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

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

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(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

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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 health care policymaking for decades. Arrow (1963) argued that provider-induced demand and moral hazard can cause individuals to receive health care services even when the marginal social cost of those services exceeds their marginal social benefit. Well designed payment models can moderate the effects of these market failures by shifting the responsibility for unnecessary costs on to providers (Ellis and McGuire, 1986). For instance, under capitation, providers bear the marginal cost of care intensity because they are paid a fixed amount to treat a patient for a period of time (e.g., Friedberg et al., 2015). Ideally, financially-motivated providers under capitation will consequently eliminate productive inefficiencies. But capitation may also cause them to keep patients enrolled longer than necessary, thereby creating new allocative inefficiencies. Since 1983, Medicare has combined capitation with a cap on hospice programs' average annual revenue to reduce both productive and allocative inefficiencies simultaneously.

In this paper, we study how an average revenue cap can affect provider behavior and health care utilization and spending by analyzing nearly two decades of hospice claims data. We show that in theory, hospice programs could undercut the cap by churning their patients. That is, they could reduce their average annual revenue by raising their year-end enrollment and live discharge rates. We show that a well-timed enrollment could reduce a hospice program's cap liability by tens of thousands of dollars. (For comparison, the average daily payment rate was approximately $150 contemporaneously.) That hospice programs could reduce their cap liabilities by enrolling new patients raises concerns about the cap's capacity to contain costs. It also creates a unique opportunity to study provider-induced demand.

We measure the extent of this churning behavior by leveraging variation in cap-related financial incentives generated by the cap's nonlinear design and the transition between fiscal years. We show that it was small: hospice programs on track to exceed the cap in a given fiscal year raised enrollment rates by 5.8% and live discharge rates by 4.3% on average in the fiscal year's fourth quarter. The marginal enrollees were less likely to have been hospitalized prior to their hospice enrollment and less likely to ultimately die in hospice care. However, the number of marginally enrolled and marginally discharged patients was far less than necessary to eliminate hospice programs' cap liabilities. In fact, we find that hospice programs exceeded the cap in 11% of program-years between 2001 and 2018 and repaid to Medicare an average of $500,000 per program-year above the cap. This research suggests that hospice programs' scope for inducing demand may have been more limited than policymakers had feared and that a cap on average annual revenue can reduce health care spending under capitation.

The Medicare hospice benefit is a significant part of the U.S. health care system. It is available to all terminally ill Medicare beneficiaries with a predicted life expectancy of six months or less. It covers services provided or arranged by a Medicare-certified hospice program, including 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, including curative care, for the duration of their hospice enrollment.[1] In 2019, approximately 52% of Medicare decedents received hospice care and Medicare payments to hospice programs were approximately $20.9 billion (MedPAC, 2022).[2] Hospice care has been associated with higher quality of care and fewer unmet patient needs at end-of-life (e.g., Teno et al., 2011).

Under the hospice benefit, Medicare pays hospice programs a fixed amount per patient-day but limits their average annual revenue with a so-called "aggregate payment cap." In 2023, the cap was $32,487 per patient on average, meaning that a hospice program that served 100 patients that year could have received no more than $3,248,700 from Medicare.[3] Any excess revenue ("cap liability," hereafter) must be repaid to Medicare retrospectively at the end of each fiscal year.[4] In practice, audits conducted by the Office of Inspector General ("OIG," hereafter) 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 hospice programs are unlikely to be 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 a formula that depends on their billing records.

[1]Medicare Benefit Policy Manual Chapter 9.

[2]The share of Medicare decedents who received hospice care decreased during the COVID-19 pandemic to 48% in 2020 (MedPAC, 2022).

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

[4]Outstanding cap liabilities are treated as debts owed to the federal government, accrue interest, and will be forwarded to the Treasury Department for debt collection if needed. See 42 CFR 418.308 and the Medicare Financial Management Manual, Chapter 4.

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 (Lee and Levy, 2012; Clemens and Gottlieb, 2014). 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 clinical gray area. Death is highly unpredictable among Medicare beneficiaries (e.g., Einav et al., 2018), it is difficult for health care providers to determine when hospice care is needed most (Sack, 2007), and there is virtually no patient cost-sharing under the Medicare hospice benefit.[5] There may therefore be scope for financially motivated hospice programs to raise revenue by persuading Medicare beneficiaries to initiate hospice care 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 several whistleblower lawsuits filed against other hospice programs have made similar allegations (Kofman, 2022; Rao, 2011). Under these circumstances, the cap can in theory raise welfare by dampening hospice programs' incentives to provide excessive hospice care. It can also enable Medicare to recoup spending *ex post*. But the cap's effectiveness depends on how hospice programs respond.

Studies show that health care providers respond to financial incentives in many contexts (e.g., Eliason et al., 2022; Clemens and Gottlieb, 2014; Chandra et al., 2012). For instance, pay-for-performance programs with nonlinear designs have been shown to significantly influence clinical practices at long-term care hospitals (Eliason et al., 2018; Einav et al., 2018) and acute care hospitals (Gupta, 2021; Norton et al., 2018). Existing research and press reports have documented some hospice programs self-reporting that they adjusted their enrollment and live discharge rates to limit

[5]Hospice patients pay up to $5 per prescription for pain and symptom management and 5% of the Medicare-approved amount for inpatient respite care. See the Medicare Hospice Benefit Manual.

their cap liabilities (Jenkins et al, 2011; Sack, 2007).[6] For instance, staff at some programs facing cap liabilities were reportedly pressured to "pad the roster with new patients" or discharge patients with "overly long stays" (Kofman, 2022). But to date, it is unclear how widespread these practices are. While studies have documented positive correlations between cap liabilities and live discharge rates (e.g., Dolin et al., 2018; Plotzke et al., 2015; Teno et al., 2014), it is unclear how much of this variation is attributable to the cap versus other differences between hospice programs.

In this paper, we contribute a comprehensive description of hospice programs' cap liabilities and causal measurements of their responses to the cap. We estimate cap liabilities for all Medicare-certified hospice programs between fiscal years 2001 and 2018 using Medicare claims for a 100% sample of Medicare beneficiaries. We find that hospice programs exceeded the cap in 11% of program-years. When they did, we find they had cap liabilities of approximately \$500,000 per year on average (or 21% of their gross Medicare revenue). We find no evidence of a discontinuity in the distribution of average annual revenue near the cap, despite observing that programs with average annual revenue between 100-110% of the cap had an approximately \$160,000 cap liability per year on average. These findings suggest that hospice programs face barriers to adjusting their admissions and discharge practices to eliminate their cap liabilities.

However, hospice programs may respond to the cap while still ending a fiscal year with some cap liabilities. We explore this possibility with a difference-in-differences research design, which leverages variation in cap-related financial incentives generated by the policy's nonlinear design and the transition between fiscal years. In particular, the policy's nonlinear design implies that hospice programs whose average annual revenues are on track to remain below the cap face no financial incentive to respond to the cap. Furthermore, that hospice programs' cap liabilities are calculated on a year-to-year basis implies that hospice programs on track to exceed the cap in an outgoing fiscal year face stronger financial incentives to reduce their cap liabilities near the end of the outgoing fiscal year than they do at the start of the next fiscal year; whereas programs on track to remain below the cap in the outgoing fiscal year do not experience a change in their cap-related financial incentives contemporaneously.

Our design overcomes two identification problems that arise in between-program or within-

[6] Jenkins et al. (2011) analyzed 107 responses to a 2008 survey sent to 193 Alabama hospice programs. Approximately 25% of respondents indicated that they adjusted admission and discharge practices to limit cap liabilities. They were slightly more for-profit than the 5,700 programs that operated in our sample period (72% versus 52%).

program comparisons alone. First, hospice programs that exceed the cap differ from hospice programs that remain below the cap in several ways. For instance, consistent with existing evidence, we find that programs that exceed the cap are more likely to be newer, smaller, and for-profit. They also treat patients with higher lifetime lengths-of-stay in hospice care (LOS), higher rates of neurological and cardiovascular conditions, and lower rates of cancer (MedPAC, 2022). It is therefore unclear which between-program differences are attributable to the cap versus other program-related factors. Second, there is seasonality in hospice utilization. For instance, enrollment rates are generally higher during the winter and lower during holidays. It is therefore unclear which within-program differences are attributable to the cap versus other time-related factors. Our research design 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.

We find that programs on track to exceed the cap in an outgoing fiscal year have 5.8% differentially higher enrollment rates during the fiscal year's last quarter on average. 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. We find that these enrollment rate differences were larger before 2011. This is consistent with the size of the incentives in the cap liability formula: until 2011, a program's cap liability could be reduced by tens of thousands of dollars if it enrolled a patient during the final days of a fiscal year. We also find that programs on track to exceed the cap in an outgoing fiscal year have 4.3% differentially higher live discharge rates during the fiscal year's last quarter on average. Overall, we find that programs on track to exceed the cap in a given fiscal year differentially decrease their average annual revenue by approximately 6.5% during the last quarter of that fiscal year on average. While these estimates support the idea that hospice programs respond to the cap on the intensive margin by churning patients, they also support the idea that programs' responses are relatively small. In particular, our estimates translate to approximately 1.54 additional enrollees and 0.37 additional live discharges per program-year on average.

We also characterize the patients who enter and exit hospice care due to these cap-induced financial incentives. Their characteristics could provide clues about who is affected by hospice programs' responses to the cap, and how. We find evidence that the marginal enrollees are differentially healthier at the time that they enroll: they are 0.9 percentage points less likely to have had a hospital stay in the previous week, they are 0.6 percentage points less likely to have had a nursing home stay in the previous week, and they have 4.5% longer remaining lifetimes on average. We also find evidence that they have differentially more and more fragmented lifetime hospice utilization: they have 2.0% longer lifetime LOS in hospice care, they have 1.9% more lifetime live discharges, and they are 0.5 percentage points less likely to ultimately die in hospice care on average. These findings support the idea that marginal enrollees had lower intrinsic demand for hospice care. The marginal live discharged patients subsequently resume hospice care at similar rates, but those who eventually resume hospice care spend differentially 4.9% more time between hospice spells on average.

Our findings that hospice programs make limited intensive margin responses to the cap raise concerns about the cap's effect on market structure. For instance, hospice programs that are unable to adjust along the intensive margin sufficiently may instead adjust along the extensive margin by closing or consolidating (Ata et al., 2012) or otherwise reducing average costs (e.g., by lowering quality). We explore this possibility by examining the association between cap liabilities and terminations of hospice programs' Medicare provider certification numbers ("CCNs," hereafter).[7] We find that CCNs linked to hospice programs with cap liabilities in one fiscal year are 5.6 percentage points more likely to be terminated in the next fiscal year on average. By comparison, the baseline termination rate is approximately 2.5% per year on average. While we caution against drawing causal inferences about the cap's effect on CCN terminations from this comparison alone, we argue that it raises questions about the cap's potential effect on market structure.

Finally, our findings contribute to several policy areas. First, several features of the U.S. health care system—such as cost-sharing, capitated payments, and certificate-of-need programs—are designed in part to correct market failures that contribute to overutilization of health care resources. However, they may also have unintended consequences for provider or patient behavior, such as changing health care consumption dynamics (e.g., Brot-Goldberg et al., 2017), cream-skimming (e.g., Park et al., 2017), or competition (e.g., Rosenkranz, 2021). If providers can meet a policy's statutory requirements without adjusting its intended outcomes, then the policy may have little of

[7]A Medicare provider agreement is terminated when the corresponding provider exists the Medicare market or experiences a change of ownership to a new owner who does not accept the agreement. To the best of our knowledge, there is no taxonomy of terminations of CCNs in the U.S. hospice industry, so we cannot distinguish exits from other events. See appendix D.3 for more information.

its intended effect (e.g., Alexander, 2020). In this paper, we study the consequences of imposing a cap on health care providers' average annual revenue. We show that hospice programs could undercut the cap by churning patients near the end of the fiscal year but, empirically, they did so only to a limited extent. Relative to a per-patient payment limit, an advantage of an average revenue cap like the one studied here is that it does not penalize providers for occasionally treating patients who unexpectedly require long-term care. On the other hand, it creates a purely financial mechanism through which the care that one patient receives can affect the care that another patient receives. We measure the extent of this financial externality in the context of the U.S. hospice industry, where studies have shown that live discharge from hospice care can be a costly disruption to care continuity (e.g., Dolin et al., 2017).

Second, while daily hospice payments vary with a measure of how regional labor costs differ from the national average (the "wage index," hereafter), the cap does not. Consequently, programs with low wage index values—and correspondingly lower daily payment rates—can provide more days of care per patient and remain below the cap. In 2020, the Medicare Payment Advisory Commission ("MedPAC," hereafter) recommended that CMS apply the wage index adjustment to the cap to "mak[e] the cap more equitable across providers" (MedPAC, 2020). Consistent with MedPAC's theory, we find that a 1% increase in a program's wage index is associated with an 0.11 percentage point increase in its likelihood of exceeding the cap and a 4.6% increase in its cap liability on average.

Third, MedPAC also recommended that CMS reduce the cap by 20% to "reduce excess payments [by Medicare to hospice programs] and generate savings for taxpayers" (MedPAC, 2020). We identify hospice programs' whose average annual revenues were on this policy margin between 2001 and 2018 (i.e., programs whose average annual revenues had been between 80-100% of the cap). They served approximately twice as many patients as programs whose average annual revenues were above the cap contemporaneously (360 unique patients per year versus 178). Our finding that hospice programs make limited intensive margin responses to the cap supports MedPAC's theory that lowering the cap could substantially reduce Medicare spending. However we caution that a more comprehensive analysis of their potential extensive margin responses—including their quality investments—is needed in light of the fact that hospice programs on this proposed policy margin are much larger than programs that have historically exceeded the cap.

Fourth, the cap is part of a broader set of Medicare policies that limit hospice utilization and spending. First, CMS requires a non-hospice doctor to certify that a potential hospice enrollee's life expectancy is six months or less before starting coverage for hospice care. Second, hospice enrollees forgo Medicare coverage for curative care for their terminal illnesses. Our finding that hospice programs make limited intensive margin responses to the cap suggests that their scope for engaging in provider-induced demand may be small in this context. But whether such policies reduce total health care spending depends on how hospice utilization affects non-hospice spending (e.g., Gruber et al., 2023; Zuckerman et al., 2015; Kelley, et al., 2013). For instance, Gruber et al. (2023) estimated that for profit hospice utilization among individuals with Alzheimer's disease and related dementias (ADRD) reduces total Medicare spending by $29,000 per patient over five years after ADRD diagnosis. We estimate that hospice programs' cap liabilities were approximately $3 billion dollars between 2001 and 2018.[8]

The remainder of this paper proceeds as follows. In section 2, we describe this study's economic and policy context, including hospice care, the U.S. hospice industry, and the cap. In section 3, we describe our data. In section 4, we report descriptive statistics. In section 5, we present our difference-in-differences analysis. In section 6, we conclude.

2 Context

2.1 Hospice care and the U.S. hospice industry

Hospice care is a bundle of end-of-life health care services. It is intended to raise patients' quality-of-life with pain and symptom relief and keep them at home with family and friends rather than an inpatient care setting. It also provides emotional support to patients and their families during and after their passing. Hundreds of thousands of individuals with cancer, ADRD, and other terminal conditions enroll in the Medicare hospice benefit each year when they choose to forgo curative care. Their length-of-stay in hospice care can range from less than two days (10th percentile), to 18 days

[8] Gruber et al. (2023) also examine the relationship between cap risk and live discharge. They use variation generated by the within-year evolution of cap risk and draw similar conclusions with respect to live discharges. Our work complements theirs by using variation generated by the transition from one fiscal year to another. We also examine the relationship between the cap and enrollment, the wage index, and market structure, whereas they examine the effect on total Medicare spending of cap-related live discharges.

(50th percentile), or to 287 days or more (90th percentile) (MedPAC, 2022).

Hospice care is provided by organizations of physicians, nurses, and home health aides called hospice agencies or hospice programs. According to MedPAC's annual reports to Congress, in 2020, there were 5,058 Medicare-certified hospice programs in the United States, an increase of approximately 120% from 2,303 programs in 2001. Approximately 4,600 (91%) were freestanding or based in a home health agency. The remainder were hospital-based (8%) or skilled nursing facility-based (<1%). Growth in the number of hospice programs has been due to growth in the number of for-profit hospice programs, which increased from 765 in 2001 to 3,680 in 2020 (MedPAC, 2022; MedPAC, 2010). Stevenson et al. (2015) described the U.S. hospice industry's market structure in 2011. They documented that many for-profit hospice programs belong to large national chains such as Vitas Healthcare, Gentiva Health Services, and Heartland Hospice. Nationally, the five largest hospice chains served a combined 15% of patients. More recently, the U.S. hospice industry has experienced growth in the number of private equity-owned hospice programs (from 106 in 2011 to 409 in 2019) (Braun et al., 2021).

Hospice programs vary in both size and scope. For instance, 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 for primary caregivers or acute symptom management. We find in the sample of Medicare claims we describe below that approximately 79% of hospice programs provided at least one day of inpatient hospice care in fiscal year 2018. The number of concurrent enrollees per hospice program also varies. 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 at this time—Vitas Healthcare Corporation of Florida—treated nearly 30,000 patients that year. Finally, some hospice programs have affiliations with nursing homes (through either contractual arrangements or common ownership), and may treat some patients in those settings (Stevenson et al., 2018).

Original Medicare is the primary payer for hospice care in the United States.[9] It pays each hospice program a lump sum rate per patient-day. The daily payments are a function of a base payment and the wage index. The base payment for a given patient-day depends on its associated

[9]Original Medicare also covered hospice care for MA enrollees during our sample period.

level of hospice care. There are four levels of hospice care that vary according to their purpose and resource intensity: routine home care ("RHC"), continuous home care ("CHC"), inpatient respite care ("IRC"), and general inpatient care ("GIC").[10] 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%). The wage index adjusts the base payment in accordance with geographic variation in labor costs. Programs operating below the 10th percentile of the wage index earned \$141 per patient-day on average in 2018. Programs operating above the 90th percentile of the wage index earned \$206 per patient-day on average contemporaneously.

2.2 Cap-induced financial incentives

We use the following stylized model to motivate our analysis. While the model omits several institutional details for expositional simplicity, we discuss these details at length in appendix A and incorporate them in our empirical work.

For each program j in each fiscal year t, let Payment_{jt} be (j,t)'s gross Medicare revenue, let Census_{jt} be a measure of its patient volume, and let Cap_t be its average revenue cap. Its average annual revenue ("average annual payment per patient" or "PPP," hereafter) is $\text{PPP}_{jt} := \text{Payment}_{jt}/\text{Census}_{jt}$ and its cap liability is:

$$\text{Liability}_{jt} := \max\left\{(\text{PPP}_{jt} - \text{Cap}_t)\cdot \text{Census}_{jt}, 0\right\} = \left\{\text{Payments}_{jt} - \text{Cap}_t\text{Census}_{jt}, 0\right\} \tag{1}$$

Let PerDiem_{jt} be the fixed amount each hospice is paid per patient-day. Assume for now that it varies with the program's location and year, but not with the level of hospice care. Prior to and including fiscal year 2011, Census_{jt} was largely equal to the number of patients who enrolled in hospice for the first time at program j during fiscal year t (the "streamlined" counting method). After and including 2012, it was largely equal to the sum of the proportion of their enrollees' lifetime lengths-of-stay in hospice care spent at (j,t) (the "proportional" counting method).[11]

[10]CMS describes RHC as intended for patients who are "generally stable" and whose symptoms "are adequately controlled;" IRC as "[a] level of temporary care provided in nursing home, hospice inpatient facility, or hospital so that a family member or friend who's the patient's caregiver can take some time off;" and both CHC and GIC as "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.

[11]Hospice programs make a preliminary estimate of their cap liabilities at the end of each fiscal year and adjust it upward for up to three years afterward as their enrollees' lifetime lengths-of-stay in hospice care increase.

We hypothesize that hospice programs on track to exceed the cap had financial incentives to *increase* hospice enrollment near the end of the fiscal year. To see why, consider a program on track to far exceed the cap in a fiscal year during the pre-2011 era.[12] Let there be $d \geq 1$ days remaining in the fiscal year. Imagine that this program has an opportunity to enroll a new patient. If enrolled, this patient will remain enrolled for $s \geq 1$ days until they die. Let $F_{jt}(s) \geq 0$ be the program's fixed cost for enrolling this patient. We imagine that this cost is increasing in the cost of inducing demand. Let $c_{jt}(s)$ be the program's average daily cost of care for this patient. If the hospice program enrolls this patient, then its payoff would be:

$$\begin{aligned} &\underbrace{\text{PerDiem}_{jt}\min\{d,s\}}_{=:A_{jt}} - \underbrace{\min\{d,s\}c_{jt}(s) - F_{jt}(s)}_{=:B_{jt}} \\ &\quad - \underbrace{\left(\text{PerDiem}_{jt}\min\{d,s\} - \text{Cap}_t\right)}_{=:C_{jt}^{\leq 2011}} + \underbrace{\text{FuturePayoff}_{jt}\left(\max\{s-d,0\}\right)}_{=:D_{jt}} \end{aligned} \tag{2}$$

Term A is the effect of enrolling the patient on the program's gross revenue in this fiscal year. Term B is the total cost of enrolling and caring for this patient during the fiscal year. Term C is the effect of enrolling the patient on the program's cap liability. Term D is the expected discounted future payoff of treating this patient for an additional $\max\{s-d,0\}$ days in the next fiscal year. Note that the hospice program does not earn net revenue from patient care that takes place in this fiscal year because it is on track to exceed the cap (i.e., the first part of term C cancels out term A).

By contrast, an otherwise identical hospice program that is not on track to exceed the cap would earn $A_{jt} - B_{jt} + D_{jt}$ for enrolling a new patient. That is, it is the same as (2) except that $C_{jt}^{\leq 2011} = 0$ because it is not on track to exceed the cap and therefore experiences no change in its cap liability. The payoff difference between a hospice program on track to exceed the cap and an otherwise identical hospice program not on track to exceed the cap is therefore:

$$\text{Cap}_t - \min\{d,s\}\text{PerDiem}_{jt} \tag{3}$$

[12] By "far exceed," we mean that its cap liability is greater than or equal to the cap. Consequently, for this hospice program, a marginal enrollment will not cause its average annual payments per patient to fall below the cap. Programs on track to marginally exceed the cap have qualitatively similar—but correspondingly milder—financial incentives.

Equation (3) suggests that for a wide range of typical values of (d, s) near the end of the fiscal year, hospice programs on track to exceed the cap have a positive differential incentive to enroll new patients relative to otherwise identical hospice programs not on track to exceed the cap contemporaneously. It also suggests that this incentive increases as $d \to 1$ and $s \to 1$. Figure 1 plots this financial incentive as a function of (d, s) when $\text{Cap}_t = \$23,000$ and $\text{PerDiem}_{jt} = \$146$, as they did for an average hospice program in 2009.

Now consider a program on track to exceed the cap in the post-2012 era. If they enroll a patient, then their payoff would be:

$$A_{jt} - B_{jt} - \underbrace{\left(\text{PerDiem}_{jt}\min\{d, s\} - \frac{\min\{d, s\}}{s}\text{Cap}_t\right)}_{=:C_{jt}^{\geq 2012}} + D_{jt} \tag{4}$$

In this case, term C shows that the program reduces its cap liability by a fraction of Cap_t because this patient's enrollment raises the program's census by the proportion of her lifetime length-of-stay in hospice care spent at (j, t). It is otherwise identical to the payoff in equation (2). If the program were not on track to exceed the cap, then its payoff would be $A_{jt} - B_{jt} + D_{jt}$, as before. Thus, the difference between these payoffs is:

$$\frac{\min\{d, s\}}{s}\text{Cap}_t - \min\{d, s\}\text{PerDiem}_{jt} \tag{5}$$

which suggests that for a wide range of typical values of (d, s) near the end of the fiscal year, hospice programs on track to exceed the cap have a positive differential incentive to enroll new patients relative to otherwise identical hospice programs not on track to exceed the cap contemporaneously. Figure 1 plots this financial incentive as a function of (d, s) when $\text{Cap}_t = \$26,160$ and $\text{PerDiem}_{jt} = \$155$, as they did for an average hospice program in 2013.

This stylized model suggests that in both the pre-2011 and post-2012 eras, hospice programs on track to exceed the cap had a greater financial incentive to enroll new patients than programs not on track to exceed the cap contemporaneously. It predicts that this incentive was stronger in the pre-2011 era than in the post-2012 era, which we test empirically below. However, the extent to which even hospice programs on track to exceed the cap act on this financial incentive and enroll new

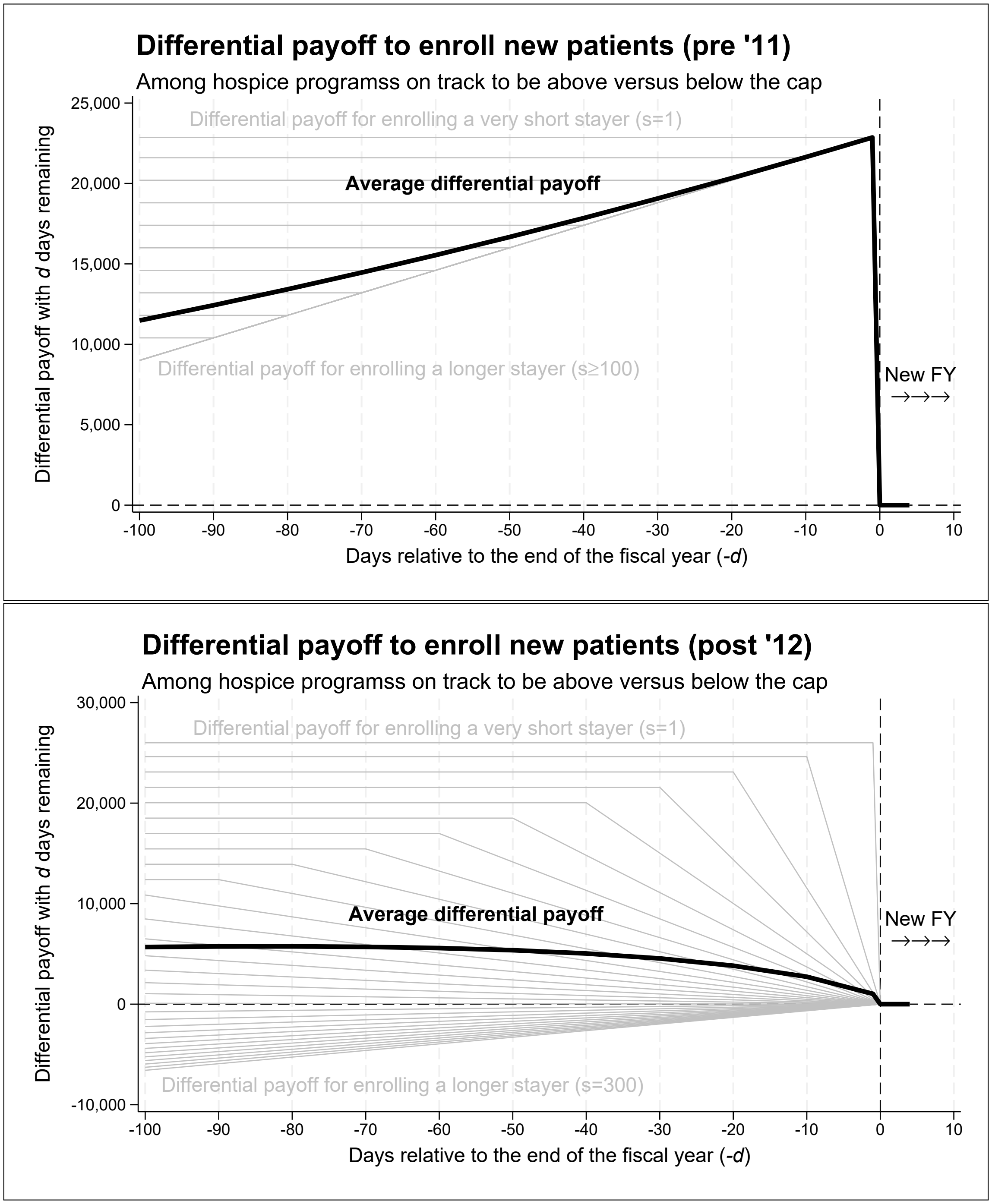


Fig. 1. These figures illustrate the financial incentives created by the cap for hospice programs to enroll new patients near the end of a fiscal year. It shows that hospice programs on track to exceed the cap in an outgoing fiscal year have a differentially positive financial incentive to enroll new patients relative to otherwise similar hospice programs not on track to exceed the cap contemporaneously. Each gray line plots the differential payoff for enrolling a patient with a length-of-stay in hospice care of $s \in \{1, 10, 20, ..., 300\}$ days when there are d days remaining in the fiscal year. The black line represents the equal-weighted average of these payoffs. The difference between the pre-2011 and post-2012 incentives is attributable to a change in how the cap census was calculated.

patients depends on non-cap factors, including treatment costs $c_{jt}(s)$, enrollment costs $F_{jt}(s)$, and discounted expected future profit $\text{FuturePayoff}_{jt}(\max\{s-d,0\})$. For instance, if marginal enrollees are healthier on average, then their enrollment cost F_{jt} may be higher because they may not yet wish to forgo curative care for their terminal illnesses. We return to this again after presenting our difference-in-differences estimates.

We also predict that hospice programs on track to exceed the cap have a greater financial incentive to live discharge their patients than hospice programs not on track to exceed the cap contemporaneously. Intuitively, this differential incentive arises largely from the fact that programs on track to exceed the cap earn no incremental revenue for each day of patient care but continue to incur an incremental treatment cost. In both the pre-2011 and post-2012 eras, this incentive is moderated by the fixed cost of making a live discharge and by the expected discounted future payoff of keeping the patient enrolled through the start of the next fiscal year. We imagine that the fixed cost of making a live discharge includes the potential reputation harm to the hospice program of live discharging a terminally ill individual, as well as the cost of motivating clinicians to carry out a financially motivated live discharge.[13]

Thus far, we have assumed that daily payments are fixed. This assumption is motivated by our observation that 98% of an average hospice program's patient-days are associated with RHC. We now relax this assumption and consider program j's choice of the level of hospice care for a given patient-day. We hypothesize that it may be motivated to reduce GIC and CHC utilization because these levels of hospice care are more resource intensive than RHC and IRC. While gross base payments for GIC and CHC are correspondingly 4-6 times higher, their net payments are zero after accounting for the cap liability.

These cap-related financial incentives to adjust the supply of hospice care sharply change during the transition from one fiscal year to another. During the last weeks of an outgoing fiscal year, hospice programs are more certain of their cap liabilities (if any) and they have less time to make compensating adjustments to reduce their cap liabilities than during the first weeks of the next fiscal year. Consequently, the expected benefit of a compensating adjustment is higher during the last weeks of an outgoing fiscal year. Time discounting may magnify this change in cap-related

[13]The fixed cost of making a live discharge also includes an indirect penalty to Census_{jt} that a hospice j may experience when a live discharged patient resumes hospice care elsewhere. We discuss this and other institutional details in appendix A and account for them in our empirical analysis.

financial incentives by making FY t's cap liabilities more salient than FY $t+1$'s cap liabilities during FY t's last weeks.

