Provider payment incentives: evidence from the U.S. hospice industry

Norma B. Coe[a] and David A. Rosenkranz[b]

December 24, 2024

(an updated version may be available here)

Abstract. Capping health care providers' average revenue can reduce allocative inefficiency under capitation. But its potential cost-savings may be undercut by health care providers who churn their patient censuses. We investigate this possibility in the U.S. hospice industry, where Medicare pays hospice programs fixed daily rates but caps their average annual revenue. By leveraging variation generated by the cap's nonlinear design and the transition between fiscal years, we find that programs on track to exceed the cap raise enrollment rates by 5.8% and live discharge rates by 4.3% in the fourth quarter, reducing financial penalties—but far from eliminating them. Marginal enrollees have longer average remaining lifetimes and more fragmented hospice spells, suggesting weaker intrinsic demand for hospice care. We discuss the cap's implications for market structure.

Keywords: Capitation; provider-induced demand; gaming; non-linear program design; Medicare; hospice

JEL No.: I0, I1, I11, I18

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[a] Perelman School of Medicine at the University of Pennsylvania, 423 Guardian Drive, Blockley Hall, Philadelphia, PA 19104, USA. Email: nbcoe@pennmedicine.upenn.edu. Declarations of interest: none.

[b] Corresponding author. Department of Economics at Fordham University, 441 E Fordham Road, Dealy Hall, Bronx, NY 10458, USA. Email: drosenkranz@fordham.edu. Declarations of interest: none.

1 Introduction

Concerns about high and rising health care costs have driven policymaking for decades. Inefficient health care spending can arise from asymmetric information and moral hazard, but well designed payment models can correct these market failures by shifting unnecessary costs onto providers (Ellis and McGuire 1986; Arrow 1963). For instance, under capitation, providers are paid fixed fees per unit of time (Friedberg et al. 2015). They therefore bear the marginal cost of care intensity and may lower costs by eliminating productive inefficiencies. But if they also treat patients longer than necessary, then capitation may nevertheless raise costs by creating new allocative inefficiencies. Can payers cut costs by controlling both productive and allocative inefficiencies simultaneously?

We investigate this question in the U.S. hospice industry, where hospice programs provide palliative care for terminally ill individuals and Medicare aims to reduce spending by combining capitation with a cap on their average annual revenue. The cap creates a maximum regulated revenue (MRR) for hospice programs given their patient volume. In theory, it can cut costs arising from unnecessarily long hospice stays because excess revenue is a cap liability that must be repaid. We show that hospice programs can undercut the cap by churning patients: a discharge can reduce revenue and an enrollment can increase the MRR by tens of thousands of dollars. Since enrollments can reduce cap liabilities, the cap may increase—not decrease—Medicare hospice spending. It also creates a unique opportunity to study provider-induced demand for end-of-life (EOL) care.

We identify churning in 20 years of hospice claims data using variation generated by the cap's nonlinear design and the transition between fiscal years. First, we observe that hospice programs on track to exceed the cap have a financial incentive to churn patients that other programs do not. Second, we observe that this incentive decreases sharply during the transition between fiscal years because cap liabilities are determined annually. We combine these observations in a difference-in-differences (DID) design that compares hospice programs on track to exceed the cap to otherwise similar programs not on track to exceed the cap during the transition between fiscal years.

We find that hospice programs on track to exceed the cap in a given fiscal year raise enrollment rates by 5.8% and live discharge rates by 4.3% on average in the fiscal year's fourth quarter. The temporal findings are telling: we find that their weekly enrollment rates differentially increase throughout the last quarter of the outgoing fiscal year before suddenly differentially decreasing by

13.9% on average in the first week of the next fiscal year. But the magnitude of this churning is small. It amounts to an additional 1.54 enrollments and 0.37 live discharges per program-year, or $30,000-$50,00 lower cap liabilities at most for an average hospice program. By contrast, we find that the 11% of program-years that exceeded the cap repaid $500,000 on average (or 21% of their gross Medicare revenue). We also find that the marginal enrollees are less likely to have been recently hospitalized or ultimately die in hospice care, suggesting that the cap causes programs to move down the demand curve and enroll patients with a lower intrinsic demand for hospice care.

Our design overcomes two identification problems that arise in within-program or between-program comparisons alone. First, programs that exceed the cap differ from others in several ways. For instance, consistent with existing evidence, we find that they are more likely to be newer, smaller, for-profit, and near one another. They also treat patients with higher lifetime lengths-of-stay in hospice care (LLOS), higher rates of Alzheimer's disease and related dementia (ADRD), and lower rates of cancer. Second, there is seasonality in hospice utilization. For instance, we find that enrollment rates are higher on average during the winter and lower on average during holidays. Our DID analysis overcomes these identification problems by comparing outcome trends during the transition between fiscal years among programs on track to be above versus below the cap.

Our findings contribute to three strands of literature in economics and health policy. First, there is a large literature studying cost containment policies, such as deductibles (e.g., Brot-Goldberg et al. 2017), prospective payments (e.g., Grabowski et al. 2011; Meltzer et al. 2002; Pauly 2000), and certificate-of-need programs (e.g., Rosenkranz 2024; Polsky et al. 2014), among others (e.g., Alexander 2020; Park et al. 2017; Ho and Pakes 2014). Relative to a patient-level revenue cap, an average revenue cap does not penalize providers for occasionally treating patients with unexpectedly long stays. However, it creates a purely financial mechanism for one patient's care to affect another's. We measure the extent of this externality in hospice, where studies have shown that live discharge can be a costly disruption to care continuity (e.g., Dolin et al. 2017). Our findings suggest that despite creating an opportunity for churning—which providers exercised to some extent—an average revenue cap can reduce Medicare spending in the market subject to the cap.[1]

Second, several studies examine how providers respond to financial incentives, such as those

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[1] Other studies have shown that hospice care can lower health care spending in other markets, in part because it is a substitute for curative care (e.g., Gruber et al. 2023; Zuckerman et al. 2015; Kelley et al. 2013). We take Medicare's goal to cap spending on hospice care as given and investigate how hospice programs have responded.

generated by reimbursement rates (e.g., Alexander and Schnell 2024; Clemens and Gottlieb 2014), bundling (e.g., Eliason et al. 2022; Einav et al. 2022), pay-for-performance programs (e.g., Gupta 2021; Eliason et al. 2018; Einav et al. 2018; Norton et al. 2018), and other factors (Chandra et al. 2012). Several studies have documented how insurers and providers may sometimes "game" payment systems to maximize profit (e.g., Gupta et al. 2024; Decarolis 2015; Dafny 2005) Outside health economics, Liebman and Mahoney (2017) found that expiring federal budgets are associated with higher year-end government spending. Similarly, we find that an annual revenue cap causes hospice programs to churn patients near the end of the fiscal year. But our findings suggest that their scope for inducing demand may be smaller than policymakers had feared. We hypothesize that programs are limited by non-pecuniary features of the Medicare hospice benefit, including that a non-hospice provider must certify that a prospective enrollee's life expectancy is 6 months or less and that hospice enrollees forgo Medicare coverage for their terminal illnesses.

Third, several studies describe the economics of the U.S. hospice industry and the cap. There is a positive correlation between cap liabilities and live discharge rates (e.g., Dolin et al. 2018; Plotzke et al. 2015; Teno et al. 2014), and surveys and press reports have identified instances where staff felt pressured to "pad the roster with new patients" or discharge patients with "overly long stays" (Kofman 2022; Jenkins et al. 2011; Sack 2007). But to date, it is unclear how widespread these practices are or whether the correlations are attributable to the cap versus other differences between hospice programs. We use the universe of Medicare hospice claims and a novel identification strategy to show that the cap causes hospice programs to raise both enrollment and live discharge rates, and to describe the marginally enrolled and live discharged populations and their outcomes.

Finally, the Medicare Payment Advisory Commission (MedPAC) recently proposed reducing the cap and pegging it to geographic variation in payment rates (MedPAC 2020). We find no evidence of bunching in the distribution of average annual revenue and a positive association between cap liabilities and the geographic component of payment rates, suggesting that MedPAC's proposal could further reduce Medicare hospice spending and "mak[e] the cap more equitable across providers" (MedPAC 2020). However, we also find a positive association between cap liabilities and exit, raising questions about the cap's effect on market structure and quality (Ata et al. 2012).

Our work is related to Gruber et al. (2023), who measure the association between a hospice program's predicted probability of exceeding the cap (cap risk) in the fiscal year of a given month m

and the probability that a patient enrolled there in month m is live discharged within twelve months. Their regression analysis resembles a two-way fixed effects (TWFE) DID regression comparing live discharge trends between programs that experience larger versus smaller increases in cap risk within a fiscal year. However, causal inference is complicated by the possibility that live discharge may both affect and be affected by cap risk. By contrast, we identify cap-induced live discharges using the transition between fiscal years, when programs on track to exceed the cap in an outgoing fiscal year experience a sharp change in their cap-induced financial incentives. We also study the cap's effect on other outcomes (e.g., enrollment) and its relationship to reimbursement rates and exit, whereas they separately study the effect of hospice care on total health care spending.

The remainder of this paper proceeds as follows. In section 2, we describe this study's economic and policy context. In section 3, we describe the cap-induced financial incentives. In section 4, we describe our data. In section 5, we report descriptive statistics. In section 6, we present our DID analysis. In section 7, we conclude.

2 Context

2.1 Hospice care and the U.S. hospice industry

Hospice care is a bundle of EOL health care services available to all terminally ill Medicare beneficiaries with a predicted life expectancy of six months or less. Its purpose is to improve a person's quality-of-life with pain and symptom relief, and keep them home with family and friends rather than an inpatient care setting. It often includes select medical services, homemaker services, and grief counseling. Medicare beneficiaries who enroll in hospice care forgo Medicare coverage for all other services related to their terminal illness for the duration of their hospice enrollment, including curative care.[2] Live discharge from hospice care may occur if the enrollee's condition improves or they choose to resume curative care. When available, a non-hospice physician involved in the beneficiary's care must be consulted in care transitions, including to certify that the beneficiary's life expectancy is six months or less before enrollment (42 CFR 418.22-26). In 2019, 52% of Medicare decedents received hospice care and Medicare spent $20.9 billion on hospice (MedPAC 2022).

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[2]Medicare Benefit Policy Manual Chapter 9.

Hospice programs are organizations of physicians, nurses, and home health aides (HHAs). There were 5,058 Medicare-certified programs in 2020 (MedPAC 2022). Most were freestanding or based in a home health agency (91%), and the remainder were hospital-based (8%) or skilled nursing facility-based (<1%). The number of programs has more than doubled since 2001, due largely to an increase in the number of for-profit hospice programs from 765 in 2001 to 3,680 in 2020 (MedPAC 2010). Stevenson et al. (2015) documented that many for-profit hospice programs belong to national chains such as Vitas Healthcare, Gentiva Health Services, and Heartland Hospice, and the five largest chains served a combined 15% of patients. The number of private equity-owned hospice programs has also grown from 106 in 2011 to 409 in 2019 (Braun et al. 2021).

Hospice programs vary in size and scope. In the sample of Medicare claims we describe below, we find that hospice programs' annual patient volumes ranged from 28 patients (10th percentile), to 166 patients (50th percentile), or to 830 patients or more (90th percentile) in fiscal year 2018. The largest hospice program in the country was Vitas Healthcare Corporation of Florida, which treated nearly 30,000 patients that year. And while virtually all hospice care occurs in a patient's residence, some hospice programs operate or contract with inpatient care facilities to provide short-term respite care or acute symptom management. We find that approximately 79% of hospice programs provided at least one day of inpatient hospice care in fiscal year 2018. Likewise, some hospice programs have affiliations with nursing homes to treat some patients in those settings (Stevenson et al. 2018). Patient characteristics—including health status—can vary considerably between programs (e.g., Rosenkranz et al. 2024; Furuno et al. 2020; Dalton and Bradford 2019; Gandhi 2012).

Care quality is an important determinant of patient welfare in hospice. But measurement is complicated by the fact that hospice enrollees' health can deteriorate quickly after hospice enrollment: the median length-of-stay in hospice care was just 18 days in 2020 (MedPAC 2022). Existing evidence on hospice quality often relies on survey-based measures, such as surviving family members' perceptions (e.g., Harrison et al. 2022; Anhang Price et al. 2015; Teno et al. 2011). In 2022, the Centers for Medicare and Medicaid Services (CMS) began reporting the Hospice Care Index (HCI), a composite measure of hospice quality based on hospice claims data, including records of skilled nursing visits and burdensome transitions, which are defined as live discharges from hospice care followed by hospital stays (e.g., CMS 2024; Plotzke et al. 2022). Hospice care is associated with higher quality of care, fewer unmet needs, and fewer hospitalizations at end-of-life (e.g., Gruber et

al. 2023; Zuckerman et al. 2015; Kelley, et al. 2013; Teno et al. 2011).

2.2   Reimbursement rates and the cap

Medicare pays hospice programs a flat rate for each patient-day. The rate is determined by a base payment and a wage index adjustment. The base payment primarily depends on the patient's level of hospice care.[3] There are four levels of hospice care: routine home care (RHC), continuous home care (CHC), inpatient respite care (IRC), and general inpatient care (GIC).[4] Base payments for GIC and CHC are approximately 4-6x higher than base payments for RHC and IRC. However, virtually all patient-days are associated with RHC (98%). Since 2016, base payments have also been higher for each patient's first 60 days in hospice care. The base payment for RHC varied from $102 in 2001 to $193 (during the first 60 days) and $151 (after the first 60 days) in 2018.

The base payment is adjusted to account for geographic variation in health care labor costs. In particular, a portion of the base payment is multiplied by a so-called "wage index" (WI) that varies between core-based statistical areas (CBSAs) and is updated annually. On average in 2018, programs operating below the 10th percentile of the WI earned $141 per patient-day and programs operating above the 90th percentile of the WI earned $206 per patient-day.

After paying hospice programs a flat rate per patient-day, Medicare limits their average annual revenue with a so-called "aggregate payment cap." The cap was originally $6,500, or 40% of average Medicare expenditures for cancer patients in their last six months of life. It was $32,487 by 2023, meaning that a hospice program that served 100 patients that year could have received no more than $3,248,700 from Medicare.[5] Any excess revenue is a cap liability that must be repaid at the end of each fiscal year.[6] In practice, audits conducted by the Office of Inspector General (OIG) suggest that CMS recovers 73-80% of each year's cap liabilities within a few years. But these audits and some press reports also suggest that cap liabilities linked to closed programs are unlikely to be

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[3]Since 2014, CMS has reduced base payment rates by 2% for hospice programs that have not complied with certain quality reporting requirements (Federal Register, vol. 80(151): 47207).

[4]RHC is intended for patients who are "generally stable;" IRC is "temporary care provided [...] so that the patient's caregiver can take some time off;" and both CHC and GIC are "crisis-like level[s] of care for short-term management of out of control patient pain[.]" See "Hospice levels of care" available at medicare.gov.

[5]The cap is approximately 180 days times the base daily payment rate for RHC. See Federal Register, vol. 48(163): 38156-7, Federal Register, vol. 80(151): 47147, and CMS Transmittal 11542, dated August 4, 2022.

[6]It is treated as a debt owed to the federal government and accrues interest. It may be forwarded to the Treasury Department for debt collection. See 42 CFR 418.308 and the Medicare Financial Management Manual, Chapter 4.

collected (OIG 2022a; OIG 2021; Waldman 2012). Hospice programs are generally aware of the cap and can predict a large portion of their cap liabilities *ex interim* using their billing records.

2.3 Motivation for the cap

The cap may be rationalized by concerns that provider-induced demand or moral hazard would otherwise lead to excessive hospice care. The provider-induced demand theory suggests that financially motivated health care providers may leverage informational asymmetries between themselves and their patients to persuade their patients to accept unnecessary health care services. Their scope for providing inefficient care is greatest in clinical "gray areas," where the expected harm to overutilization is low and uncertainty is high. For instance, studies have shown that the quantity of medical imaging is particularly sensitive to providers' reimbursement rates (Clemens and Gottlieb 2014; Lee and Levy 2012). Moral hazard can magnify the effects of provider-induced demand when patients are insulated from the marginal cost of care by health insurance.

Hospice care may be one such gray area. The timing of death is unpredictable among Medicare beneficiaries (e.g., Einav et al. 2018), it is difficult for providers to determine when hospice care is needed most (Sack 2007), and there is virtually no patient cost-sharing under the Medicare hospice benefit.[7] There may therefore be scope for financially motivated hospice programs to raise revenue by persuading Medicare beneficiaries on the margin to enroll too early or remain enrolled too long after their condition improves. Recent press reports suggest this sometimes occurs in practice. For instance, Rao (2011) reported that an administrator for a Texas-based hospice chain "strongly encouraged employees to find a way to keep patients as long as possible" (internal quotations omitted) and whistleblowers have made similar allegations elsewhere (Kofman 2022; Rao 2011). Under these circumstances, the cap can in theory cut costs by reducing payments to hospice programs that provide long stays. But the cap's effectiveness depends on how the programs respond.

3 Cap-induced financial incentives to churn patients

The following stylized model motivates our analysis. We discuss some omitted details in appendix A and account for them in our empirical work. Define the indices j for programs and t for fiscal

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[7]Patients pay up to $5 per prescription and 5% of the IRC payment rate. See the Medicare Hospice Benefit Manual.

years. Let Cap_t be year t's cap. For each program-year, let Payments_{jt} be the program's gross Medicare revenue, let Census_{jt} be its patient census, and let $\text{PPP}_{jt} := \text{Payments}_{jt}/\text{Census}_{jt}$ be its average annual revenue ("payments per patient"). Define the cap liability:

$$\text{Liability}_{jt} :=$$
$$\max\left\{\left(\underbrace{\frac{\text{Payments}_{jt}}{\text{Census}_{jt}}}_{\text{PPP}_{jt}} - \text{Cap}_t\right) \cdot \text{Census}_{jt}, 0\right\} = \max\left\{\text{Payments}_{jt} - \underbrace{\text{Cap}_t\text{Census}_{jt}}_{\substack{\text{MRR} \\ \text{Given Census}}}, 0\right\} \quad (1)$$

Equation (1) shows that the cap created a MRR given a program's patient census—any gross Medicare revenue in excess of the MRR is a cap liability and must be repaid to Medicare. Our central theoretical observation is that programs can reduce their cap liabilities by churning their patients: live discharges can reduce gross Medicare revenue and enrollments can increase the MRR.

These cap-related financial incentives change sharply during the transition between fiscal years. During the last weeks of a fiscal year t, programs are more certain of their cap liability and have less time to make compensating adjustments. Consequently, the expected benefit of a compensating adjustment is higher during fiscal year t's last weeks than fiscal year $t+1$'s first weeks. Since cap liabilities are paid after each fiscal year, time discounting may magnify this change by making fiscal year t's outcome more salient than fiscal year $t+1$'s outcome at the end of fiscal year t.

