing home's or patient's discharge efforts. If $\alpha = 0$, only the patient's financial incentives matter, whereas if $\beta = 0$, only the SNF's financial incentives matter. oc is the SNF's occupancy rate. We assume that residents do not

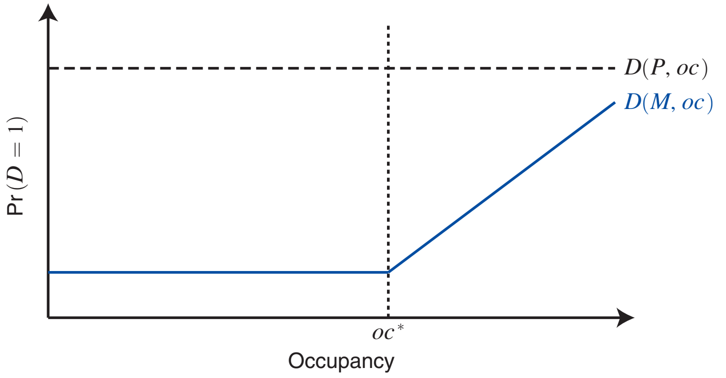

Figure 1. Predicted Discharge Profiles by Payer Type and across Occupancies

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

observe the weekly occupancy rate and do not condition their optimal effort on it. Finally, $\epsilon \sim F_\epsilon$ captures other discharge factors.

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

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

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

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

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

Online Appendix Section C formally derives this relationship. An important assumption, and one that we maintain throughout our analysis, is that the occupancy rate only affects discharge rates through providers' discharge efforts. This rules out the possibility that crowding may disproportionately affect the quality of care for Medicaid patients, which could then affect home discharges through patient health or effort. In robustness exercises, for example in online Appendix Figure E.7, we find no empirical evidence for such an operating channel.

III. Data

Our main dataset combines administrative microdata from the MDS with Medicaid and Medicare SNF claims data as well as nursing home characteristics from annual surveys. The MDS contains the universe of SNF residents for all Medicaid or Medicare-certified nursing homes, which account for 98 percent of all nursing homes. Online Appendix Section B provides further details on the various input datasets.

A. *Sample Construction and Selection*

As a first step, we merge the MDS with the claims data. These administrative claims data allow us to record payment sources and Medicaid transitions at the

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

weekly level. Next, we merge the weekly-stay data with facility information from the On-Line Survey, Certification, and Reporting system (OSCAR), accessed through Long-Term Care: Facts on Care in the US (2020). Via the number of licensed beds in OSCAR we calculate weekly occupancy rates.[9] Online Appendix Section B.3 provides more details on all data sources and how we measure occupancy rates or payer transitions.

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

B. *Machine Learning and Community Discharge Potential*

For some residents, discharges are extremely unlikely. Typically, these are residents with severe cognitive and physical disabilities and many ADLs who will stay in SNFs until death. Given our focus on marginal SNF residents who could potentially stay in the community or in a nursing home, we use an ML approach to identify and exclude patients with a very small probability of ever being discharged to the community. Similar to Einav, Finkelstein, and Mahoney (2019), we use a CART regression tree as our prediction algorithm, which is well-suited to capture the rich interactions between multiple disabilities and comorbidities that we observe in the MDS (Breiman 1984; Mullainathan and Spiess 2017; Athey and Imbens 2019). As predictors we use 174 demographic and health characteristics from the resident's initial SNF health assessment at admission. To mitigate concerns of overfitting, we choose a maximum tree depth of 10 and choose the complexity parameter that maximizes an out-of-sample R^2 via ten-fold cross-validation; see online Appendix Section D for more details. We exclude the ten percent of SNF stays with the smallest predicted probability of ever being discharged to the community.

C. *Summary Statistics*

Our final sample consists of 551,000 SNF stays and 13.3 million resident-week observations. Table 1 shows summary statistics, separately by payer type. The first column shows variable means for private payers, and the second column shows variable means for Medicaid beneficiaries. The upper panels shows descriptives on sociodemographics such as resident's age (84.3 versus 83.9 years), gender (70 percent versus 74 percent female), race (89 percent versus 85 percent white), or marital status (53 percent versus 56 percent widowed), while the lower panel shows a set of health measures taken at discharge. These include the Case Mix Index (1.1 versus 1.1), the number of ADL (12.0 versus 11.8), and the share of residents with

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

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

Table 1—Summary Statistics at Resident-Week Level

	Private		Medicaid	
	Mean	SD	Mean	SD
Panel A. Socio-demographics				
Age	84.2732	(7.7942)	83.9177	(7.8916)
Female	0.7030	(0.457)	0.7442	(0.4363)
White	0.89	(0.3129)	0.8484	(0.3586)
Black	0.0515	(0.2209)	0.0967	(0.2955)
Hispanic	0.0316	(0.1751)	0.031	(0.1734)
Married	0.2538	(0.4352)	0.2179	(0.4128)
Widowed	0.5334	(0.4989)	0.5556	(0.4969)
Divorced	0.0559	(0.2296)	0.0818	(0.274)
Panel B. Health measures				
Case mix index (CMI)	1.0971	(0.378)	1.0523	(0.3669)
Number of ADLs	12.0068	(4.2134)	11.778	(4.5409)
Clinically complex	0.5363	(0.4987)	0.467	(0.4989)
Depression	0.4651	(0.4988)	0.5285	(0.4992)
Weight loss	0.1188	(0.3235)	0.1017	(0.3022)
Impaired cognition	0.6083	(0.4881)	0.6407	(0.4798)
Behavioral problems	0.0831	(0.276)	0.0922	(0.2892)
Panel C. Occupancy rates				
Occupancy $\leq$ 85%	0.2135	(0.4098)	0.1982	(0.3987)
85% $<$ Occupancy $\leq$ 95%	0.4973	(0.5)	0.4902	(0.4999)
Occupancy $>$ 95%	0.2892	(0.4534)	0.3116	(0.4631)
Observations	7,330,679		5,994,994	

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

impaired cognition (61 percent versus 64 percent) or with behavioral problems (8.3 percent versus 9.2 percent). Private payers and Medicaid beneficiaries are thus not identical but relatively homogenous in terms of sociodemographics and health at discharge.