These predictions motivate our difference-in-differences analysis. We compare average outcome trends at programs on track to exceed the cap during an outgoing fiscal year to contemporaneous average outcome trends at programs on track to remain below the cap in that fiscal year. The outcome trends are measured during a window centered around the transition between fiscal years. We examine them separately during the pre-2011 and post-2012 eras to measure the impact of the 2011 change in the census counting method. Our outcomes are measures of enrollment rates, live discharge rates, the enrollees' and discharged patients' characteristics, rates of RHC, CHC, GIC, and IRC utilization, and resource utilization.

3 Data

The primary data for this research are the 100% Medicare hospice claims spanning 2000-2019. We extracted patient identification numbers, claim start and end dates, and program identification numbers associated with each claim. We converted these claim-level data to a (program, day, patient)-level dataset.[14] We assigned to each (program, day) realization a corresponding fiscal year (see appendix B) and aggregated the data to the (program, fiscal year)-level for fiscal years 2001-2018.

We used the hospice claims to measure payments, cap censuses, and cap liabilities. First, we distributed claim-level payments evenly across the days associated with each claim. We aggregated these payments from the claim-level to the (program, day, patient)-level and to the (program, fiscal year)-level. Second, we calculated each (program, day, patient)'s contribution to (program, fiscal year)'s cap census according to the pre-2011 and post-2012 counting methods.[15] We assumed that claims spanning 2000-2019 are sufficient to observe all hospice utilization for beneficiaries who

[14]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 programs' cap censuses. See Medicare hospice transmittal 156.

[15]Most hospice programs' were automatically switched in 2012 to the proportional counting method. However, a small and monotonically decreasing number of hospice programs continued using the streamlined counting method. In 2013, there were only 486 programs using the streamlined counting method. We do not observe which programs used which counting methods, so in this step, we assume that all programs switched to the proportional counting method in 2012.

were enrolled in hospice during FY 2001 – FY 2018.[16] We calculated each program's cap in each fiscal year using the data published by Medicare in its annual transmittals to hospice programs. We used these payment, cap census, and cap data to calculate PPP_{jt} and Liability_{jt} for each program j and FY t between FY 2001 and FY 2018.[17] We also calculated PPP_{jtd} and $\text{PPP}_{jtd}/\text{Cap}_t$ for each (j,t) and day-of-the-year d using j's cumulative payments and cap census contributions in FY t through day d.

We also rely on additional data. We analyzed live discharges (see appendix D.1), patient demographics (see appendix D.2), hospice program business records (see appendix D.3), the wage index and daily payment rates (see appendix D.4), hospitalizations (see appendix D.5), nursing home spells (see appendix D.6), hospice staff visits (see appendix D.7), each program j's proximity to other programs that exceeded the cap in year t (see appendix D.8), levels of hospice care (see appendix D.9), and ADRD diagnoses (see appendix D.10). Our measure of "proximity" between hospice programs is based on the extent of geographic overlap of the their patient populations, not distances between the addresses of their administrative offices.

4 Descriptive statistics

We begin by reporting several descriptive statistics about hospice programs and patients. Table 1 summarizes the programs' patient volumes, Medicare payments, and cap liabilities. Out of 5,685 programs in our sample, 2,214 (39%) exceeded the cap at least once and they exceeded the cap in 11% of program-years. Hospice programs that exceeded the cap treated fewer unique patients and their patients had longer LOS in hospice care that year, on average. In fiscal years when they exceeded the cap, their average annual payments per patient were 35% higher than the cap on average. In total, their average cap liabilities were $490,000. They earned $148 per patient-day on average; but only $118 per patient-day net of their cap liabilities.

Table A1 summarizes other program characteristics. Programs that exceeded the cap were more likely to be for-profit and newer. On average, they had fewer enrollments and similar numbers of

[16]Among patients whose first-observed patient-day is between FY 2004 and FY 2015, approximately 92% of their observed patient-days are associated with either their first-observed patient-day's fiscal year or the following fiscal year.

[17]Since 2013, Medicare's payments to hospice programs have been reduced by 2% due to sequestration. CMS has applied a sequestration adjustment to programs' cap liabilities. We accounted for this adjustment. See appendix C.

		Above-cap		Below-cap		
	All	All	W/I 10%		≥80%	All
	(1)	(2)	(3)	(4)	(5)	(6)
Patient volume and cap 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
Cap census	270	105	157	248	241	292
Cap census contr. per unique pat.	0.73	0.55	0.60	0.63	0.64	0.75
Frac. pat.-days stl. (pre-'11)	0.85	0.66	0.71	0.74	0.76	0.87
Frac. pat.-days prop. (pre-'11)	0.15	0.34	0.29	0.26	0.24	0.13
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
Payments per unique pat. ($)	10,306	17,648	15,771	14,888	14,260	9,353
PPP ($)	15,241	33,598	26,396	23,828	22,354	12,856
Cap liabilities and Medicare payments net of cap liabilities						
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 ($K)	3,583	2,532	3,865	5,819	5,288	3,720
Net payments per pat.-day ($)	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[100-110% of cap]	0.04	0.31	1.00	0.00	0.00	0.00
1[90-100% of cap]	0.05	0.00	0.00	1.00	0.43	0.06
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. This table reports cap-related descriptive statistics about the (program, fiscal year)-level data. On average, programs that exceed the cap have substantial cap liabilities, treat fewer patients, and earn 20% less per patient-day net of their cap liabilities ($118 vs. $148). Their patients contribute less to their annual cap censuses and have longer LOS in hospice care.

live discharges (despite treating fewer unique patients). They provided fewer skilled nursing visits per patient-day on average, and a smaller fraction of their patient-days were shared with a nursing home. Their new enrollees were less likely to have had a hospital or nursing home stay in the week prior to their hospice enrollment. Their CCNs were more likely to be terminated in the next fiscal year and they had a higher average proximity to other hospice programs that exceeded the cap contemporaneously. Table 2 describes the patients in our sample. On average, they were 82 years old, predominantly White and female, and had a lifetime LOS in hospice care of 90 days. Among them, 4.5%—or approximately 700,000 patients—began hospice care at a program-year that exceeded the cap. On average, these patients had a longer lifetime LOS in hospice care, enrolled in more programs, and were less likely to ultimately die in hospice care.

Our cap liability estimates also enable us to examine the distribution of average annual payments per patient relative to the cap. Figure 2 plots the distribution of $\text{PPP}_{jt}/\text{Cap}_t$. There is no visual indication of bunching around 1.[18] Table A2 reports the McCrary test statistic of the null hypothesis that the distribution of $\text{PPP}_{jt}/\text{Cap}_t$ is continuous at 1 (McCrary, 2008). There is no statistically significant evidence against the null hypothesis.[19] This suggests that hospice programs do not generally equilibrate their average annual payments per patient with the cap. Since doing so would produce substantial financial benefits—programs whose average annual payments per patient were between 100-110% of the cap had cap liabilities of $163,000 on average (see table 1)—this finding implies that programs' marginal adjustment costs are high.[20]

Next, we examined how cap liabilities covary with the wage index. The extent to which within-program cap liabilities covary with the wage index can tell us about hospice programs' responses to the cap because the wage index is a significant, visible, and administratively set determinant of daily payment rates. Consequently, it can affect cap liabilities in the absence of compensating adjustments to programs' patient censuses. Table A3 reports estimates from several models relating

[18] In parallel work, Gruber et al. (2023) draw a similar conclusion using a simplified measure of cap liabilities.

[19] The table also reports similar test statistics estimated from sub-samples of for-profit programs, large programs, and programs that exceeded the cap at least once, respectively. These distributions are plotted in figures A1-A3. Although the test statistic for the sub-sample of programs that exceeded the cap at least once is statistically significant, it is not of the expected sign.

[20] We investigated whether any individual hospice program's average annual payments per patient were persistently close to the cap. We found that on average during the sample period, the largest hospice program in the country—Vitas Healthcare Corporation of Florida—had an average annual cap census of approximately 11,000 patients and its average annual payments per patient were within 4.4% of the cap. We discuss this further in appendix E.

		Above-cap		Below-cap		
	All	All	W/I 10%		≥80%	All
	(1)	(2)	(3)	(4)	(5)	(6)
Demographic characteristics						
1[Female]	0.57	0.59	0.59	0.58	0.58	0.57
1[White]	0.88	0.80	0.82	0.82	0.84	0.88
1[Black]	0.08	0.13	0.10	0.10	0.09	0.08
1[Asian]	0.01	0.01	0.01	0.01	0.01	0.01
1[Hispanic]	0.02	0.04	0.04	0.05	0.03	0.02
1[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
Lifetime hospice utilization						
Hospices	1.06	1.22	1.15	1.11	1.10	1.05
1[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
1[Ever live discharged]	0.17	0.39	0.31	0.25	0.24	0.16
Lifetime LOS in hospice care	90	200	172	148	142	85
Characteristics pertaining to mortality						
1[Decedent]	0.98	0.95	0.96	0.97	0.97	0.99
Age at death (decedents)	82.1	82.9	83.1	83.1	82.9	82.1
Remaining days of life (decedents)	133	348	256	210	201	123
Remaining days of life	156	425	308	248	236	143
1[Died in hospice]	0.92	0.81	0.86	0.89	0.90	0.92
Consec. hospice days at EOL	60	98	98	91	88	58
N (patients, M)	15.6	0.7	0.3	0.7	1.7	14.9

Tab. 2. This table reports descriptive statistics about the patient-level data. On average, patients enrolling in program-years that exceed the cap have longer average lifetime LOS in hospice care, are treated at more hospice programs, and experience more live discharges. They have longer remaining lifetimes and are less likely to ultimately die in hospice care. 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. For non-decedents, remaining days of life is calculated through the end of our sample period (i.e., 12/31/2019).

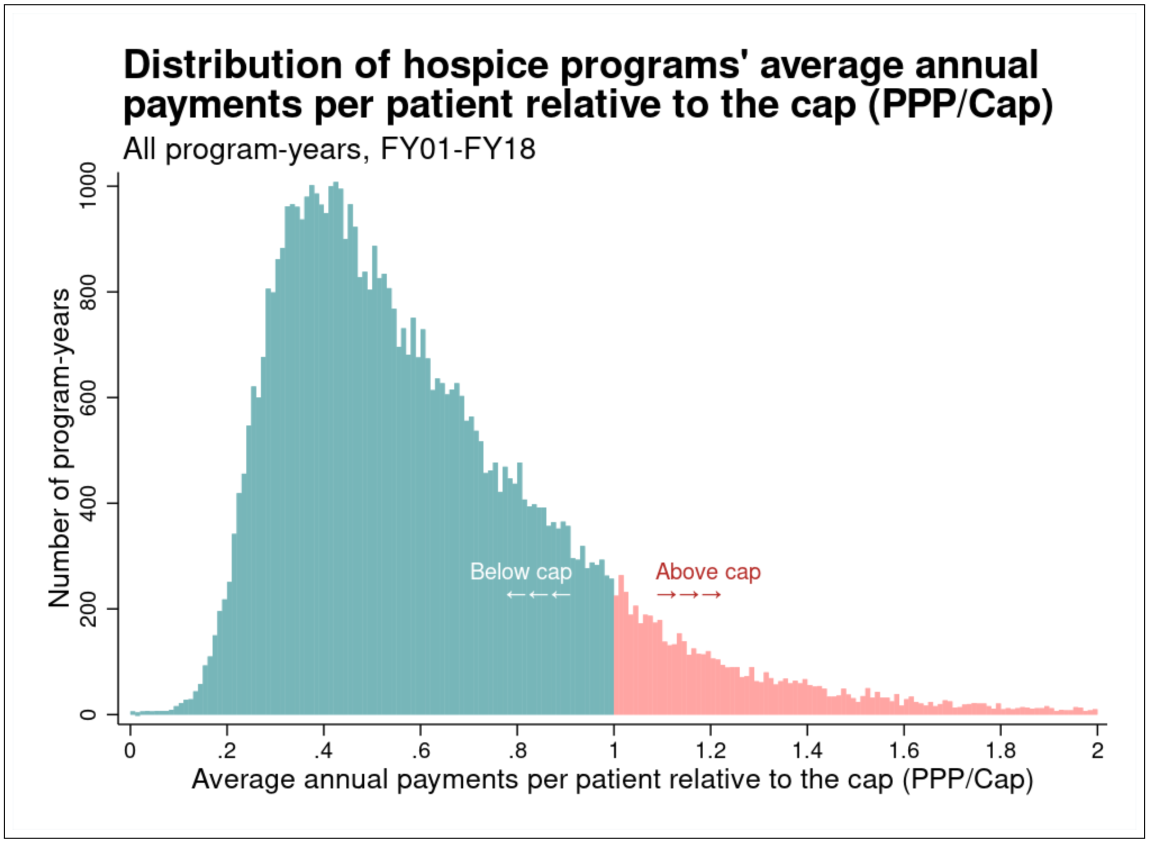


Fig. 2. This figure plots the distribution of $\text{PPP}_{jt}/\text{Cap}_{jt}$—i.e., hospice programs' average annual payments per patient relative to the cap. The figure is censored at $\text{PPP}_{jt}/\text{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See table A2.

cap-related outcomes to the wage index in the (program, fiscal year)-level data. It shows that when hospice programs experience a 1% higher wage index value, they contemporaneously experience an 0.11 percentage point higher likelihood of exceeding the cap and a 4.6% higher cap liability on average. They also experience higher gross payments and lower patient censuses—explaining the higher cap liabilities—though these associations are not individually statistically significantly different from zero. Finally, they receive 0.33% higher gross daily payments and 0.30% higher net daily payments on average. But among programs that ever exceeded the cap between FY 2001 and FY 2018, a 1% higher wage index value is associated with 0.34% higher gross daily payments and 0.20% higher net daily payments on average. Together, these estimates suggest that a portion of the wage index adjustment intended to compensate hospice programs for higher regional labor costs is repaid to Medicare through their cap liabilities. They also support MedPAC's proposal to improve equity across programs by wage-adjusting the cap.

Finally, we examined how hospice programs change after exceeding the cap. Table A4 reports estimates from several models relating outcomes to a 1-year lag indicator of whether a hospice program exceeded the cap in the (program, fiscal year)-level data. It shows that in the year after hospice programs exceed the cap, they are 19.3 percentage points more likely to exceed the cap again and their cap liabilities are 246% higher on average. They do not experience a statistically significant change to their gross payments or their number of unique patients on average. However, their cap censuses are 10.1% lower and their total number of patient-days are 10.0% higher on average. CCNs associated with programs that exceed the cap are 5.6 percentage points more likely to be terminated in the next fiscal year on average. The baseline termination rate is 2.5% per year on average.

5 Does the cap affect hospice utilization?

5.1 Research design

In the foregoing section, we examined the distribution of hospice programs' cap liabilities. Among other things, we found that their average annual payments per patient do not bunch around the cap, suggesting that their marginal adjustment costs are high. But this examination was not sufficient to determine whether hospice programs make little-to-no adjustments during the fiscal year, or whether they make large adjustments that fall short of eliminating their cap liabilities. In this section, we leverage variation in cap-related financial incentives generated by the policy's nonlinear design and the transition between fiscal years to investigate whether and how much hospice programs on track to exceed the cap in an outgoing fiscal year adjust their enrollment rates, live discharge rates, or rates of RHC, CHC, IRC, and GIC to reduce their cap liabilities.

We leverage this variation with a difference-in-differences research design. In particular, we treat the transitions between fiscal years 2001-2002, ..., 2018-2019 as eighteen distinct events and examine outcome trends during the 180-day windows centered around each event ("event windows").[21] We compare average outcome trends among hospice programs that began the event win-

[21]The relevant transition date varies slightly with each outcome. For instance, during the pre-2011 era, patients were counted toward a fiscal year's cap census until September 27, but their payments were counted until October 31. We therefore use September 27 as the transition date for enrollments and October 31 as the transition date for live discharges during the pre-2011 era. We discuss this in more detail in appendix A.

dows with high average annual payments per patient to contemporaneous average outcome trends among similar programs that began the event windows with low average annual payments per patient.[22] We average the trend differences across events.

Figure 3 illustrates the identification problems that arise in between-program and within-program comparisons alone, as well as the variation isolated by our research design. It plots average, unadjusted enrollment and live discharge rates for hospice programs grouped into nine bins of average annual payments per patient relative to the cap. It shows that on average programs with lower average annual payments per patient have higher enrollment rates, and that enrollment and live discharge rates move seasonally. But the figure also shows that on average programs with higher average annual payments per patient have higher differential enrollment and live discharge rates rates in the final weeks of an outgoing fiscal year than programs with lower average annual payments per patient. We measure this difference-in-differences with the following regression analysis.

Let e index events. As before, let j index programs, t index fiscal years, and Cap_t be the cap for fiscal year t. For each event e, let t_e^O and t_e^I be event e's outgoing and incoming fiscal years, respectively, and let w index elements of the set $W := \{\ldots, -2, -1, 1, 2, \ldots\}$ which enumerates 7-day intervals spreading outward from the first day of t_e^I, excluding the first 7-day interval of t_e^I. For each (e, j), let PPP_{ej}^O be program j's cumulative average annual payment per patient through t_e^O up to the first day of e's event window. Let the set of programs on track to exceed the cap in the outgoing fiscal years be given by $\mathcal{T} := \{(e, j) : \text{PPP}_{ej}^O \geq \text{Cap}_{t_e^O}\}$. Let the set of programs on track to remain below the cap in the outgoing fiscal year be given by $\mathcal{U} := \{(e, j) : \text{PPP}_{ej}^O < \text{Cap}_{t_e^O}\}$. Define:

$$f_{ejw}^{\text{S}} := 1[(e, j) \in \mathcal{T}]1[w < 0]\beta + \text{FE}_{ej} + \text{FE}_{ewg_{ej}} + \text{FE}_{ewg_{ej}}\text{WI}_{jt_e^O} \tag{6}$$

$$f_{ejw}^{\text{D}} := \sum_{w' \in W} 1\big[(e, j) \in \mathcal{T}\big]1[w = w']\beta_{w'} + \text{FE}_{ej} + \text{FE}_{ewg_{ej}} + \text{FE}_{ewg_{ej}}\text{WI}_{jt_e^O} \tag{7}$$

where S and D are mnemonics for static and dynamic difference-in-differences, respectively, FE_{ej}

[22] As previously discussed, we use estimates of hospice programs' actual cap liabilities in our analysis. These estimates are produced for each fiscal year using a 3-year lookback window after the end of the fiscal year because Medicare can revise a hospice program's cap liabilities for up to three years with up-to-date information about the program's patients' ongoing hospice utilization. On the first day of the event windows, the correlation between $\text{PPP}_{jtd}/\text{Cap}_t$—where PPP_{jtd} is calculated using the 3-year lookback window—and $\text{PPP}^*_{jtd}/\text{Cap}_t$—where PPP^*_{jtd} is calculated using data only through the end of a fiscal year—is approximately 0.97, suggesting that hospice programs could use existing billing records and a short-run projection of their patient volume to accurately forecast an impending cap liability.

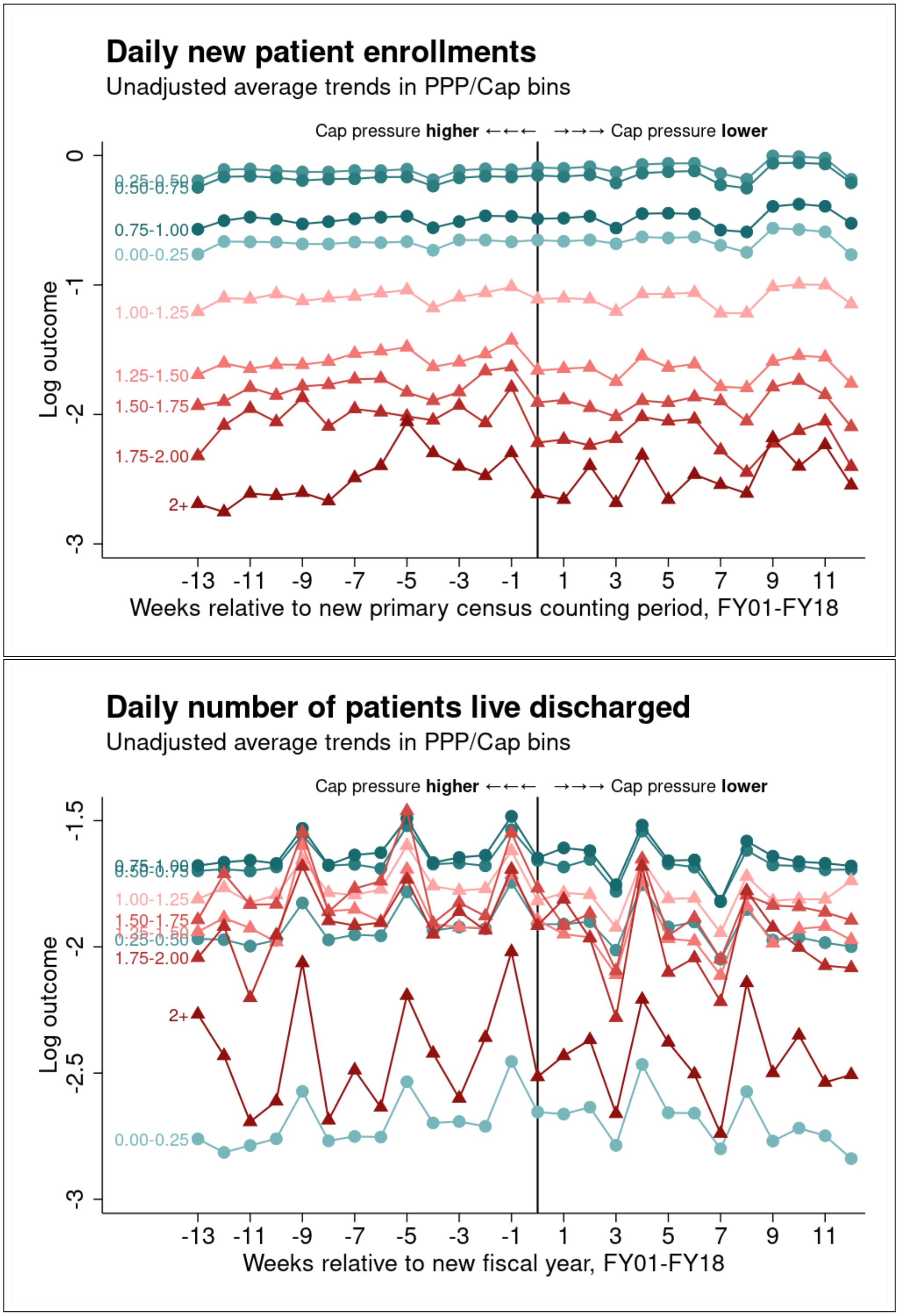


Fig. 3. This figure plots average outcome trends during the transitions between fiscal years during FY01-FY18. Hospice programs are grouped into bins based on their rolling average annual payments per patient at the beginning of the event windows. The figure shows that there are level differences between programs on track to exceed versus remain below the cap and seasonal variation in the outcomes, particularly around holidays and the end of the month. But it also shows the variation that is generated by cap-related financial incentives and isolated by our DID research design: programs on track to exceed the cap in a given fiscal year differentially enroll and live discharge more patients during the fiscal year's final weeks.

is a program fixed effect, g_{ej} (a mnemonic for "group") indexes (j, t_e^O)'s state and ownership type, $\mathrm{FE}_{ewg_{ej}}$ is a week-by-group fixed effect, and $\mathrm{WI}_{jt_e^O}$ is the wage index value for (j, t_e^O). We related f_{ejw}^{S} and f_{ejw}^{D} to the conditional expectations of binary outcomes Y_{ejw} to estimate β and $(\beta_w : w \in W)$ using ordinary least squares ("OLS," hereafter). We also related $\exp(f_{ejw}^{\mathrm{S}})$ and $\exp(f_{ejw}^{\mathrm{D}})$ to the conditional expectations of other non-negative outcomes Y_{ejw} to estimate β and $(\beta_w : w \in W)$ using the Poisson pseudo-maximum likelihood estimator ("PPML," hereafter) (Wooldridge, 1999). We estimated these models with samples spanning pre-2011 events, post-2012 events, and all events to examine how provider behavior changed when the census counting method changed in 2011.

The parameters β and $(\beta_w : w \in W)$ measure average trend differences during the event windows between programs in $\mathcal{T}$ and $\mathcal{U}$ in the same state, with the same ownership structure, and with similar wage index values (Gardner, 2021; Cengiz et al, 2019). They may be interpreted as average treatment effects on the treated of the cap in the final weeks of an outgoing fiscal year under the following assumptions. First, for each event e, average outcomes during e's event window among programs $(e, j) \in \mathcal{U}$ are unaffected by the cap. Second, the no anticipation assumption states that for each event e, average outcomes near the start of e's incoming fiscal year among programs $(e, j) \in \mathcal{T}$ are unaffected by the cap. Third, the parallel trends assumption states that for each event e, average outcome trends among programs $(e, j) \in \mathcal{T}$ at the end of e's outgoing fiscal year would have moved synchronously with contemporaneous average outcome trends among similar programs $(e, j) \in \mathcal{U}$ but for the cap.[23]

Although our research design enables us to overcome identification problems that arise in between-program and within-program comparisons alone, others may remain. First, programs $(e, j) \in \mathcal{U}$ may be affected by the cap. For instance, they may respond in an outgoing fiscal year's final weeks to the possibility that they will exceed the cap by the end of the fiscal year even while their cumulative average annual payments per patient up to that point are below the cap. To address this concern, we examine how our estimates change when we exclude from our estimation sample programs (e, j) such that $\mathrm{PPP}_{ej}^O/\mathrm{Cap}_{t_e^O} \in [0.9, 1]$. As we discuss below, excluding these programs does not significantly change our estimates. Second, programs $(e, j) \in \mathcal{T}$ may respond

[23]The sets $\mathcal{T}$ and $\mathcal{U}$ contain only those (e, j) realizations such that j was observed to treat at least one patient throughout e's event window. Within each (e, j) realization, the observations $\{(e, j, w) : w \in W\}$ are balanced. That there are no compositional changes in the estimation sample within any given event implies that we may interpret $(\beta_w : w \in W)$ as the average evolution of the average treatment effect on the treated under the foregoing assumptions.

to the cap at the start of an incoming fiscal year. For instance, for a given event e, if they enroll extra patients at the end of e's outgoing fiscal year, then they may enroll fewer patients at the start of e's incoming fiscal year due to capacity constraints (e.g., staffing shortages). In this case, we would expect to see enrollment rate trends between programs $(e, j) \in \mathcal{T}$ and programs $(e, j) \in \mathcal{U}$ diverge at the start of e's incoming fiscal year, with programs $(e, j) \in \mathcal{T}$ steadily increasing their enrollment rates over time as existing enrollees pass away or exit hospice. To address this concern, we look for evidence of such divergences in our estimates of $(\beta_w : w \in W)$. Finally, counterfactual outcome trends at the end of an outgoing fiscal year among programs $(e, j) \in \mathcal{T}$ may differ from contemporaneous outcome trends among programs $(e, j) \in \mathcal{U}$. For instance, programs $(e, j) \in \mathcal{T}$ may operate in markets with different disease seasonality or trends in patient preference for hospice care. To address this concern, we include time-interacted state, ownership type, and wage index controls to ensure that outcome trends among programs $(e, j) \in \mathcal{T}$ are compared to outcome trends among similar programs $(e, j) \in \mathcal{U}$. However, as we discuss below, excluding these terms from our analysis does not significantly change our estimates. We also benefit from granular time-series variation—the index w measures weeks—enabling us to examine outcome trend differences in a narrow band around fiscal year transition dates in the figures below.

5.2 Results

First, we examine enrollment and live discharge rates. Table 3 and figure 4 present the corresponding estimates of β and $(\beta_w : w \in W)$. The estimates show that regression-adjusted average enrollment rate differences between the outgoing fiscal year's last quarter and the incoming fiscal year's first quarter are 0.056 log points (5.8%) higher at programs on track to exceed the cap in the outgoing fiscal year than at programs on track to remain below the cap on average.[24] In fact, the estimates show that enrollment rates at programs on track to exceed the cap in an outgoing fiscal year steadily differentially increase throughout the outgoing fiscal year's last quarter, before suddenly differentially decreasing by 0.150 log points (13.9%) in the first week of the incoming fiscal year on average. With respect to live discharges, the estimates show that regression-adjusted 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 at hospice programs on track to exceed

[24]Throughout the paper, we convert log points to percent changes using the formula: Percent = $\big(\exp(\text{Log})-1\big)\times 100$.

the cap in the outgoing fiscal year than at programs on track to remain below the cap on average. For both outcomes, the magnitudes of these difference-in-differences are higher in the pre-2011 era than in the post-2012 era.

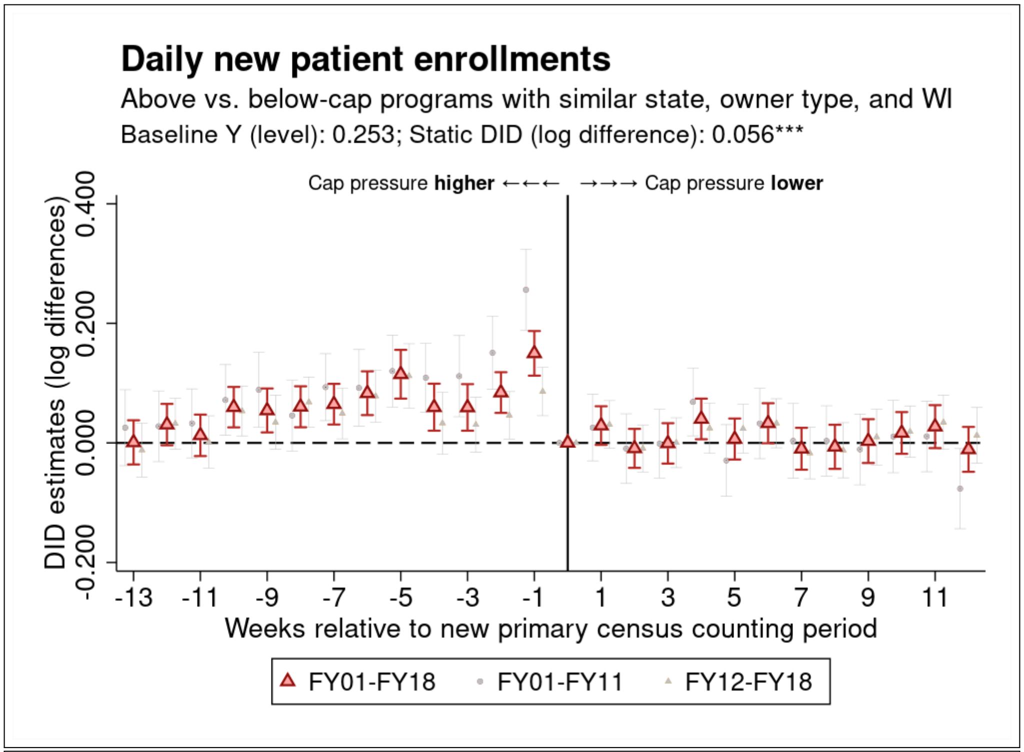
Second, we examine the marginally enrolled patients' and marginally live discharged patients' characteristics. Tables A5-A10 and figures A4-A13 present the corresponding estimates of β and $(\beta_w : w \in W)$ for the marginally enrolled patients. They show that programs on track to exceed the cap in an outgoing fiscal year differentially enroll patients in the fiscal year's last quarter with 0.020 log point (2.0%) longer lifetime LOS in hospice care, 0.019 log point (1.9%) more lifetime live discharges, 0.5 percentage point lower likelihoods of ultimately dying in hospice, 0.9 percentage point lower likelihoods of having been hospitalized in the previous week, 0.6 percentage point lower likelihoods of having been in a nursing home in the previous week, and 0.044 log point (4.5%) higher remaining lifetimes on average. We do not find a statistically significant difference in their likelihood of being discharged within 30 days of enrollment, their lifetime number of affiliations with unique hospice programs, or their likelihood of having an existing ADRD diagnosis on average. We also do not find a statistically significant difference in average $\text{Payments}_{ijt}/\text{Census}_{ijt}$ among Medicare beneficiaries i who started hospice care at j for the first time during FY t and were counted toward j's census in t in proportion to their lifetime LOS in hospice care.