In the remainder of this section, we elaborate on this observation by describing how programs' financial incentives to churn patients vary because of how Medicare measures Census_{jt}. We also describe how a 2012 change to the formula that determines Census_{jt} may have influenced their financial incentives to churn patients.

3.1 Notation and setup

Consider a program j deciding whether to enroll or live discharge a patient i on a day d near the end of a fiscal year t. (Let d be the number of days remaining in the fiscal year.) Let $g \in \{\text{E}, \text{LD}\}$ denote whether the program is facing the enrollment or live discharge decision. Let P_{jt} be its daily payment rate. Let $A \in \{0, 1\}$ be its action (enroll vs. do not enroll or live discharge vs. do not live discharge). Let $D \in \{0, 1\}$ indicate whether it is on track to exceed the cap.

The program's choice of how to act will depend on its payoffs. Let $\tilde{\pi}_{ijt}^g(A, D)$ be its payoff function, which depends on the effect of its action on its cap liability and other factors. Define $\tilde{\pi}_{ijt}^g(A, D) := \text{Liability}_{ijt}^g(A, D) + \varepsilon_{ijt}^g(A)$, where $\varepsilon_{ijt}^g(A)$ includes the program's gross profit for treating this patient in this fiscal year, the action's fixed cost, and the present value of payoffs related to this patient in future fiscal years. Let $\pi_{ijt}^g(D) := \tilde{\pi}_{ijt}^g(1, D) - \tilde{\pi}_{ijt}^g(0, D)$ be the action's net payoff to the program and let the cap-induced financial incentive for the action be:

$$\Delta\pi_{ijt}^g := \pi_{ijt}^g(1) - \pi_{ijt}^g(0) \tag{2}$$

Note that while $\Delta\pi_{ijt}^g > 0$ indicates that the action is more profitable when $D = 1$ than otherwise, it may still be unprofitable if $\pi_{ijt}^g < 0$. For instance, if the fixed cost of an enrollment is too high because the prospective patient prefers to continue curative care, then a program on track to exceed the cap will not enroll them even to reduce its cap liability. Finally, we assume that the program will act in expectation over a conditional distribution of patient characteristics.

Medicare determines the functional form of equation (2). It varies with the fiscal year because of a 2012 change to how Medicare measures patient censuses. Before 2011, Medicare used the so-called "streamlined" method. Under this method, patients who are only ever enrolled with one program contribute 1 to their program's census in the fiscal year that they enroll for the first time. They contribute 0 to their program's census in all subsequent fiscal years. However, patients who are ever enrolled with more than one program contribute to each program-year's census the fraction of their LLOS spent at that program in that fiscal year. Since 2012, Medicare has used the so-called "proportional" method at most programs.[8] Under this method, all patients contribute to each program-year's census the fraction of their LLOS spent at that program in that fiscal year. At the end of each fiscal year, programs compute that year's cap liability and update the previous three fiscal years' cap liabilities to account for their patients' ongoing hospice utilization, if any.

For brevity, we assume that a marginal enrollment or live discharge would not create a cap liability for a program not on track to exceed the cap. Therefore $\text{Liability}_{ijt}^g(A, 0) = 0$. We also assume that a marginal enrollment or live discharge would not eliminate the cap liability of a program on

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[8]Most programs were automatically switched to the proportional method in 2012. However, a small and decreasing number of programs continued using the streamlined method (only 486 programs in 2013). We do not observe which programs used which methods, so we assume that all programs switched to the proportional method in 2012.

track to exceed the cap. Programs very near the cap have qualitatively similar—but correspondingly milder—financial incentives to those we describe here. Finally, we assume that the level of hospice care is fixed because RHC is provided for 98% of an average hospice program's patient-days. We hypothesize that programs on track to exceed the cap may reduce GIC and CHC rates because they are more resource intensive but provide no marginal net revenue because of the cap.

3.2 Cap-induced financial incentives to enroll new patients

We begin with the program deciding whether to enroll a new patient (g = E). For brevity, we assume that the patient had never previously been enrolled in hospice care. Let LOS_{ijt} be the patient's length-of-stay at hospice j during fiscal year t, let LLOS_i be the patient's LLOS, and let $W_i \in \{0, 1\}$ indicate whether the patient has ever or will ever be enrolled with a different program. Note that $\text{Liability}^{\text{E}}_{ijt}(0, D) = 0$ because the patient's effect on the program's cap liability is zero if the program does not enroll the patient. Under these assumptions:

$$\Delta\pi^{\text{E}}_{ijt} = -\text{Liability}^{\text{E}}_{ijt}(1,1) = \begin{cases} \text{Cap}_t - P_{jt}\text{LOS}_{ijt} & \text{if } t \leq 2011 \text{ and } W_i = 0 \quad (3a) \\[2mm] \dfrac{\text{LOS}_{ijt}}{\text{LLOS}_i}\text{Cap}_t - P_{jt}\text{LOS}_{ijt} & \text{if } t \leq 2011 \text{ and } W_i = 1 \quad (3b) \\[2mm] \dfrac{\text{LOS}_{ijt}}{\text{LLOS}_i}\text{Cap}_t - P_{jt}\text{LOS}_{ijt} & \text{if } t \geq 2012 \quad (3c) \end{cases}$$

We make three observations about $\Delta\pi^{\text{E}}_{ijt}$ near the end of the fiscal year. First, the cap-induced financial incentive to enroll a new patient varies with the patient's characteristics, but would be positive for most patients. As we discuss below, the average program earned \$146 per patient-day and faced a cap of \$24,047 during our sample period. Therefore, equation (3a) is positive near the end of the fiscal year and equations (3b) and (3c) are positive as long as LLOS_i is not too large.[9] In our empirical analysis, we will examine whether programs on track to exceed the cap enroll more patients than otherwise similar programs not on track to exceed the cap contemporaneously. We will also examine the characteristics of the marginal enrollees.

Second, the cap-induced financial incentive to enroll a new patient was larger before 2011 be-

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[9]In practice, the program's cap liability payment at the end of a given fiscal year will depend on the patient's LLOS by years-end, not LLOS_i itself. It will subsequently make additional payments to account for updates to its patients' lifetime hospice utilization. Therefore, time discounting will diminish the impact of a large LLOS_i on present payoffs.

cause $\mathrm{Cap}_t \geq \frac{\mathrm{LOS}_{ijt}}{\mathrm{LLOS}_i}\mathrm{Cap}_t$. In our empirical analysis, we will examine whether programs on track to exceed the cap enrolled more patients before 2011 than they have since 2012, relative to otherwise similar programs not on track to exceed the cap contemporaneously.
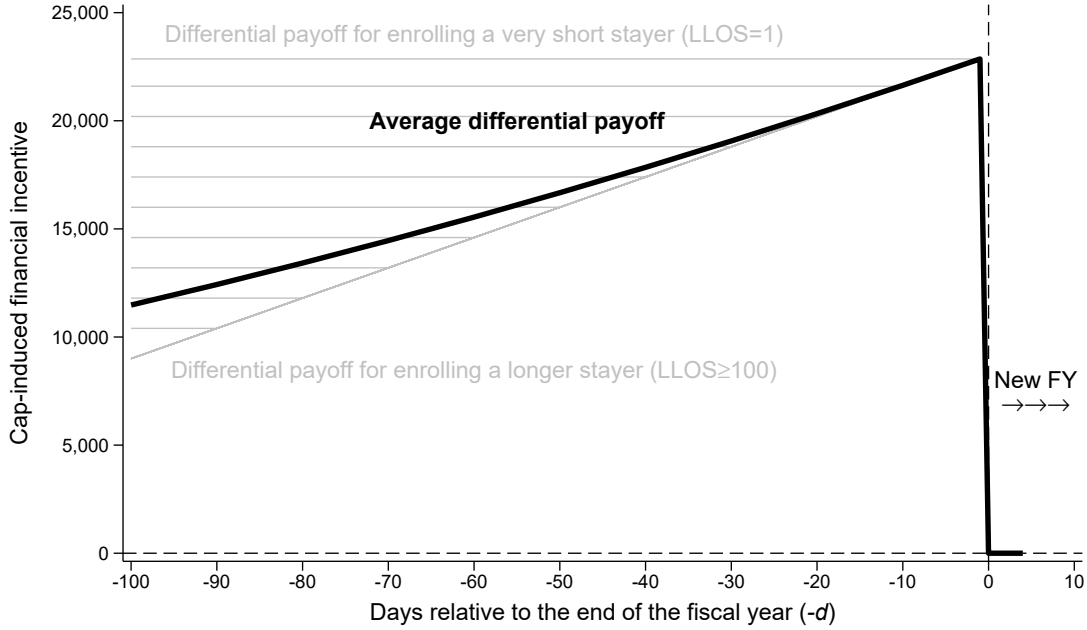
Third, the cap-induced financial incentive to enroll a new patient varies with the day d of the fiscal year. Before 2011, $\Delta\pi_{ijt}^{\mathrm{E}}$ was generally decreasing in LOS_{ijt} because $W_i = 0$ for most patients. This suggests that $\Delta\pi_{ijt}^{\mathrm{E}}$ generally increased as $d \rightarrow 0$ because $\mathrm{LOS}_{ijt} \leq d$. Since 2012, holding LLOS_i fixed, the cap-induced financial incentive to enroll a new patient has converged to zero as $d \rightarrow 0$. Figure 1 illustrates how $\Delta\pi_{ijt}^{\mathrm{E}}$ varies with LLOS_i and d for typical values of P_{jt} and Cap_t. In our empirical analysis, we will examine enrollment trends at programs on track to exceed the cap near the end of a fiscal year.

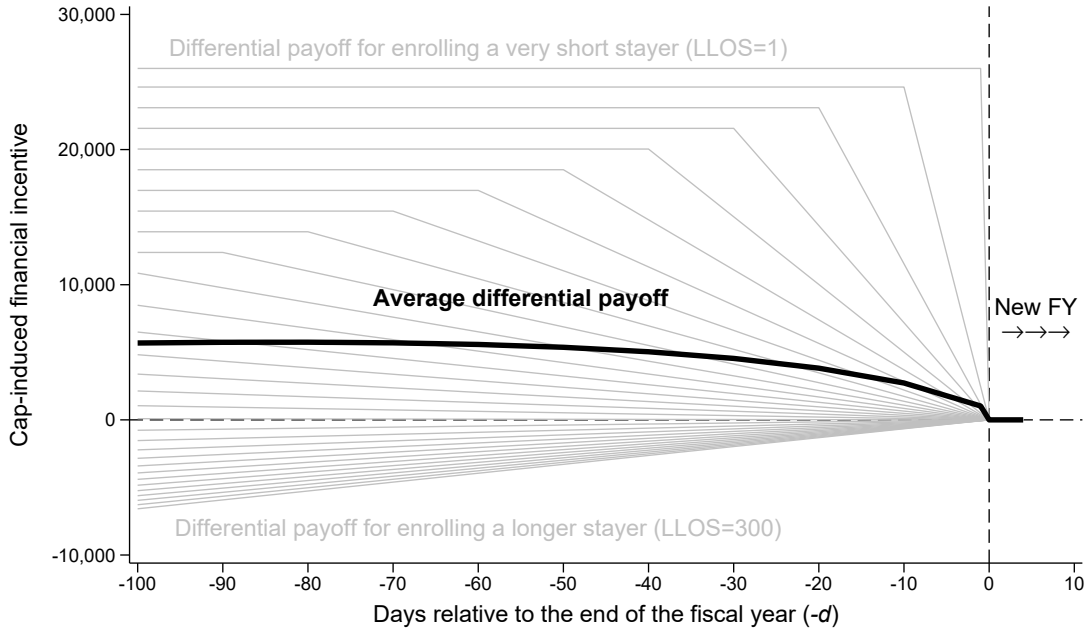## 3.3 Cap-induced financial incentives to live discharge patients

We continue with the program deciding whether to live discharge a patient ($g = \mathrm{LD}$). For brevity, we assume that the patient's first hospice enrollment occurred at this program during this fiscal year. The program's cap-induced financial incentive to live discharge the patient depends on the effect of the live discharge on the patient's lifetime utilization of hospice care. Let $\mathrm{LOS}_{ijt}(A)$ be the patient's length-of-stay at hospice j during fiscal year t, let $\mathrm{LLOS}_i(A)$ be the patient's LLOS, and let $W_i(A) \in \{0, 1\}$ indicate whether the patient has or will ever be enrolled with another program. For each of these terms K, define $\Delta K := K(1) - K(0)$ and $\%\Delta K := \Delta K / K(0)$. For brevity, we assume that $\Delta W_i \geq 0$. Under these assumptions:

$$\Delta\pi_{ijt}^{\mathrm{LD}} = -\left(\mathrm{Liability}_{ijt}^{\mathrm{LD}}(1,1) - \mathrm{Liability}_{ijt}^{\mathrm{LD}}(1,0)\right) =$$

$$\begin{cases} -\Delta\mathrm{LOS}_{ijt}P_{jt} & \text{if } t \leq 2011 \text{ and } W_i(1) = 0 \text{ and } W_i(0) = 0 \quad (4a) \\ \left(\dfrac{\mathrm{LOS}_{ijt}(1)}{\mathrm{LLOS}_i(1)} - 1\right)\mathrm{Cap}_t - \Delta\mathrm{LOS}_{ijt}P_{jt} & \text{if } t \leq 2011 \text{ and } W_i(1) = 1 \text{ and } W_i(0) = 0 \quad (4b) \\ \left(\dfrac{\mathrm{LOS}_{ijt}(1)}{\mathrm{LLOS}_i(1)} - \dfrac{\mathrm{LOS}_{ijt}(0)}{\mathrm{LLOS}_i(0)}\right)\mathrm{Cap}_t - \Delta\mathrm{LOS}_{ijt}P_{jt} & \text{if } t \leq 2011 \text{ and } W_i(1) = 1 \text{ and } W_i(0) = 1 \quad (4c) \\ \left(\dfrac{\mathrm{LOS}_{ijt}(1)}{\mathrm{LLOS}_i(1)} - \dfrac{\mathrm{LOS}_{ijt}(0)}{\mathrm{LLOS}_i(0)}\right)\mathrm{Cap}_t - \Delta\mathrm{LOS}_{ijt}P_{jt} & \text{if } t \geq 2012 \quad (4d) \end{cases}$$

(a) Streamlined method for patients with $W_i = 0$ (pre-2011)

(b) Proportional method (post-2012) or streamlined method for patients with $W_i = 1$ (pre-2011)

Fig. 1. *Graphical illustration of cap-induced financial incentives to enroll new patients.* Panel (a) plots the incentive for fiscal years before 2011 and patients with $W_i = 0$ (corresponding to equation (3a)). Panel (b) plots the incentive for fiscal years after 2012 or patients with $W_i = 1$ (corresponding to equations (3b) and (3c)). They show that programs on track to exceed the cap in an outgoing fiscal year generally benefit from enrolling new patients relative to otherwise similar hospice programs not on track to exceed the cap contemporaneously.

In equation (4b), note that $\left(\frac{\text{LOS}_{ijt}(1)}{\text{LLOS}_i(1)} - 1 \right) \leq 0$. In equations (4c) and (4d), note that $\left(\frac{\text{LOS}_{ijt}(1)}{\text{LLOS}_i(1)} - \frac{\text{LOS}_{ijt}(0)}{\text{LLOS}_i(0)} \right) \geq 0$ if and only if $\%\Delta\text{LOS}_{ijt} \geq \%\Delta\text{LLOS}_i$.

We make three observations about $\Delta\pi_{ijt}^{\mathrm{LD}}$ near the end of the fiscal year. First, the cap-induced financial incentive to live discharge a patient may be positive or negative and depends on the patient's characteristics. If $\Delta\mathrm{LOS}_{ijt} \leq 0$—which is plausible for most patients—then equation (4a) is positive. But equations (4b), (4c), and (4d) may be positive or negative in ways that depend on unknown potential outcomes. We hypothesize that the program can predict to some extent which patients would reduce its cap liability if they were live discharged. For instance, before 2011, it may identify patients who are not likely to re-enroll elsewhere if they were live discharged. After 2012, it may identify patients who are likely to remain enrolled much longer but-for a live discharge, such as those for whom $\mathrm{LOS}_{ijt}(1) \approx \mathrm{LLOS}_i(1)$ but $\mathrm{LOS}_{ijt}(0)/\mathrm{LLOS}_i(0) << 1$. In our empirical analysis, we will examine whether programs on track to exceed the cap live discharge more patients than otherwise similar programs not on track to exceed the cap contemporaneously. We will also examine the characteristics of marginally live discharged patients.

Second, the 2012 policy change increased the cap-induced financial incentive to live discharge some patients, but decreased it for others. Since only 5% of patients—including only 30% of live discharged patients—ever enroll with more than one hospice, we hypothesize that the number of patients for whom equation (4a) is positive is larger than the number of patients for whom equation (4d) is positive. In our empirical analysis, we will examine whether programs on track to exceed the cap live discharged more patients before 2011 than they have since 2012, relative to otherwise similar programs not on track to exceed the cap contemporaneously.

Third, the cap-induced financial incentive to live discharge a patient varies with the day d of the fiscal year. But while $\Delta\mathrm{LOS}_{ijt} \to 0$ as $d \to 0$, the first terms in equations (4b), (4c), and (4d) converge to functions of unknown potential outcomes. In our empirical analysis, we will examine live discharge trends at programs on track to exceed the cap near the end of a fiscal year.

4   Data

Our primary data are the 100% Medicare hospice claims spanning 2000-2019. We extracted patient and program identification numbers and claim start and end dates associated with each claim. We used these data to construct various patient and program panel datasets.[10] Our primary analytic

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[10]Almost all (patient, day) observations (99.98%) are associated with at most one program. Patients may be associated with multiple programs on days that they switch between programs. Such patient-days count toward both

samples are (program, day)- and (program, fiscal year)-level panel datasets spanning 2001-2018.[11]

We used the claims to measure hospice programs' annual gross Medicare payments and patient censuses. Payments are observed directly in the claims data.[12] Patient censuses are determined by each patient's lifetime utilization of hospice care and the counting method. We calculated each patient-day's contribution to its program-year's patient census using the streamlined method before 2011 and the proportional method thereafter. In both cases, we used records of each patient's hospice utilization during the following three fiscal years because a program-year's cap liability may be revised for up to three additional fiscal years as its patients continue using hospice care.[13]

We combined our measures of annual Medicare payments and patient censuses with publicly available data published in the Federal Register or CMS's transmittals to hospice programs about each fiscal year's cap amount and WI.[14] We used these data to calculate each program-year's average annual revenue and cap liability. We also computed for each program-year-day the program's running average annual revenue and cap liability on that day of the fiscal year.

