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# PROVIDER PAYMENT INCENTIVES:
# EVIDENCE FROM THE U.S. HOSPICE INDUSTRY

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**ABSTRACT**

Moral hazard and provider-induced demand may contribute to overutilization of scarce health care resources. The U.S. health care system includes several compensatory cost-containment mechanisms, but their effects depend on how patients and providers respond. We investigate hospice programs' responses to a cap in the Medicare hospice benefit on their average annual payments per patient. We estimate their intensive margin responses to the cap by leveraging variation in cap-related financial incentives generated by the policy's nonlinear design and the transition between fiscal years. We find that programs on track to exceed the cap in the last three months of a fiscal year raise their enrollment rates by 5.7% and their live discharge rates by 4.3% on average, reducing their cap liabilities. The marginal enrollees have longer average remaining lifetimes and are less likely to have been recently hospitalized. Their hospice spells are also more likely to be fragmented by subsequent live discharges. On the extensive margin, we find that cap liabilities are associated with terminations of Medicare provider certification numbers, suggesting that the cap impacts market structure. Current policy discussions about reducing the cap should consider its potential effect on market structure.

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# I. Introduction

Health insurance increases access to scarce health care resources but may also lead to overutilization through changing provider (provider-induced demand) or patient (moral hazard) behavior (Arrow, 1963). 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 counterbalance these potential side effects by reducing supply or demand. However, they may also have unintended consequences, 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), or have little effect on their target outcomes (e.g., Alexander, 2020). In this paper, we study provider responses to a cost-containment feature of the Medicare hospice benefit that caps hospice programs' average annual payments per patient.

Created in 1983, the Medicare hospice benefit 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, physical therapy, social services, grief counseling, and respite care. Individuals who elect the hospice benefit forgo other Medicare coverage for services that are related to their terminal illness, including curative care.[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). Early enrollment can increase the benefits of hospice care (Zuckerman et al., 2015; Kelley, et al., 2013), but live discharge from hospice care can be a costly disruption to care continuity (e.g., Dolin et al., 2017).

Under the hospice benefit, Medicare pays hospice programs a lump sum rate per patient-day but limits their average annual payments per patient with a so-called "aggregate payment cap." The cap is intended to control Medicare's hospice-related costs and enforce the target life expectancy of six months or less.[3] While the daily payments vary with a measure of how regional labor costs differ from the national average (the "wage index," hereafter), the cap does not. In 2023, the cap

[1]Medicare Benefit Policy Manual Chapter 9 – Coverage of Hospice Services Under Hospital Insurance. Hospice patients can resume curative care by withdrawing from the hospice benefit at any time. Hospice patients do not need to forgo curative care for conditions unrelated to their terminal illness.

[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 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. It is approximately 180 days times the base daily hospice payment rate for routine home care. Federal Register, vol. 48(163): 38156-7 and Federal Register, vol. 80(151): 47147.

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.[4] Any excess payment ("cap liability," hereafter) must be repaid to Medicare within five months of the end of each fiscal year ("FY," hereafter). 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.[5] 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).

In 2020, the Medicare Payment Advisory Commission ("MedPAC," hereafter) recommended two reforms to the cap (MedPAC, 2020). First, it recommended that CMS apply the wage index adjustment to the cap to "mak[e] the cap more equitable across providers[.]" Second, it recommended that CMS reduce the cap by 20% to "reduce excess payments [by Medicare to hospice programs] and generate savings for taxpayers[.]"

The impacts of such reforms depend on how hospice programs respond to the cap. Studies show that health care providers respond to financial incentives in many contexts (e.g., Eliason et al., 2020; 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). In theory, hospice programs may respond to the cap along the intensive margin by adjusting their census to decrease their average annual payments per patient. Existing research and press reports have documented some hospice programs self-reporting that they adjusted their enrollment and live discharge rates to limit 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). Studies have documented positive correlations between the cap and live discharge rates (e.g., Dolin et al., 2018; Plotzke et al., 2015; Teno et al., 2014). However, it is unclear how much of this variation is attributable to the cap versus other differences between hospice programs.