Tables A11-A12 and figures A14-A18 present the corresponding estimates of β and $(\beta_w : w \in W)$ for the marginally live discharged patients. The estimates show that programs on track to exceed the cap in an outgoing fiscal year differentially live discharge patients in the fiscal year's last quarter who would take 0.048 log point (4.9%) more days to subsequently resume hospice care on average. We do not observe a statistically significant difference in their LOS in hospice care prior to live discharge or their likelihood of subsequently resuming hospice care at any hospice program or their original hospice program.

Third, we examine trends in the intensity of active patients' hospice care.[25] Tables A13-A15 and figures A19-A25 present the corresponding estimates of β and $(\beta_w : w \in W)$. They show that programs on track to exceed the cap in a given fiscal year provided much the same rates of RHC, CHC, IRC, and GIC, suggesting that they do not adjust their levels of hospice care.[26] They

[25]Figure A26 shows that the number of active patients differentially decreases at programs on track to exceed the cap throughout the event window on average.

[26]In this analysis, we excluded programs (e, j) that provided no patient-days of RHC, CHC, IRC, or GIC, respec-



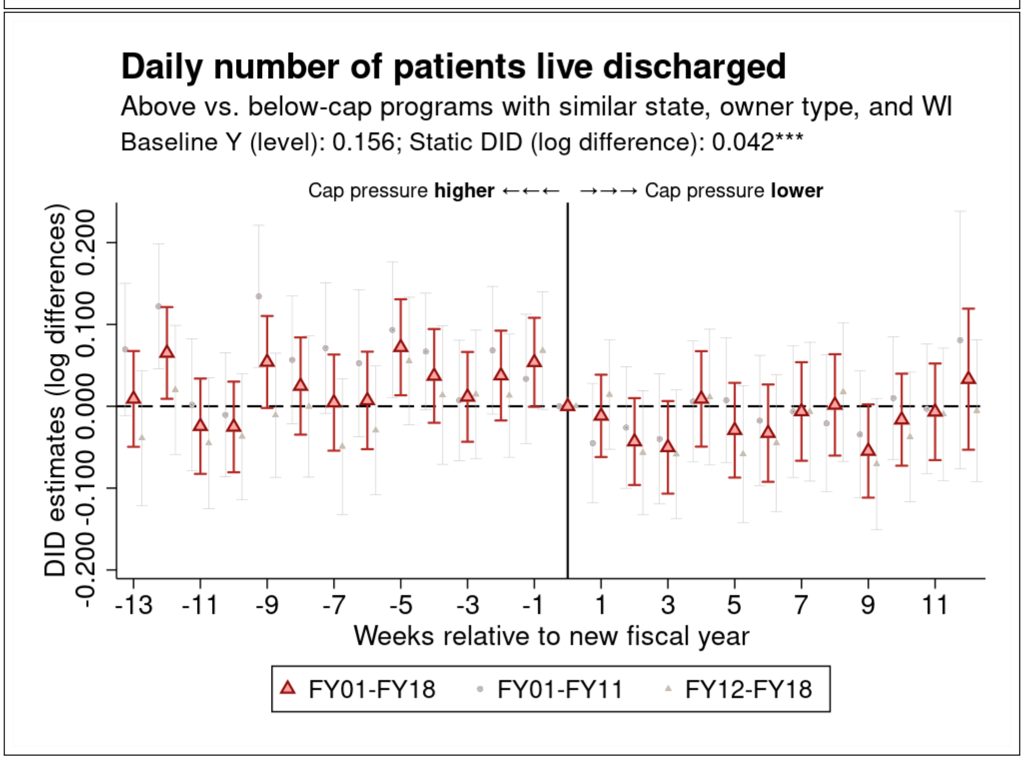


Fig. 4. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our DID analysis. Programs on track to exceed the cap raise enrollment and live discharge rates in the weeks leading up to the end of the fiscal year. See table 3. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The headings report statistics estimated from the full sample period. Baseline Y is the average value of the outcome at relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). The primary census counting periods are described in appendix A.

	Daily new enrollments (log diff.)			Daily live discharges (log diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	0.056***	0.093***	0.035***	0.042***	0.067***	0.023*
	(0.007)	(0.012)	(0.008)	(0.010)	(0.016)	(0.013)
Dynamic model: DID relative to week 0						
β_{-4}	0.060***	0.109***	0.033	0.037	0.067*	0.014
	(0.020)	(0.029)	(0.026)	(0.029)	(0.036)	(0.043)
β_{-3}	0.059***	0.112***	0.030	0.012	0.007	0.015
	(0.020)	(0.035)	(0.023)	(0.028)	(0.037)	(0.040)
β_{-2}	0.084***	0.151***	0.046**	0.038	0.068*	0.013
	(0.017)	(0.031)	(0.020)	(0.028)	(0.040)	(0.039)
β_{-1}	0.150***	0.256***	0.086***	0.054*	0.034	0.068*
	(0.019)	(0.035)	(0.021)	(0.028)	(0.040)	(0.037)
β_0	-	-	-	-	-	-
β_1	0.029*	0.026	0.031	-0.012	-0.045	0.014
	(0.016)	(0.028)	(0.020)	(0.026)	(0.037)	(0.034)
β_2	-0.009	-0.010	-0.009	-0.043	-0.026	-0.057
	(0.017)	(0.030)	(0.020)	(0.027)	(0.038)	(0.039)
β_3	-0.001	-0.001	0.000	-0.050*	-0.040	-0.059
	(0.017)	(0.029)	(0.021)	(0.029)	(0.041)	(0.040)
Estimator	PPML	PPML	PPML	PPML	PPML	PPML
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	0.253	0.259	0.249	0.156	0.210	0.125
N	1,407,530	734,925	672,605	1,372,130	713,253	658,877
Clusters	5,554	3,788	4,983	5,530	3,768	4,970
$\|\mathcal{T}\|$	5,143	1,826	3,317	5,169	1,878	3,291
$\|\mathcal{U}\|$	49,003	26,445	22,558	47,526	25,501	22,025

Tab. 3. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap raise enrollment and live discharge rates in the weeks leading up to the end of the fiscal year. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figure 4.

also show that programs on track to exceed the cap provided much the same rates of nurse visits, social worker visits, and home health aid visits on average, suggesting that they do not alter the distribution of staff visits per patient to accommodate the additional enrollees.

5.3 Sensitivity and heterogeneity analyses

Finally, we conducted a number of robustness checks and heterogeneity analyses. First, we examined whether our results were robust to (1) a longer event window; (2) excluding state, ownership, and wage index controls; and (3) excluding (e, j) realizations such that $\text{PPP}^O_{ej}/\text{Cap}_{t^O_e} \in [0.9, 1]$. We report the results of these sensitivity analyses in appendix F.1. They do not change our qualitative findings. Second, we explored whether there is evidence of meaningful heterogeneity across profit-status, cap census, proximity to other hospice programs on track to exceed the cap, and affiliation with nursing homes. We report the results of these heterogeneity analyses in appendix F.2. There is suggestive evidence that hospice programs affiliated with nursing homes have more marginal live discharges at the end of an outgoing fiscal year, especially during the pre-2011 era. We did not find other evidence of significant heterogeneity along these dimensions.

5.4 Discussion

In sum, our estimates support the idea that hospice programs respond to financial incentives generated by the cap. Programs on track to exceed the cap in an outgoing fiscal year increase enrollment rates in the fiscal year's last quarter, especially when each enrollment could instantaneously reduce their cap liability by tens of thousands of dollars during the pre-2011 era. The marginal enrollees are healthier on average (i.e., they are less likely to have been hospitalized recently, they subsequently live longer, and they subsequently have higher lifetime LOS in hospice care) and are less attached to hospice care (i.e., they experience more lifetime live discharges and are less likely to ultimately die in hospice care). These findings support the idea that marginally enrolled patients have lower intrinsic demand for hospice care. With respect to live discharges, our estimates indicate that programs on track to exceed the cap in an outgoing fiscal year increase live discharge rates in the fiscal year's last quarter on average, especially in the pre-2011 era when they were simultaneously

tively, in either t^O_e or t^I_e. However, including these programs does not significantly change our results.

enrolling more new patients and holding staffing ratios approximately fixed.

However, our estimates also support the idea that hospice programs' adjustments to the cap are small relative to their cap liabilities. In particular, they imply that programs on track to exceed the cap in an outgoing fiscal year each have 1.54 additional enrollments and 0.37 additional live discharges throughout the outgoing fiscal year's last quarter on average.[27] They do not indicate that treatment patterns (i.e., levels of hospice care or staff visits) significantly respond to the cap. Ultimately, average annual payments per patient at hospice programs on track to exceed the cap differentially decrease by 0.067 log points (6.5%) on average in the last quarter of an outgoing fiscal year, but their cap liabilities remain at approximately $490,000 on average. (See table 1 and figure A27.) That hospice programs do not further reduce their cap liabilities by enrolling more new patients or live discharging more existing patients near the end of the fiscal year—when they can plausibly accurately forecast an impending cap liability—further supports the idea that the cost of making adjustments along these margins is high. These high costs may be related to the fact that CMS requires a non-hospice doctor to certify that a potential hospice enrollee's life expectancy is six months or less and that hospice enrollees forgo curative care for their terminal illnesses.

6 Conclusion and policy implications

We study how an average revenue cap can affect provider behavior and 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 show that hospice programs could undercut the cap by churning their patients, thereby raising concerns about the cap's capacity to contain costs but also creating an opportunity to study provider-induced demand.

We find that programs on track to exceed the cap in an outgoing fiscal year increase their enrollment and live discharge rates by 5.8% and 4.3% respectively during the fiscal year's fourth quarter; and evidence that the marginal enrollees are healthier and have lower intrinsic demand for hospice care. We also find that programs that exceed the cap have an approximately $500,000 cap liability

[27]We arrived at these estimates as follows. The average daily number of new enrollments and live discharges during an incoming fiscal year's first week was 0.253 and 0.156, respectively, among programs that were on track to exceed the cap in the outgoing fiscal year. We computed $7 \times 0.253 \sum_{w<0} \big(\exp(\hat{\beta}_w) - 1\big)$ and $7 \times 0.156 \times \sum_{w<0} \big(\exp(\hat{\beta}_w) - 1\big)$ using the estimates of $(\beta_w : w < 0)$ from the new enrollments and live discharge models described in table 3.

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. In sum, our results suggests that a cap on average annual revenue can reduce health care spending under capitation. They also suggest that provider-induced demand in the U.S. hospice industry exists, but its magnitude is small.

Our work has several other policy implications. First, that hospice programs incur larger cap liabilities when the wage index raises their daily payment rates supports MedPAC (2022)'s theory that wage adjusting the cap could improve equity across hospice programs. Second, that the cap causes programs to either make costly adjustments to their census or repay a large share of their gross payments to Medicare raises concerns about the cap's effect on market structure. We find that CCNs linked to hospice programs with cap liabilities are more likely to be terminated. We caution that causal inference with respect to CCN terminations is complicated by the possibility that unobserved factors—such as poor management or decreasing residual demand for hospice care—may simultaneously influence cap liabilities and market structure. However, if the cap causes programs on the margin of profitability to exit or consolidate, then simulations that are designed to evaluate cap reforms but that do not account for the cap's effect on market structure may miss some welfare-relevant outcomes. For instance, cap-induced exit or consolidation may dampen quality competition between hospice programs because prices in the U.S. hospice industry are largely set by the Medicare hospice benefit (Gaynor and Town, 2003). We believe that identifying the causal link between the cap and market structure may be a productive area for future research.

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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 is set by CMS each year. Prior to and including 2015, the cap varied annually with the medical expenditure category of the Consumer Price Index for urban consumers published by the Bureau of Labor Statistics. Since 2016, the cap has varied annually with hospice payment rates.[28] The cap has grown from \$6,500 at the inception of the hospice benefit to \$32,487 in FY 2023.[29]

Within a given fiscal year, the cap varies across hospice programs to a limited extent. The first fiscal year assigned to a new hospice program is the first fiscal year ending at least twelve months after the hospice program received its Medicare certification. New hospice programs' first fiscal years may therefore span parts of two fiscal years. For these hospice programs, the cap is a weighted average of the two fiscal years' caps. The weights are the fraction of days that the hospice program was operating in each of the two fiscal years. The cap does not vary within a fiscal year along any other dimensions.[30]

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 are hospice programs' average annual payments per patient computed?

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

[28] Federal Register, vol. 80(151): 47207.

[29] The cap was initially 40% of Medicare's average expenditures for cancer patients in their last six months of life, or \$6,500. Since 1983, the cap has been annually increased to keep pace with inflation in medical expenditures and baseline hospice payment rates. See Federal Register, vol. 48(163):38156-7 and Federal Register vol. 80(151):47147.

[30] Medicare hospice transmittal 156.

A.4 Payments

Each hospice program's total payment in each fiscal year is the sum of the per diem payments made to that program for patient-days that fall within that fiscal year, irrespective of the day the payments were actually remitted. Mathematically, let j index hospice programs, let t index fiscal years, let i index beneficiaries, let d index days, let $a(i, j, d) := 1[i \text{ was enrolled at } j \text{ on } d]$, let $t(d)$ be the fiscal year corresponding to d, and let $\text{PD}(i, j, d)$ be the per diem payment made to j for beneficiary i's care on d. Then for every (j, t), total payments were:

$$\text{Payment}_{jt} := \sum_{d:t(d)=t} \sum_{i:a(i,j,d)=1} \text{PD}(i, j, d) \tag{A.1}$$

The per diem rate is administratively set by CMS according to a formula that varies with beneficiary, day, and program. For a given (i, j, d), the per diem rate consists of a base payment, a so-called "labor share," and a wage index adjustment.

The base payment for a given patient-day depends on the level of hospice care the patient received on that day, the patient's previous hospice utilization, the patient's program's compliance with Medicare's quality reporting requirements, and the day's fiscal year. There are four treatment types: RHC, CHC, IRC, and GIC. Their base payments are annually adjusted by Medicare to account for growth in the hospital market basket. Within each fiscal year, the base payment is generally lowest for RHC, then for IRC, then for GIC, then for CHC. Since January 1, 2016, the RHC base payments have also been higher for each patient's first 60 days in hospice care than they have been for their subsequent days. Finally, since FY 2014, CMS has reduced base payment rates by 2% for hospice programs that have not complied with certain quality reporting requirements.[31]

The base payment for each patient-day is divided into a "labor amount" and a "non-labor amount" using an administratively set "labor share." The labor share varies according to treatment type. It is 0.6871 for RHC, 0.6871 for CHC, 0.5413 for IRC, and 0.6401 for GIC, and has not changed since at least FY 2001. The labor amount is adjusted by the wage index to compensate hospice programs operating in geographic markets with higher labor costs. Each program's wage index value varies from year-to-year with how labor costs at its CBSA compare to nationwide labor costs.

The base payments, labor shares, and wage index adjustments are combined to calculate the per diem payment rates as follows. Let $k(i, d) \in \{\text{RHC}, \text{CHC}, \text{IRC}, \text{GIC}\}$ indicate whether beneficiary i received RHC, CHC, IRC, or GIC on day d. Let $\text{BP}_k(i, j, d)$ be the beneficiary's base payment rate on day d at program j for treatment type k. (Recall that for a given (j, d), $\text{BP}_k(i, j, d)$ does not vary with i unless $k = \text{RHC}$.) Let LS_k be the labor share for treatment type k. Finally, let $\text{WI}(j, t)$

[31]Federal Register, vol. 80(151): 47207.

be the wage index adjustment for program j in fiscal year t. Then the per diem rates were:

$$\mathrm{PD}(i,j,d) := \sum_k 1[k(i,d)=k]\Big(\mathrm{BP}_k(i,j,d)(1-LS_k)+\mathrm{BP}_k(i,j,d)\mathrm{LS}_k\mathrm{WI}(j,t(d))\Big) \quad \text{(A.2)}$$

A.5 Cap census

Since FY 1984, patients have been counted toward cap censuses with one of two formulas, or "counting methods:" the streamlined method and the proportional method. The particular method used for each patient depends on that patient's program and the fiscal year.

Under the streamlined method, patients who were only ever affiliated with one hospice program were counted toward that program's cap census on their first day enrolled in hospice. A patient was counted toward their program's cap census in fiscal year $t \in \{2001, \ldots, 2016\}$ if that day fell between September 28 of calendar year $t-1$ and September 27 of calendar year t. They were counted toward their program's cap 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 fell between October 1 of calendar year $t-1$ and September 30 of calendar year t. Patients who were ever affiliated with more than one program were counted toward each program's cap census proportionally. Specifically, for each fiscal year t that such a patient was enrolled in hospice and for each program j where the patient was ever enrolled, that patient's contribution to (j,t)'s cap census is that fraction of their total number of patient-days that they spent at (j,t).[32] Under the proportional method, this formula was applied for all patients—not just those who were ever affiliated with multiple programs.

All hospice programs used the streamlined method until FY 2011. (Hence, we sometimes refer to this as the "pre-2011 counting method.") Around that time, hospice programs appealed to contest the streamlined method. In response to the appeal, CMS announced in 2011 that hospice programs could elect by October 1, 2011 to have their cap censuses for fiscal years prior to 2011 recalculated using the proportional method. If a hospice program made this election, then its cap censuses for fiscal years 2012 and onward were also made using the proportional method.[33] (Hence, we sometimes refer to this as the "post-2012 counting method.")

All other programs would also be switched to the proportional method for fiscal years 2012 and onward unless they made an election to continue using the streamlined method shortly after the end of FY 2012. If they did not make this election and therefore began using the proportional method in FY 2012, then their pre-2011 cap censuses were unchanged, even if they served beneficiaries in FY

[32] 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.

[33] Medicare hospice transmittal 156.

2012 or later who had already been counted in a pre-2011 fiscal year using the streamlined method. Consequently, some beneficiaries' lifetime contributions to hospice programs' cap censuses are more than one.[34]

Those programs that elected to continue using the streamlined method after FY 2011 could elect to switch to the proportional method at any time. Once they elected to switch, their cap censuses would be calculated using the proportional method in the year that they elected to switch and in all subsequent fiscal years. CMS would also recalculate their cap censuses using the proportional method for up to three fiscal years prior to the fiscal year that they elected to switch. Once a hospice program begins using the proportional counting method, it cannot switch back. Hospice programs that received their Medicare certification on or after October 1, 2011 use the proportional method.[35]

Only 486 hospice programs used the streamlined method in FY 2013.[36] This has weakly decreased since 2013, but data identifying which programs used which methods in which fiscal years are not available. Consequently, we estimate cap liabilities assuming that all hospice programs used the streamlined method during FY 2001 - FY 2011 and the proportional method thereafter. Since most patients are only ever affiliated with one hospice program, we define the primary census counting period for each fiscal year $t \in \{2001, ..., 2011\}$ to be September 28 of calendar year $t-1$ to September 27 of calendar year t; and we define it for each fiscal year $t \in \{2012, ..., 2018\}$ to line up with the fiscal year's start and end dates.

In any given fiscal year t prior to and including FY 2016 when a hospice 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 the October 31 of calendar year $t-1$ were not counted toward any cap census. For example, consider a patient who first enrolled in hospice on September 28, 2011 at a program that was switching from the streamlined method to the proportional method between FY 2011 and FY 2012. That patient would not have been counted toward the FY 2011 cap census because the window to be counted using the streamlined method had closed on September 27, 2011. If they passed away on October 31, 2011, then they would not have been counted toward the program's FY 2012 cap census either because they passed away before FY 2012 began on November 1, 2011. If they instead passed away on November 30, 2011, then their patient-days between November 1 and 30 would have been counted toward the FY 2012 cap census in proportion to their total length-of-stay, which would have included the 34 days between September 28 and October 31. However, those 34 days would not have themselves contributed to either fiscal year's cap census. Consequently, some patients' lifetime contributions to hospice programs' cap censuses are less than one.[37]

[34]Medicare hospice transmittal 156.
[35]Medicare hospice transmittal 156.
[36]Federal Register, vol. 80(151): August 6, 2015
[37]Medicare hospice transmittal 156.

Under both the streamlined and proportional methods, patients' contributions to their hospice programs' cap censuses depend on their lifetime hospice utilization. In practice, for any given fiscal year t, CMS may retroactively adjust hospice programs' FY t cap censuses with updated utilization data collected up to fiscal year $t+3$. In each fiscal year t, hospice programs must repay an estimate of their cap libailities within five months of the end of t.[38] Their cap liabilities will be weakly larger than this estimate as some of their patients continue to use hospice care through year $t+3$. Hospice programs may be subsequently asked to repay the difference.[39] 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.

B Assigning (program, days) to fiscal years

We linked each (program, day) realization observed in the hospice claims data to its corresponding fiscal year. This link is usually based 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 hospice program's first fiscal year is that fiscal year ending at least twelve months after the program received its Medicare certification. For instance, for hospice programs that received their Medicare certifications between November 2, 2006 and November 1, 2007 (inclusive), days in this range are part of FY 2008.

We identified hospice programs' Medicare certification dates as follows. In the Medicare provider of service files ("POS files," hereafter), we identified each program's earliest observed Medicare certification date. For each hospice program j, let this date be $\text{FirstCertDay}(j)$. Similarly, let the earliest observed date associated with any of program j's Medicare claims be $\text{FirstClaimDay}(j)$. For each program j such that $\text{FirstCertDay}(j)$ is non-missing and earlier than $\text{FirstClaimDay}(j)$, we treated $\text{FirstCertDay}(j)$ as the program's Medicare certification date. But for some programs j, $\text{FirstCertDay}(j)$ is either missing or greater than $\text{FirstClaimDay}(j)$. (This represents approximately 45% of hospice programs.) We assume that this indicates an error in the POS files. For such programs j, if $\text{FirstClaimDay}(j)$ is strictly greater than January 1, 2000, then we treated $\text{FirstClaimDay}(j)$ 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 $\text{FirstClaimDay}(j)$ is January 1, 2000 for many programs.)

[38] See 42 CFR 418.308.

[39] 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.

C Sequestration adjustment

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 programs' payments 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 hospice programs' actual payments and their payments but for the sequestration reduction.[40] 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%.

D Data

D.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 Medicare Denominator 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 Medicare Denominator 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."

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

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.")

D.2 Patient demographics

We relied on the patient demographic data in the 2000-2019 Medicare Denominator files. In particular, we identified each beneficiary's date of birth, race, sex, 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. In calculating hospice patients' remaining lifetimes after enrolling in hospice, we assume that patients with missing dates of death survived until December 31, 2019. Figure A28 reports difference-in-differences estimates of equations (6) and (7) for new enrollees' life expectancies for only those hospice patients that have non-missing dates of death. They are qualitatively similar to our main results, discussed near page 11.

We also relied on the patient residence data in the hospice claims. In particular, we identified for each (program, day, patient) observation the corresponding ZIP code reported in claims associated with that observation. If a single (program, day, patient) observation was ever associated with multiple ZIP codes, we treated the ZIP code as missing for that observation.

D.3 Hospice program business records

We relied on hospice programs' business data in the 2000-2019 Medicare provider-of-service 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 a hospice program's CCN is associated with a hospice claim. See appendix B for details about how we used the claims data to identify when hospice programs began operating. We say that a hospice program's CCN is terminated in a given fiscal year if it is not associated with any hospice 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.

D.4 Wage index, daily payment rates, and the cap

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

D.5 Hospitalizations

We identified hospitalizations using the 2000-2019 MedPAR files. We linked the providers in the MedPAR files with their records in the provider-of-service files to determine which providers were hospitals and skilled nursing facilities. We determined days that hospice patients spent in a hospital and skilled nursing facility using the admission and discharge dates associated with each claim in the MedPAR files. We created a patient-level variable indicating whether each hospice patient was hospitalized within 7-days of their hospice enrollment date.

D.6 Nursing home stays

We constructed nursing home spells using the Minimum Dataset ("MDS," hereafter) and MedPAR. The MDS contains records of Medicare beneficiaries' health assessments generated when they are admitted to nursing homes ("entry assessment," hereafter), discharged from nursing homes ("discharge assessment," hereafter), and at regular intervals during their nursing home stays ("ongoing assessment," hereafter). We used these assessments to create a (patient, nursing home, day)-level dataset. Each observation corresponds to a day when an assessment was made for a patient by a nursing home. We excluded some difficult-to-parse patients and observations. For instance, we excluded assessments if that assessment's nursing home was neither the patient's previous assessment's nursing home or their subsequent assessment's nursing home. We also excluded patients if they were ever observed to have assessments from three nursing homes on the same day.

We constructed nursing home spells from the (patient, nursing home, day) data by connecting consecutive assessment dates. A patient's spell at a given nursing home began on (1) the day of the patient's first-observed assessment; (2) when an entry assessment was observed at that nursing home; (3) when an ongoing assessment was observed at that nursing home and the previous observation was an assessment at another nursing home; or (4) when an ongoing assessment was observed at that nursing home and the previous observation was a discharge assessment at the same nursing home. A patient's spell at a given nursing home ended on (1) the day of the patient's last-observed assessment; (2) when a discharge assessment was observed at that nursing home; (3) when an ongoing assessment was observed at that nursing home and the next observation was an assessment at another nursing home; or (4) when an ongoing assessment was observed at that nursing home and the next observation was an entry assessment at the same nursing home. We joined (patient, day)-level nursing home stay records derived from the MDS with (patient, day)-level skilled nursing facility stay records in the MedPAR files. We created a patient-level variable indicating whether each hospice patient experienced a nursing home stay within 7-days of their hospice enrollment date.

D.7 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.

D.8 Measuring each program-year's proximity to other program's that exceeded the cap in that year

We constructed a measure of each program-year (j, t)'s proximity to other programs that exceeded the cap in that year using the extent of overlap of hospice programs' patient populations. For each ZIP code z in each fiscal year t, define the set of hospice programs serving patients in (z, t) as J_{zt}. For each program j, define I_{jzt} as the set of patients living in z and being treated in (j, t). For each (j, z, t) such that $j \in J_{zt}$, define the average fraction of other hospice programs that operate in (z, t) and exceed the cap in FY t weighted by their share of (z, t)'s hospice patient population as:

$$D_{jzt} := \sum_{j' \in J_{zt} \setminus \{j\}} 1[\text{Over the cap}]_{j't} \left(\frac{|I_{j'zt}|}{\sum_{j' \in J_{zt} \setminus \{j\}} |I_{j'zt}|} \right) \tag{D.3}$$

Then for each (j,t), define the average of D_{jzt} weighted by the share of (j,t)'s patient volume across (z,t) as:

$$D_{jt} := \sum_{z:j\in J_{zt}} D_{jzt}\left(\frac{|I_{jzt}|}{\sum_{z:j\in J_{zt}} |I_{jzt}|}\right) \tag{D.4}$$

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 enrolled in hospices that exceeded the cap.

D.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 say that one unit of 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 say that one unit of RHC was provided on each of the first fourteen days and one unit of GIC was provided on 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 the number of units of RHC, CHC, GIC, or IRC provided to each patient by each program on each day across all claims.

D.10 ADRD diagnoses

We identified which hospice patients had an ADRD diagnosis prior to their first observed enrollment in hospice care using the records in the Chronic Conditions Data Warehouse.

E Additional descriptive statistics

The cap liability statistics we report in section 4 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, as discussed in section 2.

Our cap liability estimates indicate that cap risk is geographically clustered and autocorrelated. Figure A29 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. Figure A30 plots for the set of programs that exceeded the cap at least once the association between (1) the number of fiscal years between FY 2001 and FY 2018 that they were operating and (2) the average fraction of those years that they exceeded the cap. Programs that exceeded the cap at least once exceeded it in 49% of their observed years of operation between FY 2001 and FY 2018 on average.

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 A31 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 A32 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).

F Difference-in-differences

F.1 Robustness checks

We examined whether our results were robust to three alternative difference-in-differences specifications. First, we examined whether they are robust to adding 60 days to either side of the event windows.[41] Hospice programs are still placed into $\mathcal{T}$ and $\mathcal{U}$ based on their cumulative average annual payments per patient at the beginning of the baseline 180-day window. Second, we examined whether our results are robust to excluding the state, ownership, and wage index controls. In other words, we replaced $\mathrm{FE}_{ewg_{ej}} + \mathrm{FE}_{ewg_{ej}} \times \mathrm{WI}^{O}_{ej}$ in equations (6) and (7) with FE_{ew}. Finally, we examined whether our results are robust to excluding (e, j) realizations such that $\mathrm{PPP}^{O}_{ej}/\mathrm{Cap}_{t^{O}_{e}} \in [0.9, 1]$. These robustness checks will respectively help us assess whether our estimates are sensitive to the event window, control variables, or any potential compensating adjustments made by hospice programs that were on track to be below—but close to—the cap.

Figures A33-A34 plot the estimates computed from these alternative specifications alongside the estimates from our main specifications. Estimates from the "longer window" specification suggest that hospice programs that are on track to exceed the cap in an outgoing fiscal year have differentially lower enrollment rates in the outgoing fiscal year before the outgoing fiscal year's last three months. Overall, these estimates suggest that our main qualitative findings are not sensitive to these alternative specifications.