We also relied on several additional data sources. First, we used the hospice claims and 2000-2019 Master Beneficiary Summary Files (MBSF) to measure aspects of each patient's lifetime hospice utilization. We defined each patient's first enrollment date as the first day of their first observed claim. We defined a live discharge as any transition between distinct programs or any break in a patient's hospice claims spanning 1+ days that does not coincide with their date of death as reported in the MBSF. We defined each patient's LLOS as their total number of days in hospice care during 2000-2019. We defined their lifetime number of enrollments with distinct programs analogously. We determined each patient-day's level of hospice care (RHC, CHC, GIC, or IRC) and whether a staff visit occurred using the revenue center codes associated with each claim.

Second, we used the hospice claims and MBSF to identify several other patient characteristics.

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programs' cap censuses. See Medicare hospice transmittal 156.

[11]We use 2000 and 2019 data to reduce left- and right-censoring in measures of patients' lifetime hospice utilization.

[12]For claims that spanned several days, we distributed payments evenly across the days associated with that claim. We accounted for several details in the payment formula, including the effect of a 2013 sequestration and how days are assigned to fiscal years for the purposes of counting annual revenue.

[13]Among patients whose first observed patient-day was between FY 2004 and FY 2015, 92% of their patient-days are associated with either their first observed patient-day's fiscal year or the following fiscal year. We accounted for several details in the patient census formulas, including how patients were counted during the short transition between counting methods in 2011 and how days are assigned to fiscal years for the purposes of counting patients.

[14]We accounted for the fact that the cap assigned to new hospice programs is different during their first fiscal year.

We identified each hospice patient's date of birth, race, sex, and date of death in the MBSF.[15] We defined a decedent to be a patient whose date of death was on or before the end of our sample period, December 31, 2019. We defined each patient's remaining days of life (RDOL) as the difference between their enrollment date and the earlier of their date of death or the end of our sample period. We defined each patient as dying during hospice care if a hospice claim encompasses their date of death. We also used the MBSF to identify each patient-year's ZIP code of residence, which we used to measure geographic overlap between each program's patients and patients at programs with cap liabilities. We refer to this as the program's proximity to over-cap programs. Following Ankuda et al. (2023), we categorized the ICD diagnosis codes on each patient's first hospice claim into medical conditions, including ADRD and cancer.

Third, we used the 2000-2019 provider-of-service (POS) files to identify hospice program characteristics. In particular, we identified each program's name and state, and whether the program was for-profit, not for-profit, or government-owned. We also used the programs' original participation dates and their earliest observed hospice claims to determine their starting years and ages. We defined a hospice program to be exiting in a given fiscal year if we do not observe that program's Medicare provider certification number (CCN) in the following year's claims.[16]

Fourth, we used the 2000-2019 Medicare Provider Analysis and Review files (MedPAR) the Minimum Dataset (MDS), and the Medicare outpatient claims data. MedPAR contains records of Medicare beneficiaries' hospital and skilled nursing facility (SNF) stays. We extracted the admission and discharge date associated with each MedPAR claim to determine patient-days spent in a hospital or SNF. The MDS contains health assessments conducted by NHs when a patient begins and ends a NH stay, and at regular intervals during their NH stay. We identified patient-days spent at a NH by linking sequences of MDS assessments and merging them with MedPAR's records of SNF stays. We identified ED visits by combining the MedPAR files (which contain records of ED visits linked to hospital stays) and the outpatient files (which contain records of other ED visits).[17]

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[15]It is not common for one patient to have multiple distinct realizations of these variables. When that happens, we assigned them to whichever realization was reported first.

[16]A Medicare provider agreement is terminated when the corresponding provider exits the Medicare market or experiences a change of ownership to an owner who does not accept the agreement. To the best of our knowledge, there is no taxonomy of hospice program CCN terminations, so we cannot distinguish exits from other events.

[17]See appendix B for more information about our data.

5   Descriptive statistics

5.1   The distribution of cap liabilities

Table 1 summarizes the programs' patient volumes, Medicare payments, and cap liabilities. Column (1) shows that hospice programs exceeded the cap in 11% of program-years during 2001-2018. Column (2) shows that 2,214 programs (39%) exceeded the cap at least once and their cap liabilities were $490,000 per year on average. Columns (2) and (6) show that programs that exceeded the cap treated fewer unique patients than other programs, but for more patient-days on average. Columns (3) and (4) show that programs just above the cap also had significant cap liabilities—$163,000 per year, on average. MedPAC (2020) proposed reducing the cap by 20%; column (5) reports descriptive statistics for programs with average annual revenue below but within 20% of the cap. It shows that they treated more than twice as many patients as programs that exceeded the cap.

Tables A1 and A2 summarize other program and patient-level characteristics.[18] They show that programs that exceeded the cap were newer (6 years vs 13 years) and smaller (106 enrollments vs 293 enrollments) on average. They were also more likely to be for-profit (88% vs 47%) and more likely to exit in the next fiscal year (8% vs 2%). The tables also show that patients whose first enrollment was associated with a program-year that exceeded the cap had longer average LLOS (200 vs 85 days) and RDOL (425 vs 143 days), were more likely to experience a live discharge (39% vs 16%), and were less likely to die in hospice care (81% vs 92%). They were also more likely to have ADRD (24% vs 19%) and less likely to have cancer (21% vs 35%). This variation makes it difficult to draw causal inferences about the cap's effect from between-program comparisons alone, and motivates our DID analysis around the transition between fiscal years.

Figure 2 plots the distribution of $\text{PPP}_{jt}/\text{Cap}_t$ and table A3 reports the McCrary (2008) test of the hypothesis that the distribution of $\text{PPP}_{jt}/\text{Cap}_t$ is continuous at 1. There is no evidence of bunching around 1.[19] This implies that programs' marginal adjustment costs are high because even programs with average annual revenue between 100-110% of the cap had cap liabilities of $163,000

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[18]Appendices C and D present additional tables and figures referenced in the main text.

[19]In parallel work, Gruber et al. (2023) draw a similar conclusion using a simplified measure of cap liabilities. Table A3 reports similar results for sub-samples of for-profit programs, large programs, and programs that exceeded the cap at least once, respectively. Although the test statistic for the sub-sample of programs that have exceeded the cap is marginally significant, its sign indicates bunching above the cap, which does not indicate evidence of learning.

| | All | Above-cap | | | Below-cap | |
| | | All | W/I 10% | ≥80% | All | |
	(1)	(2)	(3)	(4)	(5)	(6)
Patient volume and census						
Patient-days	23,493	20,774	26,495	36,372	33,864	23,846
Unique patients	353	178	250	375	360	376
Patient-days per unique patient	71	122	107	101	97	65
Patient census	270	105	157	248	241	292
Gross Medicare payments						
Payments ($K)	3,640	3,023	4,028	5,819	5,288	3,720
Payments per pat.-day ($)	146	148	150	149	149	146
Average annual revenue (PPP) ($)	15,241	33,598	26,396	23,828	22,354	12,856
Cap liabilities and net Medicare payments						
Cap ($)	24,047	24,932	25,217	25,137	25,093	23,932
PPP/Cap	0.63	1.35	1.05	0.95	0.89	0.53
Cap liability ($K)	56	490	163	0	0	0
Net payments per pat.-day ($)	143	118	143	149	149	146
Place in the distribution of cap liabilities						
1[Above cap]	0.11	1.00	1.00	0.00	0.00	0.00
1[80-100% of cap]	0.12	0.00	0.00	1.00	1.00	0.13
1[Below cap]	0.89	0.00	0.00	1.00	1.00	1.00
N (program-years)	57,412	6,602	2,018	2,926	6,824	50,810
Unique programs	5,685	2,214	1,279	1,605	2,517	5,300

Tab. 1. *Program characteristics pertaining to the cap.* This table reports descriptive statistics about the (program, fiscal year)-level data.

per year on average. A notable exception is Vitas Healthcare Corporation of Florida, which we find in appendix E had an average annual revenue within 4.4% of the cap on average during 2001-2018. A recent OIG report suggests that it may have inappropriately billed CHC and GIC days during this time; if true, this suggests that the cap may have limited the alleged fraud (OIG 2022b).

5.2   Cap liabilities and the wage index

Next, we examined the association between the WI and cap liabilities. The WI creates geographic variation in programs' daily payment rates, but not in the cap. MedPAC (2020) proposed WI-adjusting the cap to make it "more equitable across providers." We estimated models of the form $Y_{jt} = \beta \mathrm{WI}_{jt} + \Gamma X_{jt} + \varepsilon_{jt}$, where Y_{jt} is an outcome for program j in fiscal year t, WI_{jt} is the natural log of the WI, and X_{jt} is a vector of other characteristics, including program and year fixed effects.
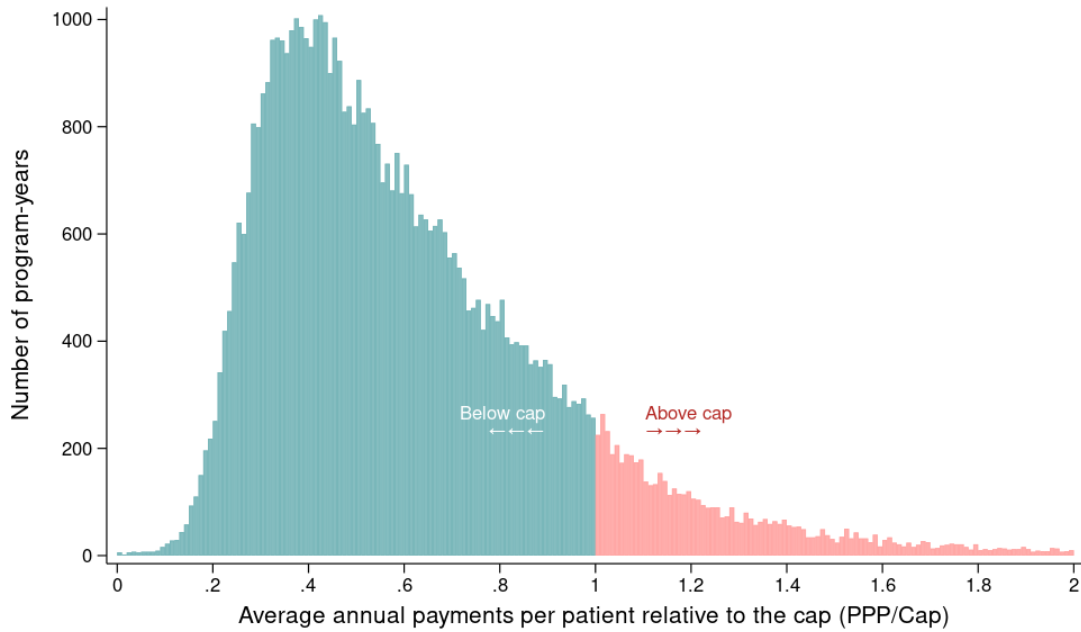
Fig. 2. *Distribution of average annual revenue relative to the cap (PPP/Cap).* This figure plots the distribution hospice programs' average annual revenue relative to the cap between 0 and 2. There is no visual indication of bunching near 1. Table A3 reports the corresponding McCrary test results (McCrary 2008).

Table A4 reports our results. We find that a 1% higher WI is associated with an 0.11 percentage point (pp) higher likelihood of exceeding the cap and a 4.6% higher cap liability on average.[20] This higher cap liability is explained by higher gross Medicare revenue: we find that a 1% higher WI is associated with a 0.33% increase in gross Medicare payments per patient-day. On aggregate, we find that a 1% higher WI is associated with higher gross Medicare payments and lower patient censuses—explaining the higher cap liabilities—though these associations are not individually statistically significantly different from zero. In sum, these estimates support MedPAC's claim that WI-adjusting the cap would improve equity across programs because a portion of the WI adjustment intended to compensate programs for higher local labor costs is repaid in cap liabilities.

5.3   What happens after programs exceed the cap?

Next, we examined how programs change after exceeding the cap. MedPAC (2020) proposed reducing the cap by 20%. Figure 2 suggests that in the absence of a compensating response, this proposal would cause a significant number of programs to exceed the cap more often. What hap-

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[20]Throughout the paper, we convert log differences to percent changes by: Percent $= \left(\exp(\mathrm{Log}) - 1\right) \times 100$.

pens to programs that exceed the cap in future fiscal years? We estimated models of the form $Y_{jt} = \beta 1[\text{Over Cap}]_{jt-1} + \Gamma X_{jt} + \varepsilon_{jt}$, where Y_{jt} is an outcome for program j in fiscal year t, $1[\text{Over Cap}]_{jt-1}$ indicates that the program exceed the cap in the last fiscal year, and X_{jt} is a vector of other characteristics, including program and year fixed effects.

Table A5 reports our results. It shows that exceeding the cap in one fiscal year is associated with a 19.3pp higher likelihood of exceeding it again in the following fiscal year, and a 246% higher average cap liability. It also shows that programs that exceed the cap in one fiscal year have 10.1% lower patient censuses but 10.0% more patient-days in the following fiscal year, on average. Importantly, it shows that CCNs associated with programs that exceed the cap are 5.6pp more likely to be terminated in the next fiscal year on average. By comparison, the baseline termination rate is 2.5% per year on average. We caution that causal inference is complicated by the possibility that unobserved factors—such as poor management or decreasing residual demand for hospice care—may confound our estimates. But together with our previous finding that programs below and within 20% of the cap treat more patients on average, these associations raise concerns about the potential effect of reducing the cap on market structure and hospice access.

6 Do programs churn patients because of the cap?

6.1 Research design

6.1.1 Setup

The foregoing section shows that programs exceed the cap by wide margins and there is no evidence of bunching in the distribution of average annual revenue. These findings suggest that marginal adjustment costs are high by the end of the fiscal year. But do programs end a fiscal year with cap liabilities having not made any adjustments? Or do their adjustments fall short of eliminating their cap liabilities? Motivated by our theoretical observations in section 3, we now leverage variation in cap-related financial incentives generated by the policy's nonlinear design and the transition between fiscal years to investigate how programs respond to an impending cap liability.

In particular, we treat the transitions between fiscal years 2001-2002, ..., 2018-2019 as eighteen distinct events and examine outcome trends during the 180 days surrounding each event ("event

windows"). For most outcomes, the transition date is the start of the fiscal year, which was November 1 until 2017 and October 1 thereafter. For others, the appropriate transition date differs because of Medicare's census counting methods. Under the streamlined method (before 2011), patients who were never treated by more than one program were counted until September 27. Other patients were counted until the end of the fiscal year. Under the proportional method (after 2012), all patients were counted until the end of the fiscal year. For census related outcomes, the transition date is September 28 until 2011 (since most patients are treated by one program at most) and the start of the fiscal year thereafter. We call it the transition between "primary census counting periods."

We define a program to be on track to exceed the cap in an outgoing fiscal year if its running average annual revenue exceeds the cap at the start of the event window.[21] We use a DID research design to compare outcomes between programs on track to exceed the cap in an outgoing fiscal year and observably similar programs not on track to exceed the cap contemporaneously.

6.1.2   Estimation

Define the indexes e for events, j for programs, and t for fiscal years. Let t_e be event e's outgoing fiscal year and let Cap_e be the cap in t_e. Let PPP_{ej} be program j's running average annual revenue at the start of e's event window. Let the set of programs on track to exceed the cap in t_e be $\mathcal{T}_e :=$ $\{j : \text{PPP}_{ej} \geq \text{Cap}_e\}$ and let $\mathcal{U}_e$ be the others. Let $\mathcal{T} := \cup_e \{(e, j) : j \in \mathcal{T}_e\}$ be the set of all treated programs and let $\mathcal{U}$ be likewise for the untreated programs. Let $W := \{..., -2, -1, 0, 1, 2, ...\}$ enumerate 7-day intervals relative to each event's transition date and let w index elements of W. Finally, define the static treatment indicator $D_{ejw}^{\text{Sta.}} := 1[j \in \mathcal{T}_e]1[w < 0]$ and the dynamic treatment indicator $D_{ejww'}^{\text{Dyn.}} := 1[j \in \mathcal{T}_e]1[w = w']$. We estimate stacked DID regression models of the form:

$$Y_{ejw} = \beta D_{ejw}^{\text{Sta.}} + \text{FE}_{ej} + \text{FE}_{ew} + \varepsilon_{ejw} \tag{5}$$

$$Y_{ejw} = \sum_{w' \in W \setminus \{0\}} D_{ejww'}^{\text{Dyn.}} \beta_{w'} + \text{FE}_{ej} + \text{FE}_{ew} + \varepsilon_{ejw} \tag{6}$$

where Y_{ejw} is an outcome, FE_{ej} is an event-program fixed effect, and FE_{ew} is an event-week fixed effect interacted with each program's state, ownership, and WI at the start of the event window.[22]

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[21]It is plausible that programs can forecast an impending cap liability by this time. The correlation between each program's running cap liability and the running cap liability it would have without the 3-year look-back period is 0.97.

[22]We include state interactions because there is some heterogeneity in cap liabilities across states. See appendix E.

For binary outcomes, we estimated equations (5)-(6) using ordinary least squares (OLS) and interpret the coefficients as percentage point differences. For other outcomes, we estimated analogous equations using the Poisson pseudo-maximum likelihood estimator (PPML) and interpret the coefficients as log point differences (Wooldridge 1999). The stacked estimator overcomes the so-called "negative weighting" issue that can arise in two-way fixed effects (TWFE) OLS DID estimators (e.g., Goodman-Bacon 2021). The parameters β and $(\beta_w : w \in W)$ measure average trend differences during the event windows between programs in $\mathcal{T}_e$ and $\mathcal{U}_e$ in the same state, with the same ownership type, and with similar WI values (Gardner 2021; Cengiz et al. 2019).[23]

6.1.3 Identification

DID identifies the average treatment effect on the treated (ATT) of the cap at the end of an outgoing fiscal year under the following assumptions. First, average outcomes among untreated programs are unaffected by the cap during the event windows ("clean controls"). Second, average outcomes among treated programs are unaffected by the cap at the start of the incoming fiscal years ("clean slate"). Third, average outcome trends between treated and untreated programs would have moved synchronously at the end of the outgoing fiscal years but for the cap ("parallel trends").[24]

To illustrate, figure 3 plots average enrollment rates among programs that differ by their average annual revenue at the start of the event window. It shows that enrollment rates vary seasonally, and are consistently lower among programs on track to exceed the cap. Combined with our findings in section 5, these observations suggest that causal inference from within- or between-program comparisons alone may be complicated by other factors that covary with programs or time. But the figure also shows that programs on track to exceed the cap during the outgoing fiscal year have higher differential enrollment rates in the year's last quarter. We attribute this variation to the cap.