D. *Occupancy Rates*

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

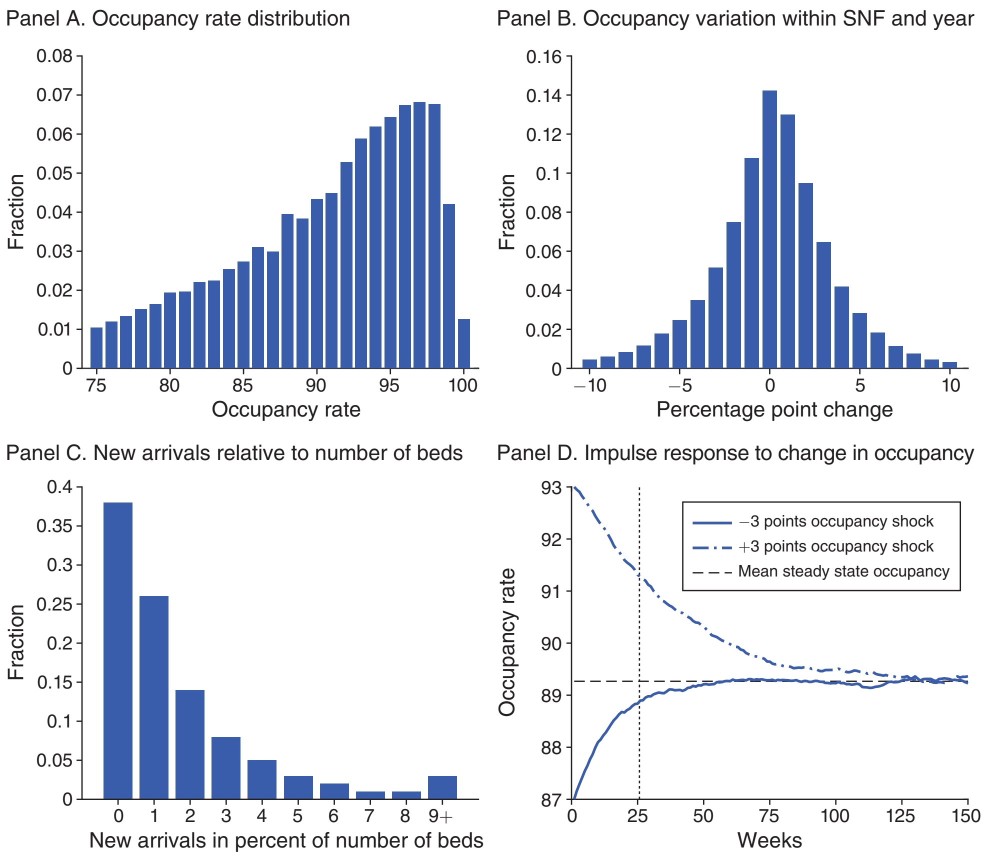

Figure 2. Variation in Occupancy Rates and New Arrivals by SNF and Week

Notes: The unit of observation for panels A, B, and C is the SNF-week level.Panel A shows variation in occupancy rates. Panel B shows the *residual* variation conditional on SNF-year fixed effects. Panel C summarizes the frequency of weekly arrivals, divided by the number of licensed beds. Panel D 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.

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

Figure 2, panel D displays the impulse-response function of occupancy rates to a 3 percentage point increase and decrease in occupancy relative to the sample average. Specifically, we construct an occupancy transition matrix from the data and simulate its profile over time. The response functions indicate that it takes 100 weeks (or two years) until the occupancy rate reaches its mean steady state again.

However, it takes only 25 to 30 weeks until half of the effect has dissipated. This roughly coincides with the average length of stay of 25.7 weeks in our sample, as indicated by the vertical line in Figure 2, panel D.

E. *Monthly CA Sample for Event Study*

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

Note that the "buyin" indicator records Medicaid coverage with a delay of about three months. This delay captures the difference between the date of *filing* the Medicaid application and the date of *approval*. The application date marks the (retrospectively set) onset of Medicaid coverage for SNF care. It is the recorded coverage start in the Medicaid claims data used in our fixed effects approach. By contrast, in our event study approach, depending on how long approval takes, the buyin measure that we use here records Medicaid coverage with a delay. This is because states have up to 90 days to review and process a Medicaid application for long-term care; further, it also takes time to compile the extensive paperwork (American Council on Aging 2019). To account for this time gap and to maintain a consistent measure of Medicaid coverage, we lead the buyin indicator by three months and indicate the three month period from -1 to $+2$ as a transition period in the event studies. Online Appendix Section B.4 illustrates and discusses this transition period. Otherwise, we maintain the same sample selection criteria as for the resident-week sample for the fixed effects approach; see Section IIIA. When aggregating the data at the monthly level and focusing on California, we obtain 1,158,557 patient-month observations; 20 percent of those are Medicaid-months after patients have transitioned, and a total of 76 percent of all patient-month observations stem from private payers that have not transitioned by the end of our observation period.

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

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

IV. Empirical Strategy

A. *Fixed Effects Approach*

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

$$(2) \qquad Y_{ijst} = \sum_{k=65}^{100} \gamma^k \times oc_{jt-1}^k + \sum_{k=65}^{100} \delta^k \times oc_{jt-1}^k \times Mcaid_{is} + \eta_s + \eta_{jy} + \eta_m + \mathbf{Z}_i'\alpha + \mathbf{X}_{it}'\beta + \epsilon_{ijst}.$$

Here, Y_{ijst} is an indicator equal to one if nursing home j discharges resident i to the community in week-of-stay s and calendar week t. oc_{jt-1}^k is an indicator that turns on if the (rounded) one-week lagged occupancy rate equals $k = 65, \ldots, 100$ percent in nursing home j in calendar week t–1. $Mcaid_{is}$ 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 $\gamma^k + \delta^k$. We interpret them 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 (η_m). Robust standard errors, ϵ_{ijst}, control for within-resident correlation. We also correct for administratively assessed and time-varying differences in the case mix index $(\mathbf{X}_{it})$ and time-invariant sociodemographics $(\mathbf{Z}_i)$; see Table 1.[14] We also estimate a "binned" version of equation (2). It replaces oc^k with three occupancy *group* indicators that turn on for occupancies (i) below or equal 85 percent, (ii) between 85 and 95 percent, and (iii) at or above 95 percent.