F.2 Heterogeneity analysis

We explored whether the difference-in-differences in our main analysis meaningfully vary across ownership type, cap census, proximity to other hospice programs on track to exceed the cap, and affiliation with a nursing home. In particular, we substituted $1[(e, j) \in \mathcal{T}]1[w < 0]\beta$ with $1[w < 0]X^{O}_{ej}\beta^{\mathrm{X}} + 1[(e, j) \in \mathcal{T}]1[w < 0]\beta^{\mathrm{T}} + 1[(e, j) \in \mathcal{T}]1[w < 0]X^{O}_{ej}\beta^{\mathrm{XT}}$ in equation (6) for covariates X^{O}_{ej} measured at the start of the event windows. Likewise, we substituted $1[(e, j) \in \mathcal{T}]1[w = w']\beta_{w'}$ with $1[w = w']X^{O}_{ej}\beta^{\mathrm{X}}_{w'} + 1[(e, j) \in \mathcal{T}]1[w = w']\beta^{\mathrm{T}}_{w'} + 1[(e, j) \in \mathcal{T}]1[w = w']X^{O}_{ej}\beta^{\mathrm{XT}}_{w'}$ in equation (7). In order to examine heterogeneity by profit status, we defined X^{O}_{ej} as an indicator for whether hospice j was for-profit in fiscal year t^{O}_{e}. In order to examine heterogeneity across cap census, we defined X^{O}_{ej} as the log of program j's cumulative cap census in FY t^{O}_{e} at the beginning

[41] We therefore incidentally exclude a small number of hospice programs that are not continuously observed throughout the new 300-day event window but were observed continuously throughout the baseline 180-day event window.

of e's event window. In order to examine heterogeneity across proximity to other hospice programs on track to exceed the cap, we defined X^{O}_{ej} as the log of program j's proximity to programs in $\mathcal{T}$ at the beginning of e's event window, as described in appendix D.8 for details. In order to examine heterogeneity by association with a nursing home, we defined X^{O}_{ej} as an indicator for whether hospice j shared any patient-day with a nursing home in fiscal year t^{O}_{e}.

Figures A35-A38 report β^{XT} and $(\beta^{\text{XT}}_{w'} : w \in W)$ for the specifications pertaining to enrollments. Figures A39-A42 report β^{XT} and $(\beta^{\text{XT}}_{w'} : w \in W)$ for the specifications pertaining to live discharges. We do not find statistically significant evidence of meaningful heterogeneity.

		Above-cap		Below-cap		
	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						
1[Patient-day at a NH]	0.22	0.13	0.18	0.22	0.24	0.24
1[At least one NH patient]	0.96	0.90	0.94	0.96	0.96	0.96
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. This table reports descriptive statistics about the (program, fiscal year)-level data. On average, programs that exceed the cap are newer, more likely to operate for profit, and have a higher proximity to other programs that exceed the cap contemporaneously. They enroll fewer patients, live discharge a larger fraction of patients, and enroll fewer patients with a recent hospital or nursing home stay. Finally, they are more likely to close in the following year. See the discussion near page 18.

	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. A2. This table reports McCrary test statistics of the null hypothesis that the distribution of average annual payments per patient relative to the cap is continuous at 1. The test statistics support the idea that hospice programs' average annual payments per patient do not bunch around the cap. "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. The bandwidths are selected based on the mean squared error of the density estimators (Cattaneo et al., 2018). Figure 2 plots this distribution for column (1) (i.e., the full distribution). Figures A1-A3 plot the distributions for the sub-samples corresponding to columns (2)-(4). See the discussion near page 18.

	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
Period FE	Y	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y	Y
Only ever over	-	-	-	-	-
$\bar{Y}$	0.113	177,361	3,106	3,673,515	15,163
N	56,193	17,550	17,480	56,202	56,193
Clusters	5,246	2,082	2,075	5,246	5,246

	Medicare payments per patient-day			
	Gross	Net	Gross	Net
	(6)	(7)	(8)	(9)
Log(WI)	0.328***	0.301***	0.341***	0.203***
	(0.038)	(0.037)	(0.060)	(0.056)
Estimator	PPML	PPML	PPML	PPML
Hospice FE	Y	Y	Y	Y
Period FE	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y
Only ever over	-	-	Y	Y
$\bar{Y}$	147	143	147	136
N	56,202	56,202	18,425	18,425
Clusters	5,246	5,246	2,233	2,233

	Annual cap census contribution per patient	Cap census	Number of unique patients	Number of patient-days
	(10)	(11)	(12)	(13)
Log(WI)	0.002	-0.103	-0.084	-0.044
	(0.009)	(0.083)	(0.088)	(0.125)
Estimator	PPML	PPML	PPML	PPML
Hospice FE	Y	Y	Y	Y
Period FE	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y
Only ever over	-	-	-	-
$\bar{Y}$	0.730	273	357	23,619
N	56,202	56,202	56,202	56,202
Clusters	5,246	5,246	5,246	5,246

Tab. A3. This table reports estimates from models relating outcomes to the wage index. It supports the idea that the wage index is associated with cap liabilities. Mathematically, for hospice programs j and fiscal years t, let $f_{jt} := \beta \log(\mathrm{WI}_{jt}) + \Gamma X_{jt}$. We relate f_{jt} to the conditional expectations of binary outcomes Y_{jt} to estimate β using OLS. We relate $\exp(f_{jt})$ to the conditional expectations of other non-negative outcomes Y_{jt} to estimate β using PPML. Program-level cluster-robust SEs in parentheses. See the discussion near page 20.

	1[Over cap] (1)	Liability (2)	Liability per unique patient (3)	Gross Medicare payments (4)	PPP (5)	1[CCN terminated] (6)
$1[\text{Over cap}]_{jt-1}$	0.193***	1.242***	0.725***	0.074	0.162***	0.056***
	(0.010)	(0.058)	(0.064)	(0.055)	(0.008)	(0.003)
Estimator	OLS	PPML	PPML	PPML	PPML	OLS
Hospice FE	Y	Y	Y	Y	Y	-
Period FE	Y	Y	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y	Y	Y
$\bar{Y}$	0.112	191,840	2,985	3,911,340	15,261	0.025
N	51,203	15,497	15,451	51,210	51,203	52,918
Clusters	4,878	1,893	1,887	4,879	4,878	5,375

	Medicare payments per patient-day		Annual cap census contribution per patient	Cap census	Number of unique patients	Number of patient-days
	Gross (7)	Net (8)	(9)	(10)	(11)	(12)
$1[\text{Over cap}]_{jt-1}$	-0.008***	-0.063***	-0.074***	-0.107**	-0.025	0.095**
	(0.002)	(0.004)	(0.003)	(0.046)	(0.044)	(0.044)
Estimator	PPML	PPML	PPML	PPML	PPML	PPML
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
Age & ownership FE	Y	Y	Y	Y	Y	Y
$\bar{Y}$	147	144	0.726	286	376	25,053
N	51,210	51,210	51,210	51,210	51,210	51,210
Clusters	4,879	4,879	4,879	4,879	4,879	4,879

Tab. A4. This table reports estimates from models relating outcomes to a 1-year lag indicator of whether a hospice program exceeded the cap. It supports the idea that hospice programs that exceed the cap in one fiscal year are more likely to exceed it again in the next fiscal year. It also supports the idea that CCNs associated with programs that exceed the cap are more likely to be terminated. Mathematically, for hospice programs j and fiscal years t, let $f_{jt} := \beta 1[\text{PPP}_{jt-1} > \text{Cap}_{t-1}] + \Gamma X_{jt}$. We relate f_{jt} to the conditional expectations of binary outcomes Y_{jt} to estimate β using OLS. We relate $\exp(f_{jt})$ to the conditional expectations of other non-negative outcomes Y_{jt} to estimate β using PPML. Program-level cluster-robust SEs in parentheses. See the discussion near page 21.

	Enrollees' lifetime LOS in hospice care (log diff.)			Enrollees' lifetime num. of unique programs (log diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	0.020***	0.021*	0.020**	0.003*	0.003	0.003
	(0.007)	(0.012)	(0.009)	(0.002)	(0.003)	(0.002)
Dynamic model: DID relative to week 0						
β_{-4}	0.025	0.021	0.028	-0.004	-0.004	-0.003
	(0.026)	(0.043)	(0.033)	(0.007)	(0.011)	(0.008)
β_{-3}	0.008	-0.014	0.022	-0.008	-0.006	-0.009
	(0.026)	(0.044)	(0.034)	(0.007)	(0.012)	(0.008)
β_{-2}	0.029	-0.020	0.063**	0.001	0.000	0.001
	(0.026)	(0.042)	(0.032)	(0.007)	(0.011)	(0.008)
β_{-1}	0.041	0.042	0.039	0.003	0.005	0.001
	(0.026)	(0.040)	(0.034)	(0.007)	(0.011)	(0.008)
β_0	-	-	-	-	-	-
β_1	0.003	-0.022	0.020	-0.007	-0.020*	0.000
	(0.027)	(0.044)	(0.034)	(0.006)	(0.011)	(0.008)
β_2	0.014	0.000	0.024	0.004	-0.008	0.010
	(0.026)	(0.043)	(0.033)	(0.007)	(0.012)	(0.008)
β_3	0.011	0.005	0.013	-0.000	-0.001	0.000
	(0.025)	(0.041)	(0.033)	(0.006)	(0.010)	(0.008)
Estimator	PPML	PPML	PPML	PPML	PPML	PPML
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	182.306	217.524	162.169	1.219	1.282	1.184
N	1,142,852	601,872	540,980	1,142,852	601,872	540,980
Clusters	5,534	3,782	4,965	5,534	3,782	4,965
$\lvert\mathcal{T}\rvert$	3,047	1,130	1,917	3,047	1,130	1,917
$\lvert\mathcal{U}\rvert$	41,185	22,238	18,947	41,185	22,238	18,947

Tab. A5. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who ultimately have longer average lifetime LOS in hospice care. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of enrollees. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A4 and A5.

	Enrollees' lifetime num. of live discharges (log diff.)			Fraction of enrollees who die in hospice care (% point diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	0.019**	0.028**	0.013	-0.005***	-0.005*	-0.004**
	(0.008)	(0.012)	(0.011)	(0.002)	(0.003)	(0.002)
Dynamic model: DID relative to week 0						
β_{-4}	-0.025	-0.026	-0.023	-0.001	0.005	-0.005
	(0.027)	(0.041)	(0.037)	(0.006)	(0.011)	(0.006)
β_{-3}	0.000	0.030	-0.024	-0.007	-0.019	-0.001
	(0.027)	(0.041)	(0.037)	(0.006)	(0.012)	(0.006)
β_{-2}	-0.005	-0.013	0.002	0.006	0.003	0.008
	(0.029)	(0.047)	(0.036)	(0.006)	(0.011)	(0.006)
β_{-1}	0.015	0.039	-0.005	-0.011**	-0.019*	-0.006
	(0.027)	(0.039)	(0.037)	(0.005)	(0.011)	(0.006)
β_0	-	-	-	-	-	-
β_1	-0.039	-0.092**	0.002	-0.003	-0.000	-0.005
	(0.027)	(0.039)	(0.036)	(0.005)	(0.011)	(0.006)
β_2	-0.027	-0.068	0.002	0.000	0.003	-0.001
	(0.028)	(0.045)	(0.036)	(0.005)	(0.011)	(0.006)
β_3	0.013	0.020	0.006	-0.004	-0.010	-0.001
	(0.028)	(0.040)	(0.038)	(0.006)	(0.011)	(0.006)
Estimator	PPML	PPML	PPML	OLS	OLS	OLS
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	0.604	0.804	0.489	0.866	0.781	0.915
N	1,123,808	591,490	532,318	1,138,993	604,196	534,797
Clusters	5,513	3,766	4,951	5,508	3,787	4,942
$\lvert\mathcal{T}\rvert$	3,028	1,124	1,904	2,892	1,116	1,776
$\lvert\mathcal{U}\rvert$	40,484	21,826	18,658	41,216	22,351	18,865

Tab. A6. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who ultimately have more lifetime live discharges and are less likely to die in hospice. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of enrollees. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A6 and A7.

	Fraction of enrollees who were hospitalized prior to enrollment (% point diff.)			Fraction of enrollees who were NH residents prior to enrollment (% point diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	-0.009***	-0.021***	-0.003	-0.006***	-0.008**	-0.004*
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)
Dynamic model: DID relative to week 0						
β_{-4}	-0.018**	-0.041***	-0.006	-0.009	-0.012	-0.007
	(0.007)	(0.013)	(0.009)	(0.006)	(0.011)	(0.008)
β_{-3}	-0.010	-0.025**	-0.002	-0.011	-0.013	-0.010
	(0.007)	(0.012)	(0.009)	(0.007)	(0.012)	(0.008)
β_{-2}	-0.011	-0.029**	-0.001	-0.020***	-0.020*	-0.020**
	(0.007)	(0.012)	(0.009)	(0.007)	(0.011)	(0.008)
β_{-1}	-0.022***	-0.040***	-0.011	-0.004	-0.006	-0.003
	(0.007)	(0.012)	(0.009)	(0.006)	(0.010)	(0.008)
β_0	-	-	-	-	-	-
β_1	-0.003	0.000	-0.005	-0.012*	-0.014	-0.011
	(0.007)	(0.012)	(0.009)	(0.006)	(0.011)	(0.008)
β_2	-0.013*	-0.022*	-0.008	-0.010	-0.010	-0.011
	(0.007)	(0.013)	(0.009)	(0.007)	(0.011)	(0.008)
β_3	-0.012*	-0.035***	0.001	-0.013**	-0.016	-0.012
	(0.007)	(0.013)	(0.009)	(0.007)	(0.011)	(0.008)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	0.279	0.259	0.276	0.222	0.216	0.225
N	1,150,420	606,384	544,036	1,150,420	606,384	544,036
Clusters	5,540	3,788	4,974	5,540	3,788	4,974
$\|\mathcal{T}\|$	3,050	1,132	1,918	3,050	1,132	1,918
$\|\mathcal{U}\|$	41,478	22,418	19,060	41,478	22,418	19,060

Tab. A7. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who were less likely to have had a hospital or nursing home stay in the week prior to enrollment. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of enrollees. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A8 and A9.

	Fraction of enrollees who are discharged within 30 days (% point diff.)			Enrollees' remaining days of life (log diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	0.001	0.004	-0.000	0.044***	0.065***	0.023**
	(0.001)	(0.003)	(0.002)	(0.009)	(0.015)	(0.010)
Dynamic model: DID relative to week 0						
β_{-4}	0.003	0.002	0.003	0.076***	0.112**	0.042
	(0.005)	(0.009)	(0.006)	(0.029)	(0.049)	(0.033)
β_{-3}	0.010*	0.013	0.008	0.052*	0.094**	0.013
	(0.006)	(0.013)	(0.005)	(0.029)	(0.048)	(0.034)
β_{-2}	0.003	0.004	0.002	0.051*	0.073	0.032
	(0.005)	(0.010)	(0.005)	(0.030)	(0.051)	(0.033)
β_{-1}	0.004	0.006	0.004	0.061**	0.120***	-0.001
	(0.005)	(0.009)	(0.006)	(0.029)	(0.047)	(0.035)
β_0	-	-	-	-	-	-
β_1	0.002	-0.001	0.003	0.022	0.044	0.001
	(0.005)	(0.009)	(0.005)	(0.030)	(0.048)	(0.034)
β_2	0.004	-0.002	0.006	0.030	0.033	0.025
	(0.005)	(0.009)	(0.005)	(0.030)	(0.051)	(0.034)
β_3	0.006	0.011	0.002	0.031	0.062	0.001
	(0.005)	(0.009)	(0.006)	(0.030)	(0.049)	(0.035)
Estimator	OLS	OLS	OLS	PPML	PPML	PPML
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	0.089	0.113	0.075	396	580	291
N	1,150,420	606,384	544,036	1,141,473	600,555	540,918
Clusters	5,540	3,788	4,974	5,534	3,782	4,965
$\|\mathcal{T}\|$	3,050	1,132	1,918	3,045	1,128	1,917
$\|\mathcal{U}\|$	41,478	22,418	19,060	41,142	22,200	18,942

Tab. A8. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who have longer remaining lifetimes. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of enrollees. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A10 and A11

	PPP$_{ijt}$ among enrollees counted proportionally in their first (j,t) (log diff.)		
	(1)	(2)	(3)
Static model: Year-end average DID			
β	0.013	0.032	0.011
	(0.008)	(0.027)	(0.009)
Dynamic model: DID relative to week 0			
β_{-4}	0.019	0.103	0.011
	(0.030)	(0.100)	(0.031)
β_{-3}	0.006	-0.017	0.008
	(0.030)	(0.101)	(0.032)
β_{-2}	0.029	0.066	0.025
	(0.029)	(0.098)	(0.030)
β_{-1}	0.015	0.035	0.013
	(0.030)	(0.093)	(0.031)
β_0	-	-	-
β_1	0.029	0.160*	0.016
	(0.030)	(0.096)	(0.031)
β_2	0.027	0.098	0.020
	(0.029)	(0.090)	(0.031)
β_3	0.006	-0.054	0.010
	(0.030)	(0.103)	(0.031)
Estimator	PPML	PPML	PPML
Event range	01-18/11	01-10	12-18
Hospice FE	Y	Y	Y
Period FE	Y	Y	Y
B-line Y	28,473	55,131	26,054
N	634,382	93,435	540,947
Clusters	5,392	2,982	4,965
$\lvert\mathcal{T}\rvert$	2,289	372	1,917
$\lvert\mathcal{U}\rvert$	22,320	3,373	18,947

Tab. A9. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients counted toward a cap census in proportion to their lifetime LOS in hospice care with much the same PPP$_{ijt}$ in their first jt. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of enrollees counted toward cap censuses in proportion to their lifetime LOS in hospice care. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figure A12.

	Fraction of enrollees with ADRD (% point diff.)		
	(1)	(2)	(3)
Static model: Year-end average DID			
β	0.003	0.000	0.003
	(0.002)	(0.004)	(0.002)
Dynamic model: DID relative to week 0			
β_{-4}	0.008	0.001	0.008
	(0.008)	(0.014)	(0.008)
β_{-3}	0.018**	0.009	0.018**
	(0.008)	(0.014)	(0.008)
β_{-2}	0.004	-0.011	0.004
	(0.008)	(0.013)	(0.008)
β_{-1}	0.009	-0.011	0.009
	(0.008)	(0.013)	(0.008)
β_0	-	-	-
β_1	0.008	-0.010	0.008
	(0.008)	(0.014)	(0.008)
β_2	0.015*	-0.009	0.015*
	(0.008)	(0.014)	(0.008)
β_3	-0.004	-0.013	-0.004
	(0.008)	(0.014)	(0.008)
Estimator	OLS	OLS	OLS
Event range	01-18	01-11	12-18
Hospice FE	Y	Y	Y
Period FE	Y	Y	Y
B-line Y	0.438	0.436	0.438
N	1,150,420	606,384	1,150,420
Clusters	5,540	3,788	5,540
$\lvert\mathcal{T}\rvert$	3,050	1,132	3,050
$\lvert\mathcal{U}\rvert$	41,478	22,418	41,478

Tab. A10. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who have much the same rates of ADRD. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of enrollees. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figure A13.

	Discharged patients' LOS in hospice care prior to discharge (log diff.)			Discharged patients' days until resumption of hospice care (if any) (log diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	0.013	0.013	0.014	0.048**	0.059**	0.034
	(0.008)	(0.013)	(0.011)	(0.019)	(0.028)	(0.024)
Dynamic model: DID relative to week 0						
β_{-4}	-0.022	-0.029	-0.016	0.014	-0.058	0.105
	(0.027)	(0.040)	(0.037)	(0.069)	(0.103)	(0.083)
β_{-3}	-0.007	0.006	-0.016	0.127*	0.158	0.086
	(0.028)	(0.040)	(0.038)	(0.067)	(0.100)	(0.085)
β_{-2}	-0.001	-0.013	0.008	0.092	0.188*	-0.044
	(0.028)	(0.041)	(0.040)	(0.065)	(0.097)	(0.084)
β_{-1}	0.008	0.042	-0.017	-0.014	-0.102	0.092
	(0.027)	(0.038)	(0.036)	(0.064)	(0.093)	(0.082)
β_0	-	-	-	-	-	-
β_1	-0.053*	0.017	-0.103***	-0.003	-0.014	0.011
	(0.028)	(0.039)	(0.038)	(0.068)	(0.101)	(0.090)
β_2	-0.014	-0.012	-0.016	0.011	0.050	-0.045
	(0.028)	(0.040)	(0.038)	(0.067)	(0.100)	(0.085)
β_3	0.006	0.031	-0.012	-0.018	-0.034	-0.001
	(0.030)	(0.043)	(0.040)	(0.069)	(0.103)	(0.087)
Estimator	PPML	PPML	PPML	PPML	PPML	PPML
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	285	276	293	245	331	159
N	676,718	359,077	317,641	498,173	248,878	249,295
Clusters	5,458	3,718	4,904	5,290	3,595	4,767
$\lvert\mathcal{T}\rvert$	2,403	1,015	1,388	1,955	838	1,117
$\lvert\mathcal{U}\rvert$	23,694	12,898	10,796	17,160	8,643	8,517

Tab. A11. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently experience a longer spell without hospice care. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of live discharged patients. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A14 and A15.

	Fraction of discharged patients who later resume at any program (% point diff.)			Fraction of discharged patients who later resume at the same program (% point diff.)			Fraction of discharged patients who later resume at a different program (% point diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Static model: Year-end average DID									
β	-0.003	-0.005	-0.002	0.001	-0.000	0.002	-0.004	-0.004	-0.003
	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)	(0.005)
Dynamic model: DID relative to week 0									
β_{-4}	-0.016	0.007	-0.033**	-0.011	0.020	-0.035**	-0.005	-0.013	0.002
	(0.011)	(0.016)	(0.016)	(0.011)	(0.016)	(0.015)	(0.012)	(0.017)	(0.017)
β_{-3}	-0.008	0.004	-0.018	-0.001	0.010	-0.011	-0.007	-0.006	-0.008
	(0.011)	(0.017)	(0.015)	(0.011)	(0.017)	(0.014)	(0.012)	(0.016)	(0.016)
β_{-2}	-0.023**	-0.008	-0.035**	-0.006	0.005	-0.016	0.016	-0.013	0.019
	(0.011)	(0.016)	(0.015)	(0.011)	(0.016)	(0.015)	(0.011)	(0.016)	(0.016)
β_{-1}	-0.008	0.010	-0.021	-0.017*	0.005	-0.034**	0.010	0.005	0.013
	(0.011)	(0.016)	(0.015)	(0.010)	(0.015)	(0.014)	(0.011)	(0.016)	(0.015)
β_0	-	-	-	-	-	-	-	-	-
β_1	-0.023**	-0.009	-0.035**	-0.019*	-0.013	-0.024*	-0.005	0.003	-0.011
	(0.011)	(0.017)	(0.015)	(0.011)	(0.017)	(0.014)	(0.012)	(0.018)	(0.016)
β_2	-0.027**	-0.027*	-0.027*	-0.017	-0.002	-0.030**	-0.009	-0.026	0.004
	(0.011)	(0.016)	(0.015)	(0.011)	(0.017)	(0.015)	(0.011)	(0.016)	(0.015)
β_3	-0.017	-0.003	-0.029*	-0.016	0.004	-0.031*	-0.002	-0.006	0.002
	(0.012)	(0.017)	(0.016)	(0.012)	(0.017)	(0.016)	(0.012)	(0.017)	(0.017)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Event range	01-18	01-11	12-18	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
B-line Y	0.703	0.684	0.722	0.310	0.335	0.287	0.393	0.349	0.435
N	682,363	362,278	320,085	682,363	362,278	320,085	682,363	362,278	320,085
Clusters	5,469	3,734	4,918	5,469	3,734	4,918	5,469	3,734	4,918
$\lvert\mathcal{T}\rvert$	2,409	1,018	1,391	2,409	1,018	1,391	2,409	1,018	1,391
$\lvert\mathcal{U}\rvert$	23,902	13,023	10,879	23,902	13,023	10,879	23,902	13,023	10,879

Tab. A12. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently resume hospice care at much the same rates. See the discussion near page 26. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of live discharged patients. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A16, A17, and A18.

	Fraction of patient-days with RHC (% point diff.)			Fraction of patient-days with CHC (% point diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	-0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dynamic model: DID relative to week 0						
β_{-4}	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{-3}	0.000	-0.000	0.000	0.000	0.000^{**}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{-2}	0.000	-0.000	0.000	0.000	0.000^{**}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{-1}	0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_0	-	-	-	-	-	-
β_1	0.000	0.000	0.000	0.000	0.000^{**}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_2	0.000	0.000	0.000	-0.000	0.000^{**}	-0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_3	-0.000	-0.000	0.000	0.000	0.001^{***}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	0.989	0.987	0.991	0.004	0.002	0.005
N	1,419,834	741,624	678,210	456,274	254,462	201,812
Clusters	5,558	3,790	4,993	3,384	2,189	2,450
$\lvert\mathcal{T}\rvert$	5,263	1,910	3,353	2,334	849	1,485
$\lvert\mathcal{U}\rvert$	49,346	26,614	22,732	15,215	8,938	6,277

Tab. A13. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' levels of hospice care in the weeks leading up to the end of the fiscal year. See the discussion near page 29. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of active patients. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A19 and A20. The estimation samples exclude programs (e, j) such that program j provided zero units of RHC or CHC, respectively, in either t_e^O or t_e^I.

	Fraction of patient-days with IRC (% point diff.)			Fraction of patient-days with GIC (% point diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Static model: Year-end average DID						
β	-0.000	-0.000	-0.000	0.000*	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dynamic model: DID relative to week 0						
β_{-4}	0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{-3}	-0.000	-0.000*	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{-2}	-0.000***	-0.000**	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{-1}	-0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_0	-	-	-	-	-	-
β_1	-0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_2	-0.000**	-0.001***	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_3	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Event range	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y
B-line Y	0.003	0.002	0.003	0.008	0.011	0.005
N	974,974	490,308	484,666	987,220	554,216	433,004
Clusters	4,214	3,004	3,766	4,045	3,108	3,433
$\lvert\mathcal{T}\rvert$	2,468	946	1,522	2,251	1,029	1,222
$\lvert\mathcal{U}\rvert$	35,031	17,912	17,119	35,719	20,287	15,432

Tab. A14. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' levels of hospice care in the weeks leading up to the end of the fiscal year. See the discussion near page 29. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of active patients. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A21 and A22. The estimation samples exclude programs (e, j) such that program j provided zero units of IRC or GIC, respectively, in either t_e^O or t_e^I.

	Fraction of patient-days with a nurse visit (% point diff.)			Fraction of patient-days with a home health aid visit (% point diff.)			Fraction of patient-days with a social worker visit (% point diff.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Static model: Year-end average DID									
β	0.000	0.002**	-0.000	0.001	0.007***	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Dynamic model: DID relative to week 0									
β_{-4}	0.004***	0.013***	0.001	0.003**	0.009***	0.001	0.001**	0.004***	0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
β_{-3}	0.003***	0.007***	0.001	0.001	0.004	-0.000	0.000	0.001	0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.000)	(0.001)	(0.000)
β_{-2}	0.001	0.007***	-0.000	0.002	0.009**	-0.001	-0.000	0.000	-0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.000)	(0.001)	(0.000)
β_{-1}	-0.001	0.004	-0.002**	-0.004**	0.001	-0.005**	-0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
β_0	-	-	-	-	-	-	-	-	-
β_1	0.003***	0.009***	0.001	0.001	0.000	0.002**	-0.000	0.000	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
β_2	0.002**	0.007**	0.001	0.001	0.004	0.001	0.000	0.001	-0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.000)	(0.001)	(0.000)
β_3	0.003**	0.005*	0.002*	-0.001	0.001	-0.002	0.001*	-0.001	0.001**
	(0.001)	(0.003)	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Event range	01-18	01-11	12-18	01-18	01-11	12-18	01-18	01-11	12-18
Hospice FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
B-line Y	0.219	0.174	0.233	0.324	0.231	0.352	0.040	0.040	0.041
N	999,622	321,412	678,210	999,622	321,412	678,210	999,622	321,412	678,210
Clusters	5,246	3,474	4,993	5,246	3,474	4,993	5,246	3,474	4,993
$\|\mathcal{T}\|$	4,356	1,003	3,353	4,356	1,003	3,353	4,356	1,003	3,353
$\|\mathcal{U}\|$	34,091	11,359	22,732	34,091	11,359	22,732	34,091	11,359	22,732

Tab. A15. This table reports estimates of β and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (6) and (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their rates of staff visits per patient-day in the weeks leading up to the end of the fiscal year. See the discussion near page 29. Program-level cluster robust SEs are in parenthesis. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of active patients. Estimates of $(\beta_w : w \in \{-13, ..., 12\})$ are plotted in figures A23-A25.

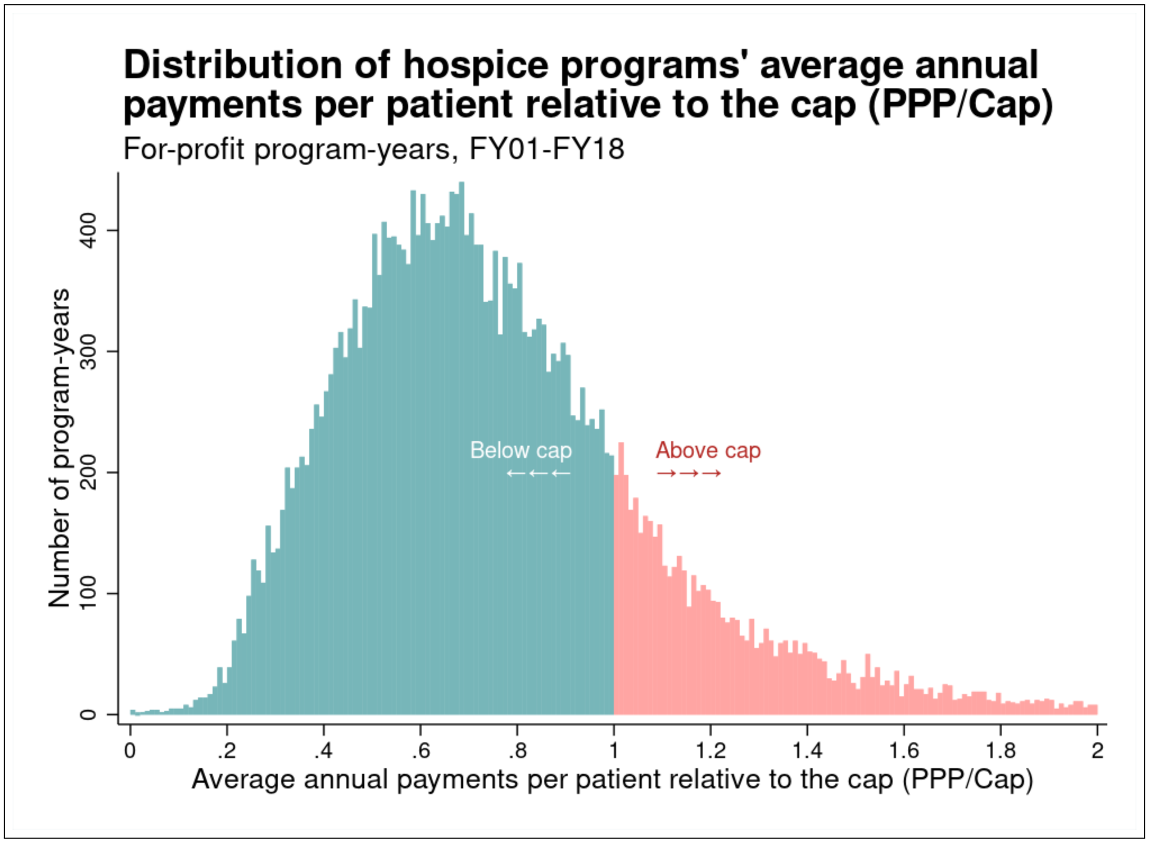

Fig. A1. This figure plots the distribution of $\text{PPP}_{jt}/\text{Cap}_{jt}$ for for-profit hospice programs. The figure is censored at $\text{PPP}_{jt}/\text{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See the discussions near page 18 and table A2.