This approach has limitations. First, the clean controls assumption would be violated if untreated programs respond to a potential cap risk. We therefore examine whether our estimates are sensitive to excluding programs whose running average annual revenue is 90-100% of the cap at the start of the event window. Second, the clean slate assumption would be violated if treated programs reach a capacity constraint and enroll fewer patients at the start of a new fiscal year because of excess

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[23]Gardner (2021) shows that the stacked OLS estimator produces a weighted average of each event's trend differences, with weights that increase in the event's sample size and the parity between $|\mathcal{T}_e|$ and $|\mathcal{U}_e|$.

[24]We balance our sample by restricting $\mathcal{T}_e$ and $\mathcal{U}_e$ to contain only programs operating throughout e's event window.
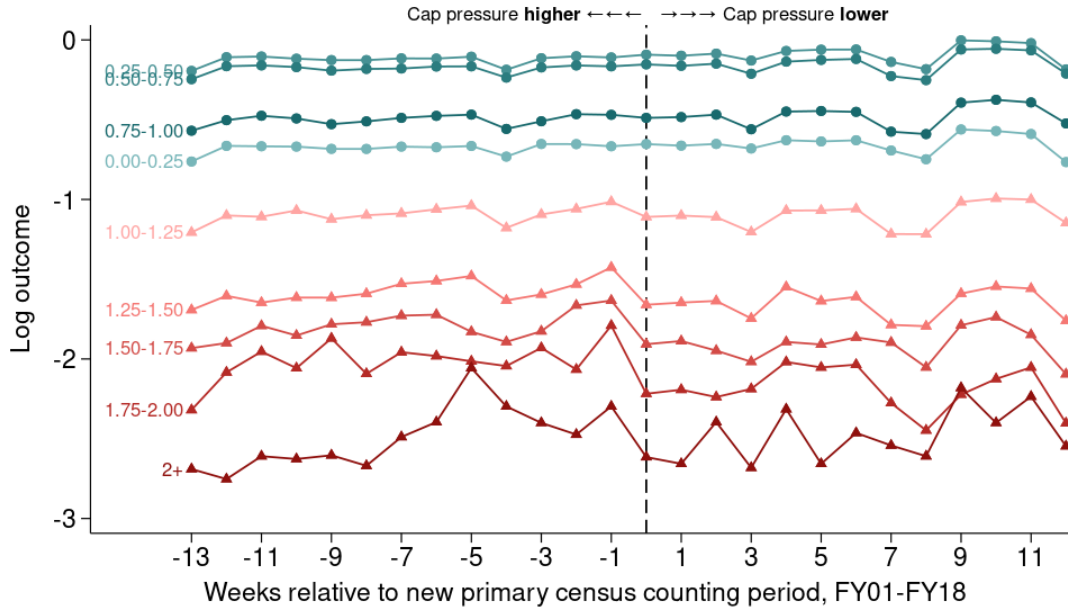
Fig. 3. *Illustration of the DID identification strategy.* This figure plots the log number of new patient enrollments per program-day during the transitions between fiscal years 2001-2002,...,2017-2018. In each transition, programs are grouped based on their running average annual revenue just before week -13. Each group's label is reported on the left. Each line plots the average within each group. In sum, the figure shows that programs on track to exceed the cap in an outgoing fiscal year had a differentially higher number of new patient enrollments in the final weeks of the outgoing fiscal year; but comparable enrollment rate trends at the start of the new fiscal year.

enrollment at the end of the preceding fiscal year. We therefore examine whether enrollment rate trends between treated and untreated programs diverge during the incoming fiscal years, with enrollment rates among treated programs differentially increasing as their excess enrollees pass away or exit hospice. We also investigate whether staff visit rates differentially decrease among treated programs. Finally, the parallel trends assumption would be violated if treated programs operate in markets with seasonally different preferences for hospice care (e.g., due to seasonally different disease incidence rates). We therefore interact FE_{ew} with state, ownership type, and WI controls. We also benefit from granular time-series variation—the index w measures weeks—enabling us to examine outcome trend differences in a narrow window around the transition dates.

6.2 Results

6.2.1 Churning

Our main results document the cap's effect on churning. First, table 2 shows that average enrollment rate differences between the outgoing fiscal year's last quarter and the incoming fiscal year's

	Daily new enrollments (log Δ)		Daily live discharges (log Δ)	
	(1)	(2)	(3)	(4)
$D^{\text{Sta.}}_{ejw}$	0.056***	0.093***	0.042***	0.067***
	(0.007)	(0.012)	(0.010)	(0.016)
	[0.000]	-	[0.000]	-
$D^{\text{Sta.}}_{ejw} \times 1[\text{Post2012}]$	-	-0.058***	-	-0.044**
	-	(0.014)	-	(0.021)
	-	[0.000]	-	[0.031]
Estimator	PPML	PPML	PPML	PPML
Baseline Y	0.253	0.253	0.156	0.156
Effective obs.	1,407,530	1,407,530	1,372,130	1,372,130
Clusters	5,554	5,554	5,530	5,530

Tab. 2. *Static DID estimates of churning.* Program-level cluster robust SEs are in parenthesis. All models include program FE and week FE interacted with state, ownership type, and WI controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Baseline Y is the average value of the outcome when $w = 0$ among treated programs. Effective obs. is the number of non-singleton observations that are not separated by a fixed effect (Correia et al. 2020; Correia 2017). Dynamic estimates are plotted in figure 4. Holm (1979) adjusted p in brackets enable multiple comparisons-robust inference at the 5% level for any churning (columns (1) and (3)) and any change in churning (columns (2) and (4)).

first quarter are 0.056 log points (5.8%) higher among programs on track to exceed the cap in the outgoing fiscal year. It also shows that average live discharge rate differences between the outgoing fiscal year's last quarter and the incoming fiscal year's first quarter are 0.042 log points (4.3%) higher among programs on track to exceed the cap in the outgoing fiscal year.

Second, we examined the impact of the 2012 reform to the census counting method. We interacted the treatment indicators D in equations (5)-(6) with an indicator equal to 0 if event e's outgoing fiscal year is 2011 or earlier, and 1 otherwise. Table 2 reports our results. It shows that programs on track to exceed the cap in an outgoing fiscal year have had lower differential enrollment and live discharge rates since 2012, consistent with the idea that the transition to the proportional counting method moderated their cap-induced financial incentives to churn patients.

Third, we examined the dynamic DID in enrollment and live discharge rates. The temporal findings are telling: figure 4 shows that enrollment rates differentially increase throughout the outgoing fiscal year's last quarter before differentially decreasing by 0.150 log points (13.9%) in the first week of the new fiscal year. Consistent with our motivating theory in section 3, this pattern is more pronounced under the streamlined method (before 2011) than it has been since. We do not observe evidence against the clean slate and parallel trends assumptions: the treated and untreated programs' outcomes appear to move synchronously in the new fiscal year.

(a) Daily new enrollments

(b) Daily live discharges
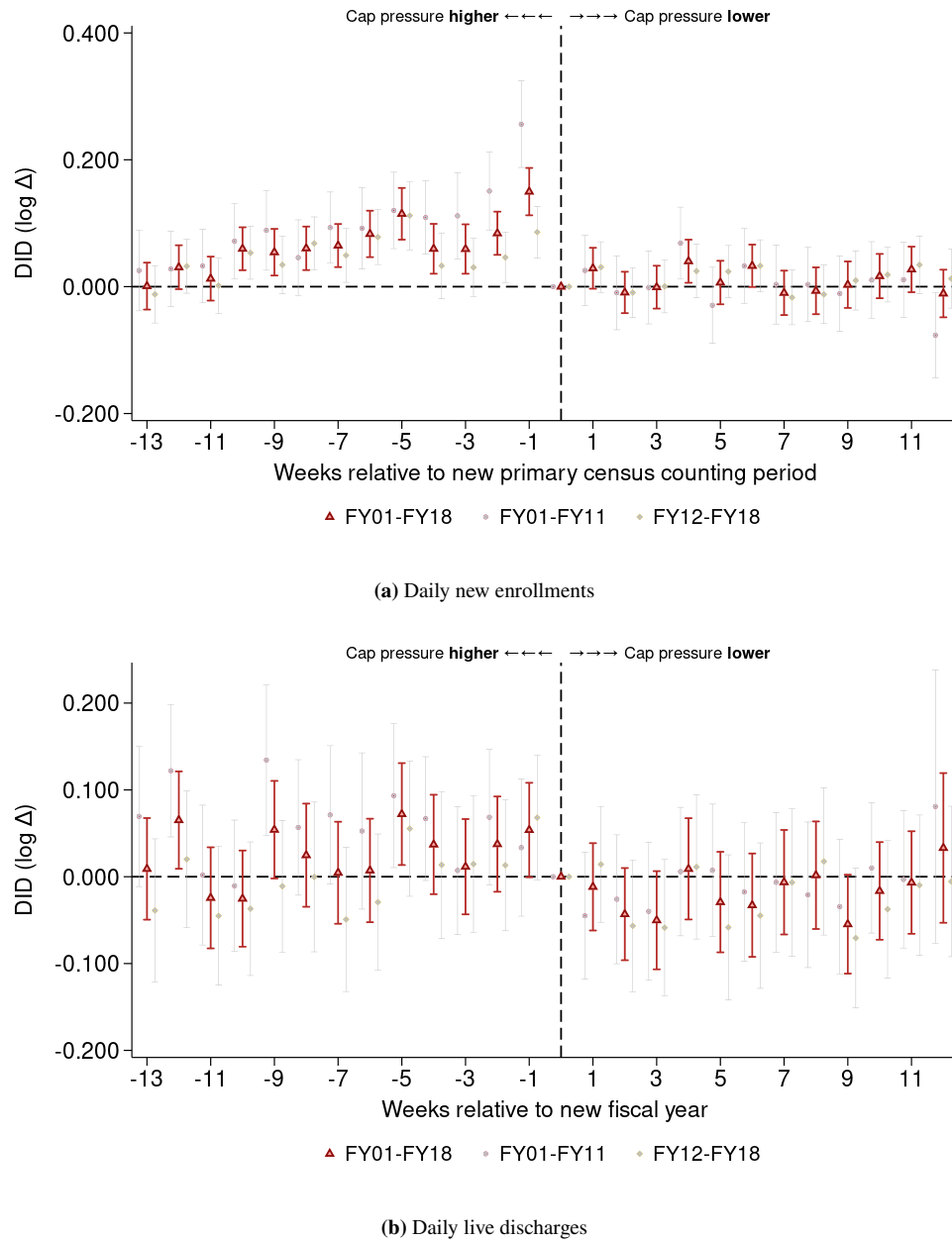
Fig. 4. *Dynamic DID estimates of churning.* The 95% CIs are computed with program-level cluster-robust SEs. All models include program FE and week FE interacted with state, ownership type, and WI controls. Static estimates are reported in table 2.

6.2.2 Marginally enrolled and live discharged patients

We next estimated equations (5)-(6) using outcomes that describe the enrolled and live discharged patients. Table 3 shows that programs on track to exceed the cap in an outgoing fiscal year differentially enroll patients who appear healthier on average. They are 0.9pp less likely to have had a recent hospital stay, 0.6pp less likely to have had a recent NH stay, and they have an 0.044 log point (4.5%)

| | Before enrolling, fraction with: | | | |
| | hosp. stay (pp Δ) | NH stay (pp Δ) | RDOL (log Δ) | LLOS (log Δ) |
	(1)	(2)	(3)	(4)
$D_{ejw}^{\text{Sta.}}$	-0.009***	-0.006***	0.044***	0.020***
	(0.002)	(0.002)	(0.009)	(0.007)
	[0.000]	[0.006]	[0.000]	[0.029]
Estimator	OLS	OLS	PPML	PPML
Baseline Y	0.270	0.222	396	182.306
Effective obs.	1,150,420	1,150,420	1,141,473	1,142,852
Clusters	5,540	5,540	5,534	5,534

| | Fraction discharged in 30 days (pp Δ) | Lifetime number of: | | Fraction who die in hospice (pp Δ) |
| | | live discharges (log Δ) | programs (log Δ) | |
	(5)	(6)	(7)	(8)
$D_{ejw}^{\text{Sta.}}$	0.001	0.019**	0.003*	-0.005***
	(0.001)	(0.008)	(0.002)	(0.002)
	[0.354]	[0.048]	[0.107]	[0.026]
Estimator	OLS	PPML	PPML	OLS
Baseline Y	0.089	0.604	1.219	0.866
Effective obs.	1,150,420	1,123,808	1,142,852	1,138,993
Clusters	5,540	5,513	5,534	5,508

Tab. 3. *Static DID estimates for marginal enrollees.* Program-level cluster robust SEs are in parenthesis. Observations are weighted by the number of new enrollees. All models include program FE and week FE interacted with state, ownership type, and WI controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Baseline Y is the average value of the outcome when $w = 0$ among treated programs. Effective obs. is the number of non-singleton observations that are not separated by a fixed effect (Correia et al. 2020; Correia 2017). Dynamic estimates are plotted in figure A1. Holm (1979) adjusted p in brackets enable multiple comparisons-robust inference at the 5% level for differential health indicators (columns (1)-(3)) and lifetime hospice utilization (columns (4)-(8)).

higher RDOL on average. They also appear less connected to hospice care: on average, they have an 0.020 log point (2.0%) longer average LLOS (despite having a 4.5% higher RDOL), 0.019 log point (1.9%) more lifetime live discharges, and 0.5pp lower likelihoods of dying in hospice care.

Table 4 shows that programs on track to exceed the cap live discharge patients who would take 0.048 log point (4.9%) more days to resume hospice care on average. But otherwise, we do not observe a statistically significant difference in the live discharged patients' LOS before the live discharge, their likelihood of resuming hospice care, or their likelihood of experiencing a hospital or ED stay within one week of their live discharge.

6.2.3 Hospice care for active patients

We next estimated equations (5)-(6) with outcomes measuring hospice care for active patients. Table 5 shows that programs on track to exceed the cap in an outgoing fiscal year provided much

	Prior		Fraction with a burdensome transition:	
	LOS	LLOS	Hospital stay	ED visit
	(log Δ)	(log Δ)	(pp Δ)	(pp Δ)
	(1)	(2)	(3)	(4)
$D_{ejw}^{\text{Sta.}}$	0.013	0.012	-0.004	-0.005
	(0.008)	(0.008)	(0.003)	(0.003)
	[0.121]	[0.234]	[0.367]	[0.237]
Estimator	PPML	PPML	OLS	OLS
Baseline Y	285	455	0.309	0.256
Effective obs.	676,718	676,718	682,363	682,363
Clusters	5,458	5,458	5,469	5,469

	Days until resumption	Fraction who later resume hospice:		
	(if any)	Anywhere	Same program	Elsewhere
	(log Δ)	(pp Δ)	(pp Δ)	(pp Δ)
	(5)	(6)	(7)	(8)
$D_{ejw}^{\text{Sta.}}$	0.048**	-0.003	0.001	-0.004
	(0.019)	(0.003)	(0.003)	(0.003)
	[0.064]	[0.428]	[0.819]	[0.366]
Estimator	PPML	OLS	OLS	OLS
Baseline Y	245	0.703	0.310	0.393
Effective obs.	498,173	682,363	682,363	682,363
Clusters	5,290	5,469	5,469	5,469

Tab. 4. *Static DID estimates for marginal live discharged patients.* Program-level cluster robust SEs are in parenthesis. Observations are weighted by the number of live discharged patients. All models include program FE and week FE interacted with state, ownership type, and WI controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Baseline Y is the average value of the outcome when $w = 0$ among treated programs. Effective obs. is the number of non-singleton observations that are not separated by a fixed effect (Correia et al. 2020; Correia 2017). Dynamic estimates are plotted in figure A2. Holm (1979) adjusted p in brackets enable multiple comparisons-robust inference at the 5% level for differential pre-discharge characteristics (column (1)) and post-discharge outcomes (columns (2)-(8)).

the same rates of RHC, CHC, IRC, and GIC, suggesting that they do not adjust their levels of hospice care. It also shows that they provided much the same rates of nurse visits, social worker visits, HHA visits, and nurse visits in the last three days of life on average, suggesting that they do not alter the distribution of staff visits per patient to accommodate the additional enrollees.

6.2.4 Heterogeneity analysis

Next, we estimated equations (5)-(6) after interacting the indicators D with program characteristics to examine treatment effect heterogeneity. First, we examined whether programs differentially churn patients based on their ownership type because a program's mission may affect its sensitivity to cap liabilities. Second, we examined whether programs differentially churn patients based on their patient volume or age because older programs with more patients may have more experience and resources to churn patients. Third, we examined whether programs differentially churn patients

	Fraction of patient-days with a visit by:			Fraction of decedents with a nurse visit
	Nurse (pp Δ)	HHA (pp Δ)	Social worker (pp Δ)	in last 3 days (pp Δ)
	(1)	(2)	(3)	(4)
$D_{ejw}^{\text{Sta.}}$	0.000	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.002)
	[0.603]	[0.388]	[0.357]	[0.594]
Estimator	OLS	OLS	OLS	OLS
Baseline Y	0.219	0.324	0.040	0.877
Effective obs.	999,622	999,622	999,622	778,423
Clusters	5,246	5,246	5,246	5,147

	Fraction of patient-days with:			
	RHC (pp Δ)	CHC (pp Δ)	IRC (pp Δ)	GIC (pp Δ)
	(5)	(6)	(7)	(8)
$D_{ejw}^{\text{Sta.}}$	-0.000	-0.000	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
	[0.387]	[0.682]	[0.605]	[0.191]
Estimator	OLS	OLS	OLS	OLS
Baseline Y	0.989	0.004	0.003	0.008
Effective obs.	1,419,834	456,274	974,974	987,220
Clusters	5,558	3,384	4,214	4,045

Tab. 5. *Static DID estimates for active patients.* Program-level cluster robust SEs are in parenthesis. Observations are weighted by the number of active patients (columns (1)-(3) and (5)-(8)) or decedents (column (4)). In columns (5)-(8), for each event, we excluded programs that did not provide any patient-days of that level of hospice care during that event's window. All models include program FE and week FE interacted with state, ownership type, and WI controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Baseline Y is the average value of the outcome when $w = 0$ among treated programs. Effective obs. is the number of non-singleton observations that are not separated by a fixed effect (Correia et al. 2020; Correia 2017). Dynamic estimates are plotted in figure A3. Holm (1979) adjusted p in brackets enable multiple comparisons-robust inference at the 5% level for differential staffing (columns (1)-(4)) and levels of care (columns (5)-(8)).

based on their proximity to other over-cap programs because programs near other over-cap programs cap may incur smaller reputational penalties for live discharges or compete more for prospective enrollees. Table 6 shows that new programs differentially live discharge more patients near the end of the fiscal year. But we do not find other significant associations between churning and a program's ownership type, patient volume, age, or proximity to other over-cap programs.