This first approach uses rich fixed effects along with administrative data, but does not exploit within-patient transitions to Medicaid. For that purpose, we employ an event study approach detailed below (and similar to Dobkin et al. (2018)). Combined and benchmarked against each other, the two approaches allow us to assess the relevance of possible time-invariant unobservables at the patient level. By exploiting within-patient variation and plotting lead and lag event study coefficients, we assess the plausibility of important identifying assumptions, possible anticipation effects, and control for sample composition effects. The fixed effects approach, by contrast, has the advantage to rely on the full sample and is closely linked to Figure 1 and the theory. Moreover, homogenizing our sample and focusing on elderly SNF residents, who *all* were initially private payers, further helps to minimize concerns that patient-level unobservables act as systematic confounding factors.

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

[14] $\mathbf{Z}_i$ includes the predicted length of stay (obtained by regressing length of stay on health at admission and predicting at the individual level).

B. *Event Study Approach*

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

$$Y_{ij\tau} = \sum_{\tau=-6}^{-2} \mu_\tau + \sum_{\tau=0}^{12} \mu_\tau + \mathbf{X}_{it}'\beta + \eta_{mos} + \eta_m + \eta_i + \eta_{jt} + \epsilon_{ijst}, \tag{3}$$

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

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

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

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

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

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

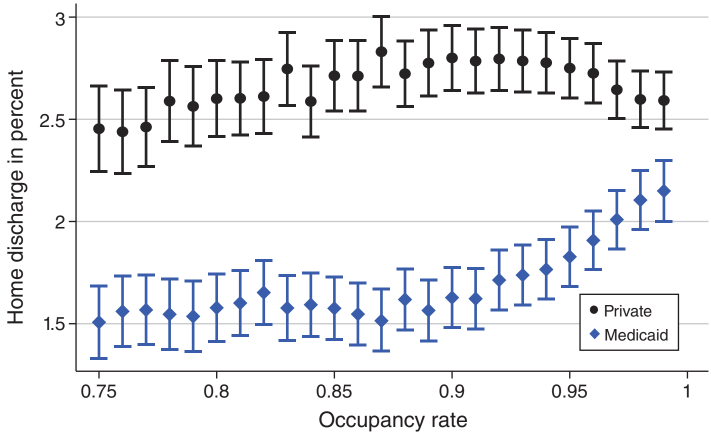

Figure 3. Home Discharge Rates by Payer Type and Occupancy Rate

Source: Long-Term Care Minimum Dataset, 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 percent confidence intervals. Figure 3 is the empirical analogue to Figure 1. We exclude estimates for 100 percent occupancy due to measurement error, which biases the point estimate toward the sample mean.

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

V. Empirical Results

A. *Results from Fixed Effects Approach*

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

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

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

	(1)	(2)	(3)	(4)
Medicaid × occupancy $\leq$ 85%	−0.0078	−0.0078	−0.0079	−0.0097
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Medicaid × occupancy $>$ 85% and $\leq$ 95%	−0.0092	−0.0093	−0.0094	−0.0109
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Medicaid × occupancy $>$ 95%	−0.0050	−0.0051	−0.0051	−0.0064
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Patient incentives:				
Medicaid × occupancy $\leq$ 85%	−0.0078	−0.0078	−0.0079	−0.0097
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Discharge rate private payers:	0.0272			
(at 85% $<$ occupancy $\leq$ 95%)				
Change in percent:	−28.7%	−28.7%	−29%	−35.7%
Provider incentives:				
(Medicaid ×occupancy $>$ 95%) −	0.0029	0.0027	0.0028	0.0033
(Medicaid × occupancy $\leq$ 85%)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Discharge rate private payers:	0.0272			
(At 85% $<$ occupancy $\leq$ 95%)				
Change in percent:	10.7%	9.9%	10.3%	12.1%
LOS-week FE	X	X	X	X
SNF-year FE		X	X	X
Month FE			X	X
Sociodem. controls				X
Observations	13,325,673	13,325,673	13,325,673	13,325,673
R^2	0.0575	0.0512	0.0512	0.0572

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

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

When relating the home discharge differential to the overall SNF discharge rate of private payers to any destination (5.9 percent at medium occupancy), a 0.97 ppt lower home discharge rate (column 4) translates into a 16 percent reduction in the overall discharge rate. Considering the almost 100 percent out-of-pocket price difference between private payers and Medicaid beneficiaries, we obtain a price elasticity of demand of 0.16, in line with the standard health care demand elasticity estimates (Aron-Dine, Einav, and Finkelstein 2013). We return to a more formal calculation in Section VI.

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

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

Relating the 0.33 ppt change in the home discharge differential to the overall discharge rate of 5.9 percent, we find a 6 percent higher discharge rate for Medicaid patients. However, provider reimbursement increases by only about 15–18 percent (Section IB) when substituting a Medicaid patient with a private payer, implying a provider elasticity of 6 percent/18 percent $=$ 0.33, about twice as large as the patient elasticity. However, note that this provider elasticity estimate is a lower bound because (i) not all newly arriving patients are private patients, (ii) about 10 percent of private patients transition to Medicaid before discharge, and (iii) it takes time to fill an empty bed, during which the nursing home forgoes Medicaid revenue.[16] We use the structural model in Section VI to quantify the role of these components. Indeed, we find a much larger provider elasticity of around 1.

Robustness.—Online Appendix Section B.3 shows robust results when we use an alternative occupancy measure from bed counts in California (online Appendix Figure B.3), and correct for idiosyncratic measurement error in OSCAR's bed count information using an IV approach; see online Appendix Table B.3.