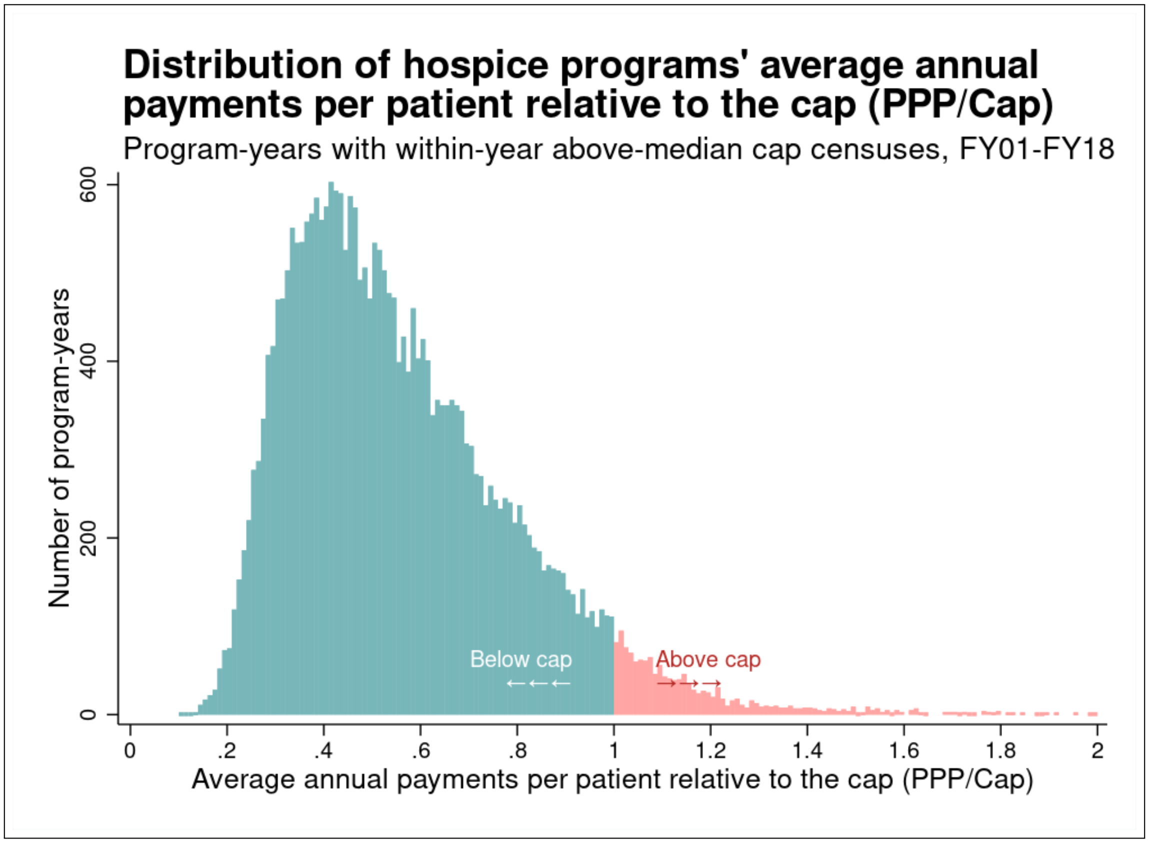

Fig. A2. This figure plots the distribution of $\mathrm{PPP}_{jt}/\mathrm{Cap}_{jt}$ for hospice programs with above-median annual cap censuses. The figure is censored at $\mathrm{PPP}_{jt}/\mathrm{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See the discussions near page 18 and table A2.

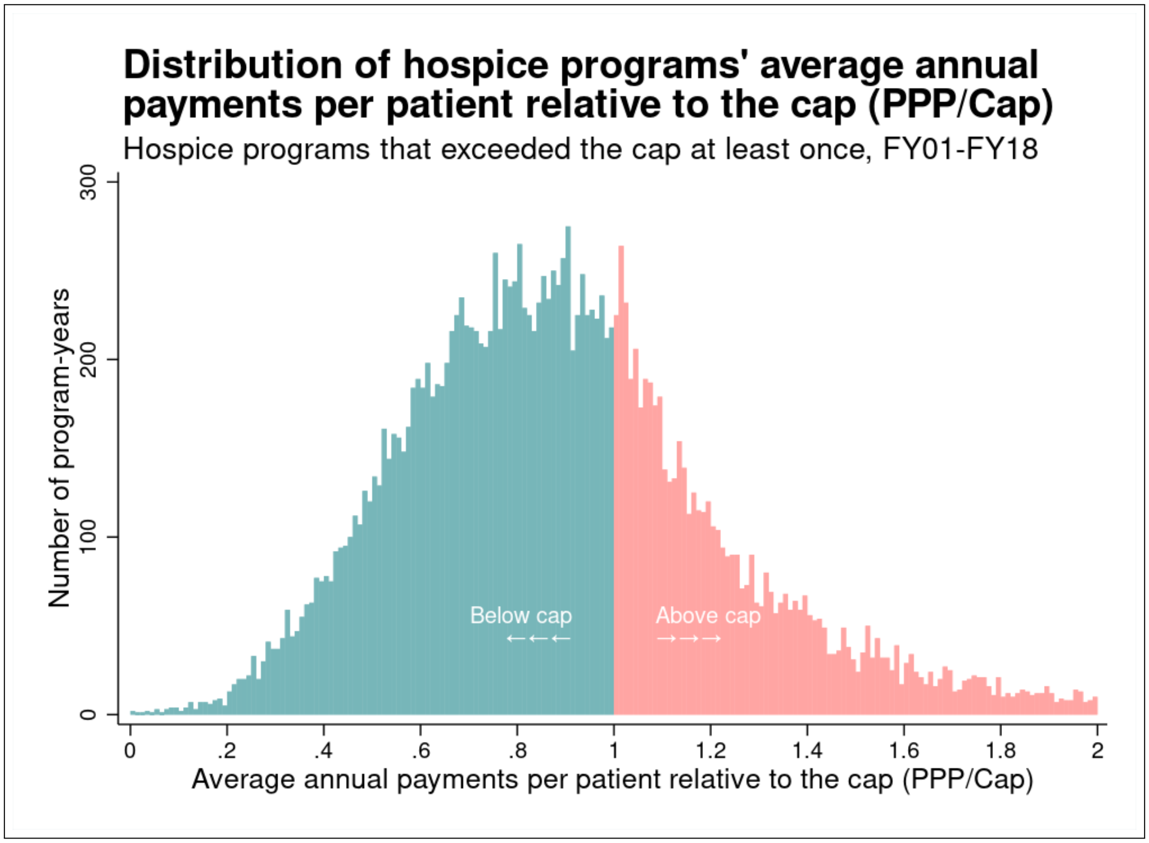

Fig. A3. This figure plots the distribution of $\text{PPP}_{jt}/\text{Cap}_{jt}$ for hospice programs that ever exceed the cap. The figure is censored at $\text{PPP}_{jt}/\text{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See the discussions near page 18 and table A2.

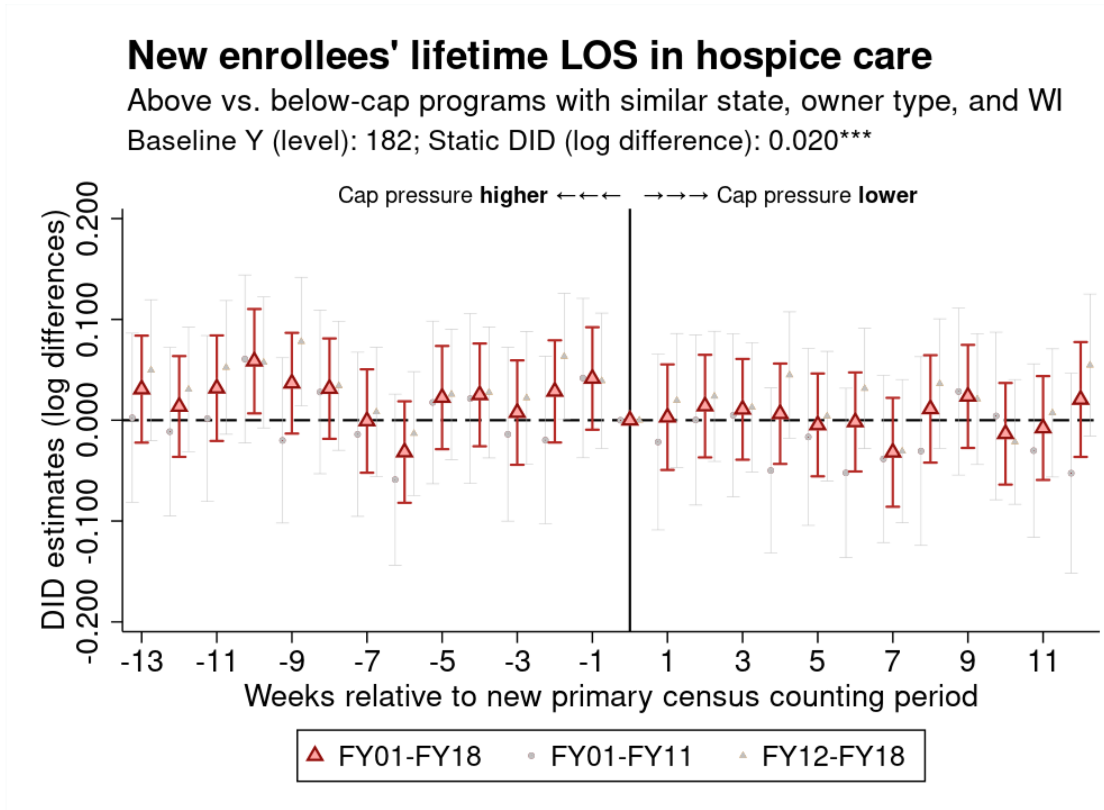

Fig. A4. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who ultimately have longer average lifetime LOS in hospice care. See table A5 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

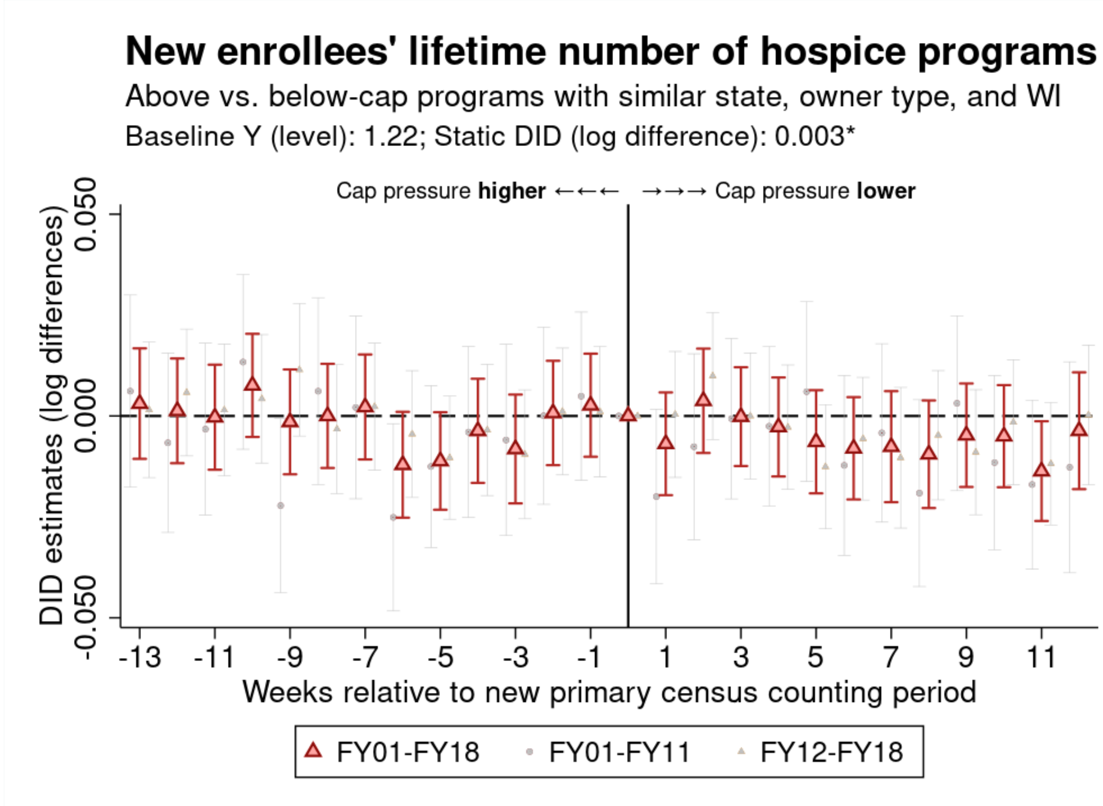

Fig. A5. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who subsequently receive care at much the same number of unique hospice programs. See table A5 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

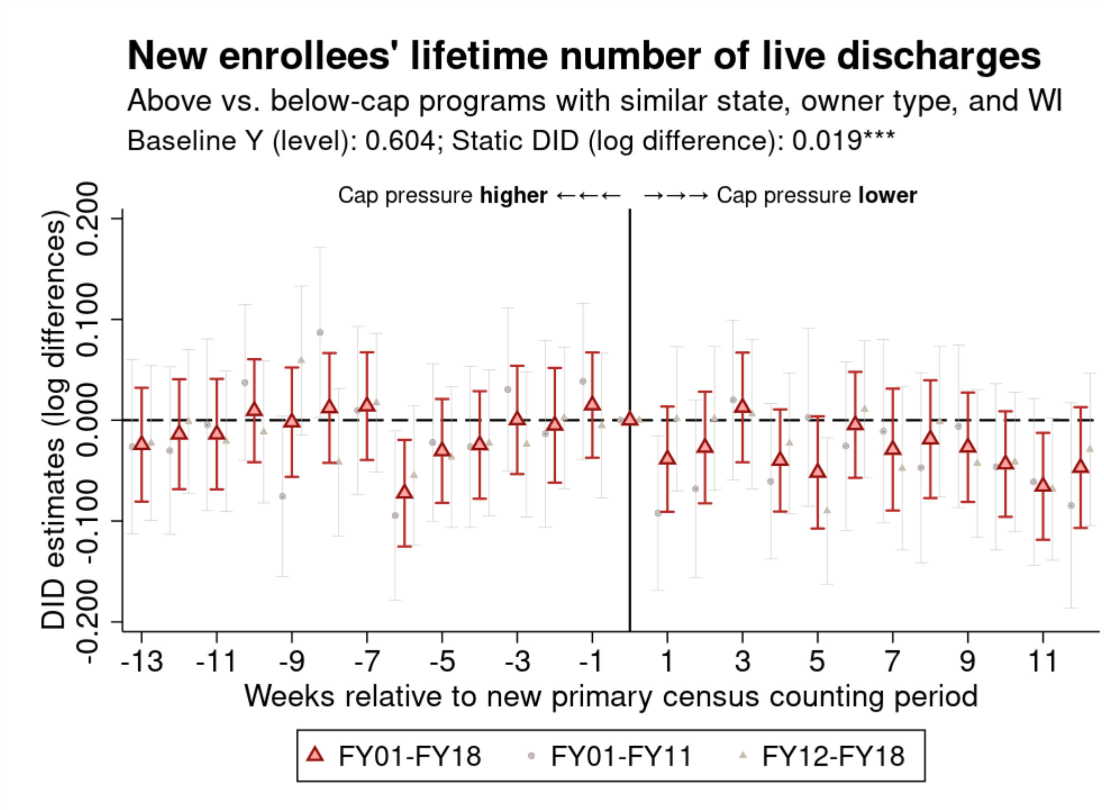

Fig. A6. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who subsequently experience more lifetime live discharges. See table A6 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

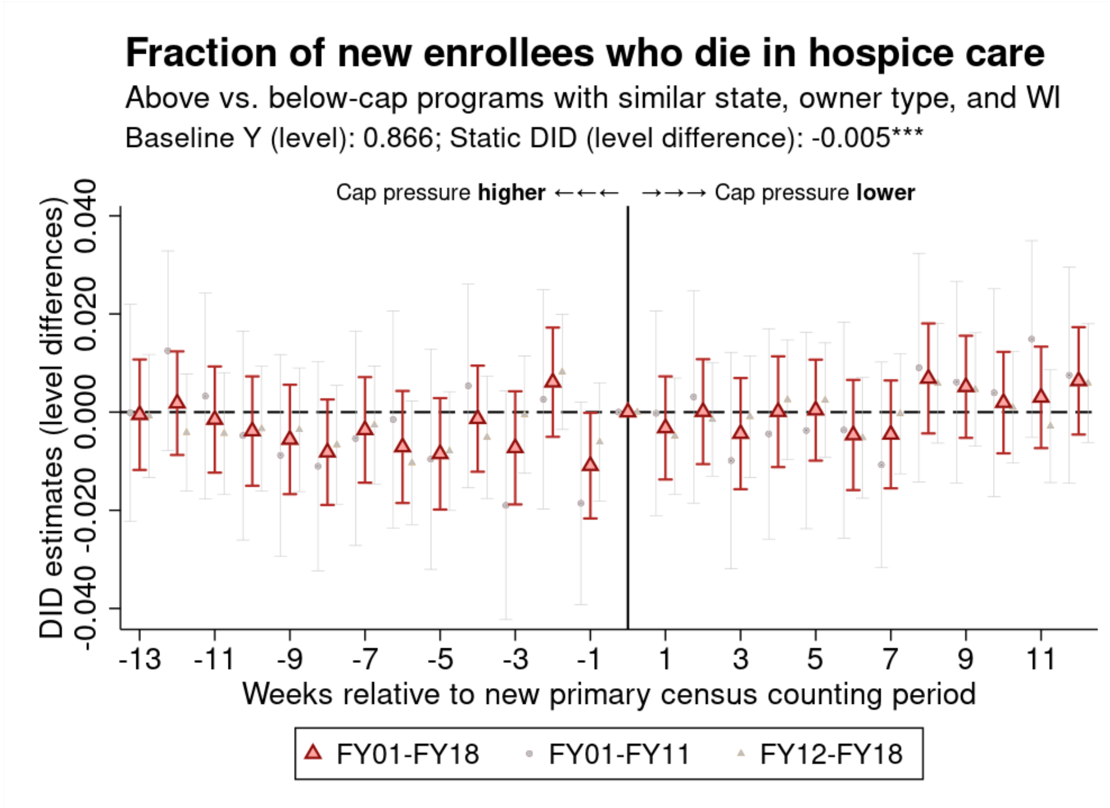

Fig. A7. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are less likely to ultimately die in hospice care. See table A6 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

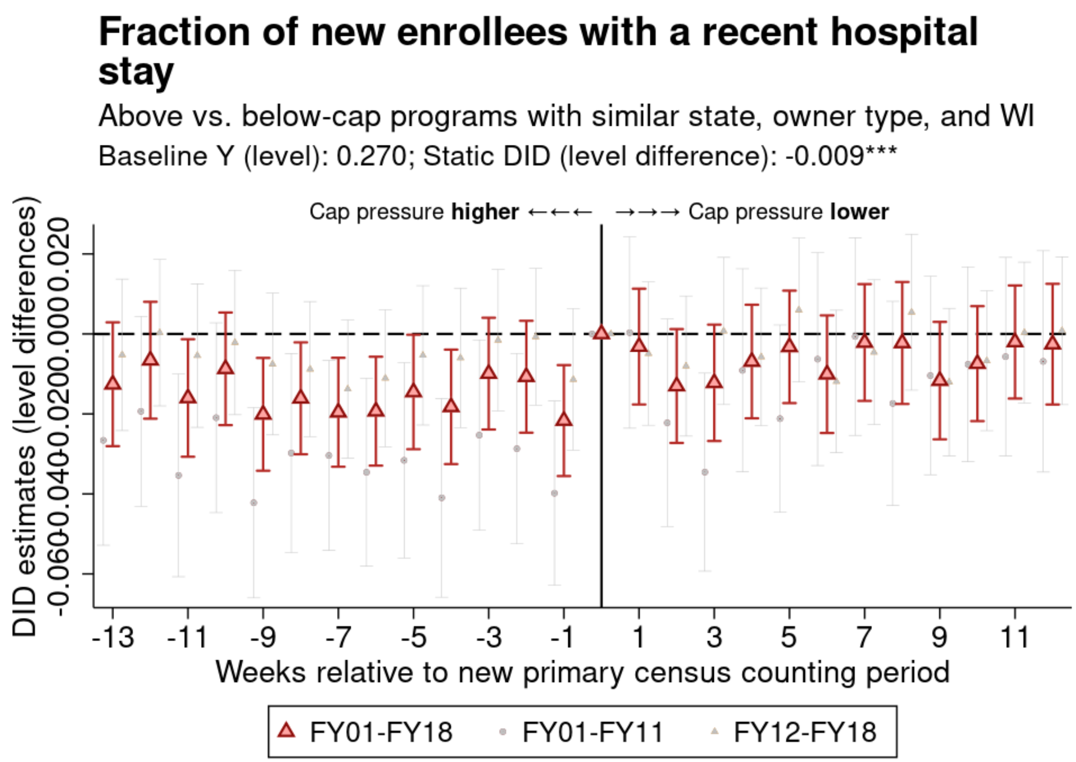

Fig. A8. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are less likely to have had a hospital stay in the week prior to enrollment. See table A7 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

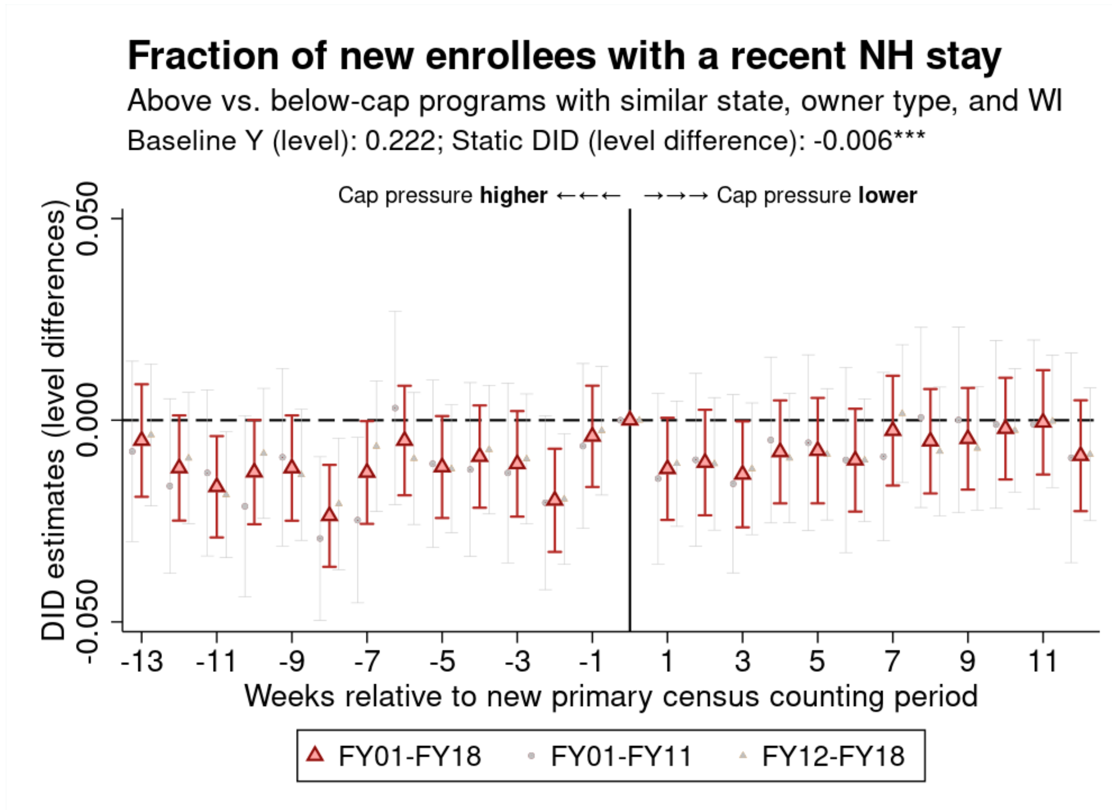

Fig. A9. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are less likely to have had a nursing home stay in the week prior to enrollment. See table A7 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

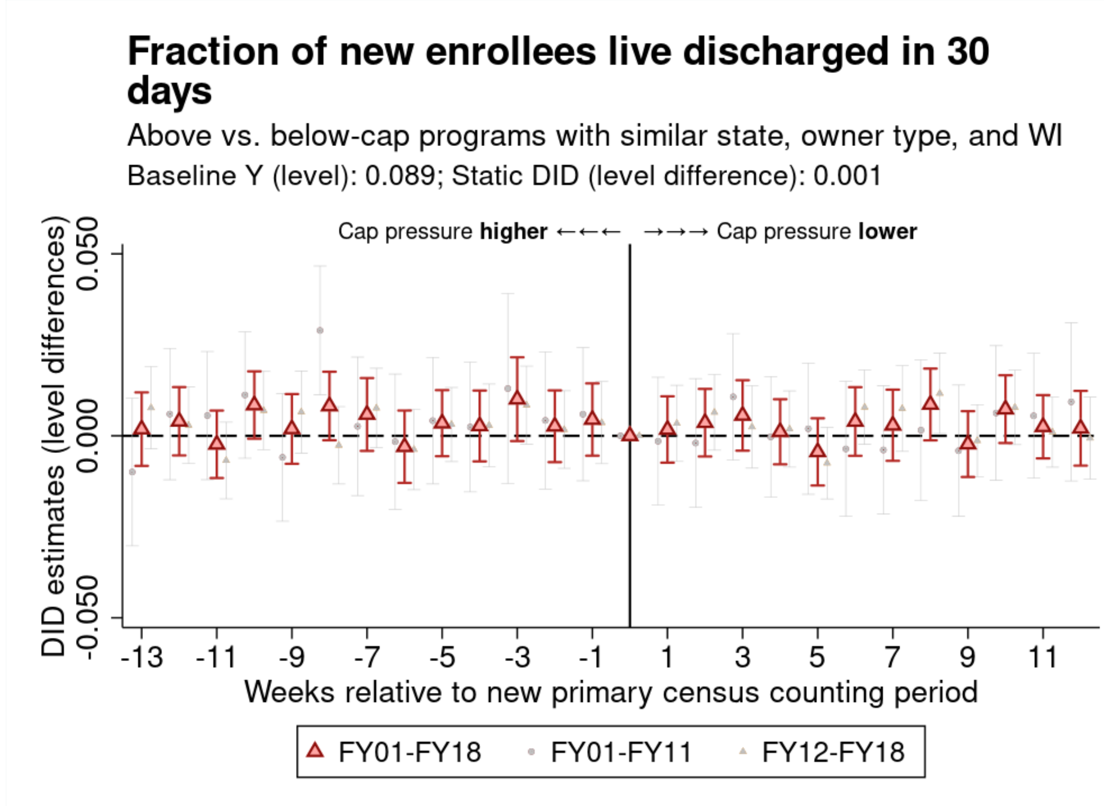

Fig. A10. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are live discharged within 30 days of enrollment at much the same rate. See table A8 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

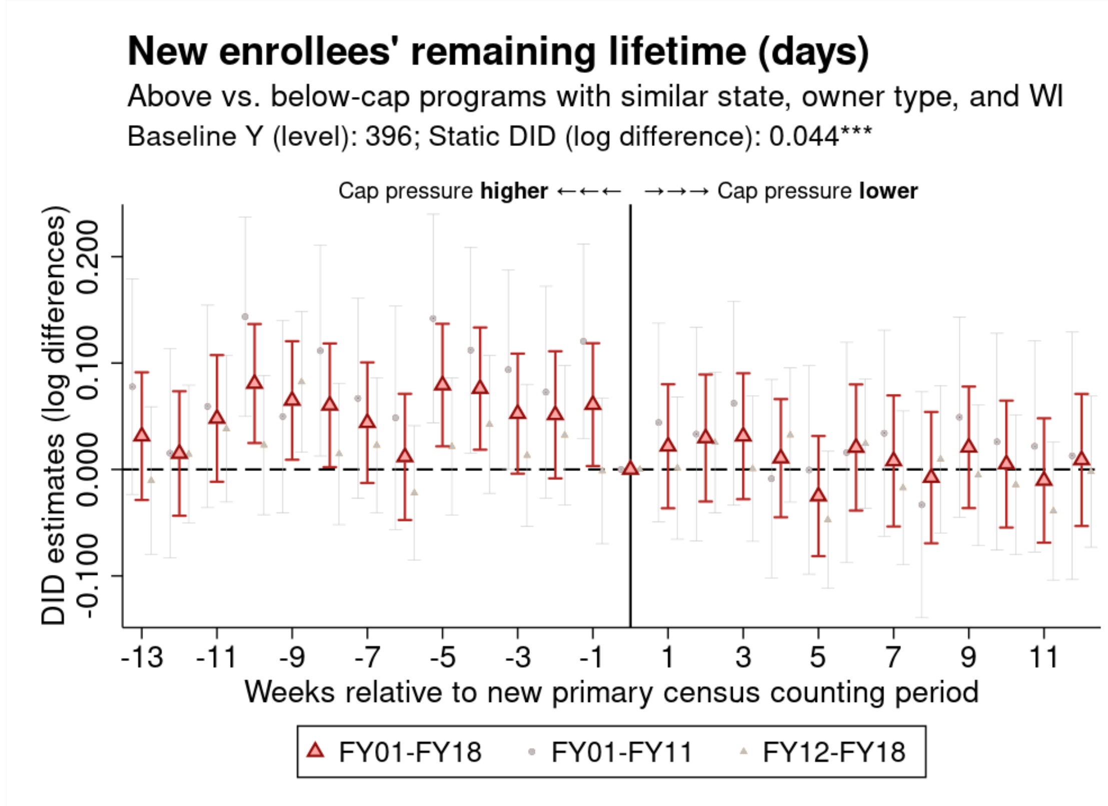

Fig. A11. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who have longer remaining lifetimes. See table A8 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

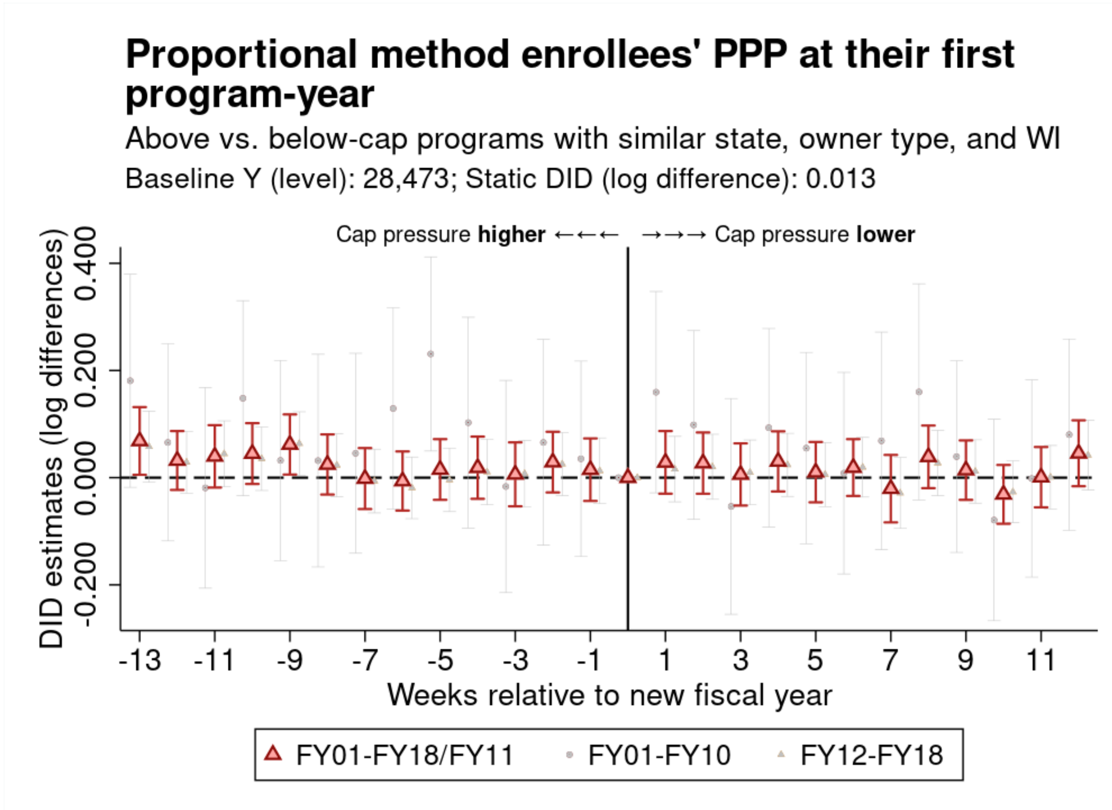

Fig. A12. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients counted toward a cap census in proportion to their lifetime LOS in hospice care with much the same PPP_{ijt} in their first (j, t). See table A9 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees counted toward cap censuses in proportion to their lifetime LOS in hospice care. The primary census counting periods are described in appendix A.