6.3 Sensitivity analyses

We conducted several sensitivity analyses. In particular, we examined whether our main results are sensitive to (1) a longer event window; (2) excluding state, ownership, and WI controls; and (3) excluding programs whose running average annual revenue was 90-100% of the cap at the start of the event windows. Figure A6 presents our results. The estimates are qualitatively similar.

| | Interactions with $D_{ejw}^{\text{Sta.}}$ | | | |
| | 1[Profit] | Log(Census) | 1[Age $\geq$ 4] | Proximity |
Outcome	(1)	(2)	(3)	(4)
Enrollments	0.007	0.004	0.011	0.017
(log Δ)	(0.019)	(0.005)	(0.013)	(0.039)
	[0.725]	[0.576]	[0.514]	[0.709]
Estimator	PPML	PPML	PPML	PPML
Baseline Y	0.253	0.253	0.253	0.253
Effective obs.	1,407,530	1,407,530	1,407,348	1,388,613
Clusters	5,554	5,554	5,553	5,540
	Interactions with $D_{ejw}^{\text{Sta.}}$			
	1[Profit]	Log(Census)	1[Age $\geq$ 4]	Proximity
Outcome	(5)	(6)	(7)	(8)
Live discharges	0.030	0.003	0.049**	-0.093*
(log Δ)	(0.030)	(0.008)	(0.019)	(0.051)
	[0.384]	[0.689]	[0.047]	[0.134]
Estimator	PPML	PPML	PPML	PPML
Baseline Y	0.156	0.156	0.156	0.156
Effective obs.	1,372,130	1,372,130	1,371,948	1,358,042
Clusters	5,530	5,530	5,529	5,516

Tab. 6. *Static DID estimates for heterogeneity analysis.* Each interaction term is measured at the start of the event windows. Program-level cluster-robust SEs are in parenthesis. All models include program FE and week FE interacted with state, ownership type, and WI controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Baseline Y is the average value of the outcome when $w = 0$ among treated programs. Effective obs. is the number of non-singleton observations that are not separated by a fixed effect (Correia et al. 2020; Correia 2017). Dynamic estimates are plotted in figures A4 and A5. Holm (1979) adjusted p in brackets enable multiple comparisons-robust inference at the 5% level for heterogeneity among enrollments (columns (1)-(4)) and live discharges (columns (5)-(8)).

6.4 Discussion

In sum, our DID analysis shows that hospice programs churn patients because of a cap on their average annual revenue. First, we find that programs on track to exceed the cap increase enrollment and live discharge rates. Second, we find evidence that the marginal enrollees are healthier on average and less connected to hospice care, which supports the idea that the cap causes programs to move down the demand curve. Third, we find that marginally live discharged patients wait longer to resume hospice care but are otherwise similar to inframarginally live discharged patients. Fourth, we do not find evidence that churning reduces staff visit rates (a measure of care quality) or the level of hospice care. Finally, we find evidence that a 2012 reform diminished churning.

Our estimates support the idea that programs' adjustments to the cap are small relative to their cap liabilities. In particular, they imply that programs on track to exceed the cap during a fiscal year's fourth quarter enroll 1.54 more patients and live discharge 0.37 more patients on average. During 2001-2018, 1.54 additional enrollees would have raised a hospice program's MRR by at most $25,643 (in 2001) to $44,181 (in 2018), and 0.37 additional live discharges would have lowered

its gross revenue by at most \$3,391 (in 2001) to \$5,960 (in 2018).[25] By contrast, programs that ultimately exceed the cap had an average cap liability of \$490,000.

Why don't programs churn more? We examined whether churning is associated with for-profit programs (that might be more sensitive to the cap), older programs (that might be more familiar with the cap), larger programs (that might invest in forecasting cap liabilities), or programs far from others on track to exceed the cap (that might compete less for marginal enrollees). Table A1 shows that these factors predict year-end cap liabilities; but among programs on track to exceed the cap, we did not find significant or consistent associations between these characteristics and churning. Instead, our findings support the idea that the cost of churning is high. This high cost may be attributable to non-pecuniary features of the Medicare hospice benefit, which requires that a non-hospice provider be consulted in enrollment and live discharge decisions, whenever possible, and that Medicare beneficiaries who enroll in hospice care forgo coverage for their terminal illnesses. It may also be related to legal concerns about inappropriate admissions (Gruber et al. 2023). That the marginal enrollees appear healthier on average supports the idea that programs on track to exceed the cap attempt to enroll patients for whom overcoming these constraints is increasingly costly.

Our results suggest that more research is needed to understand the effect of hospice enrollment and live discharge on patient welfare. Live discharge can be a costly disruption to care continuity, but it may be justified by changes in a patient's health status or preferences (Dolin et al. 2017). It is plausible that cap-induced live discharges are more harmful than inframarginal live discharges because they are financially motivated. But we did not find evidence that the marginally live discharged patients were in poorer health on average—as we would expect if their discharges were inappropriate—or were less likely to subsequently resume hospice care. Likewise, hospice enrollment can theoretically harm Medicare beneficiaries by reducing their access to curative care. But if the marginal enrollees had a "lack of knowledge" about hospice until the cap motivated programs to engage in more aggressive marketing, then their decision to enroll may indicate that they have better information about EOL care (Jenkins et al. 2011). Describing the timing and circumstances

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[25]With respect to enrollments, the cap was \$16,651 (in 2001) and \$28,689 (in 2018). If 1.54 additional patients were enrolled and had a LLOS of one day, then they would have raised their hospice program's MRR by $1.54 \times \$16,651 = \$25,643$ (in 2001) and $1.54 \times \$28,689 = \$44,181$ (in 2018). With respect to live discharges, daily payment rates for RHC at a program with a WI of 1 were \$102 (in 2001), and \$193 (in 2018, up to the first 60 days) or \$151 (in 2018, after the 60th day). If 0.37 additional patients were live discharged 90 days before the end of the fiscal year and would have remained enrolled for 90 days but for their live discharge, then their live discharge would have reduced their program's annual revenue by $0.37 \times 90 \times \$102 = \$3,391$ (in 2001) and $0.37 \times (60 \times \$193 + 30 \times \$151) = \$5,960$ (in 2018).

of hospice care consultations may be an especially fruitful direction for future research.

7 Conclusion

We study how an average revenue cap can affect provider behavior, health care utilization, and spending under capitation. In particular, we study a cap in the Medicare hospice benefit on hospice programs' average annual revenue. We find that programs on track to exceed the cap in an outgoing fiscal year increase enrollment and live discharge rates by 5.8% and 4.3% respectively during the fiscal year's fourth quarter. Characteristics of the marginal enrollees support the idea that the cap caused programs to move down the demand curve and enroll patients with a lower intrinsic demand for hospice care. We also find that programs that exceed the cap have an approximately $500,000 cap liability per year on average and that the wage index—a significant, visible, and administratively set determinant of payment rates—is nevertheless a significant predictor of cap liabilities.

The cap may have effects beyond churning. First, it may have a "deterrence effect" that induces programs to enroll a different distribution of patients year-round. However, we found that programs with an average annual revenue between 100-110% of the cap had an average cap liability of $163,000 per year, and no evidence of bunching in the distribution of average annual revenue. These findings are consistent with the idea that any such deterrence effect is concentrated among the small number of programs that far exceed the cap, and might have exceeded it further but for the deterrence effect. If MedPAC (2020)'s proposal to WI-adjust and reduce the cap by 20% is enacted, then it may be feasible to use subsequent changes in hospice care to identify the deterrence effect. Second, the cap may affect market structure. While we measure a positive association between cap liabilities and CCN terminations, we believe that identifying the causal effect of the cap on net entry and market composition is a critical next step for policymakers.

In sum, we find that adding a cap on average annual revenue to a fixed price payment model can reduce health care spending in the market segment under the cap. Although hospice programs could and did undercut the cap by churning their patients, they fell far short of minimizing their cap liabilities, which totaled $185 million per year on average during 2001-2018. Their scope for inducing demand may be small because of non-pecuniary features of the Medicare hospice benefit.

Acknowledgments

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX

A   Application of the payment cap

A.1   What determines the cap?

The cap was \$6,500 in the first year of the Medicare hospice benefit. It was chosen to be equal to 40% of Medicare's average expenditures for cancer patients in their last six months of life. Until 2015, it grew each year with the medical expenditure category of the Consumer Price Index for urban consumers. Since 2016, it has grown with hospice payment rates.[26]

    The cap is fixed across hospice programs within a given fiscal year, except for new programs. Each new program's first fiscal year is the first fiscal year ending at least twelve months after the program received its Medicare certification. New programs' first fiscal years may therefore span parts of two fiscal years. For these programs, the cap is a weighted average of the two fiscal years' caps. The weights are the fraction of days that the program operated in each of the fiscal years.[27]

A.2   What is a fiscal year?

For every fiscal year t through FY 2016, the fiscal year began on November 1 of calendar year $t - 1$ and ended on October 31 of calendar year t. In FY 2017, the fiscal year began on November 1, 2016 and ended on September 30, 2017. Since FY 2018, each fiscal year t has begun on October 1 of calendar year $t - 1$ and ended on September 30 of calendar year t.

A.3   How does Medicare compute each program's average annual revenue?

In each fiscal year, each hospice program's average annual revenue is the program's gross Medicare revenue divided by its patient census. The patient census accounts for the possibility that each Medicare beneficiary may utilize the hospice benefit across multiple program-years.

A.3.1   Revenue

Each program's gross Medicare revenue in each fiscal year is the sum of its daily payments for that fiscal year's patient-days, regardless of the day the payments were actually remitted. As discussed in the main text, the daily payments depend on the program's wage index, the level of hospice care, and, since 2016, whether the day is after the patient's 60th day in hospice care.

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[26]Federal Register, vol. 48(163):38156-7, vol. 80(151): 47207, and vol. 80(151):47147.
[27]Medicare hospice transmittal 156.

A.3.2 Patient census

During our sample period, patient censuses were determined by either the streamlined or proportional counting method:

1. Streamlined method

   a. *Patients who are only ever enrolled with one program.* These patients are counted toward a program's census on their first day in hospice care. For each fiscal year $t \in \{2001, ..., 2016\}$, if that day fell between September 28 of calendar year $t - 1$ and September 27 of calendar year t, then the patient was counted toward the program's census in fiscal year t. They were counted toward their program's census in FY 2017 if that day fell between September 28, 2016 and September 30, 2017. Finally, since FY 2018, they have been counted toward their program's cap census in a fiscal year t if that day was in fiscal year 2018.

   b. *Patients who are ever enrolled with two or more programs.* These patients contribute toward a program-year's census the fraction of their LLOS spent in that program-year.[28]

2. Proportional method: All patients contribute toward a program-year's census the fraction of their LLOS spent in that program-year.

All programs used the streamlined method until 2011. That year, Medicare rolled out the proportional method and programs have been steadily switching to the proportional method since then. First, CMS announced in 2011 that all programs would be switched to the proportional method starting in 2012 unless they elected to continue using the streamlined method. Second, programs that elected to continue using the streamlined method after FY 2011 could elect to switch to the proportional method at any time. Third, since October 1, 2011, new programs must use the proportional method. Once a program begins using the proportional method, it cannot switch back.

When programs switch from the streamlined method to the proportional method, some of their previous fiscal years' censuses could simultaneously be recalculated using the proportional method. Programs that elected to switch during the initial wave had a one-time opportunity to recalculate their censuses for all fiscal years before 2011 using the proportional method. Programs that elected to switch afterward could recalculate their censuses using the proportional method for up to three prior fiscal year. Patients treated by programs that switched but did not recalculate their prior censuses might ultimately contribute more than "1" to their programs' censuses in their lifetimes.[29]

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[28]If a beneficiary is enrolled with two hospice programs on the same say, then that day counts toward both program's cap censuses and raises the beneficiary's total number of beneficiary-days by two. For example, this may occur on days when beneficiaries are switching from one hospice program to another. See Medicare hospice transmittal 156.

[29]Medicare hospice transmittal 156.

We do not observe when a program switched from the streamlined or proportional method, or for which fiscal years, if any, they recalculated their patient censuses. Only 486 programs used the streamlined method by FY 2013.[30] Consequently, we assume that all programs used the streamlined method during FY 2001 - FY 2011 and the proportional method thereafter.

The patient census formulas inform our empirical analysis in several other ways. First, since most patients are only ever affiliated with one program, we define the primary census counting period for each fiscal year t before 2011 to be September 28 of calendar year $t - 1$ to September 27 of calendar year t. We define it it to be equal to the fiscal after 2012. Second, in any given fiscal year t before FY 2016, when a program switched from the streamlined method in FY $t - 1$ to the proportional method in FY t, patient-days between September 28 of calendar year $t - 1$ and October 31 of calendar year $t - 1$ were not counted toward any census. Consequently, some patients' lifetime contributions patient censuses are less than one.[31]

Third, under both the methods, a patient's contribution to their programs' censuses depend on their LLOS and the number of distinct programs where they ever enroll. Neither of these inputs are observed unless the patient is a decedent. In practice, at the end of each fiscal year, programs must estimate their cap liabilities using available data and repay the estimate within 5 months.[32] CMS may retroactively adjust this estimate with updated data for up to three subsequent fiscal years and hospice programs must repay the difference.[33] Therefore, our definitions of cap-related variables such as Liability_{jt}, Census_{jt}, and PPP_{jt} are with respect to this three-year look-back period.

A.4 Sequestration

The Budget Control Act of 2011 triggered a sequestration reduction to Medicare spending which cut hospice payments made on or after April 1, 2013 by 2 percent. In response, CMS applied a sequestration adjustment to the cap liability formula. First, CMS computed each program's annual gross Medicare revenue but for the 2% sequestration reduction. Second, CMS compared this pre-sequestration amount to the cap to compute a pre-sequestration cap liability. Third, CMS reduced the pre-sequestration cap liability by the percentage difference between the program's actual annual gross Medicare revenue and their annual gross Medicare revenue but for the sequestration reduction.[34] After FY 2013—when payments were only reduced for part of the fiscal year—CMS's sequestration adjustment is equivalent to reducing the cap by 2%.

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[30]Federal Register, vol. 80(151): August 6, 2015

[31]Medicare hospice transmittal 156.

[32]See 42 CFR 418.308.

[33]Federal Register, Volume 80(151): August 6, 2015. See also the CMS Manual System: Pub 100-02 Medicare Benefit Policy, transmittal 156, dated June 1, 2022.

[34]Opinion of Judge Bress in the matter of *Silverado Hospice, Inc. vs. Xavier Becerra*, filed August 1, 2022.

A.5   Comparison to MedPAC's cap liability estimates

The cap liability statistics we report in section 5 are consistent with those reported elsewhere. For instance, MedPAC (2020) reports that in 2002, average cap liabilities were \$470,000 among 2.6% of programs that exceeded the cap. We estimate that they were \$471,000 among 3.4% of programs that exceeded the cap. They also estimate that in 2014, cap liabilities were \$370,000 among 12.1% of programs that exceeded the cap. We estimate that they were \$390,000 among 13.9% of programs. These differences are attributable in part to differences in our calculation methodologies. MedPAC assumed that each patient's cap census contribution in each fiscal year is updated to account for that patient's hospice utilization in the following 14-15 months. We assumed that it is updated to account for that patient's hospice utilization in the following three years to reflect that CMS may reopen a given program-year's cap liability during the following three fiscal years.

B   Data

B.1   Discharge codes

Each hospice claim is associated with one of several discharge codes. We grouped the discharge codes into five categories: discharged home, discharged to another hospice, discharged to another health care institution, discharged to an unknown location (collectively, "discharged alive") and discharged dead. We validated the discharge codes in three steps:

1. For each claim, if the patient was observed in the same hospice on the day after the claim's last day, then we disregarded the discharge code on that claim. If they were observed in a different hospice on the day after the claim's last day, then we treated that claim as ending in a code for "discharged to another hospice." If the claim's last day coincided with the patient's date of death in the MBSF file, then we treated that claim as ending in a code for "discharged dead."

2. Otherwise, if a claim ended in a code for "discharged to another hospice," but the patient was not observed in any hospice on the next day, then we treated that claim as ending in a code for "discharged to an unknown location."

3. Otherwise, if a claim ended in a code for "discharged dead," but the patient's date of death in the MBSF file was after the last day of the claim, then we treated that claim as ending in a code for "discharged to an unknown location."

After we assigned a discharge code to each claim, we assigned to each (program, day, patient) observation all discharge codes from claims associated with that (program, patient) and ending on that day. There were cases where multiple discharge codes for "discharged to another institution," "discharged home," and "discharged to an unknown location" were each assigned to the same (program, day, patient) observation because the (program, patient) had multiple claims ending on that day. In such cases, we eliminated all but one discharge code using the following priority ranking: "discharged to another institution," then "discharged home," and then "discharged to unknown." (By construction, no (program, day, patient) observation has multiple discharge codes if any of the codes indicate "discharged dead" or "discharged to another hospice.")

B.2   Patient demographics

We linked the Medicare claims data to the Medicare Beneficiary Summary File (MBSF) for years 2000-2019. We identified each beneficiary's sex, race, date of birth, and date of death. It is not

common for one beneficiary to have multiple distinct realizations of these variables. When that happens, we assigned the beneficiary to whichever realization was reported first. We also identified each beneficiary's ZIP code of residence in each year. To calculate each hospice patient's remaining days of life after enrolling in hospice (RDOL), we assumed that patients with missing dates of death survived until December 31, 2019. (We re-estimated our DID analysis for RDOL including only decedents. The results were qualitatively similar.)

B.3   Hospice program business records

We relied on hospice programs' business data in the 2000-2019 Medicare provider-of-service (POS) files. In particular, we identified each program's ownership type (i.e., for-profit, not for-profit, public, or other/unknown), county, state, and facility name. We also used the programs' original participation dates and their earliest observed hospice claims to determine their ages.

We also used the hospice claims data to identify the first and last dates that a program's CCN is associated with a hospice claim.[35] We say that a program's CCN is terminated in a given fiscal year if it is not associated with any claims in the next fiscal year. CCNs are terminated when their underlying provider agreements are terminated (Medicare State operations Manual §2779). Provider agreements may be voluntarily terminated when a provider exits, when a provider goes bankrupt (Medicare Financial Management Manual, Chapter 3, §140.6.2), or when an institutional provider (such as a hospice program) undergoes a change of ownership and the new owner does not accept the institutional provider's existing provider agreement (Medicare State Operations Manual §3210.5A). Provider agreements may also be involuntarily terminated for several reasons, including because of a failure to make a "satisfactory overpayment arrangement[]," (Medicare State Operations Manual §3028D). To the best of our knowledge, there have been no systematic taxonomies of CCN terminations in the U.S. hospice industry, so we cannot distinguish exits from other events.