Moreover, online Appendix Section E.3 uses unique pricing data at the SNF-year level from Pennsylvania and California to stratify the total discharge differentials by private rates and by the markup of private rates over Medicaid rates. Online Appendix Figure E.8a shows larger discharge differentials in facilities who charge higher private rates. Online Appendix Figure E.8b shows that, the larger the private rate mark-ups, the larger the probability that Medicaid beneficiaries get discharged when SNFs operate at capacity.

[16] For instance, only 78 percent of new arrivals are private payers (Table 4) and providers forgo two weeks of revenues over a 30 week stay (Figure E.13, considering a 50 percent weekly refill rate, and Table 5). Hence, the short-term increase in reimbursement is not (up to) 18% but rather $(30-2)/30 \times (1+0.78 \times 0.18) - 1 = 0.064 =$ 6.4 percent. Thus, considering these factors in the structural model, the actual elasticity is closer to 1.

Online Appendix Figure E.1 shows that discharge rates to other nursing homes (online Appendix Figure E1.b) but also patient mortality (online Appendix Figure E.1c) might be elevated when SNFs operate at capacity. We attribute the pattern in online Appendix Figure E.1c to potential compositional changes in the patient population. At higher occupancy, providers likely discharge healthier patients first. Online Appendix Section E.1 provides an in-depth analysis and extensive robustness tests. First, we investigate differences in time-varying patient health by payer type and occupancy. As observable patient health measures are quite balanced across the populations—see online Appendix Table D.2—the pattern remains robust when adding them as controls. Second, we document that changes in mortality are concentrated among patients with the lowest discharge potential as estimated by our ML approach (see online Appendix Section D); online Appendix Figure E.2 shows the results. Excluding those and rerunning the entire structural analysis leaves the patient and provider elasticities largely unchanged. Online Appendix E provides details.

Finally, note that our implicit assumption of SNFs providing equal quality of care independent of payer type represents federal and state law (see Section IB). If SNFs (illegally) provide lower quality of care to Medicaid patients, then Figure 3's discharge differential overstates the role of patient incentives. A more nuanced version of this concern is that providers may lower the (service) quality of care for Medicaid patients at higher occupancies; for example, they may spend less time with patients. While this could be interpreted as a form of provider discharge effort through the lens of our model, we find no evidence for differential changes in patient health at higher occupancy rates; see online Appendix Figure E.7. We return to this point in the next section.

B. *Results from Event Study Approach*

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

Patient Incentives.— We start with the low occupancy environment ($\leq$ 85 percent) where capacity constraints are not binding. Here, provider incentives are muted but patient incentives are at play. Figure 4 shows no evidence for anticipatory behavior during the pretransition period. This corroborates our research design and provides evidence against a model of a rational, fully forward-looking patient who would reduce her discharge efforts in anticipation of a future drop in out-of-pocket prices (Dalton, Gowrisankaran, and Town 2020). The point estimates are close to zero, and all confidence bands overlap with the zero line on the y-axis. We then

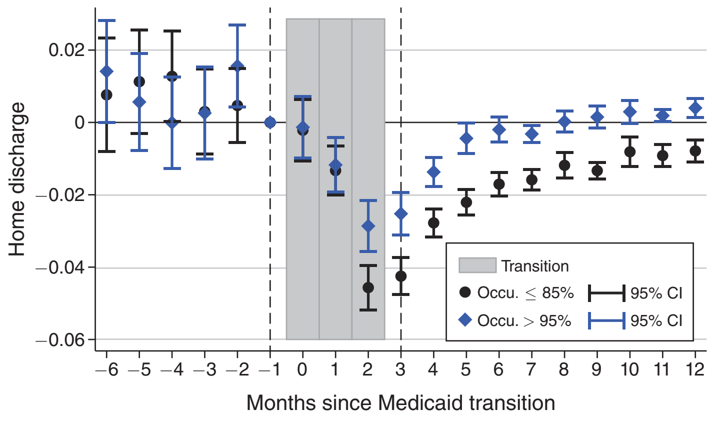

Figure 4. Event Study: Medicaid Transition at Low and High Occupancies

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

observe a gradual decline in discharge rates over the transition period, which we attribute to the timing of the Medicaid application and its approval. As shown, relative discharge rates then gradually increase again over the posttransition period. The pattern suggests that some patients (or their relatives) reduce discharge efforts for a few months, possibly to make outpatient care arrangements. For example, Medicaid coverage for HCBS care requires an additional application. Also, HCBS waitlisted applicants at the time (and still do today). The effect sizes remain negative and statistically significant throughout the posttransition period, indicating that patients reduce their discharge efforts as their out-of-pocket prices drop from the full private rate to near zero. Even at $\tau = +6$, in the low occupancy environment, discharge rates are about 2 ppt lower than before the transition, representing patient incentives at lower marginal prices.

Table 3 presents the DD analogue for Figure 4, binning occupancy environments into three categories: (i) below or equal 85 percent, (ii) between 85 and 95 percent, and (iii) at or above 95 percent. As above, each column in the upper panel represents a DD model where we add sets of control variables stepwise from columns 1 to 4. The model in column 3 mirrors our preferred model in Table 2, column 4. It shows an average posttransition decline in monthly discharge rates of 3.1 ppt or −23.9 percent due to patient incentives. The estimates are again robust to adding patient fixed effects, SNF-year, and month fixed effects (column 2) and sociodemographic controls (column 3) as well as the Gardner (2021) correction and using a two-stage DD model (column 4). Finally, note that the monthly coefficient estimates carry three to four times the effect sizes of the weekly estimates, as expected.