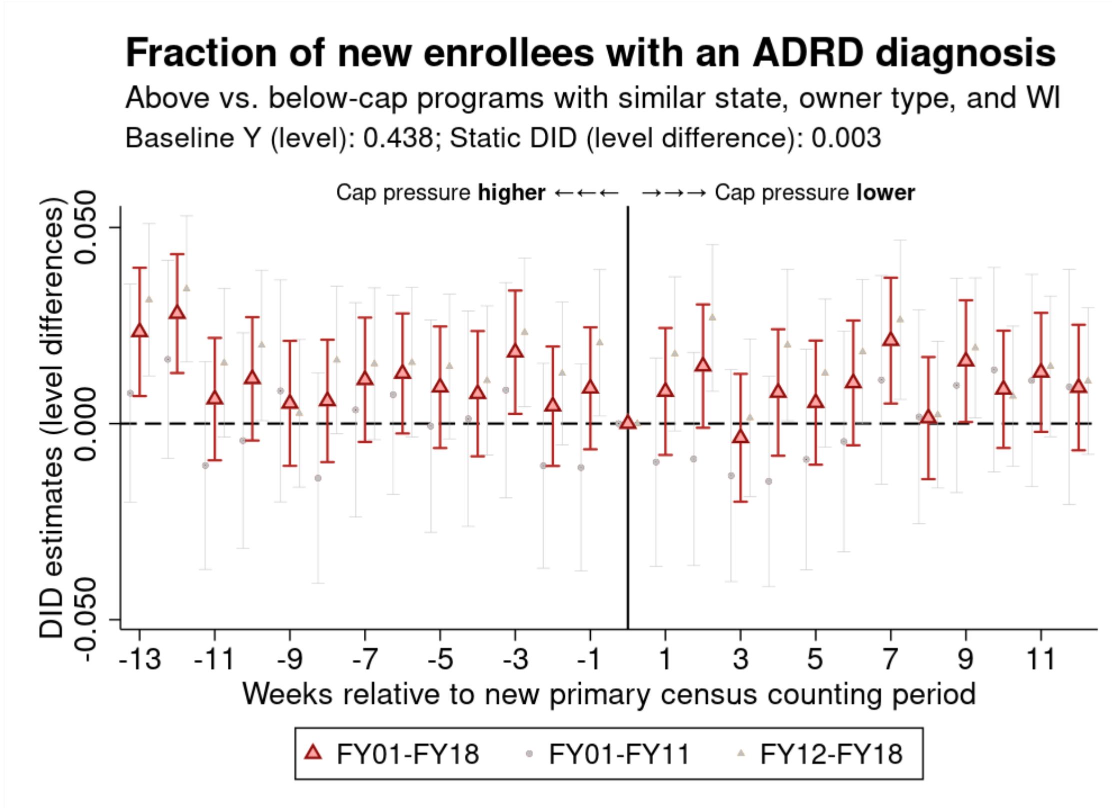

Fig. A13. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year with much the same rates of ADRD. See table A10 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

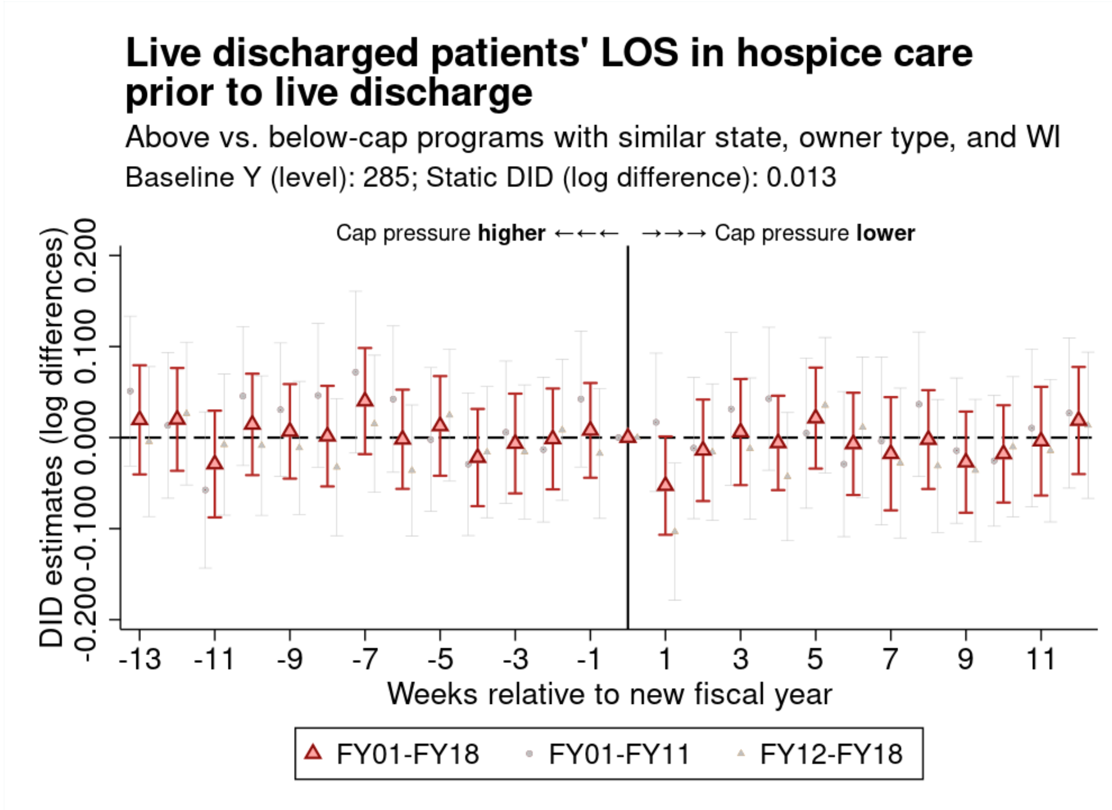

Fig. A14. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who previously had much the same average LOS in hospice care. See table A11 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of live discharged patients.

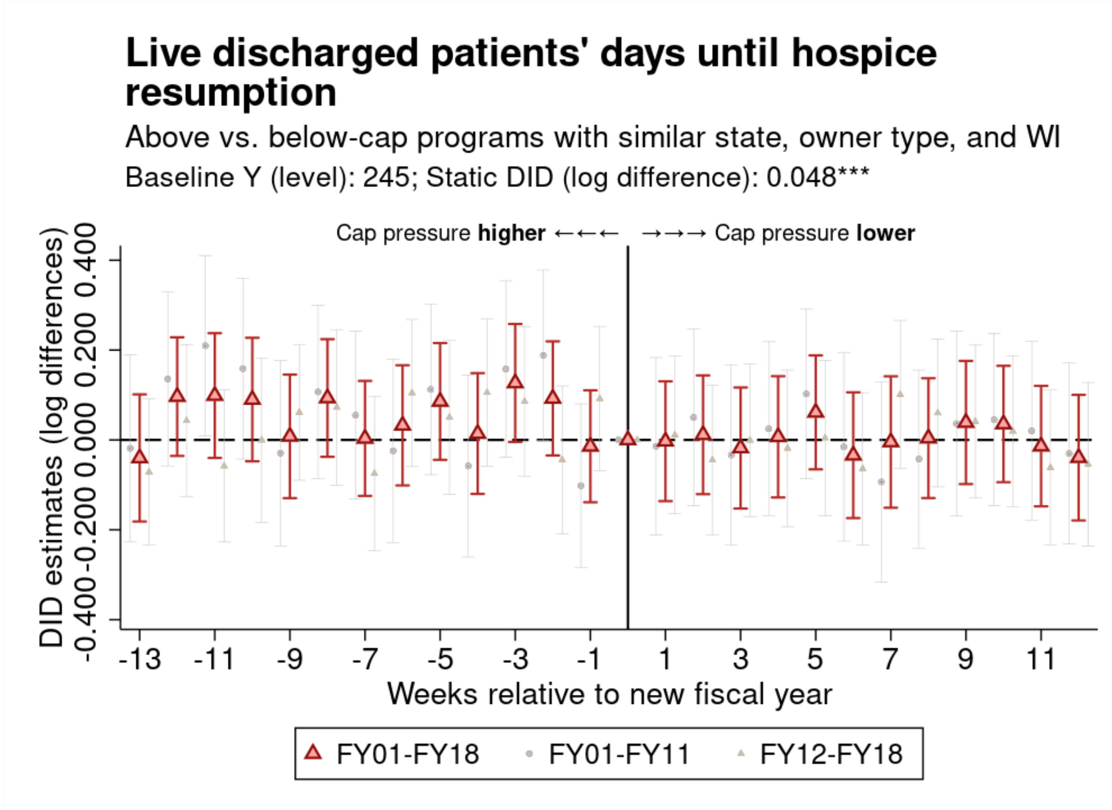

Fig. A15. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently experience a longer spell without hospice care. See table A11 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of live discharged patients.

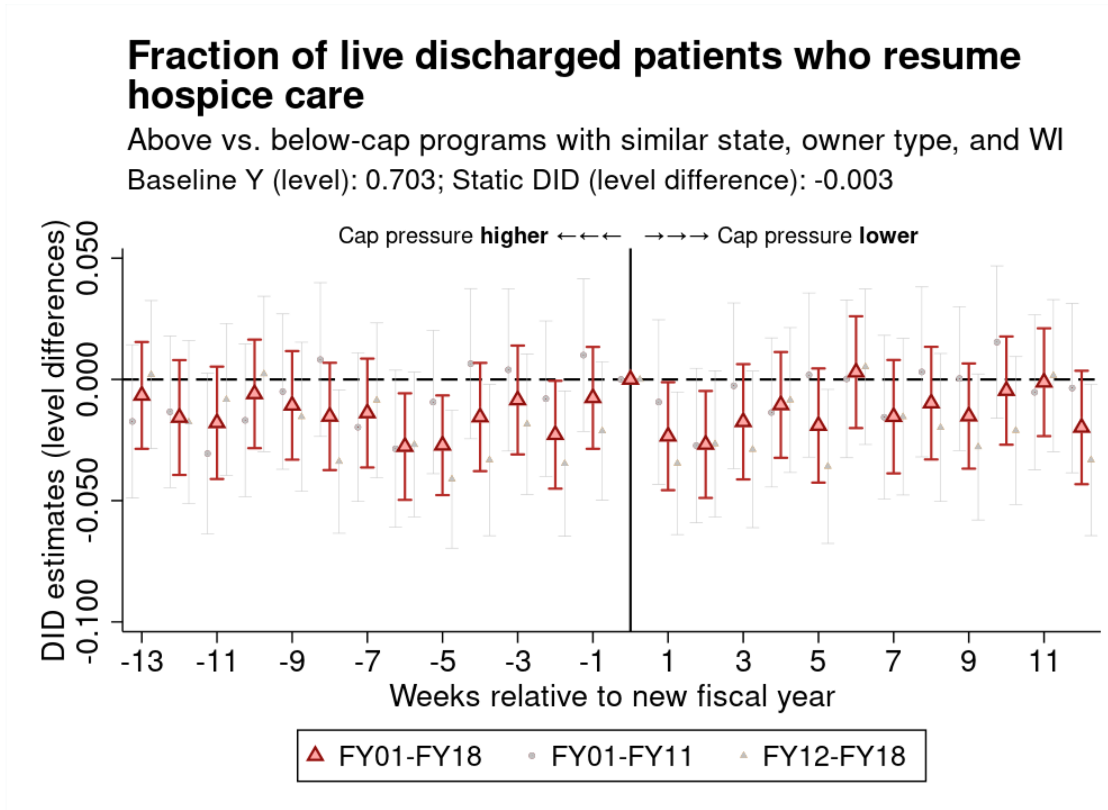

Fig. A16. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently resume hospice care anywhere at much the same rates. See table A12 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of live discharged patients.

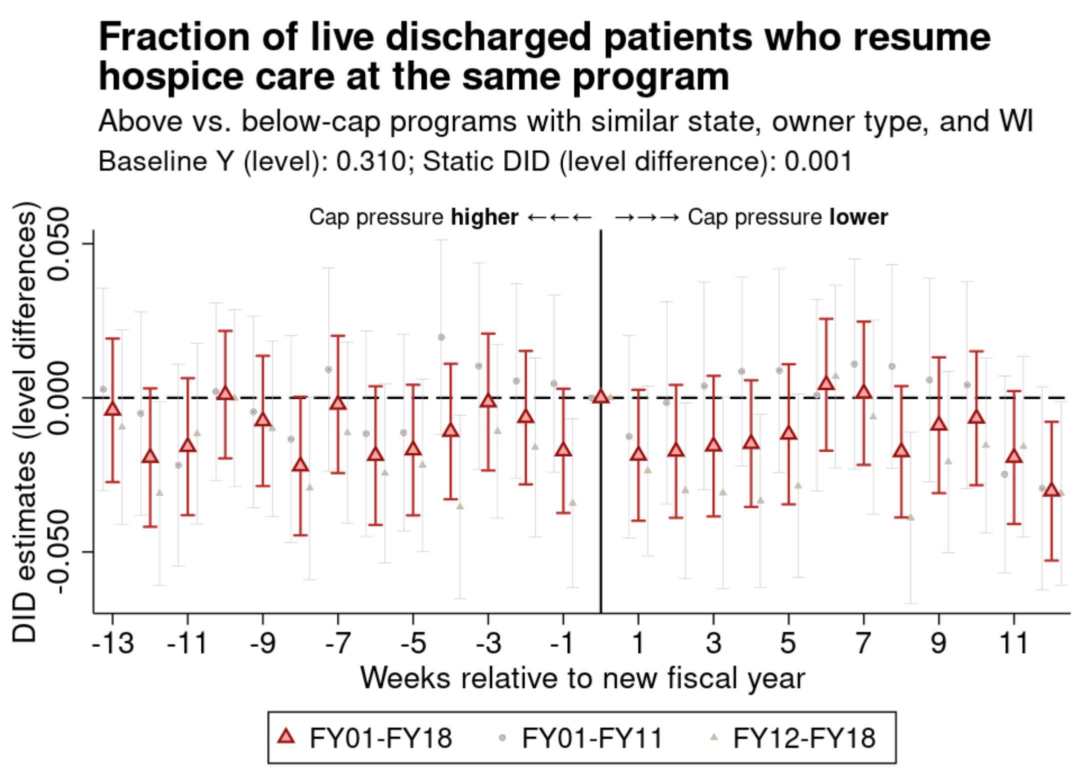

Fig. A17. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently resume hospice care at the same program at much the same rates. See table A12 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of live discharged patients.

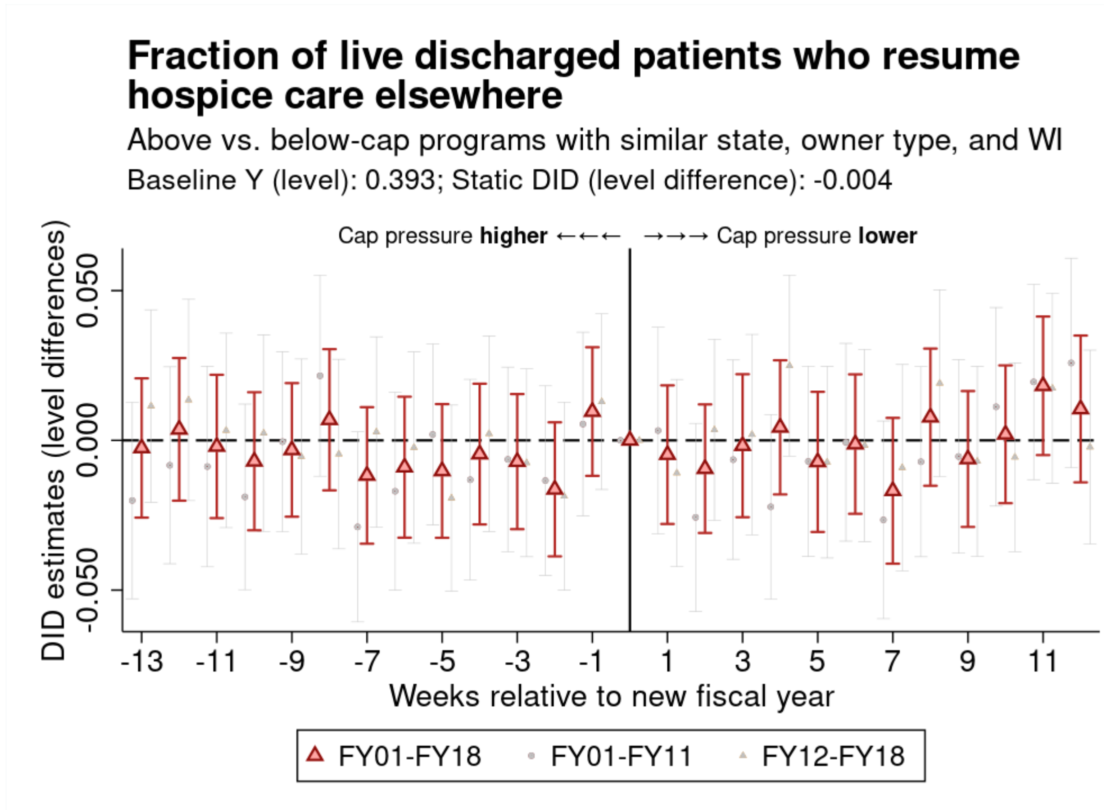

Fig. A18. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently resume hospice care at a different program at much the same rates. See table A12 and the discussion near page 26. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of live discharged patients.

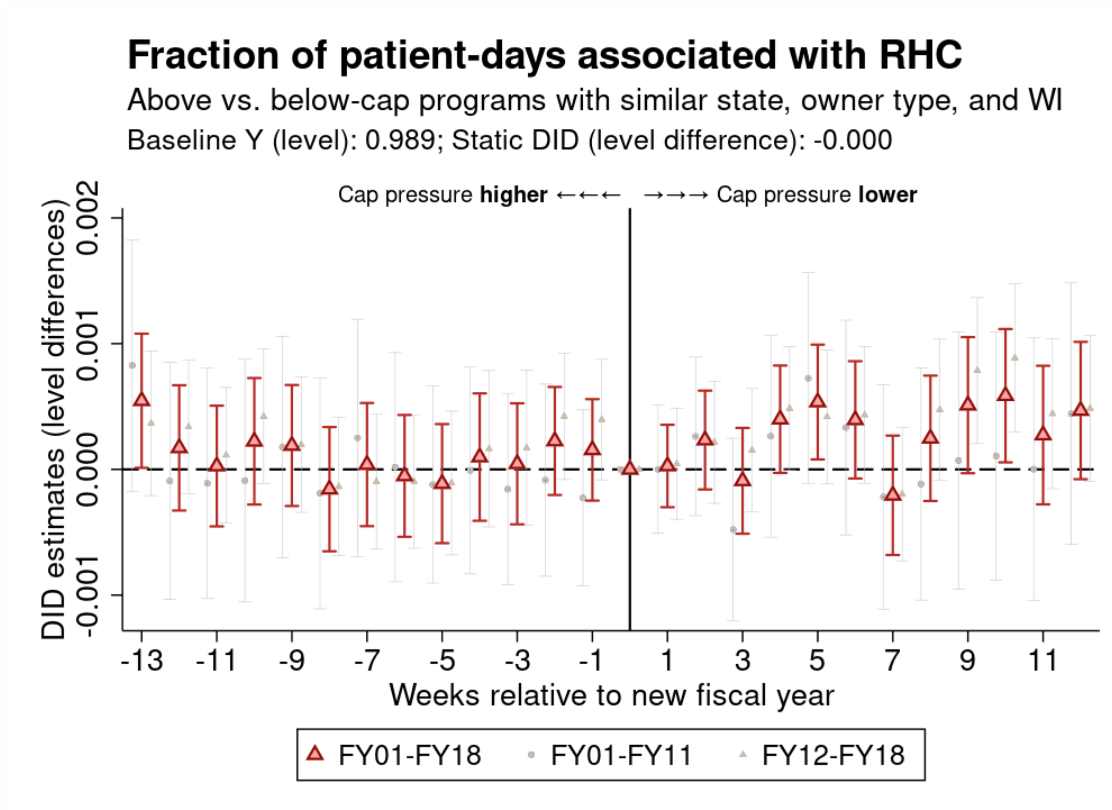

Fig. A19. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' RHC rates in the weeks leading up to the end of the fiscal year. See table A13 and the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of active patients.

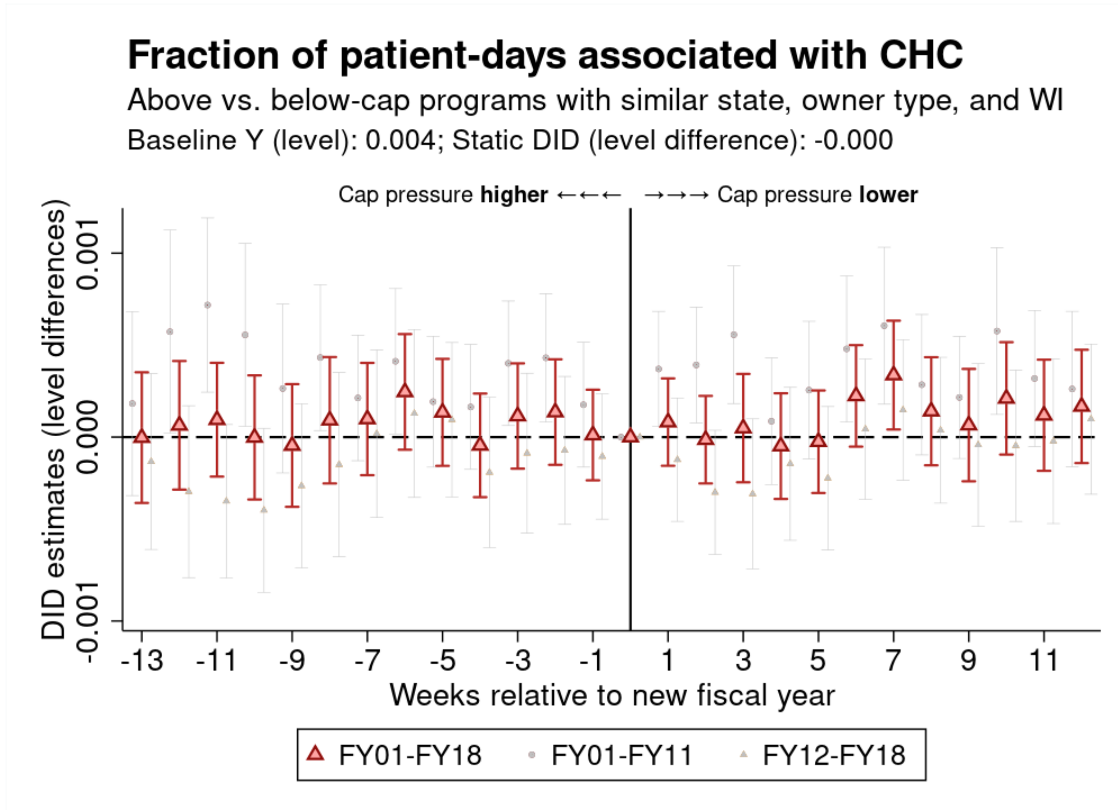

Fig. A20. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' CHC rates in the weeks leading up to the end of the fiscal year. See table A13 and the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of active patients.

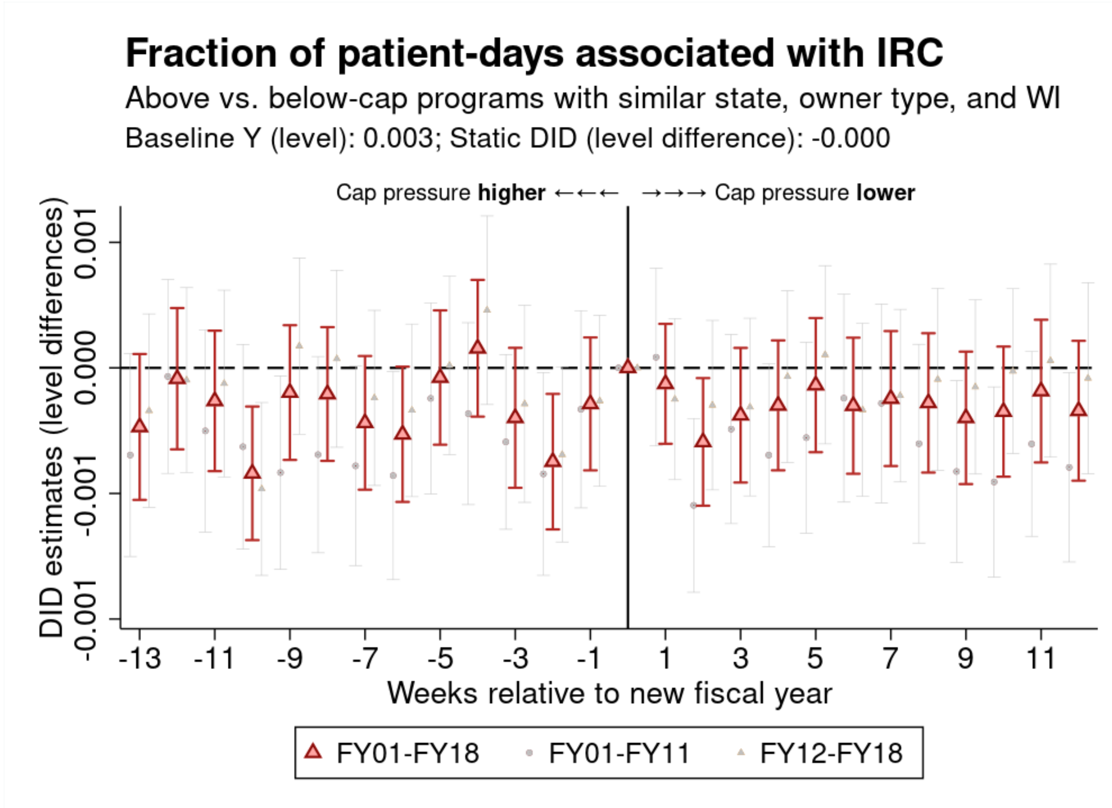

Fig. A21. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' IRC rates in the weeks leading up to the end of the fiscal year. See table A14 and the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of active patients.

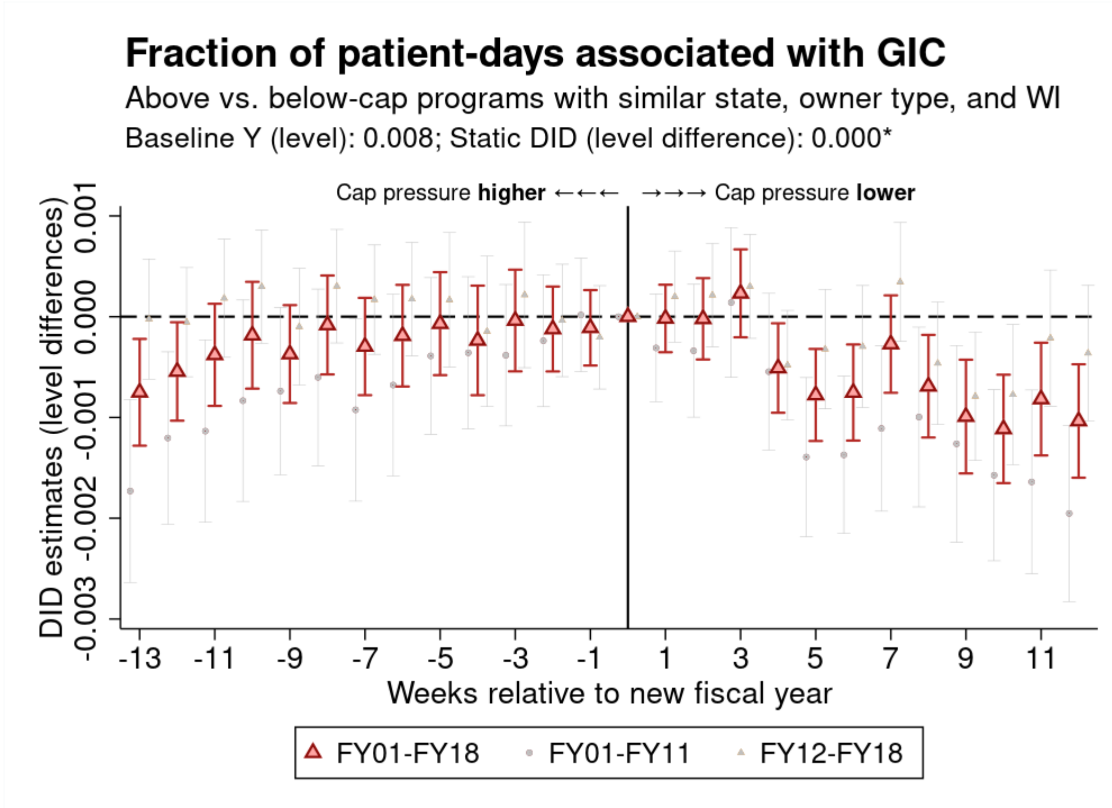

Fig. A22. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' GIC rates in the weeks leading up to the end of the fiscal year. See table A14 and the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of active patients.