B.4   Assigning (program, days) to fiscal years

We linked each (program, day) in the hospice claims data to its corresponding fiscal year. This link is usually based on which fiscal year's start and end dates contain each day. For instance, days between November 1, 2007 and October 31, 2008 (inclusive) are linked to fiscal year 2008. However, a new program's first fiscal year is that fiscal year ending at least twelve months after the program received its Medicare certification. For instance, the first fiscal year of a program that was certified between November 2, 2006 and November 1, 2007 (inclusive) is FY 2008.

We identified each program's Medicare certification dates as follows. In the POS files, we

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[35]See appendix B.4 for details about how we used the claims data to identify when programs began operating.

identified each program's earliest observed Medicare certification date. For each program j, let this date be FirstCertDay(j). Similarly, let the earliest observed date associated with any of program j's Medicare claims be FirstClaimDay(j). For each program j such that FirstCertDay(j) is non-missing and earlier than FirstClaimDay(j), we treated FirstCertDay(j) as the program's Medicare certification date. But for some programs j, FirstCertDay(j) is either missing or greater than FirstClaimDay(j). (This represents approximately 45% of programs.) We assume that this indicates an error in the POS files. For such programs j, if FirstClaimDay(j) is strictly greater than January 1, 2000, then we treated FirstClaimDay(j) as the program's Medicare certification date. (This represents approximately 20% of hospice programs.) Otherwise, we assume that the first fiscal year ending 12 months after program j's Medicare certification is 2000 or earlier. (This calculation involves the date January 1, 2000 because our sample of the Medicare claims data begins in calendar year 2000, so FirstClaimDay(j) is January 1, 2000 for many programs.)

B.5   Wage index, daily payment rates, and the cap

We relied on WI, daily payment rates, and cap data published by Medicare in its transmittals to hospice programs and in the Federal Register. During FY 2001-FY 2018, the WI data were reported at the MSA-level, CBSA-level, or county-level. We linked the MSAs and CBSAs with counties to enable linking hospice programs to the WI.

B.6   Hospital and ED visits

We identified hospitalizations using the 2000-2019 MedPAR files. We linked the providers in the MedPAR files with their records in the POS files to determine which providers were hospitals and SNFs. We determined days that hospice patients spent in a hospital and SNF using the admission and discharge dates associated with each claim in the MedPAR files. We created variables indicating whether each hospice patient had a hospital stay in the week before their hospice enrollment. We also created variables indicating whether they had a hospital stay in the week after their live discharge to measure burdensome transitions.

We also identified ED stays using the 2000-2019 MedPAR files and outpatient claims. In the MedPAR files, we identified claims that included an ED visit using the ed charge amount variable. We assumed that the ED visit occurred on the first day of those claims. In the outpatient claims data, we identified claims that included an ED visit using revenue center codes 0450-0459 and 0981. We assumed that the ED visit occurred on the corresponding revenue center dates when available, or on the first day of the claim otherwise. We created variables indicating whether each hospice patient had an ED stay in the week after their live discharge dates to measure burdensome transitions.

B.7   Nursing home stays

We constructed NH spells using the Minimum Dataset (MDS) and MedPAR. The MDS contains records of Medicare beneficiaries' health assessments generated when they are admitted to NHs, discharged from NHs, and at regular intervals during their NH stays. We constructed NH spells by connecting consecutive assessment dates. We excluded some difficult-to-parse patients and assessments. For instance, we excluded assessments if that assessment's NH was neither the patient's previous assessment's NH or their subsequent assessment's NH. We also excluded patients if they were ever observed to have assessments from three NHs on the same day.

A patient's spell at a given NH began on (1) the day of the patient's first-observed assessment; (2) when an entry assessment was observed at that NH; (3) when an ongoing assessment was observed at that NH and the previous assessment occurred elsewhere; or (4) when an ongoing assessment was observed at that NH and the previous assessment was a discharge assessment at the same NH. A patient's spell at a given NH ended on (1) the day of the patient's last-observed assessment; (2) when a discharge assessment was observed at that NH; (3) when an ongoing assessment was observed at that NH and the next assessment occurred elsewhere; or (4) when an ongoing assessment was observed at that NH and the next assessment was an entry assessment at the same NH.

We identified NH stays by joining records of NH stays in the MDS with records of SNF stays in MedPAR. We created a patient-level variable indicating whether each hospice patient experienced a NH stay in the week before their hospice enrollment date.

B.8   Hospice staff visits

We identified days that a hospice staff visit occurred using the hospice claims data. In particular, we used the revenue center codes associated with each claim to identify skilled nurse, social worker, and home health aide visits associated with each claim-day. These visits were not reported from 2000 to 2007, so we exclude these years of data in analyses related to staff visits. We also identified for each decedent whether they experienced a nurse visit in the last three days of life.

B.9   Levels of hospice care

We identified the level of hospice care associated with each patient-day using the claims data. Each claim includes several revenue center lines reporting that for a span of days, a number of units of RHC, CHC, GIC, or IRC were provided on those days. For RHC, GIC, and IRC, the units are measured in days. For CHC, the units are measured in hours (prior to and including 2006) or fifteen minute increments (since 2007). We converted the CHC units to days. For most claims, the dates and units on each revenue center line are sufficient to determine the level of hospice care provided

on each claim-day. For instance, for claims spanning seventeen days and reporting 17 units of RHC, we infer that RHC was provided on each day. Similarly, for claims spanning seventeen days and reporting 14 units of RHC on day 1 and 3 units of GIC on day 15, we infer that RHC was provided during the first fourteen days and GIC was provided during the final three days. We distributed the units of each level of hospice care evenly across a given claim's days if we could not determine which levels of hospice care were provided on which day. We aggregated the (claim, day)-level data to the (provider, day, patient)-level by summing units of RHC, CHC, GIC, or IRC across all claims associated with that provider-day-patient.

B.10   Measuring each program-year's proximity to other program's that exceeded the cap in that year

We measure each program-year's proximity to other programs that exceeded the cap using the overlap between their patient populations. Define the indexes j for programs, z for ZIP codes, and t for fiscal years. Let J_{zt} be the set of programs that treated patients in (z, t). Let I_{jzt} be the set of patients living in (z, t) and being treated in (j, t). Finally, define the fraction of (z, t)'s patients being treated by programs other than j that exceeded the cap as:

$$D_{jzt} := \sum_{j' \in J_{zt} \setminus \{j\}} 1[\text{Over the cap}]_{j't} \left(\frac{|I_{j'zt}|}{\sum_{j' \in J_{zt} \setminus \{j\}} |I_{j'zt}|} \right) \tag{B.1}$$

To illustrate, consider programs $A, B, C \in J_{zt}$. Assume that B treated 50 patients in (z, t) and C treated 25 patients in (z, t). Assume that B exceeded the cap but C did not. Then $D_{Azt} = \frac{50}{75}$, indicating that two-thirds of z's hospice patients who were treated by other programs were treated by programs that exceeded the cap.

We define each (j, t)'s proximity to over-cap competitors as the average of D_{jzt}, weighted by the share of (j, t)'s patients who resided in (z, t):

$$D_{jt} := \sum_{z: j \in J_{zt}} D_{jzt} \left(\frac{|I_{jzt}|}{\sum_{z: j \in J_{zt}} |I_{jzt}|} \right) \tag{B.2}$$

This is a measure of proximity in the sense that it is increasing in the extent of geographic overlap between (j, t)'s patients and patients who enrolled with other hospice programs that exceeded the cap. To illustrate, consider a program A that treated 50 patients in ZIP code z_1 and 50 patients in ZIP code z_2 in fiscal year t. Assume that $D_{Az_1t} = \frac{2}{3}$ and $D_{Az_2t} = 0$. Then $D_{At} = \frac{1}{3}$.

B.11 Medical conditions

We categorized the ICD diagnosis codes in the hospice claims following Ankuda et al. (2023). For each hospice enrollee, we identified whether their ICD diagnosis codes were consistent with one of thirteen medical conditions: Alzheimer's disease and related dementia (ADRD), acute myocardial infarction (AMI), cancer, cerebrovascular disease, chronic kidney disease (CKD), chronic obstructive pulmonary disease (COPD), coronary artery disease, diabetes, end-stage renal disease (ESRD), flu, heart failure, pneumonia, and septicemia. We grouped the ICD diagnosis codes into these medical condition categories using the list at the end of this subsection. For each patient, we created indicator variables for these conditions based on the hospice claim(s) associated with their first observed day in hospice care.

1. ADRD

   - ICD-9: 3310, 33111, 33119, 33182, 29010, 29011, 29012, 29013, 29020, 29021, 29040, 29041, 29042, 29043, 29410, 29411, 29420, 29421, 3312, 3317, 2900, 2903, 797
   - ICD-10: G300, G301, G308, G309, F0150, F0151, F0280, F0281, F0390, F0391, G3101, G3109, G3183, G311, G94

2. AMI

   - ICD-9: 410
   - ICD-10: I21, I22

3. Cancer

   - ICD-9: 140, 209
   - ICD-10: C

4. Cerebrovascular disease

   - ICD-9: 850, 851, 852, 853, 854
   - ICD-10: S06

5. CKD

   - ICD-9: 5854, 5855, 5859
   - ICD-10: N184, N185, N189

6. COPD

   - ICD-9: 49120, 49121, 49122, 4910, 4911, 4918, 4919, 4920, 4928, 4940, 4941, 490, 496
   - ICD-10: J410, J411, J418, J430, J431, J432, J438, J439, J440, J441, J449, J470, J471, J479, J40, J42

7. Coronary artery disease

   - ICD-9: 411, 412, 413, 414
   - ICD-10: I20, I23, I24, I25

8. Diabetes

   - ICD-9: 250
   - ICD-10: E08, E09, E10, E11, E12, E13

9. ESRD

   - ICD-9: 5856
   - ICD-10: N186

10. Flu

    - ICD-9: 487, 488
    - ICD-10: J09, J10, J11

11. Heart failure

    - ICD-9: 39891, 40201, 40211, 40291, 40401, 40403, 40411, 40413, 40491, 40493, 42820, 42821, 42822, 42823, 42830, 42831, 42832, 42833, 42840, 42841, 42842, 42843, 4280, 4281, 4289
    - ICD-10: I50810, I50811, I50812, I50813, I50814, I0981, I5020, I5021, I5022, I5023, I5030, I5031, I5032, I5033, I5040, I5041, I5042, I5043, I5082, I5083, I5084, I5089, I110, I130, I132, I501, I509

12. Pneumonia

    - ICD-9: 48230, 48231, 48232, 48239, 48240, 48241, 48242, 48249, 48281, 48282, 48283, 48284, 48289, 4800, 4801, 4802, 4803, 4808, 4809, 4820, 4821, 4822, 4829, 4830, 4831, 4838, 481, 485, 486

- ICD-10: J15211, J15212, J1281, J1289, J1520, J1529, A481, J120, J121, J122, J123, J129, J150, J151, J153, J154, J155, J156, J157, J158, J159, J160, J168, J180, J181, J188, J189, J13, J14

13. Septicemia

    - ICD-9: 99591, 03689, 03810, 03811, 03812, 03819, 03840, 03841, 03842, 03843, 03844, 03849, 09889, 77183, 78552, 78559, 99592, 99593, 99594, 0031, 0202, 0223, 0270, 0271, 0362, 0363, 0369, 0380, 0382, 0383, 0388, 0389, 0545, 1125, 7907

    - ICD-10: A3989, A4101, A4102, A4150, A4151, A4152, A4153, A4159, A4181, A4189, A5486, R6510, R6511, R6520, R6521, R7881, A021, A207, A227, A267, A327, A391, A392, A393, A394, A399, A400, A401, A403, A408, A409, A411, A412, A413, A414, A419, A427, B007, B377, R571, R578

C   Tables referenced in the main text

	All	Above-cap			Below-cap	
		All	W/I 10%	≥80%	All	
	All	All	W/I 10%	≥80%	All	
	(1)	(2)	(3)	(4)	(5)	(6)
Age and ownership						
Age	12.27	6.20	7.28	8.27	8.76	13.06
1[For profit]	0.52	0.88	0.87	0.84	0.83	0.47
1[Not for profit]	0.36	0.06	0.07	0.09	0.10	0.40
1[Government]	0.05	0.01	0.01	0.01	0.01	0.06
Enrollments and live discharges						
New enrollments	271	106	158	248	242	293
Live discharges	56	57	62	77	72	56
% hospitalized within 7 days of enrollment	0.34	0.23	0.26	0.28	0.29	0.36
% in a NH within 7 days of enrollment	0.27	0.19	0.24	0.28	0.29	0.28
% elsewhere within 7 days of enrollment	0.47	0.63	0.57	0.52	0.50	0.45
Staffing						
Skilled nurse visits per patient-day	0.23	0.19	0.21	0.21	0.21	0.23
Social worker visits per patient-day	0.05	0.03	0.04	0.04	0.04	0.05
Home health aide visits per patient-day	0.24	0.25	0.27	0.28	0.28	0.24
Levels of hospice care						
Fraction of patient-days with RHC	0.98	0.99	0.99	0.99	0.99	0.98
Fraction of patient-days with CHC	0.00	0.00	0.00	0.00	0.00	0.00
Fraction of patient-days with IRC	0.00	0.00	0.00	0.00	0.00	0.00
Fraction of patient-days with GIC	0.01	0.00	0.00	0.00	0.01	0.01
Other characteristics						
Proximity to other over-cap programs	0.11	0.24	0.20	0.18	0.17	0.10
1[CCN terminated in next FY]	0.03	0.08	0.04	0.02	0.02	0.02
N (program-years)	57,412	6,602	2,018	2,926	6,824	50,810
Unique programs	5,685	2,214	1,279	1,605	2,517	5,300

Tab. A1. *Additional descriptive statistics about hospice programs.* This table reports descriptive statistics computed from (program, fiscal year)-level data. See the discussion in section 5.1.

	All	Above-cap All	W/I 10%	Below-cap ≥80%	All
	(1)	(2)	(3)	(4)	(5)	(6)
Demographic characteristics						
Female (%)	0.57	0.59	0.59	0.58	0.58	0.57
White (%)	0.88	0.80	0.82	0.82	0.84	0.88
Black (%)	0.08	0.13	0.10	0.10	0.09	0.08
Asian (%)	0.01	0.01	0.01	0.01	0.01	0.01
Hispanic (%)	0.02	0.04	0.04	0.05	0.03	0.02
N. Amer. Native (%)	0.00	0.00	0.00	0.00	0.00	0.00
Age at enrollment	81.7	81.7	82.3	82.4	82.3	81.7
Medical conditions at hospice enrollment						
ADRD (%)	0.19	0.24	0.26	0.21	0.22	0.19
AMI (%)	0.01	0.00	0.00	0.00	0.00	0.01
Cancer (%)	0.34	0.21	0.23	0.25	0.26	0.35
Cerebrovasc. disease (%)	0.00	0.00	0.00	0.00	0.00	0.00
CKD (%)	0.02	0.02	0.02	0.01	0.02	0.03
COPD (%)	0.11	0.11	0.12	0.10	0.11	0.11
Coronary artery disease (%)	0.07	0.07	0.07	0.06	0.06	0.07
Diabetes (%)	0.06	0.04	0.06	0.05	0.05	0.06
ESRD (%)	0.02	0.01	0.02	0.02	0.02	0.02
Flu (%)	0.00	0.00	0.00	0.00	0.00	0.00
Heart failure (%)	0.14	0.15	0.14	0.12	0.13	0.14
Pneumonia (%)	0.02	0.01	0.01	0.01	0.01	0.02
Septicemia (%)	0.02	0.01	0.01	0.01	0.01	0.02
Hospital and NH stays before enrollment						
Hospital (%)	0.40	0.26	0.29	0.35	0.33	0.41
NH (%)	0.27	0.24	0.27	0.28	0.30	0.28
Neither (%)	0.42	0.56	0.51	0.46	0.45	0.41
Lifetime hospice utilization						
Hospices (#)	1.06	1.22	1.15	1.11	1.10	1.05
Ever multiple hospices (%)	0.05	0.18	0.13	0.10	0.09	0.05
Live discharges (#)	0.22	0.60	0.44	0.34	0.32	0.20
Ever live discharged (%)	0.17	0.39	0.31	0.25	0.24	0.16
LLOS (#)	90	200	172	148	142	85
Characteristics pertaining to mortality						
Decedent (%)	0.98	0.95	0.96	0.97	0.97	0.99
RDOL (#)	156	425	308	248	236	143
Died in hospice (%)	0.92	0.81	0.86	0.89	0.90	0.92
N (patients, M)	15.6	0.7	0.3	0.7	1.7	14.9

Tab. A2. *Descriptive statistics about hospice patients.* This table reports descriptive statistics computed from patient-level data. Each patient is linked to a program-year based on the program and fiscal year associated with their first day in hospice care. They are assigned to a column based on the program's cap liability in that day's fiscal year. See the discussion in section 5.1.