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

	(1)	(2)	(3)	(4)
Medicaid × occupancy $\leq$ 85%	−0.0369	−0.0422	−0.0312	−0.0292
	(0.0027)	(0.0026)	(0.0025)	(0.0011)
Medicaid × occupancy $>$ 85% and $\leq$ 95%	−0.0699	−0.0465	−0.0258	0.0066
	(0.0015)	(0.0017)	(0.0016)	(0.0004)
Medicaid × occupancy $>$ 95%	−0.0254	−0.0266	−0.0171	0.0086
	(0.0026)	(0.0024)	(0.0023)	(0.002)
Patient incentives:				
Medicaid × occupancy $\leq$ 85%	−0.0369	−0.0422	−0.0312	−0.0292
	(0.0027)	(0.0026)	(0.0025)	(0.0011)
Pre-transition discharge rate:	0.1306			
Change in percent:	−28.2%	−32.3%	−23.9%	−22.4%
Provider incentives:				
(Medicaid × occupancy $>$ 95%) −	0.0115	0.0156	0.0141	0.0379
(Medicaid × occupancy $\leq$ 85%)	(0.0036)	(0.0034)	(0.0033)	(0.0023)
Change in percent:	8.8%	11.9%	10.8%	29.0%
LOS-month FE	X	X	X	X
Patient FE		X	X	X
SNF-year control		X	X	X
Month FE		X	X	X
Sociodem. controls			X	
Gardner (2001) correction				X
Observations	1,158,557	1,158,557	1,158,557	1,158,557
R^2	0.0944	0.1277	0.1587	N/A

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

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

Robustness.—As discussed, one concern is that private payers may be on different asset spend-down schedules in inpatient and outpatient settings. Our calculations for California—also see Section VIIA—suggest a price tag for SNF care of US$5,400 per month, but only US$1,956 per month for community LTC settings (in 2005 dollars). To assess the robustness of our findings to differences in spend-down schedules, we rescale the time to Medicaid transitions. Specifically, we revisit the event study under a threefold faster spend-down rate in the community. Intuitively, if we observe a patient transitioning to Medicaid six months after discharge, we rescale that time to $6/3 = 2$ months. Online Appendix Figure E.5 shows qualitatively and quantitatively very similar results.

We also test for changes in patient health around the time of Medicaid transitions (online Appendix Figure E.7a to h). For this exercise, we use time-varying health measures. The purpose is twofold. First, it allows us to test if the Medicaid transition could be confounded by health shocks or may be a reaction to those. Second, it allows us to (imperfectly) test for health effects after Medicaid transitions in high and low occupancy environments. It also tests the key assumption that quality of care does not decrease after patients transition to Medicaid. In addition to our standard health measures (Table 1), pressure ulcers are a standard quality of care outcome measure. Online Appendix Figure E.7 shows no consistent pattern of more deterioration in quality for Medicaid patients overall or in high occupancy environments.

Finally, we revisit the responsiveness to financial incentives among Medicaid patients, who face cost sharing during the first days of a month. Plotting discharge probabilities by the day-of-the month shows clear bunching for Medicaid beneficiaries, but not for private payers (online Appendix Figure E.9). To map the bunching evidence into a patient elasticity, we estimate a stylized patient discharge model that captures (potential) forward-looking behavior by a discount factor. We find that a static model provides the best fit to the observed bunching behavior and estimate a patient elasticity of less than 0.2 across specifications; see online Appendix Section E.4.

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

VI. Structural Model of Discharges

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

A. *The Empirical Model*

Discharge Probabilities.—Consistent with our fixed effects empirical model, we start from the theoretical discharge equation (1) and assume that exogenous discharge factors ϵ are uniformly distributed. This allows us to express the discharge probability per period as

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

Here, D denotes any discharge, which includes endogenous community discharges (our focus) but also discharges to a hospital, a different nursing home, or death—all captured by $D^{other,\tau}$, which we assume to be exogenous to discharge efforts.[17]

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

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

where u is the resident's gross utility from a period of nursing home care relative to the gross utility of discharge, which we normalize to zero. The out-of-pocket price p^{τ} enters utility negatively and is scaled by the price coefficient κ, which is the marginal utility of income. 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

[17] Equation (5) assumes constant marginal effects of discharge efforts. A true relationship that is inherently nonlinear violates this assumption, and predicted discharge probabilities may exceed 100 percent when $D^{other,\tau}$ is large. In our setting, weekly discharge probabilities range between 3 and 8 percent, alleviating these concerns. While our model could be viewed as a linear approximation of a potentially nonlinear relationship between effort and discharges, we note that our counterfactual predictions will be biased if this exercise extrapolates a misspecified linear relationship out of sample.

SNF. To simplify, we set the utility from a discharge equal to the utility from a home discharge, η^{home}.[18] Residents choose the optimal discharge effort given by

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

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

Provider's Effort Choice.—The SNF observes the payer type and forms expectations over residents' optimal effort levels. By contrast, residents' taste shocks, η^{SNF} and η^{home}, and their discharge effort, e^{res}, are unobservable for the nursing home.[19] To derive the optimal provider effort, $e^{SNF,*}$, we impose that, during the period, providers choose e^{SNF} and realize the weekly flow payoff:

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

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

Discharges, arrivals, and Medicaid transitions are random events, realized at the *end* of the period. Arrivals and Medicaid transitions are exogenous. The weekly refill probability $\Phi(oc)$ and the per-period Medicaid transition probability ψ determines them. Discharges, by contrast, depend on endogenous discharge efforts; together with arrivals, they determine the occupancy rate in the other beds oc.

To simplify, we assume that discharge managers do not coordinate their discharge efforts between residents and do not internalize the effect of their "focal" discharge decision on the occupancy rate and discharges in other beds, which are both endogenous equilibrium objects. Instead, we assume that, in equilibrium, the discharge manager takes the time series process of the occupancy rate in other beds as given and chooses the discharge effort in the focal bed optimally. We model occupancy

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

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

rate transitions as a Markov process, which is characterized by a period-to-period transition matrix, Θ. This transition matrix denotes the conditional probability mass function over next week's occupancy rate, oc', conditional on today's occupancy rate, oc: $\Theta(oc, oc') = \Pr(oc' | oc)$.