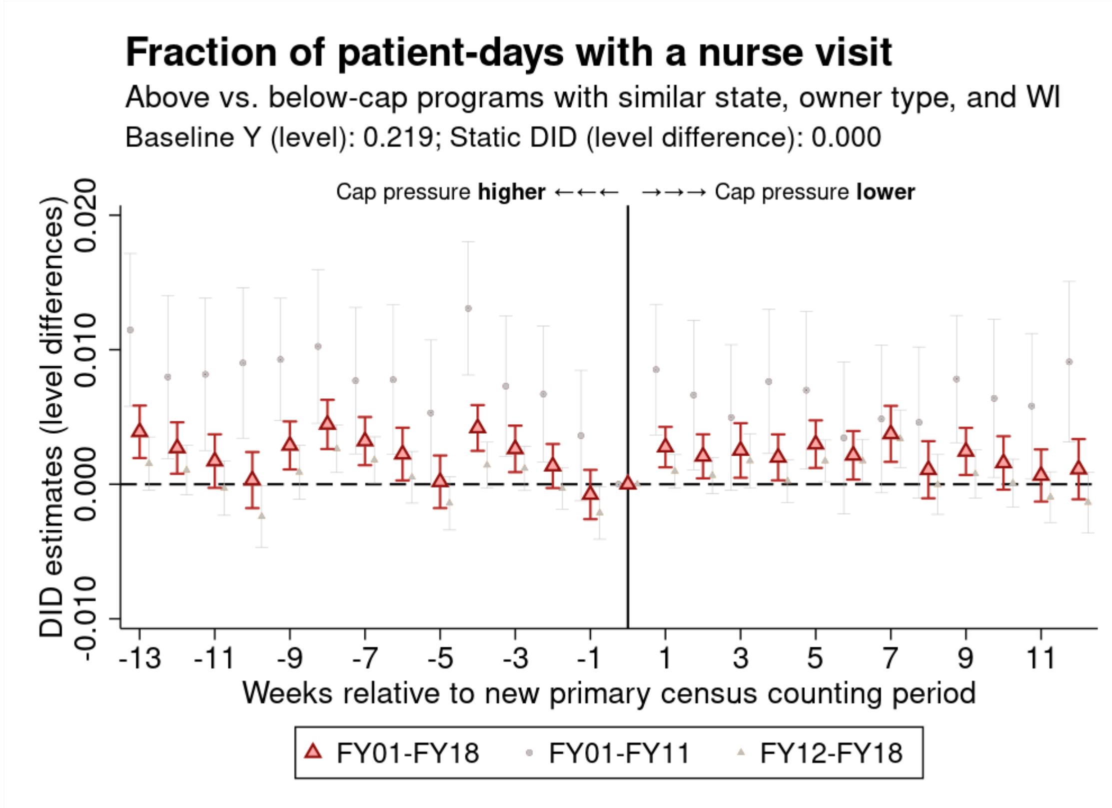

Fig. A23. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their nurse visit rates in the weeks leading up to the end of the fiscal year. See table A15 and the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of active patients.

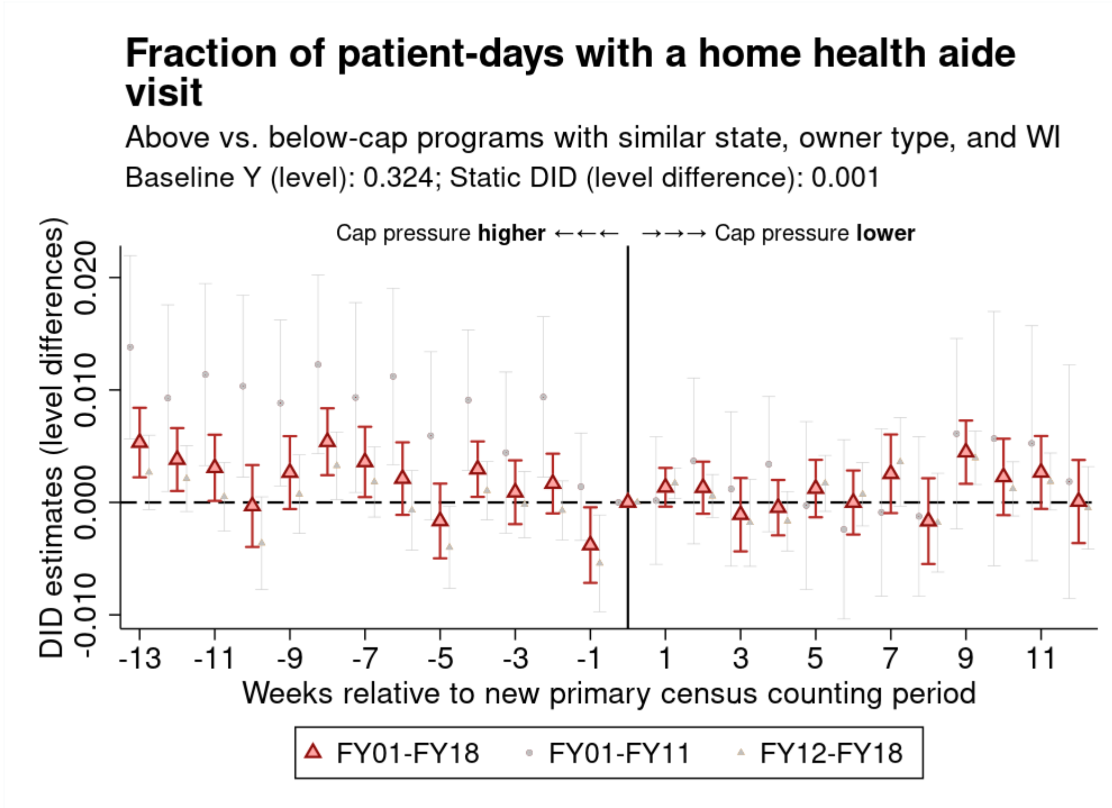

Fig. A24. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their home health aid visit rates in the weeks leading up to the end of the fiscal year. See table A15 and the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of active patients.

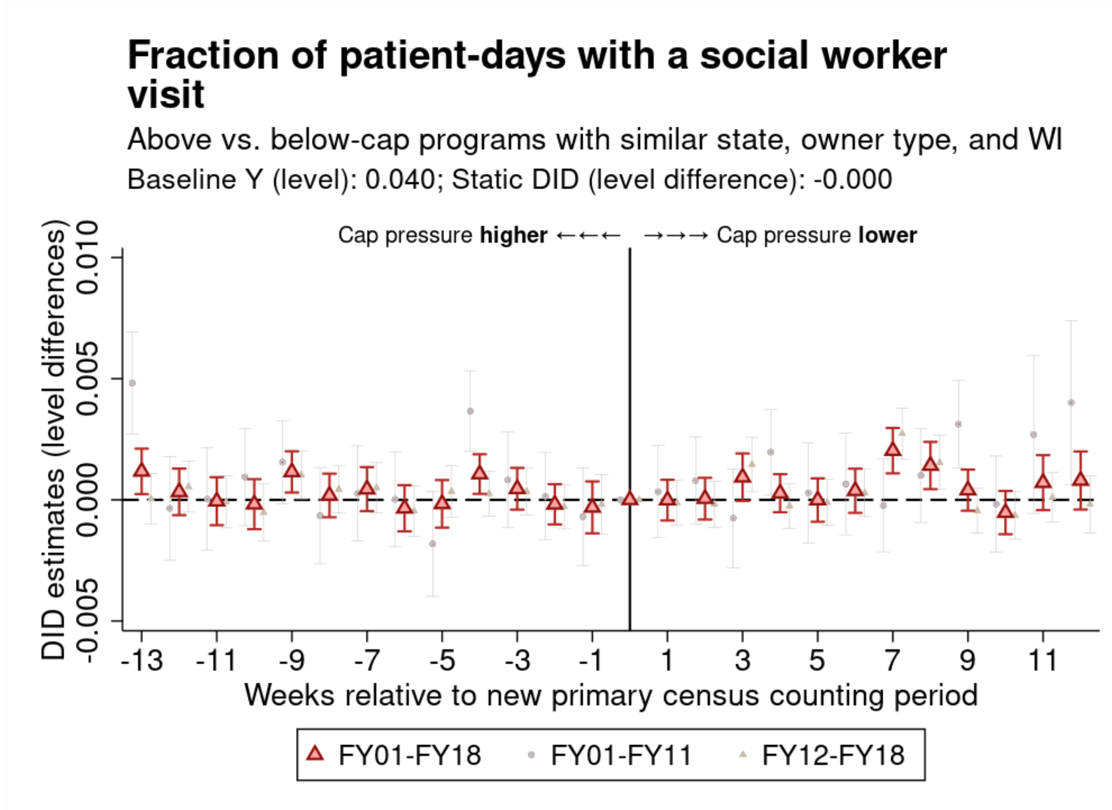

Fig. A25. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their social worker visit rates in the weeks leading up to the end of the fiscal year. See table A15 and the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of active patients.

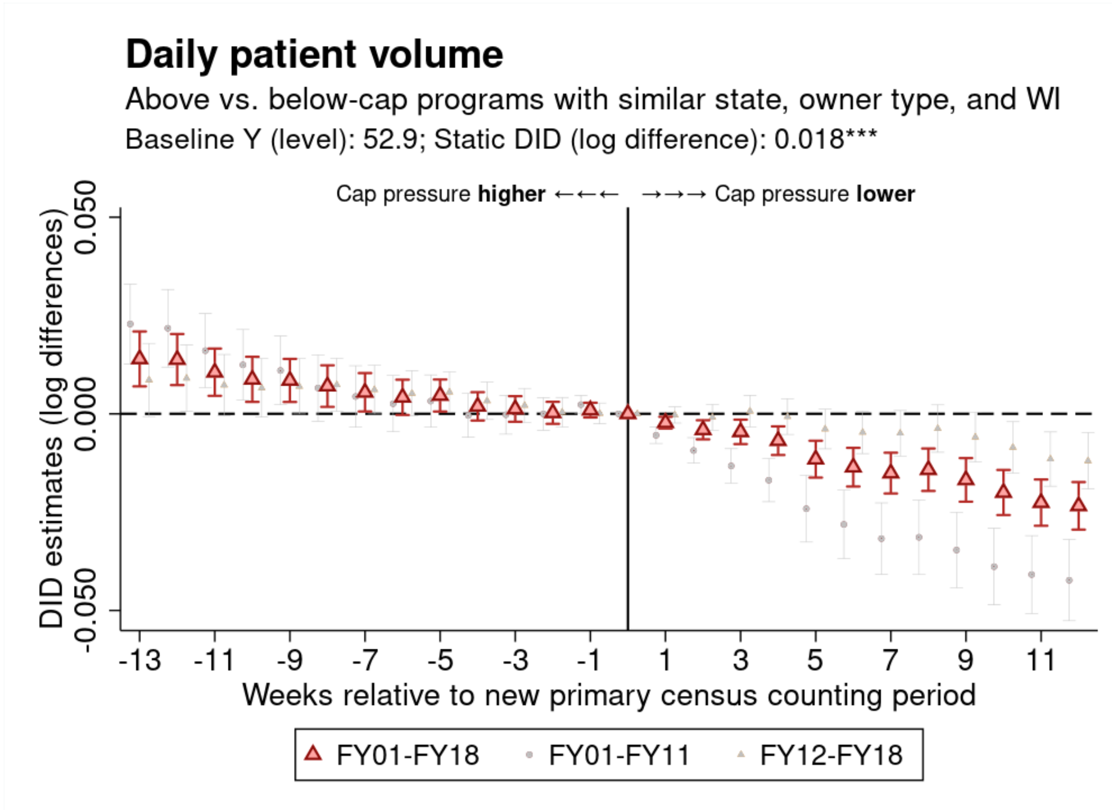

Fig. A26. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap differentially decrease their active patient volume throughout the event window. See the discussion near page 29. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6).

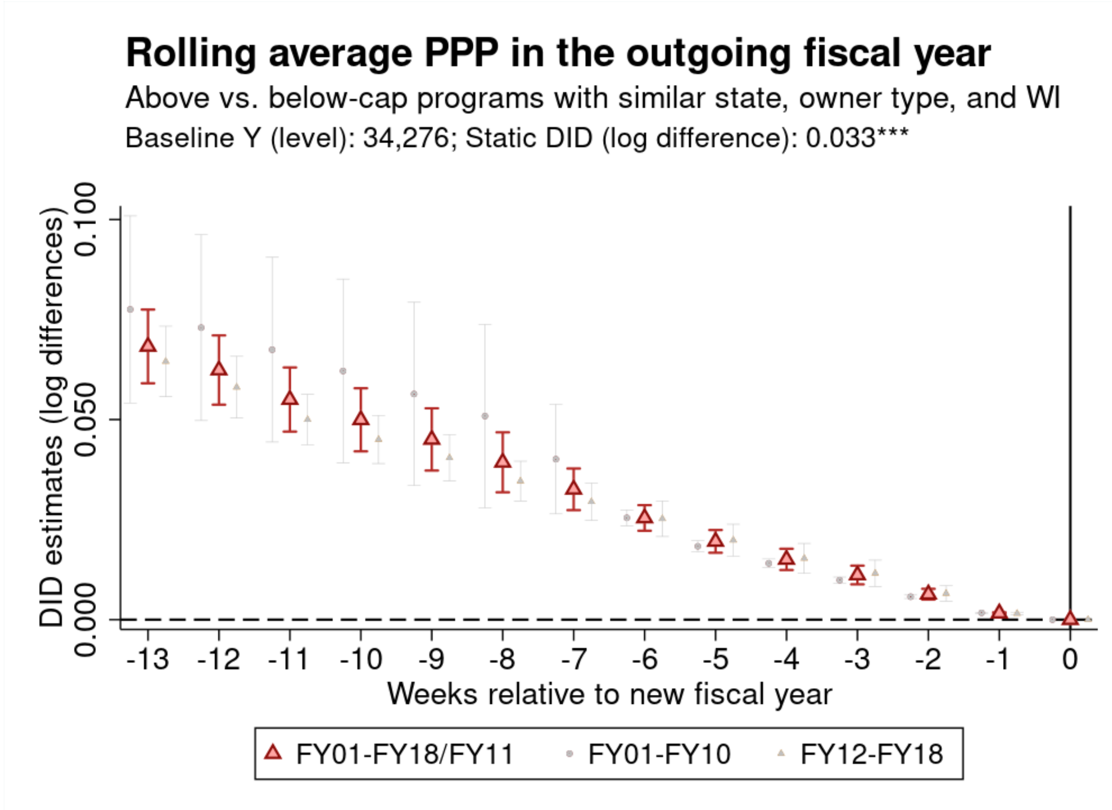

Fig. A27. This figure plots estimates of $(\beta_w : w \in W, w \leq 0)$ from equation (7) in our difference-in-differences analysis. Estimates corresponding to $w > 0$ are excluded because average annual payments per patient are fixed after the end of the fiscal year. The figure supports the idea that programs on track to exceed the cap differentially decrease their average annual payments per patient prior to the end of the fiscal year. See the discussions near page 30. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6).

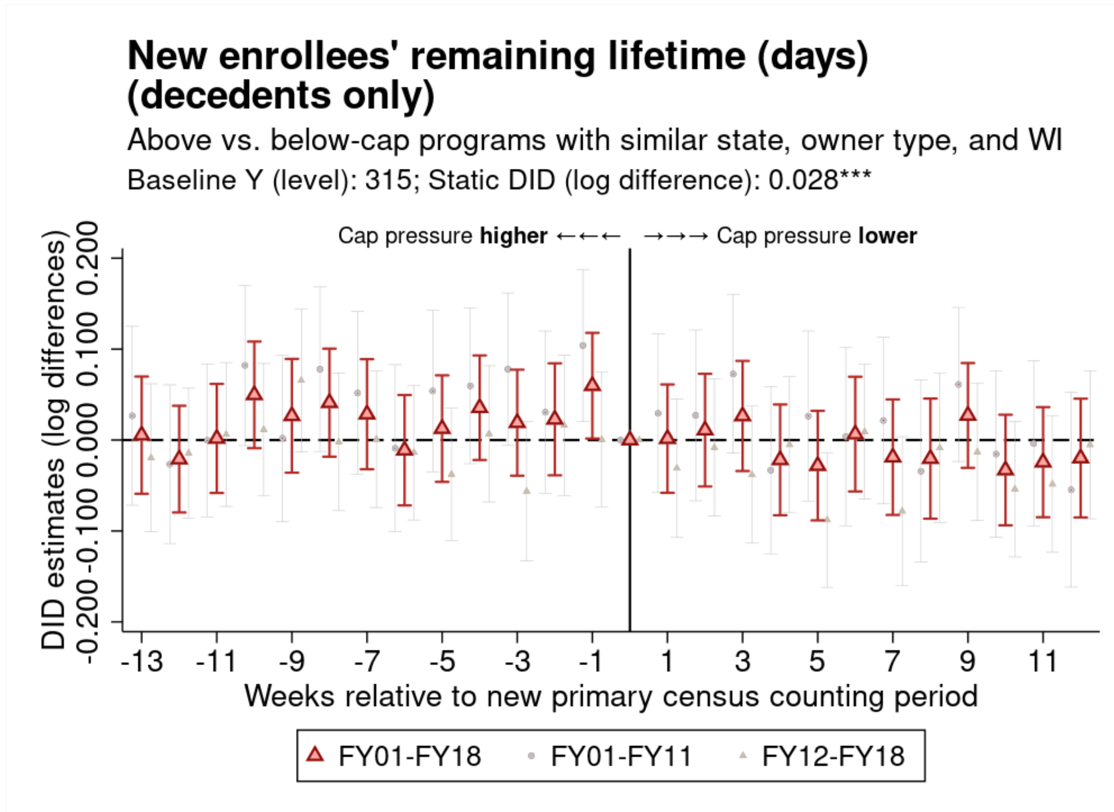

Fig. A28. This figure plots estimates of $(\beta_w : w \in W)$ from equation (7) for the alternative definition of remaining lifetime discussed in appendix D.2. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who have longer remaining lifetimes. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs. The heading reports statistics estimated from the full sample period. Baseline Y is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of β from equation (6). Observations are weighted by the number of enrollees. The primary census counting periods are described in appendix A.

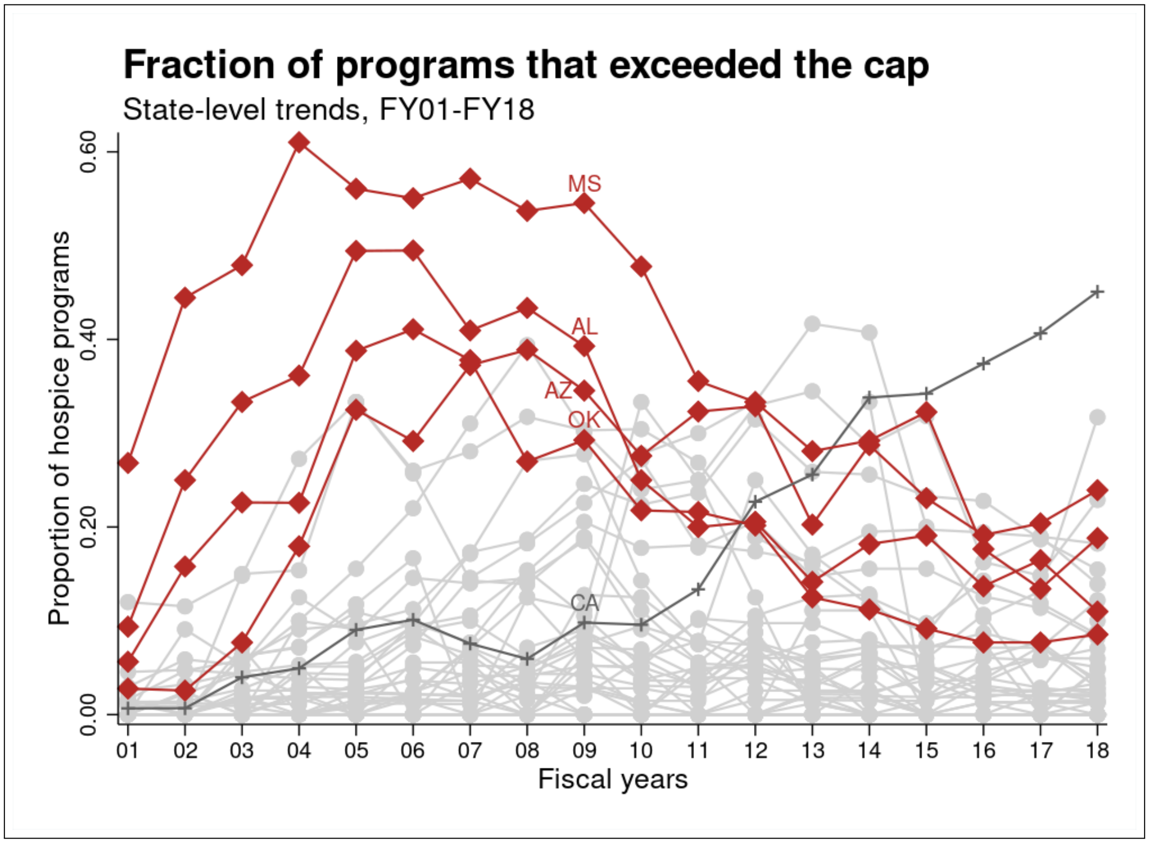

Fig. A29. This figure plots state-level trends in the proportion of hospice programs that exceeded the cap between fiscal years 2001 and 2018. It shows that cap liabilities were particularly prevalent in MS, AL, OK, AZ, and CA during this period. See the discussions in section E.

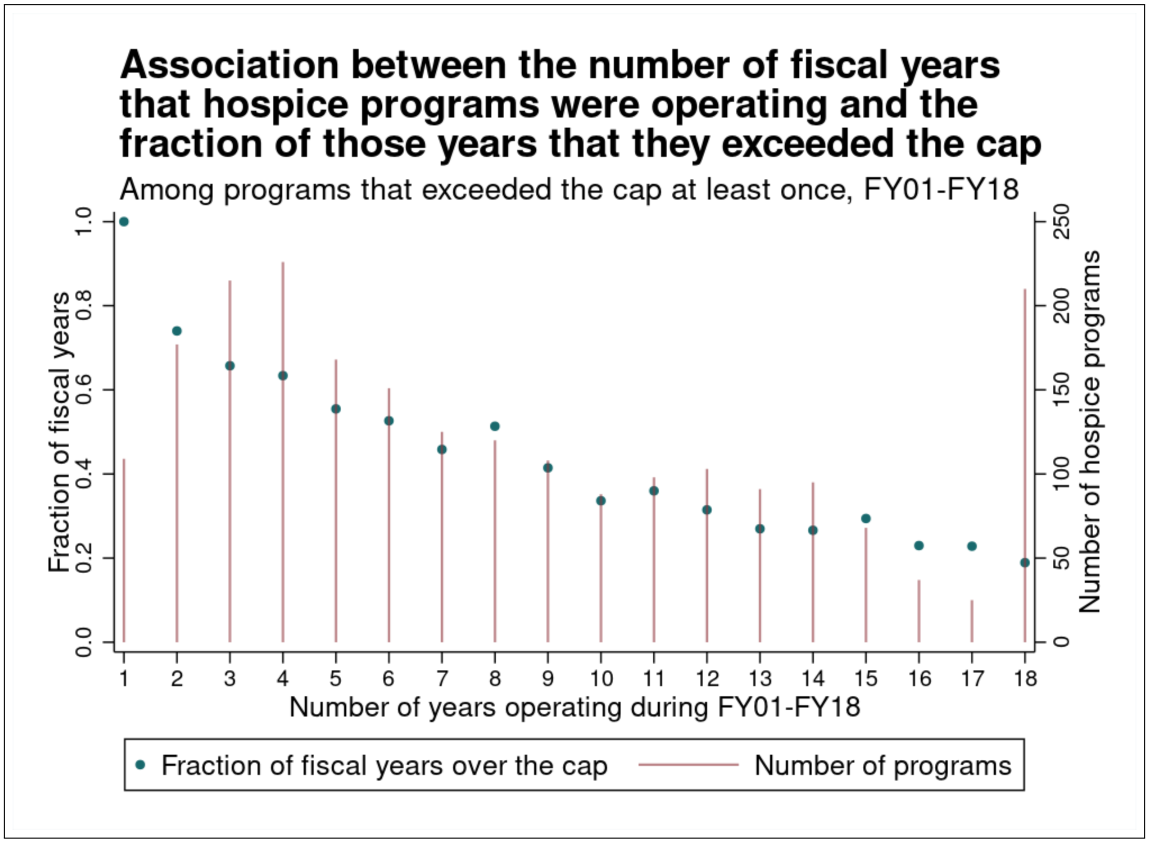

Fig. A30. This figure plots the joint distribution between the number of years that hospice programs operated between FY 2001 and FY 2018 and the fraction of those years that they exceeded the cap. It only includes programs that exceeded the cap at least once. It shows that hospice programs that exceed the cap at least once often exceed it multiple times. See the discussions in section E.

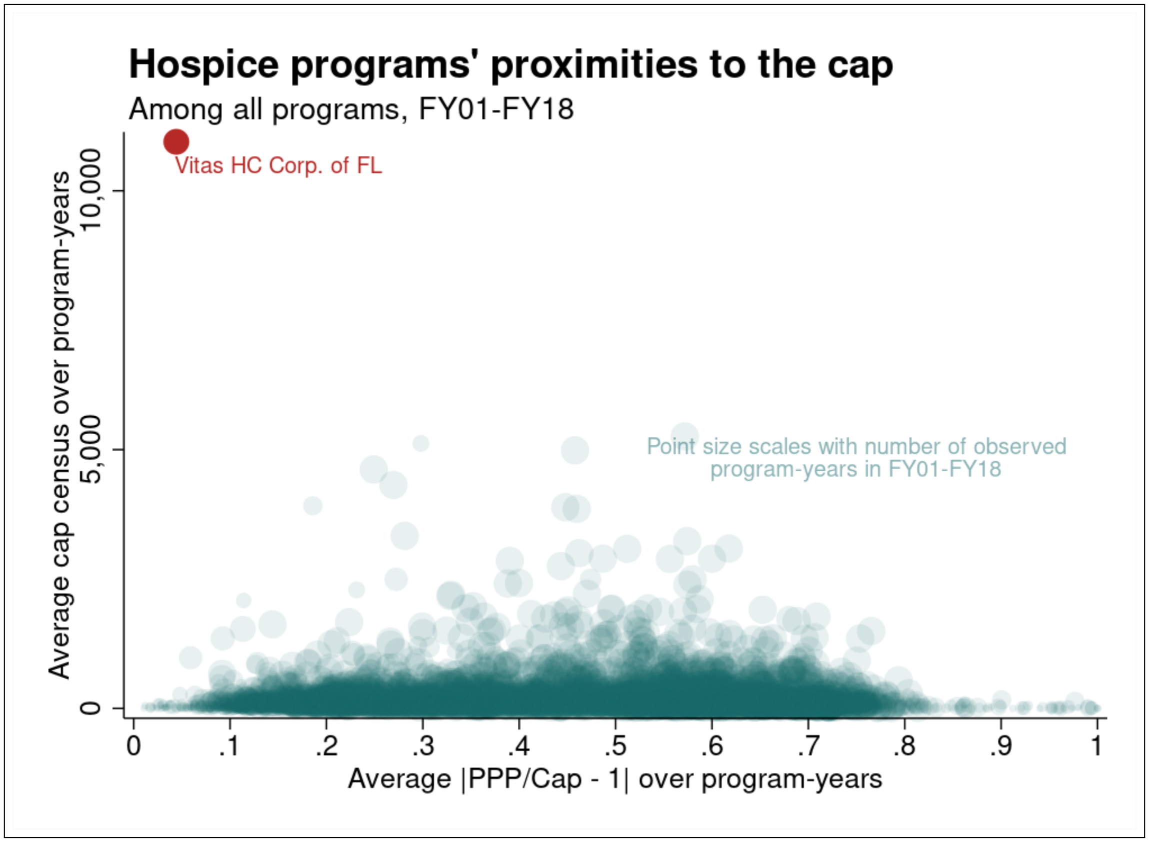

Fig. A31. This figure plots the joint distribution between the number of years that hospice programs are observed in our sample between FY 2001 and FY 2018, their average annual cap censuses, and their average proximities to the cap during this time. It supports the idea that most hospice programs do not persistently equilibrate their average annual payments per patient 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. The x-axis is censored at 1 for visual clarity. See the discussions in section E.

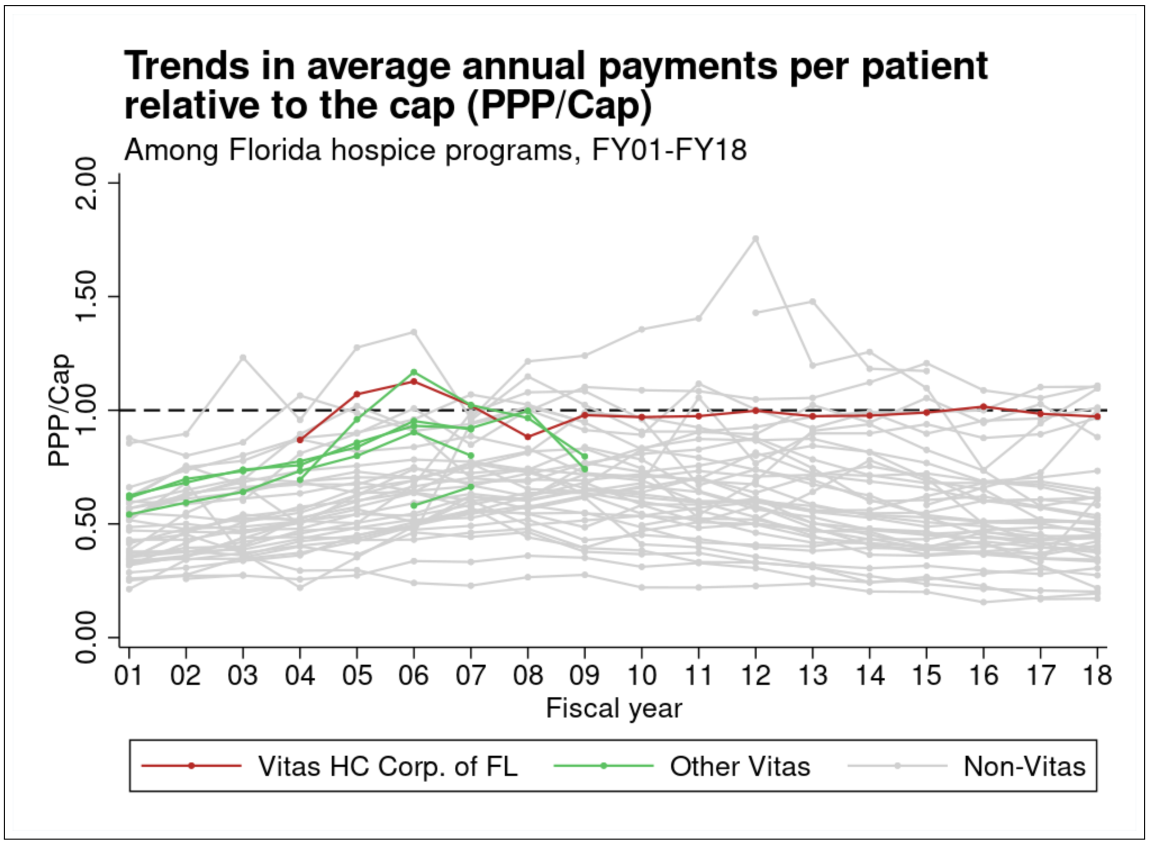

Fig. A32. This figure plots trends in $\mathrm{PPP}_{jt}/\mathrm{Cap}_{jt}$—i.e., hospice programs' average annual payments per patient relative to the cap—among Florida hospice programs. It shows that Vitas Healthcare Corporation of Florida has nearly equilibrated its average annual payments per patient with the cap since 2009. Other Vitas hospice programs were identified by the word "Vitas" in their facility name. See the discussions in section E.