	Samples			
	Full	For-profit	Cap census above annual median	Ever over the cap
	(1)	(2)	(3)	(4)
Estimates				
Test statistic	0.0962	0.1788	-0.9371	2.0079
p-value	0.9234	0.8581	0.3487	0.0447
Upper bandwidth				
Range	0.143	0.156	0.157	0.135
Observations	6,602	5,795	1,432	6,602
Effective observations	2,622	2,410	909	2,497
Lower bandwidth				
Range	0.198	0.187	0.222	0.150
Observations	50,810	23,683	27,273	12,449
Effective observations	6,740	5,132	3,550	3,528

Tab. A3. *McCrary test results.* This table reports McCrary test statistics of the null hypothesis that the distribution of average annual revenue relative to the cap is continuous at 1 (McCrary 2008). "Above annual median," means that a program-year's cap census was above that year's median cap census. The number of "effective observations" in each column is the number of observations within the upper and lower bandwidths (Cattaneo et al. 2018). Figure 2 plots the full distribution. See the discussion in section 5.1.
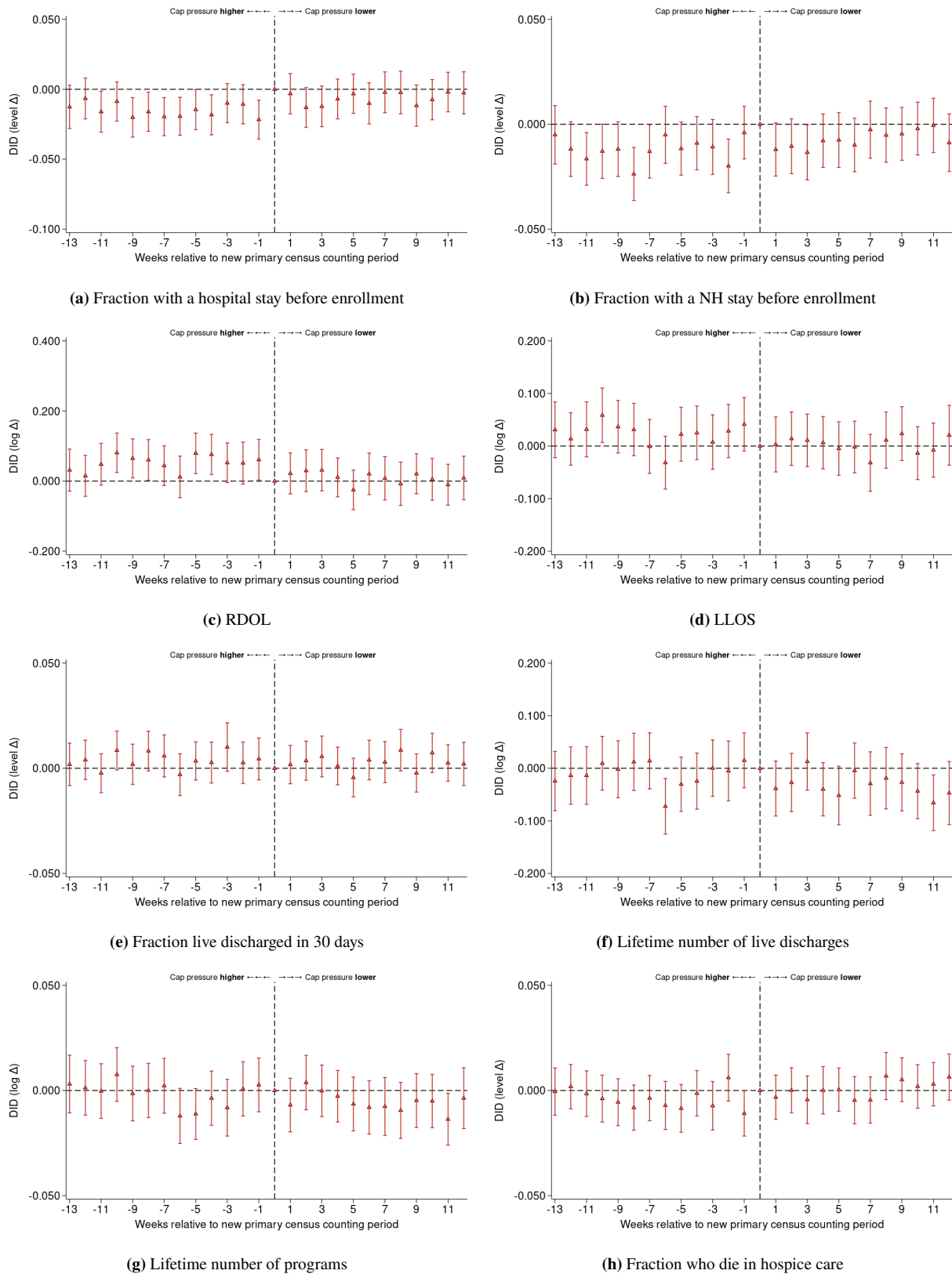
	1[Over cap]	Liability	Liability per unique patient	Gross Medicare payments	PPP
	(1)	(2)	(3)	(4)	(5)
Log(WI)	0.115***	4.544***	2.870**	0.226	0.415***
	(0.023)	(1.047)	(1.138)	(0.169)	(0.063)
Estimator	OLS	PPML	PPML	PPML	PPML
Hospice FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y	Y
$\bar{Y}$	0.113	177,361	3,106	3,673,515	15,163
Effective obs.	56,193	17,550	17,480	56,202	56,193
Clusters	5,246	2,082	2,075	5,246	5,246

	Gross Medicare payments per day	Annual census contribution per patient	Patient census	Number of unique patients	Number of patient-days
	(6)	(7)	(8)	(9)	(10)
Log(WI)	0.328***	0.002	-0.103	-0.084	-0.044
	(0.038)	(0.009)	(0.083)	(0.088)	(0.125)
Estimator	PPML	PPML	PPML	PPML	PPML
Hospice FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y	Y
$\bar{Y}$	147	0.730	273	357	23,619
Effective obs.	56,202	56,202	56,202	56,202	56,202
Clusters	5,246	5,246	5,246	5,246	5,246

Tab. A4. *Associations between program outcomes and the wage index.* Program-level cluster-robust SEs in parentheses. $\bar{Y}$ is the sample mean of the outcome. Effective obs. is the number of non-singleton observations that are not separated by a fixed effect (Correia et al. 2020; Correia 2017). See the discussion in section 5.2.
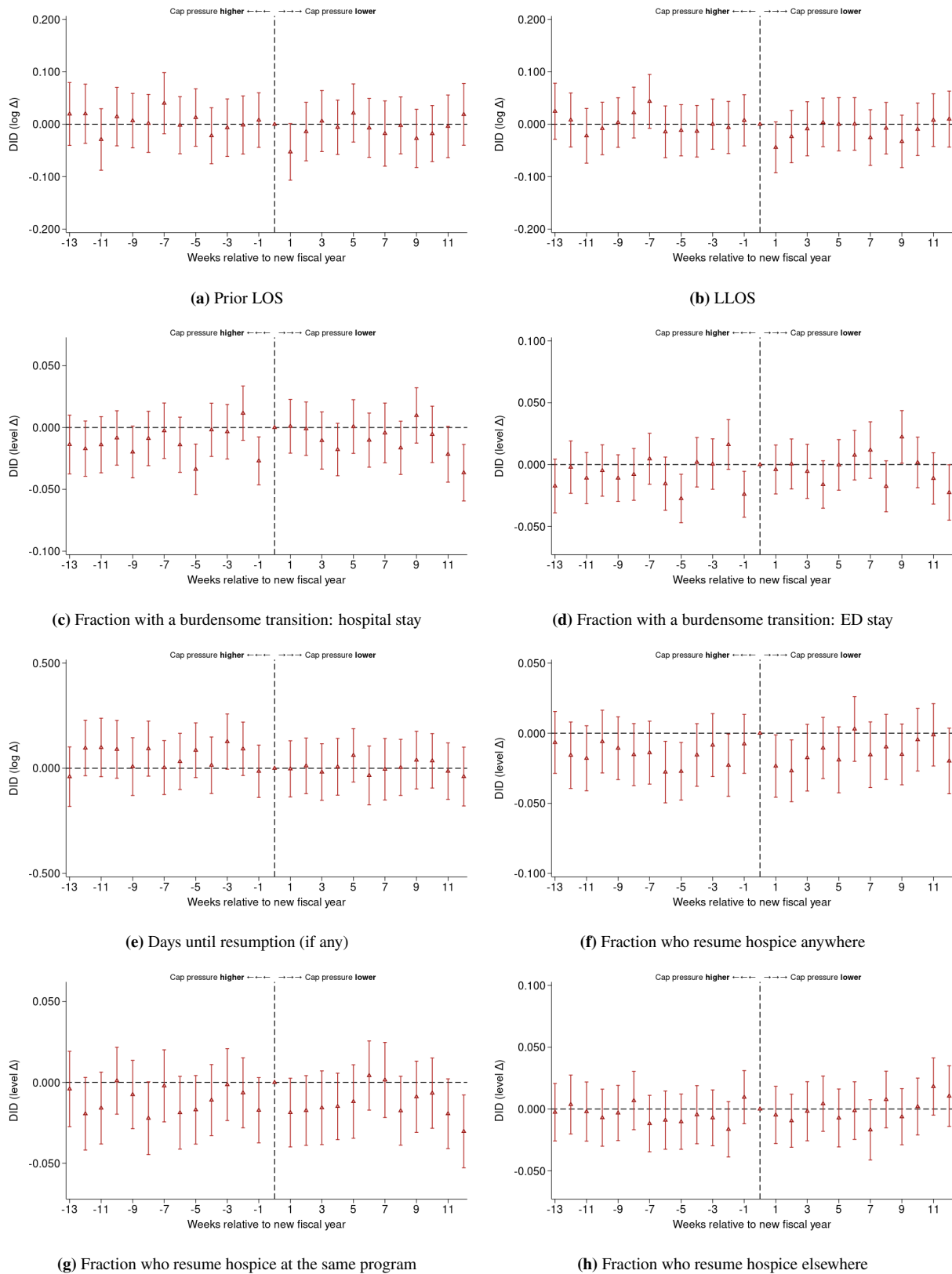
	1[Over cap] (1)	Liability (2)	Liability per unique patient (3)	Gross Medicare payments (4)	PPP (5)
1[Over cap]$_{jt-1}$	0.193***	1.242***	0.725***	0.074	0.162***
	(0.010)	(0.058)	(0.064)	(0.055)	(0.008)
Estimator	OLS	PPML	PPML	PPML	PPML
Hospice FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y	Y
$\bar{Y}$	0.112	191,840	2,985	3,911,340	15,261
Effective obs.	51,203	15,497	15,451	51,210	51,203
Clusters	4,878	1,893	1,887	4,879	4,878

	Gross Medicare payments per day (6)	Annual census contribution per patient (7)	Patient census (8)	Number of unique patients (9)	Number of patient-days (10)	1[CCN terminated] (11)
1[Over cap]$_{jt-1}$	-0.008***	-0.074***	-0.107**	-0.025	0.095**	0.056***
	(0.002)	(0.003)	(0.046)	(0.044)	(0.044)	(0.003)
Estimator	PPML	PPML	PPML	PPML	PPML	OLS
Hospice FE	Y	Y	Y	Y	Y	-
Year FE	Y	Y	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y	Y	Y
$\bar{Y}$	147	0.726	286	376	25,053	0.025
Effective obs.	51,210	51,210	51,210	51,210	51,210	52,918
Clusters	4,879	4,879	4,879	4,879	4,879	5,375

Tab. A5. *Associations between program outcomes and exceeding the cap in the previous fiscal year.* Program-level cluster-robust SEs in parentheses. $\bar{Y}$ is the sample mean of the outcome. Effective obs. is the number of non-singleton observations that are not separated by a fixed effect (Correia et al. 2020; Correia 2017). See the discussion in section 5.3.
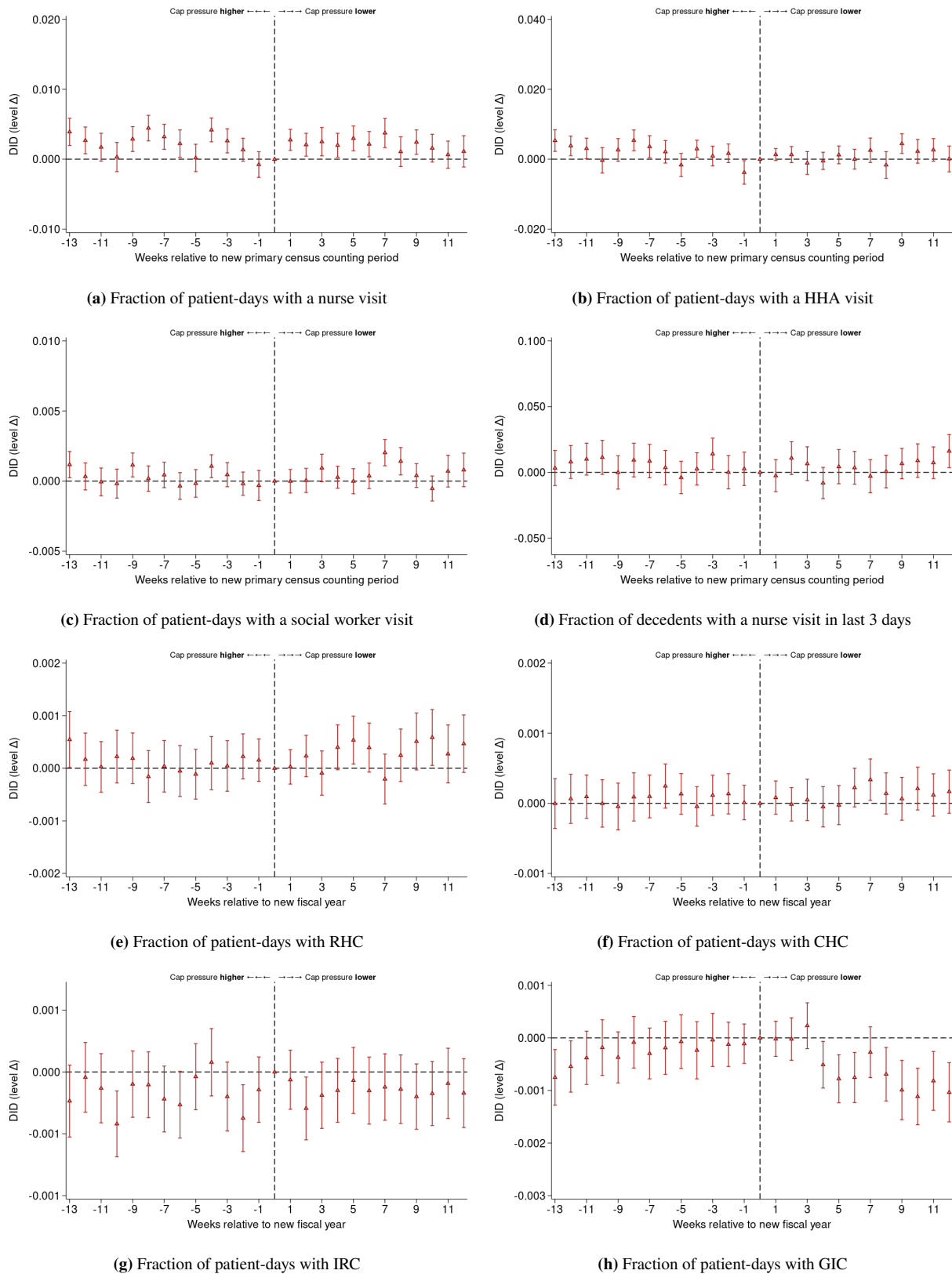
D   Figures referenced in the main text

(a) Fraction with a hospital stay before enrollment

(b) Fraction with a NH stay before enrollment

(c) RDOL

(d) LLOS

(e) Fraction live discharged in 30 days

(f) Lifetime number of live discharges

(g) Lifetime number of programs
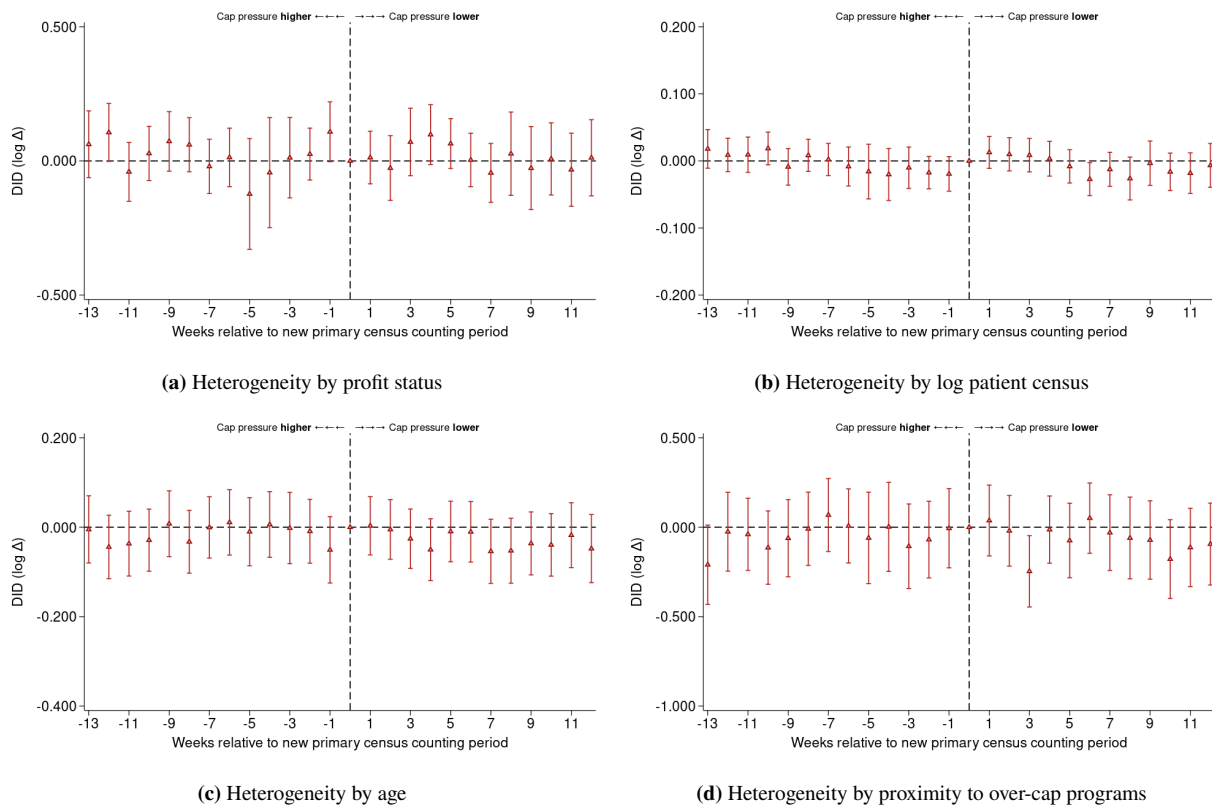

(h) Fraction who die in hospice care

Fig. A1. *Dynamic DID estimates for outcomes related to new enrollees.* This figure is a companion to table 3. The 95% CIs are computed with program-level cluster-robust SEs. All models include program FE and week FE interacted with state, ownership type, and WI controls. Observations are weighted by each program-day's number of new enrollees. See the discussion in section 6.2.2.