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

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

where δ is a discount factor and

$$(9) \qquad E\left[V | 0, oc, e^{SNF}\right] = \sum_{oc'} \Theta(oc, oc') \times \Big\{ \left[1 - \Phi(oc')\right] \times V(0, oc') + \Phi(oc') \times \left[\rho V(P, oc') + (1 - \rho) V(M, oc')\right] \Big\},$$

$$(10) \quad E\left[V | M, oc, e^{SNF}\right] = \sum_{oc'} \Theta(oc, oc') \times \Big\{ \left[1 - \Pr\left(D = 1 | e^{SNF}, M\right)\right] \times V(M, oc') + \Pr\left(D = 1 | e^{SNF}, M\right) \times \left[\left(1 - \Phi(oc')\right) \times V(0, oc') + \Phi(oc') \times \left(\rho V(P, oc') + (1 - \rho) V(M, oc')\right)\right] \Big\},$$

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

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

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

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

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

Finally, we deliberately focus on a static model where patients react to spot prices. While the literature has provided evidence for both behavior consistent with rational forward-looking agents as well as myopic behavior focusing on spot prices (Aron-Dine et al. 2015; Einav, Finkelstein, and Schrimpf 2015; Brot-Goldberg et al. 2017; Dalton, Gowrisankaran, and Town 2020), our modeling choice is motivated by the empirical evidence and institutional context. Specifically, consistent with spot prices, we find no empirical evidence that vulnerable nursing home patients respond strategically in anticipation of their Medicaid transition. In additional robustness exercises exploiting cost-sharing variation among Medicaid patients, we also find that a myopic model of patient behavior provides the best fit for the observed timing of discharges; see online Appendix Section E.4. Turning to the institutional context, we note that our analysis focuses on a very old vulnerable population where two thirds have impaired cognition

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

Table 4—Structural Parameter Estimates

Panel A. Estimated outside model	
Refill probability Φ	See online Appendix Figure E.11.
Occupancy transition matrix Θ	Estimated from weekly sample.
Pr(transition to Medicaid) ψ	1.1%
Pr(private at admission) ρ	78.0%
Discharge rate to nonhome destinations, private $D^{other,P}$	3.19%
Discharge rate to nonhome destinations, Medicaid $D^{other,M}$	1.46%
Daily private rate $r^P/7$	\$258
Daily Medicaid rate $r^M/7$	\$214
Panel B. Calibrated	
Discount factor δ	$0.95^{\frac{1}{52}}$
Cost of effort $c(e)$	e^2
Utility SNF care per day u	0.5
Panel C. Estimated inside model	
SNF effort α	0.021
	[0.020, 0.026]
Resident effort β	0.177
	[0.174, 0.184]
Resident price κ	0.030
	[0.027, 0.035]
Daily marginal cost of care $mc/7$	111.4
	[111.1, 121.8]
SNF elasticity ϵ^{SNF}	1.2
Resident elasticity ϵ^{res}	0.2

Notes: Panel A summarizes the parameters that we estimate outside of the model. The discharge rates to nonhome destinations denote the sample average weekly discharge rate to other (nonhome) destinations by payer type. Panel B summarizes the calibrated parameters. Panel C summarizes the parameters that we estimate inside the model along with their 95 percent bootstrap confidence intervals. The estimated private and Medicaid rates as well as the marginal costs are presented as daily rates (per patient and day) to facilitate the interpretation. We conduct inference via bootstrapping. All estimates are for the full sample. See main text for details.

and more than half have depression. On average, residents are in their 80s with a short and highly uncertain life expectancy (online Appendix Table D.2).

B. *Estimation Strategy*

Parameters Estimated outside the Model.— Panel A of Table 4 lists parameters estimated outside of the structural model. A period is one week. We then estimate the weekly refill probabilities Φ—see online Appendix Section E.5—and use the empirical week-to-week occupancy transition matrix $\Theta(oc, oc')$ for estimation.[21] We estimate payer type transitions from private to Medicaid from observed week-to-week changes (in 1.1 percent). We estimate that 78 percent of newly admitted residents initially pay out-of-pocket after excluding Medicare beneficiaries. To calculate

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

$D^{other,\tau}$, we measure the average discharge rate by payer type to any nonhome destinations by payer type by summing over the various discharge destinations in online Appendix Figure E.1. Finally, the out-of-pocket rate and the Medicaid reimbursement rate correspond to the average rates in Pennsylvania and California in the sample period. We convert these rates to 2022 dollars using the consumer price index.

Calibrated Parameters.—Panel B of Table 4 lists all calibrated parameters. Note that we require a scale normalization on either the cost of effort or the effects of patient effort on discharge, β, as we cannot separately identify them from the observable relationship between out-of-pocket prices p^P and discharge rates. In the baseline analysis, we assume $c(e) = e^2$; see online Appendix Section C.3 for more details. Finally, we normalize the utility from nursing home care (0.5 per day) as we can only identify utility up to scale. This is because utility affects discharges through effort, which is again scaled by the factor β.

Parameters Estimated within the Model.—As key structural parameters, we estimate the daily marginal cost of nursing home care per resident, *mc*, the price coefficient, κ, and the effort parameters α and β. We estimate the parameters using a nested fixed point procedure and conduct inference via bootstrapping; see online Appendix Section C.3. To estimate the parameters, we match the model predictions to the empirical discharge profiles in Figure 3. Specifically, we estimate $\theta = (\alpha, \beta, \kappa, mc)$ by minimizing the sum of squared differences between discharge rates predicted by the model, $D_{\tau,oc}(\theta)$ and observed home discharge rates $\hat{D}_{\tau,oc}$:

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

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

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

[22] Online Appendix Section C.1 provides more discussion on the identification of β and κ.

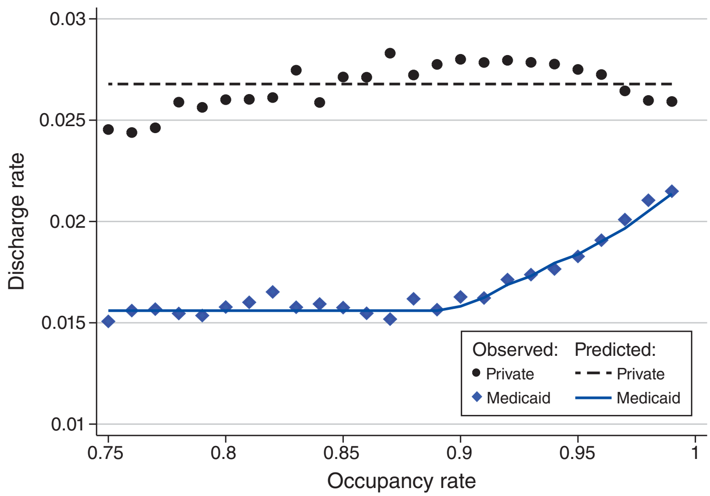

Figure 5. Observed Discharge Pattern and Model Fit

Notes: The figures show the estimated home discharge rates for private payers and Medicaid beneficiaries from Figure 3, denoted by dots (private) and diamonds (Medicaid), along with the corresponding model predictions captured by the dashed line (private) and the solid line (Medicaid).