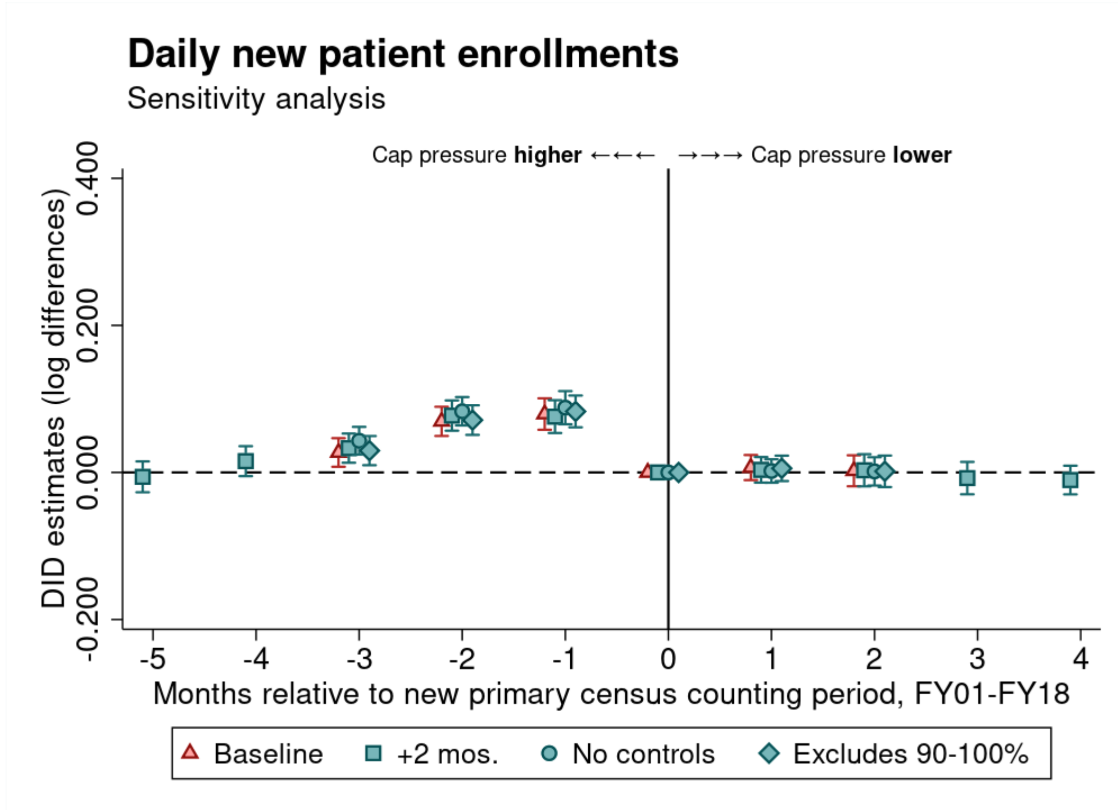

Fig. A33. This figure plots estimates of $(\beta_w : w \in W)$ from a monthly version of equation (7) in our difference-in-differences analysis. It also plots corresponding estimates from the robustness checks discussed in section F.1. It supports the idea that programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year, and suggests that our baseline estimates are not sensitive to several variations of the analysis discussed in section 5. The 95% confidence intervals are computed with program-level cluster-robust SEs.

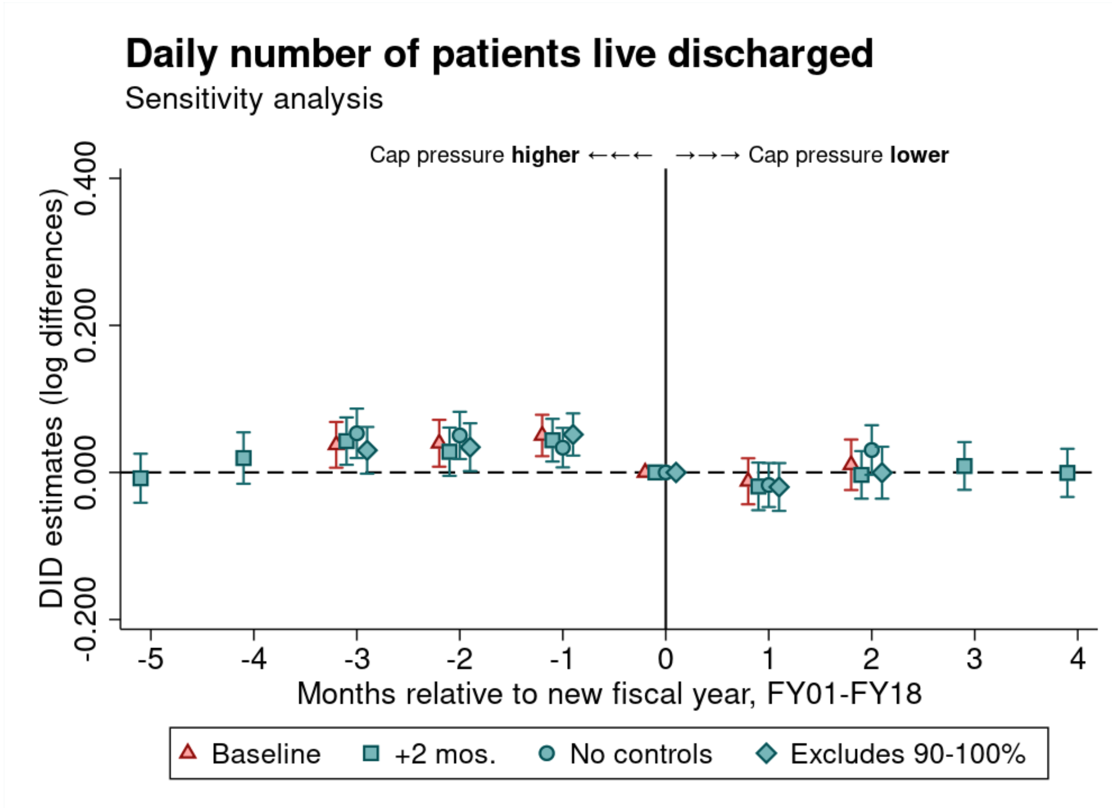

Fig. A34. This figure plots estimates of $(\beta_w : w \in W)$ from a monthly version of equation (7) in our difference-in-differences analysis. It also plots corresponding estimates from the robustness checks discussed in section F.1. It supports the idea that programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year, and suggests that our baseline estimates are not sensitive to several variations of the analysis discussed in section 5. The 95% confidence intervals are computed with program-level cluster-robust SEs.

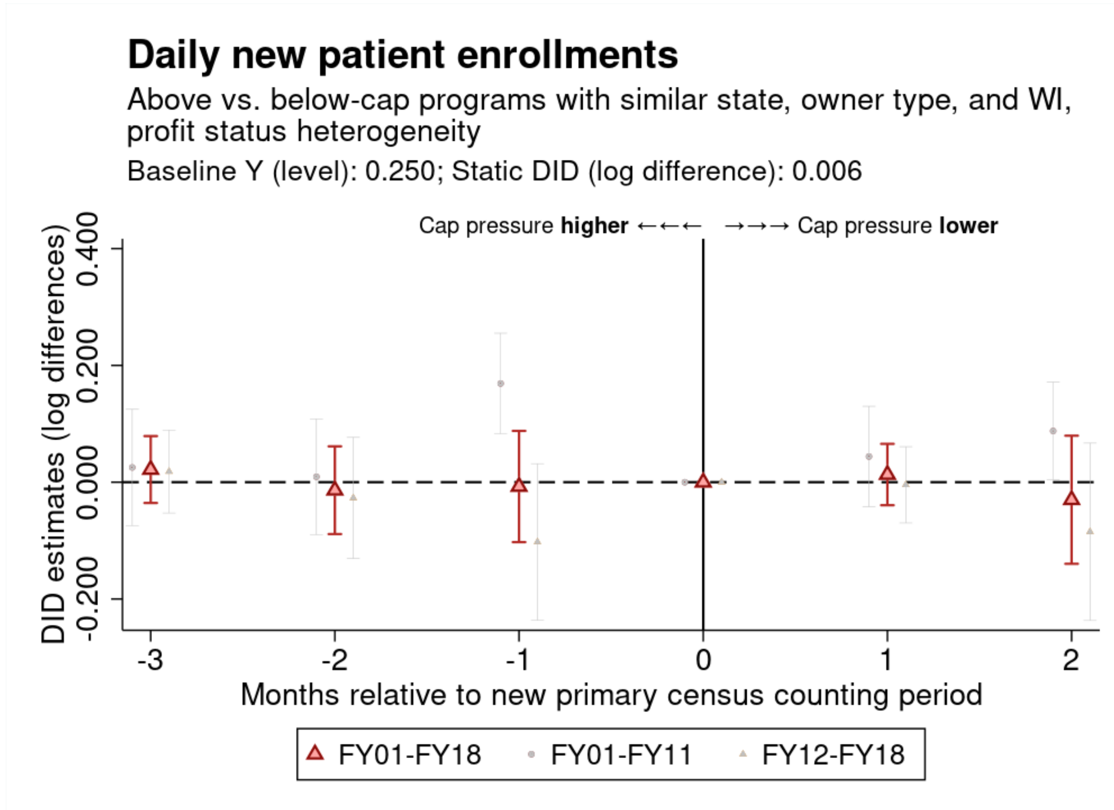

Fig. A35. This figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that for-profit and not for-profit programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.

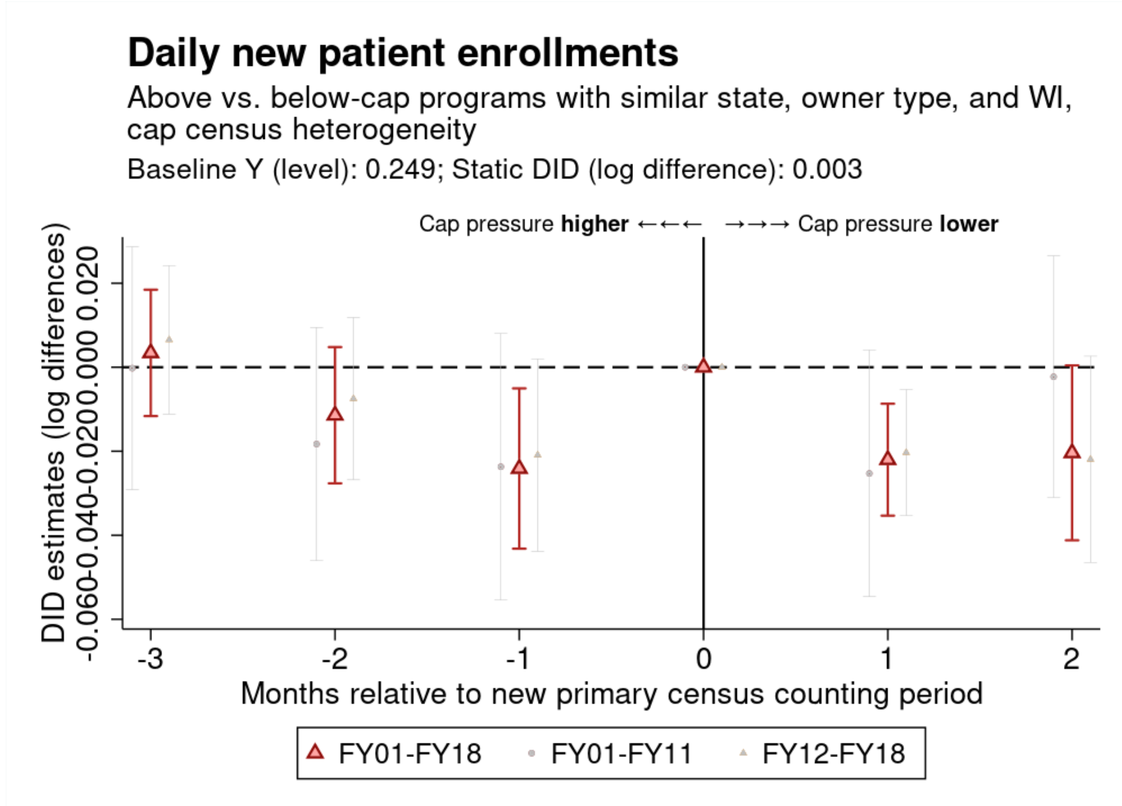

Fig. A36. This figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that large and small programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.

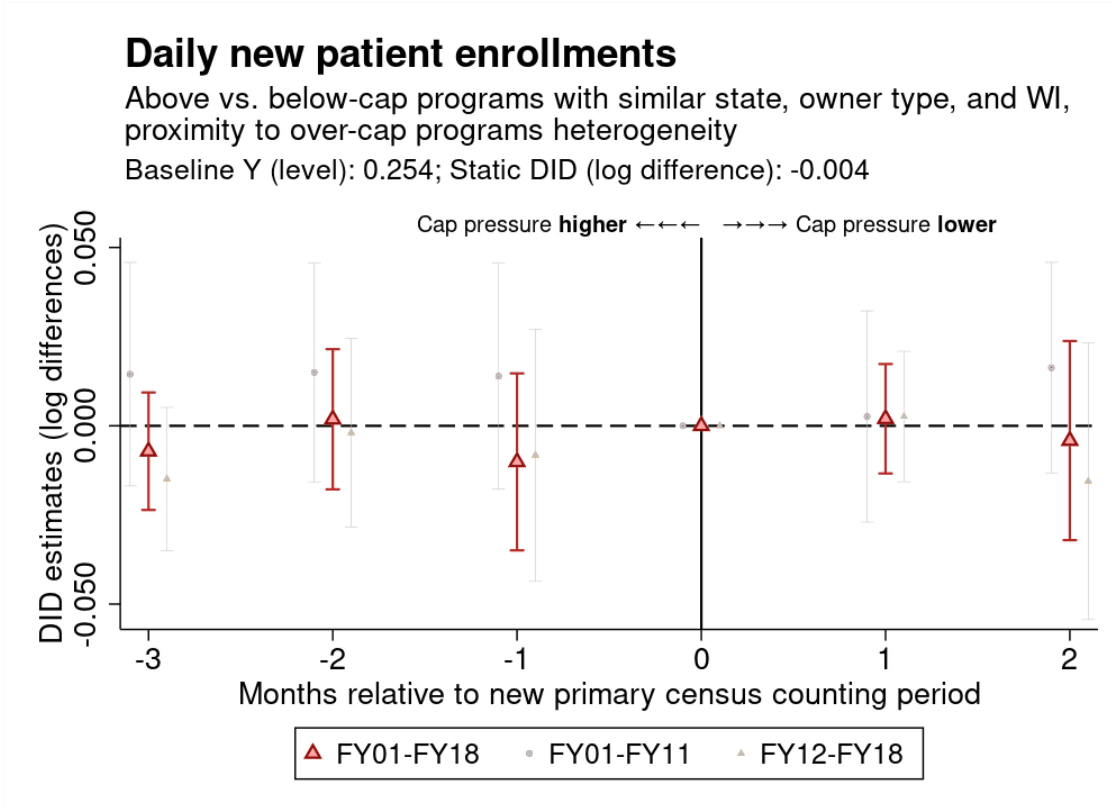

Fig. A37. This figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates whether they are near or far from other programs that are also on track to exceed the cap contemporaneously. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.

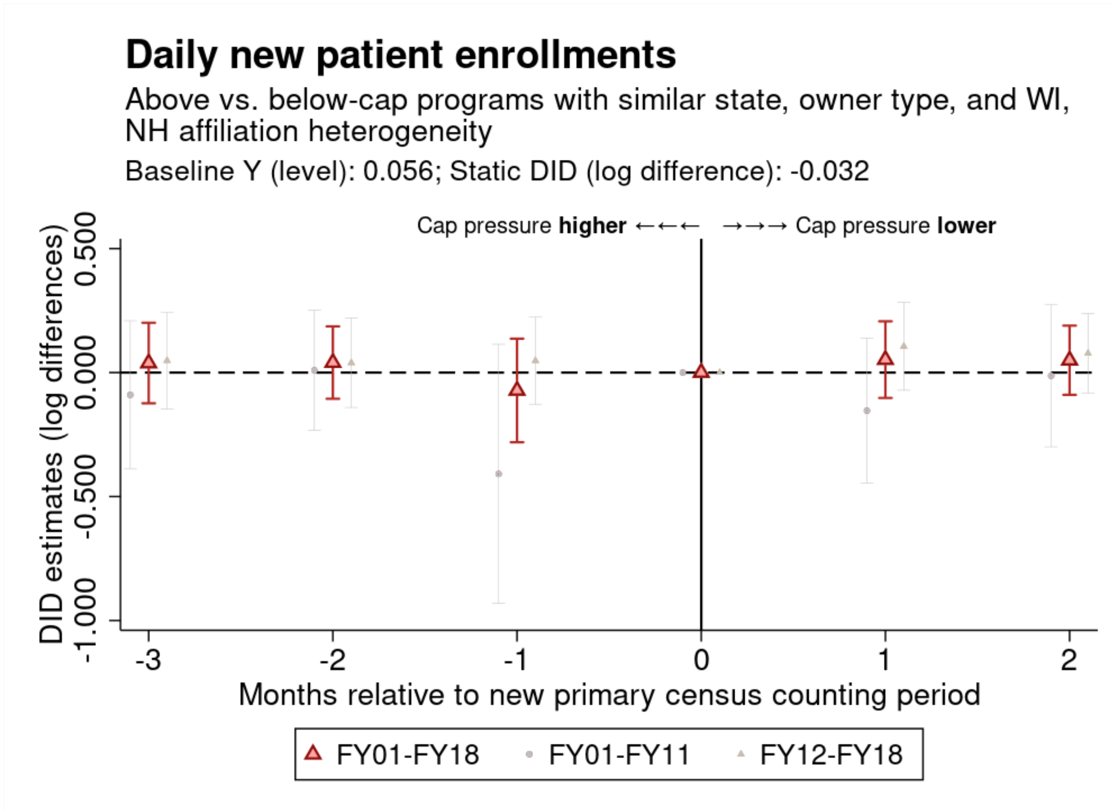

Fig. A38. This figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates whether they are affiliated with a nursing home or not. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.

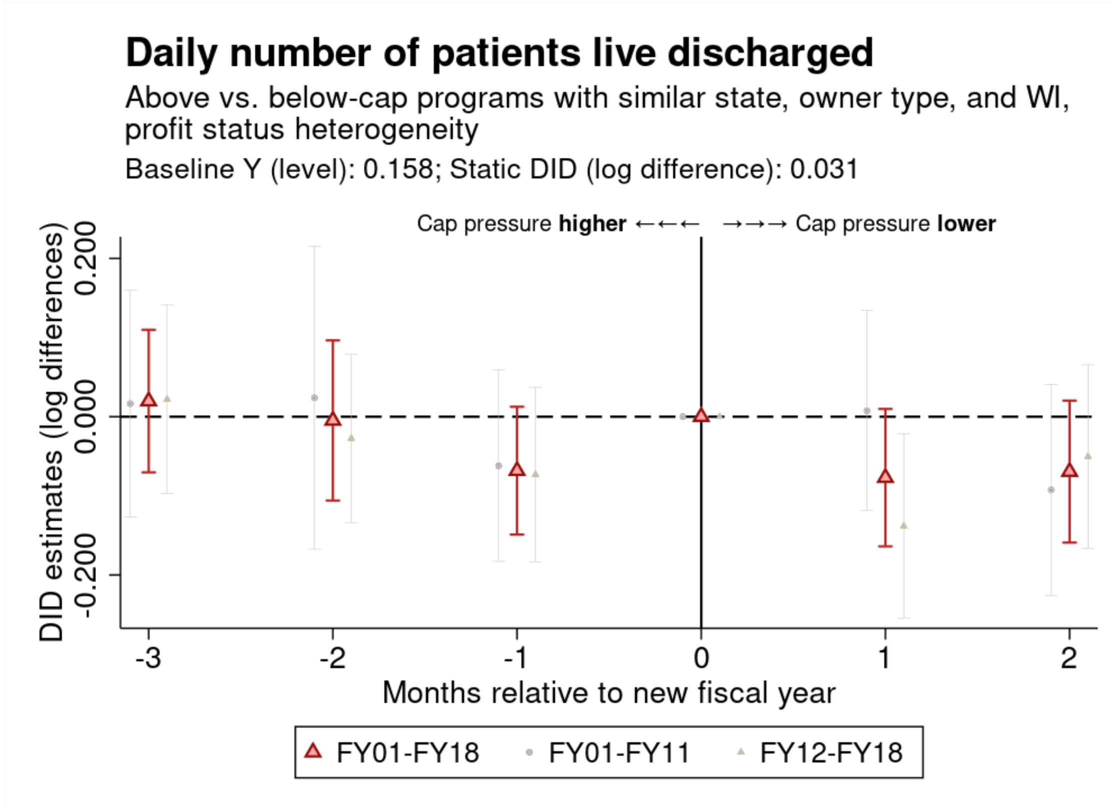

Fig. A39. This figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that for-profit and not for-profit programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at much the same rates. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.

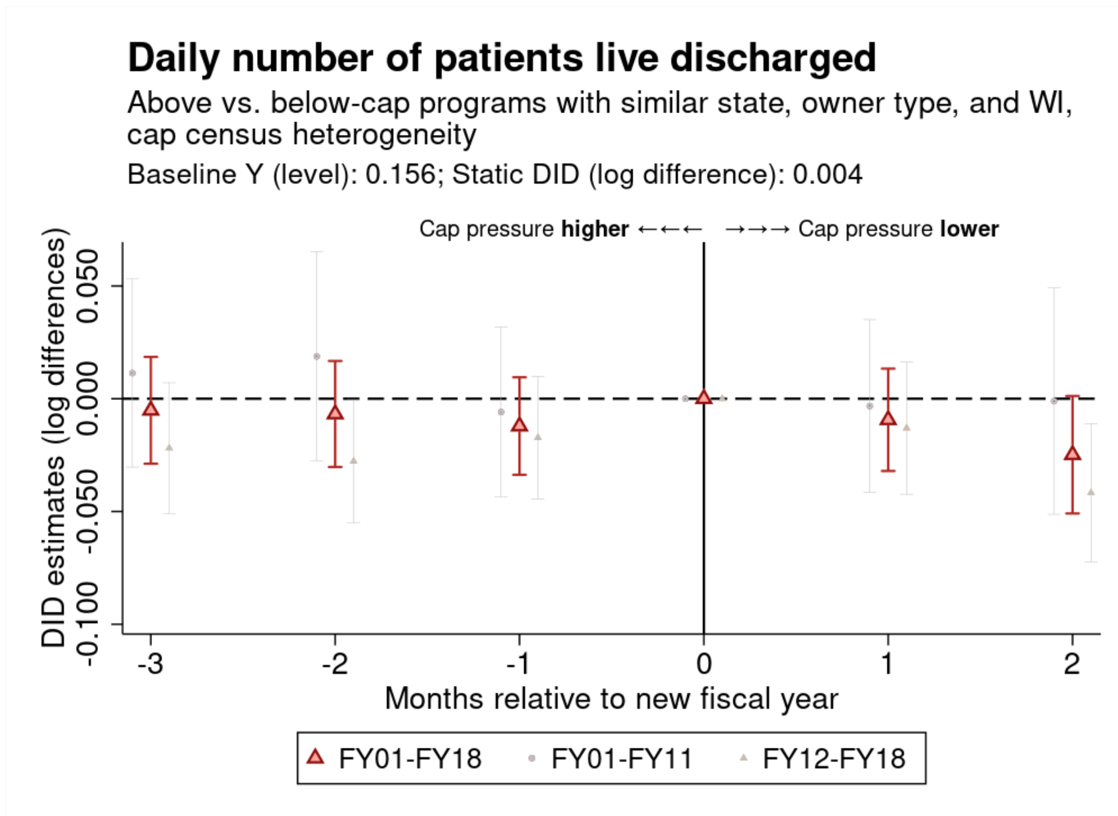

Fig. A40. This figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that large and small programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at much the same rates. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.

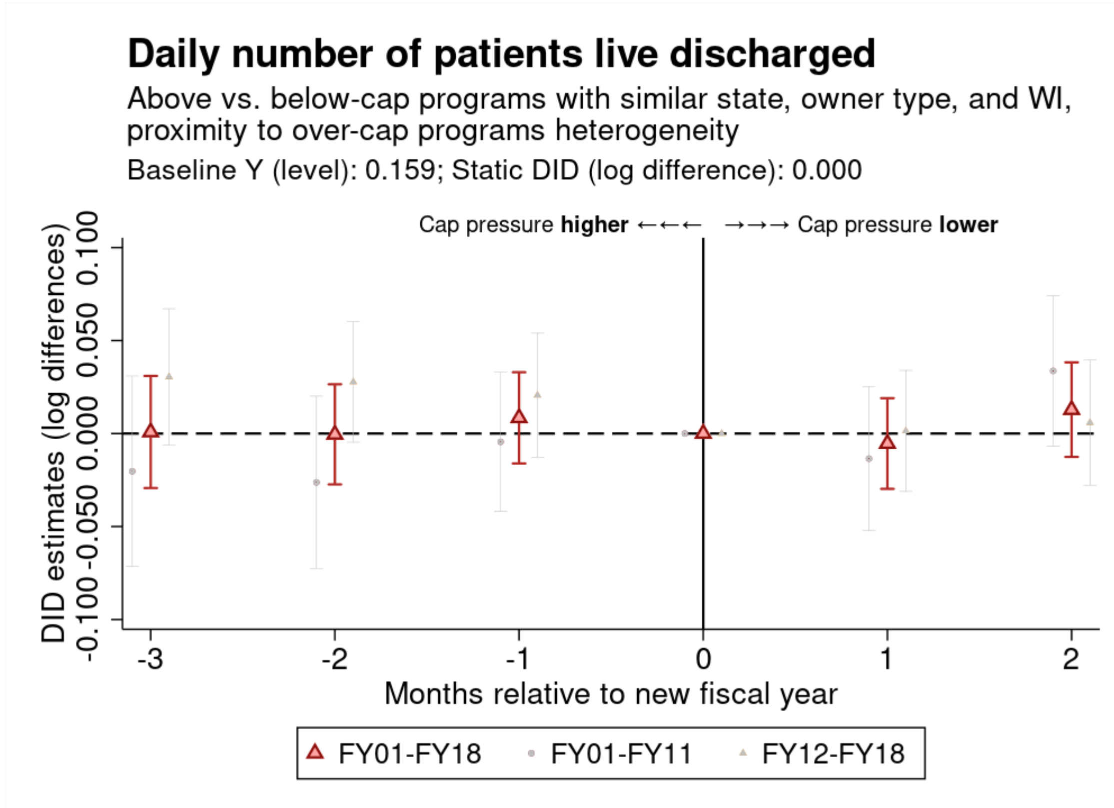

Fig. A41. This figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at much the same rates whether they are near or far from other programs that are also on track to exceed the cap contemporaneously. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.

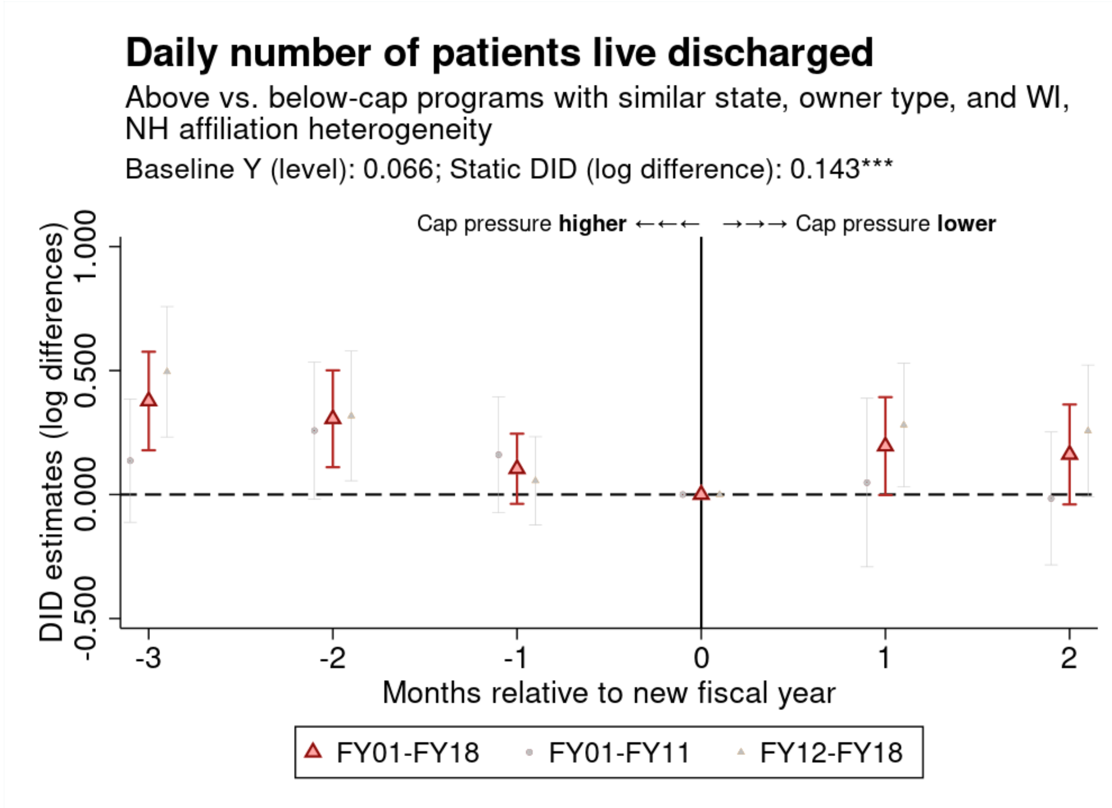

Fig. A42. This figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (7) described in appendix F.2. It supports the idea that programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at higher rates when they are affiliated with a nursing home. The figure includes estimates for the full sample period, the pre-2011 era, and the post-2012 era. The 95% confidence intervals are computed with program-level cluster-robust SEs.