(a) Prior LOS

(b) LLOS

(c) Fraction with a burdensome transition: hospital stay

(d) Fraction with a burdensome transition: ED stay

(e) Days until resumption (if any)

(f) Fraction who resume hospice anywhere

(g) Fraction who resume hospice at the same program

(h) Fraction who resume hospice elsewhere

Fig. A2. *Dynamic DID estimates for outcomes related to live discharged patients.* This figure is a companion to table 4. The 95% CIs are computed with program-level cluster-robust SEs. All models include program FE and week FE interacted with state, ownership type, and WI controls. Observations are weighted by each program-day's number of live discharged patients. See the discussion in section 6.2.2.
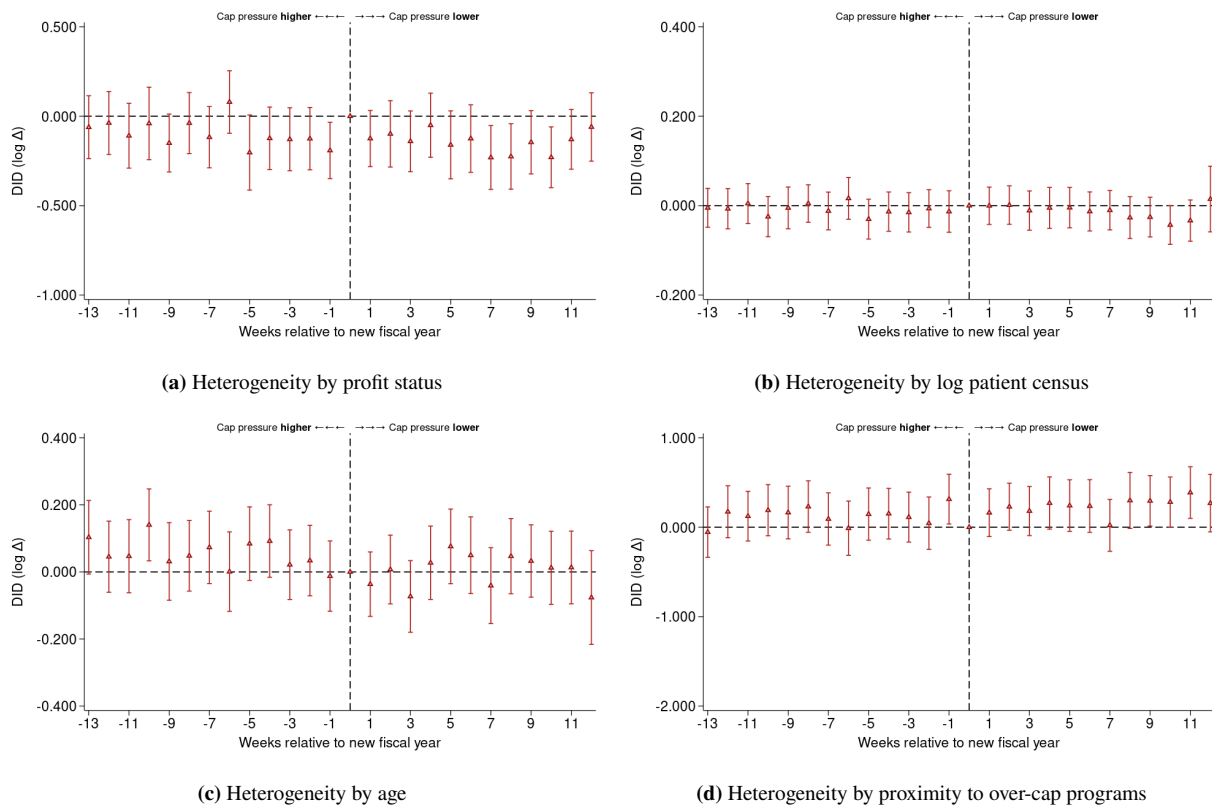
(a) Fraction of patient-days with a nurse visit

(b) Fraction of patient-days with a HHA visit

(c) Fraction of patient-days with a social worker visit

(d) Fraction of decedents with a nurse visit in last 3 days

(e) Fraction of patient-days with RHC

(f) Fraction of patient-days with CHC

(g) Fraction of patient-days with IRC

(h) Fraction of patient-days with GIC

Fig. A3. *Dynamic DID estimates for outcomes related to active patients.* This figure is a companion to table 5. The 95% CIs are computed with program-level cluster-robust SEs. All models include program FE and week FE interacted with state, ownership type, and WI controls. Observations are weighted by each program-day's number of active patients (panels (a)-(c) and (e)-(h)) or the number of decedents (panel (d)). See the discussion in section 6.2.3.

(a) Heterogeneity by profit status

(b) Heterogeneity by log patient census

(c) Heterogeneity by age

(d) Heterogeneity by proximity to over-cap programs

Fig. A4. *Dynamic DID estimates for heterogeneity analysis related to a program's number of new enrollments.* This figure is a companion to table 6. The 95% CIs are computed with program-level cluster-robust SEs. All models include program FE and week FE interacted with state, ownership type, and WI controls. See the discussion in section 6.2.4.

(a) Heterogeneity by profit status

(b) Heterogeneity by log patient census

(c) Heterogeneity by age

(d) Heterogeneity by proximity to over-cap programs

Fig. A5. *Dynamic DID estimates for heterogeneity analysis related to a program's number of live discharges.* This figure is a companion to table 6. The 95% CIs are computed with program-level cluster-robust SEs. All models include program FE and week FE interacted with state, ownership type, and WI controls. See the discussion in section 6.2.4.
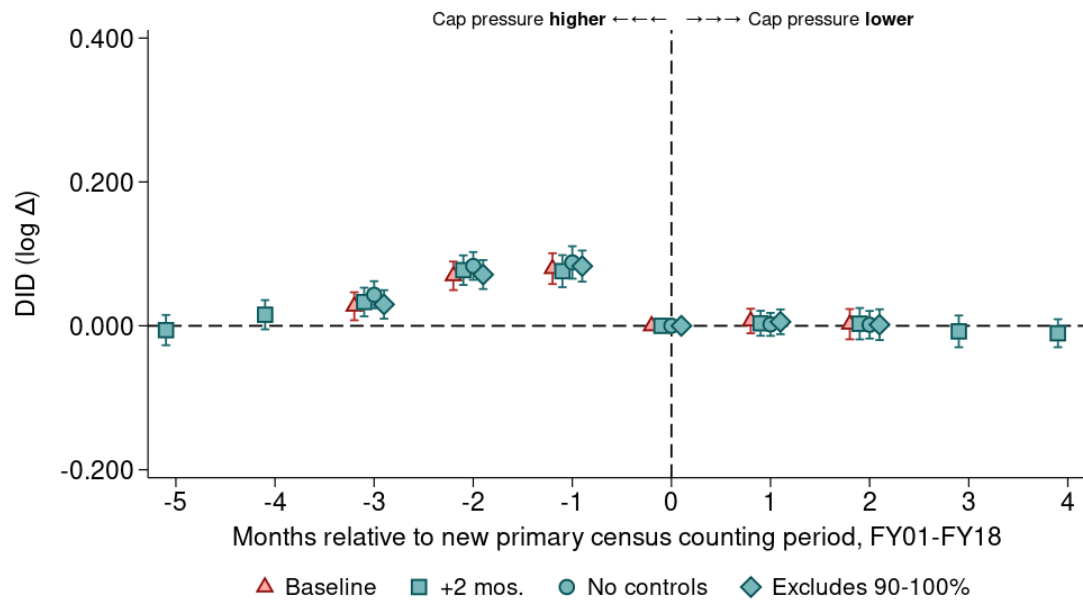
(a) Daily number of new patient enrollments
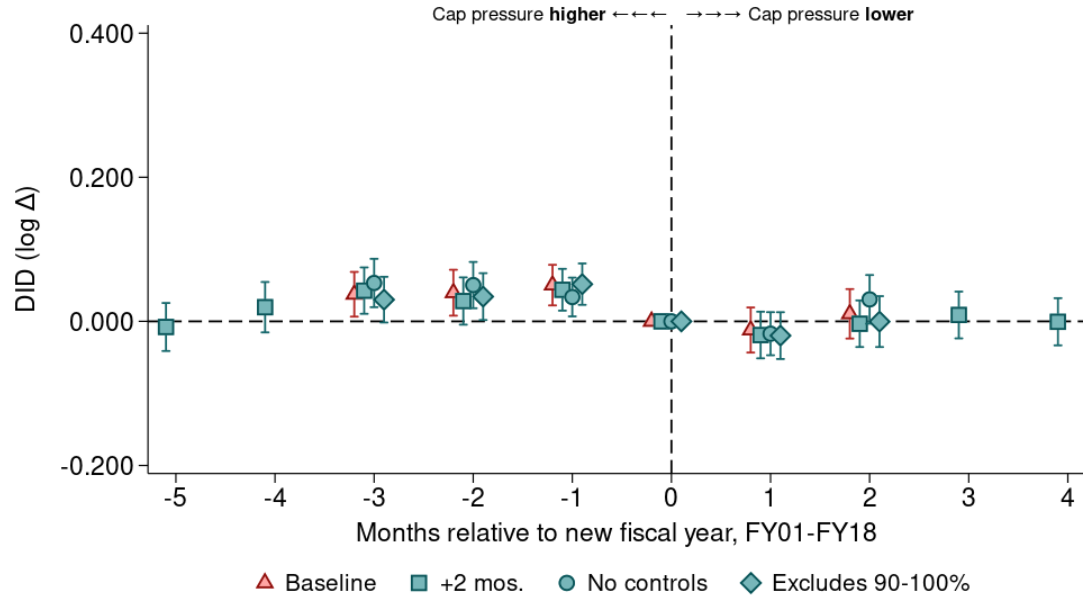
(b) Daily number of live discharges

Fig. A6. *Dynamic DID estimates for sensitivity analysis.* This figure plots results of the sensitivity analysis discussed in section 6.3. The 95% CIs are computed with program-level cluster-robust SEs.

E   Additional descriptive statistics

E.1   Geographic variation in cap liabilities

Figure A7 plots state-level trends in the average annual fraction of hospice programs that exceeded the cap. It shows that between 2001 and 2009, a larger fraction of hospice programs in MS, AL, AZ, and OK exceeded the cap than in other states. It also shows that since 2010, an increasing fraction of hospice programs in California have exceeded the cap.
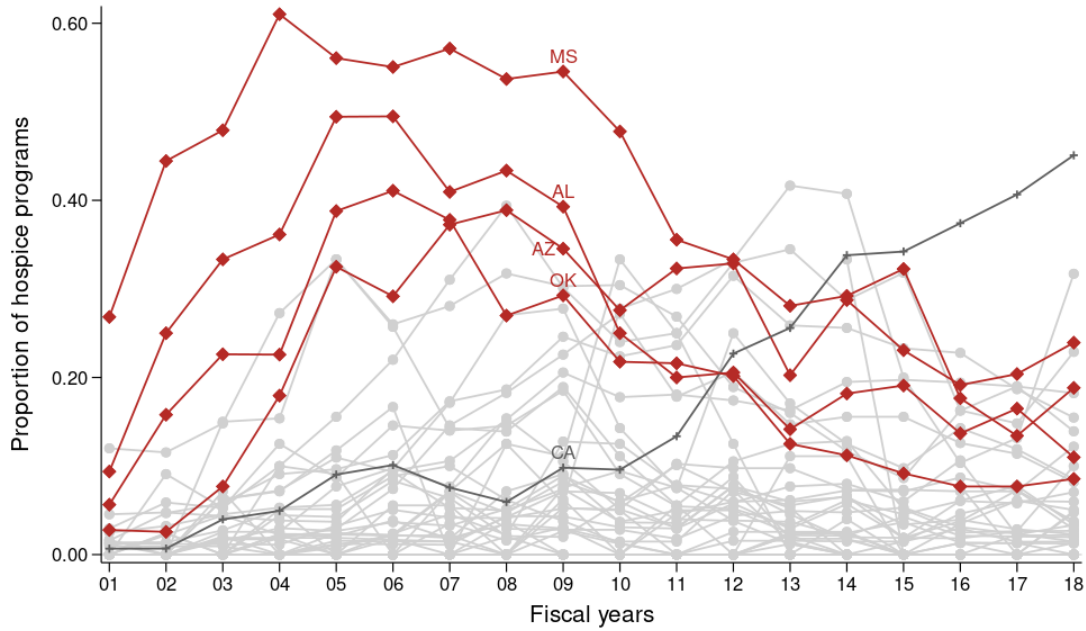

Fig. A7. *Geographic variation in cap liabilities.* This figure plots state-level trends in the proportion of hospice programs that exceeded the cap between fiscal years 2001 and 2018. It shows that cap liabilities were particularly prevalent in MS, AL, OK, AZ, and CA during this period.
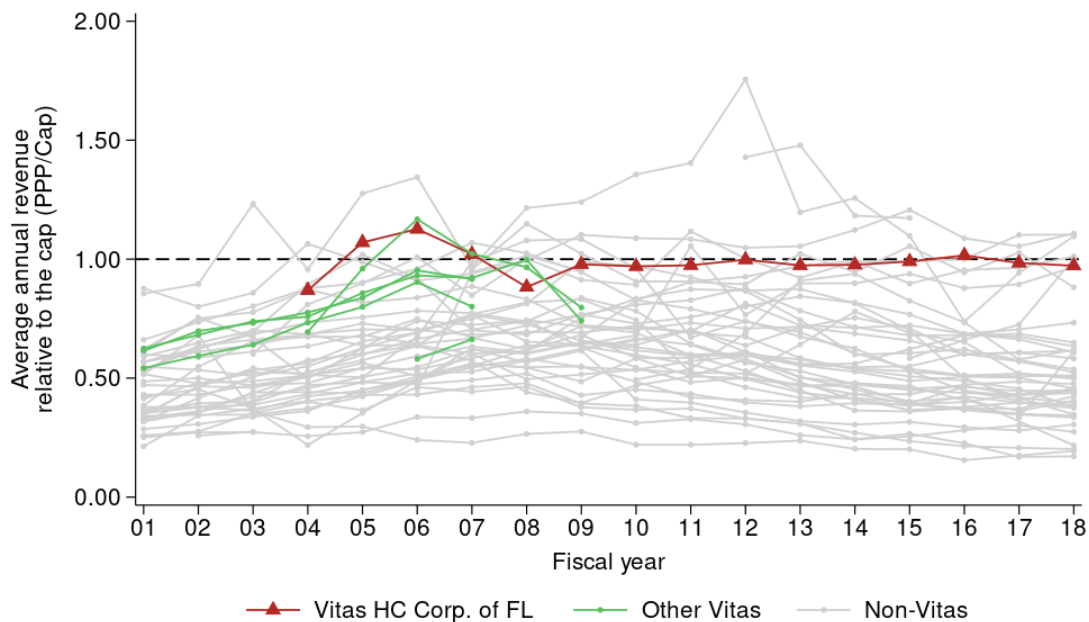
E.2   Vitas Healthcare Corporation of Florida

We also investigate whether any individual hospice program's average annual payments per patient are persistently close to the cap. For each hospice program j, we computed $\text{Dist}_j := T_j^{-1} \sum_t |\text{PPP}_{jt}/\text{Cap}_t - 1|$ and $\text{Census}_j := T_j^{-1} \sum_t \text{Census}_{jt}$, where T_j is the number of fiscal years that program j is observed between FY 2001 and FY 2018. Figure A8(a) plots the joint distribution of $(\text{Dist}_j, \text{Census}_j, T_j)$. It shows that most hospice programs are not persistently close to the cap. It also shows that those hospice programs that are persistently within 10% of the cap are either observed for a short time or have small patient censuses—with one exception: the figure shows that Vitas Healthcare Corporation of Florida operated for 15 fiscal years between

FY 2001 and FY 2018 and, in this time, it had an average annual patient census of approximately 11,000—the highest in the country—and an average annual payment per patient within 4.4% of the cap per year on average. Figure A8(b) plots trends in its $\text{PPP}_{jt}/\text{Cap}_t$. It shows that between 2006-2008, Vitas consolidated its operations in Florida into one program. The program's average annual payments per patient were almost exactly equal to the cap between FY 2009 and FY 2018. In other words, Vitas appears to have nearly maximized average annual payments per patient in Florida for ten straight years.

While it is difficult to determine Vitas's strategy, a recent OIG report suggests that Vitas Healthcare Corporation of Florida may have inappropriately billed Medicare. After auditing a sample claims associated with Vitas Healthcare Corporation of Florida between 2017 and 2019, OIG alleged that "Vitas received at least \$140 million in improper Medicare reimbursement for hospice services that did not comply with Medicare requirements." According to OIG, these payments were associated with claims for CHC and GIC that were "not supported" by clinical records. See OIG (2022b).
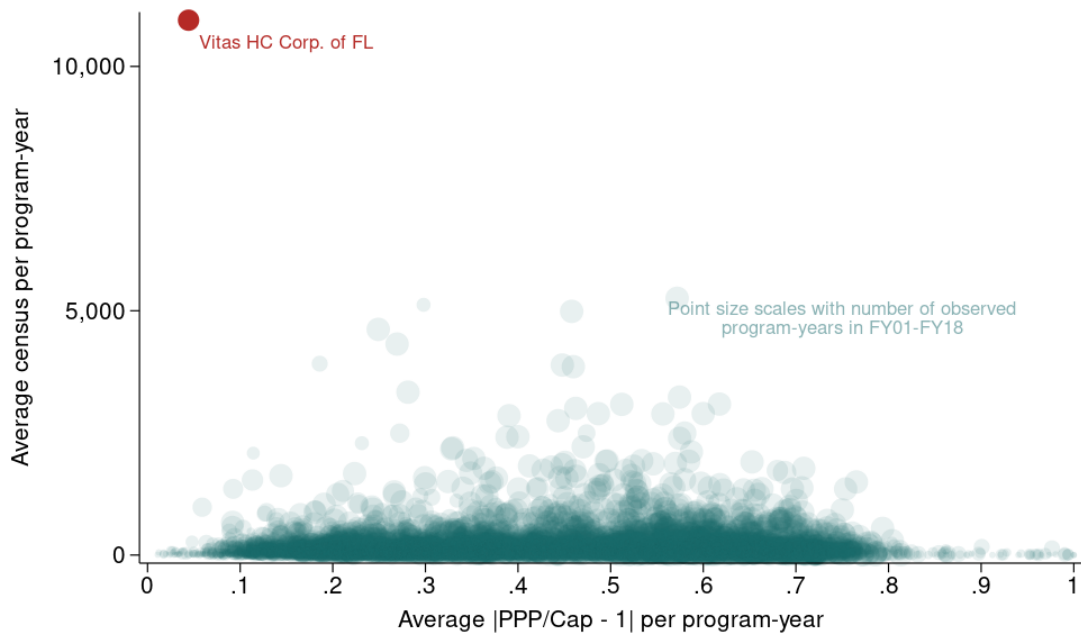
(a) Joint distribution between hospice programs' patient censuses and their proximity to the cap

(b) Trends in Florida-based hospice programs' proximities to the cap

Fig. A8. *Vitas Healthcare Corporation of Florida and the cap during FY2001-FY2018.* Panel (a) plots the joint distribution between each hospice program's average annual patient census and their average proximity to the cap. It supports the idea that most programs do not persistently equilibrate their average annual revenue with the cap. However, it also shows that Vitas Healthcare Corporation of Florida is by far the largest hospice program in the country and persistently close to the cap. Panel (b) plots trends in Florida-based hospice programs' proximities to the cap. It shows that after a period of consolidation between Vitas's Florida-based hospice programs, Vitas Healthcare Corporation of Florida's average annual revenue was persistently close to the cap.