C. *Results*

First of all, the model provides a very good fit to the observed community discharge rates in Figure 5. Panel C of Table 4 lists the estimated model parameters. Patients dislike paying higher out-of-pocket prices, $\hat{\kappa} > 0$. Both discharge effort parameters are positive, $\hat{\alpha} > 0$ and $\hat{\beta} > 0$, implying that provider and resident discharge efforts increase the discharge probability. Finally, we estimate a marginal cost of US$111 per day, which is considerably smaller than the marginal cost estimate of US$212 in Hackmann (2019) (in 2022 dollars). The main reason for the cost difference is likely the different time horizons between the two settings. Hackmann (2019) studies the optimal pricing and nurse staffing decisions over the course of a *full* calendar year. Our setting explores high-frequency variation in occupancy rates on a week-to-week basis. While nursing homes can employ some staff on a short-term notice, due to contracts, labor market rigidities, and shortages, SNFs cannot easily adjust most labor input in response to short-term fluctuations in the patient composition. For these reasons, we expect lower marginal (variable) costs in our setting.

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

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

VII. Policy Implications

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

Using data on individuals aged 80 and older from the Medical Expenditure Survey (MEPS)—see AHRQ (2022)—and the Consumer Expenditure Survey (CEX)—see BLS (2023)—we find mean annual expenditures of US\$1,741 for formal home health care (provided by professional caregivers) and of US\$22,061 for all other medical care and cost of living expenditures including housing and food (all in 2022 dollars). Adding the opportunity costs of informal care provided by family members to these expenses (Skira 2015; Barczyk and Kredler 2018), we obtain $\$1{,}741 + \$22{,}061 + \$11{,}784 = \$35{,}592$ per year or \$98 per person and day. This is considerably lower than the daily Medicaid rate of US\$214 used in our model. Hence, Medicaid spending could be lowered by $(\$214 - \$98) \times 7$ days $\times\, \Delta^{weeks} = \$812 \times \Delta^{weeks}$ if the resident's nursing home stay was shortened by Δ^{weeks} weeks.

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

B. *Policy Counterfactuals*

Building on the estimated model, we evaluate three policy counterfactuals that change the discharge incentives for patients and providers. When simulating their effects on the length of stay and Medicaid spending, we account for endogenous changes in occupancy rates, which in turn affect provider discharge efforts.[24] In the counterfactual simulations, we add an outer loop to the optimization problem that searches for a fixed point in the discharge profiles; see online Appendix Section G for details.

Voucher Program.—Our first policy is a voucher program that requires Medicaid beneficiaries to pay the full private rate out-of-pocket. The program compensates Medicaid beneficiaries for their expected outlays through a lump-sum transfer, which equals the expected length of stay, 24.2 weeks, times the weekly private rate of US$1,806. This amounts to a lump-sum of US$43,723 per Medicaid stay.[25] The program affects resident and provider incentives in opposite directions. Medicaid beneficiaries have an incentive to shorten their stays. Providers are indifferent between private and Medicaid residents as they generate identical weekly profits. Therefore, nursing homes will minimize their discharge effort for Medicaid beneficiaries.

Figure 6, panel A shows that private payers and Medicaid beneficiaries have the same community discharge rate profile under the voucher program. As indicated in the Table 5, column 2, Medicaid beneficiaries' length of stay would decrease by 6.1 weeks, which reduces occupancy to 86.4 percent. Medicaid saves the baseline 30.3 weeks of Medicaid reimbursement worth \$1,498 each or $\$1{,}498 \times 30.3 = \$45{,}434$ in total, but provides transfers (to beneficiaries) worth \$43,723 under this policy. The costs for the additional 6.1 weeks spent in the community are 6.1 weeks $\times$ 7 days $\times\ \$98 = \$4{,}198$ per reduced Medicaid stay. Hence, overall expenditures increase by $\$43{,}723 + \$4{,}198 - \$45{,}434 = \$2{,}487$ per Medicaid stay, or about $\$2{,}487/\$45{,}434 = 5.5$ percent.[26]

Discharge Bonus.—Motivated by the randomized discharge experiment of Norton (1992), our second policy considers a bonus payment counterfactual. It rewards nursing homes for successful community discharges, independent of the

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

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

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

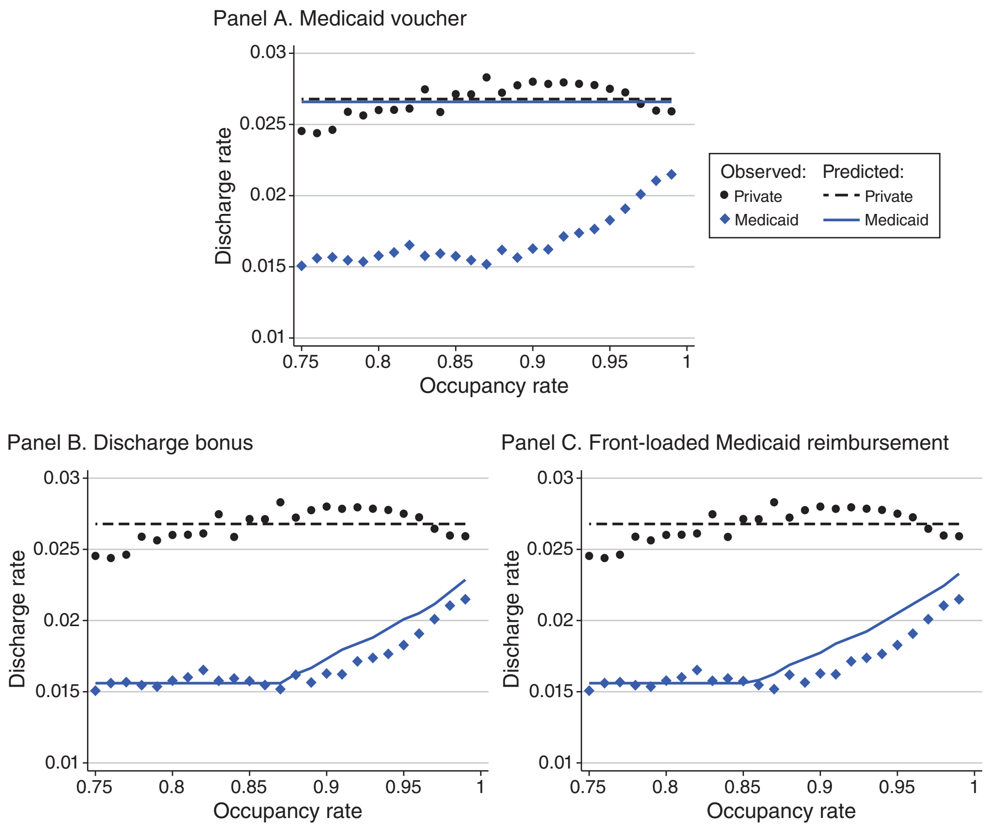

Figure 6. Simulated Discharge Rates under Different Policies

Notes: The figures show the estimated home discharge rates for private payers and Medicaid beneficiaries from Figure 3, denoted by dots (private) and diamonds (Medicaid), along with the corresponding model predictions captured by the dashed line (private) and the solid line (Medicaid). Panel B shows model predictions under a voucher policy. The home discharge rates predicted by the model are identical between private and Medicaid patients in this counterfactual. The solid Medicaid is denoted slightly below the dashed prediction line for private payers for expositional reasons. Panel B presents the model predictions under a provider bonus payment for community discharges within 30 days. Panel C shows model predictions under prospective front-loaded Medicaid payments where we reduce the Medicaid rate by 2 percent and compensate providers by an up-front payment as described in the text.

underlying patient or provider effort.[27] Figure 6, panel B shows an increase in provider efforts at high occupancies. This reduces the length of stay by 0.4 weeks, which reduces Medicaid spending by $0.4 \times 7 \times (\$214 - \$98) = \$357$ per stay (Table 5). Considering that Medicaid would pay nursing homes the bonus of US\$986 for 38 percent of all stays (that end in a community discharge), suggests only a very small cost increase of $0.38 \times \$986 - \$357 = \$17$ per stay, 1.7 percent of the bonus amount or 0.04 percent of Medicaid spending per stay.

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

Table 5—Simulated Length of Stay and Cost Savings under Policy Counterfactuals

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

Note: 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.

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 percent but compensate providers for the forgone Medicaid revenues with an up-front payment. Specifically, the provider receives an up-front compensation of 2 percent of the expected baseline Medicaid revenues per stay (2 percent $\times$ 30.3 $\times$ 7 $\times$ \$214) whenever a new Medicaid beneficiary arrives or a private payer transitions into Medicaid.[28] 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). We also note that provider profits must weakly increase in this counterfactual as they can always maintain their baseline discharge efforts leaving revenues, costs, and hence profits unchanged.

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

C. *Discussion*

We find that targeting provider incentives is more cost effective than increasing patient cost sharing in shortening the length of Medicaid SNF stays. However, note that this paper does not explicitly quantify patient welfare. While targeting provider incentives maintains financial risk protection for patients, a comprehensive assessment of patient welfare would require a quantification of the causal effects on patient health and well-being. Such an analysis is beyond the scope of this paper

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

and inherently difficult to carry out, even with high-quality administrative data. For example, to label incremental use of LTC as "waste," in our view, researchers require time-varying and high-quality comprehensive physical and mental health care measures as well as quality-of-life measures. However, especially the latter are usually based on self-reports and inherently difficult to collect among very old LTC patients with cognitive challenges. Nevertheless, several pieces of evidence mitigate concerns over the potentially detrimental health effects from earlier SNF discharges under alternative payment models.

First, only 4 percent of Medicaid community discharges are readmitted to a nursing home within 30 days, consistent with the literature (Mor et al. 2007a) and the policy goal of promoting community-based care over institutional care. Second, patients who are discharged at high occupancy rates, triggered by provider incentives, have an identical readmission rate than patients discharged at low occupancy rates.[29] Third, pairing bonus payments inversely to the readmission rate and requiring explicit discharge protocols are likely useful measures to further improve discharge outcomes (cf. Jones 1986). Finally, in complementary analyses, we find no evidence that shorter nursing home stays (on the margin) lead to increases in hospitalization or mortality rates or a worse health at discharge; see online Appendix Section D.4. in Hackmann and Pohl (2018).

VIII. Conclusion

We develop an empirical framework to separate the effects of patient and provider incentives on nursing home discharges to the community. Using administrative claims data on half a million nursing home stays in the United States, we find that providers respond significantly more elastically to financial incentives than patients. We estimate a patient elasticity of 0.2, consistent with the literature, and a provider elasticity of around 1.

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

Our findings inform future policies on how to contain long-term care spending. Given its large and growing fiscal consequences, containing LTC spending is of high policy relevance to state Medicaid programs. Hence, states continue to experiment with a variety of Medicaid waiver programs to contain spending, illustrating how little is known on how to best align patient and provider incentives with the costs of long term care to the Medicaid program. Currently, the 52 state-level Medicaid

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

systems provide the only permanent public insurance coverage for long-term care in the United States, resulting in a patchwork of policy proposals without systematic randomization and evaluation (Finkelstein 2020). One possible pathway to harness cost savings would be through the growing number of Medicaid managed care organizations that contract providers on behalf of state agencies and Medicaid beneficiaries (Graham et al. 2018; Medicaid and CHIP Payment and Access Commission 2022). Our findings suggests that targeting provider incentives through alternative payment models may be more effective than targeting patient incentives in promoting community discharges.

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