[4]CMS Transmittal 11542, dated August 4, 2022. We discuss in more detail how Medicare calculates annual payments and patient volume below, including how patients are allocated across fiscal years and hospice programs.

[5]See 42 CFR 418.308 and the Medicare Financial Management Manual, Chapter 4.

[6]Jenkins et al. (2011) analyzed 107 responses to a 2008 survey sent to 193 Alabama hospice programs. Approximately 25% of respondents indicated that their program adjusted admission and discharge practices to limit cap liabilities. By comparison, approximately 5,700 hospice programs operated in the U.S. between 2001 and 2018. The survey respondents were slightly more for-profit than the program-years between 2001 and 2018 in our national sample (72% versus 52%).

In this paper, we begin by describing the distribution of cap liabilities. Although we do not observe cap liabilities directly, we estimate them for all Medicare-certified hospice programs between fiscal years 2001 and 2018 using Medicare claims for a 100% sample of Medicare beneficiaries.[7] We find that programs that ultimately exceed the cap have an approximately $500,000 cap liability per year on average (or 21% of their gross Medicare payments); and that programs that exceeded the cap at least once exceeded it in approximately half of their years of operation between 2001 and 2018 on average. We find no evidence of a discontinuity in the distribution of average annual payments per patient near the cap, despite observing that programs with average annual payments per patient between 100-110% of the cap have an approximately $170,000 cap liability on average. Finally, we find that a 1% increase in a program's wage index is associated with an 0.1 percentage point increase in its likelihood of exceeding the cap and a 4.7% increase in its cap liability on average.

These findings suggest that hospice programs face barriers to adjusting their census to minimize their cap liabilities. But they are 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 minimizing their cap liabilities. We explore these possibilities 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 payments per patient 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-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," hereafter), 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

[7]As we discuss further below, our estimates account for details in how patients are counted toward hospice programs' annual census, how these counting methods have changed over time, the sequestration adjustment, a three-year lookback period for finalizing cap liabilities, and adjustments made for new hospice programs in their first year.

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. In our difference-in-differences analysis, we examine outcome trends during the transition between fiscal years among programs on track to be above versus below the cap in the same state, with the same ownership type, and with similar wage index values.

We find that programs on track to exceed the cap in an outgoing fiscal year have 5.7% differentially higher enrollment rates during the fiscal year's last three months on average. The temporal findings are telling: we find that their enrollment rates differentially increase throughout the last three months of the outgoing fiscal year; then, during the first week of the next fiscal year, their enrollment rates differentially decrease by approximately 16.3% on average. 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 three months on average.[8] Overall, we find that programs on track to exceed the cap in a given fiscal year differentially decrease their average annual payments per patient by approximately 6.9% during the last three months of that fiscal year on average. While these estimates support the idea that hospice programs respond to the cap on the intensive margin by raising enrollment and live discharge rates, they also support the idea that their responses are relatively small. In particular, our estimates translate to approximately 1.55 additional enrollees and 0.36 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 have 1.0 percentage point lower likelihoods of having a hospital stay in the previous week, 0.6 percentage points lower likelihoods of having a nursing home stay in the previous week, and 6.0% 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, 1.9% more lifetime live discharges, and 0.5 percentage point lower likelihoods of ultimately dying in hospice on average. The marginal live

[8] In parallel work, Gruber et al. (2023) 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, as discussed further below, whereas they examine the effect on total Medicare spending of cap-related live discharges.

discharged patients subsequently resume hospice care at similar rates, but those who eventually resume hospice care spend differentially 4.8% 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 choose to adjust along the extensive margin by closing or consolidating (Ata et al., 2012). We explore this possibility by examining the association between cap liabilities and terminations of hospice programs' Medicare provider certification numbers ("CCNs," hereafter).[9] We find that CCNs linked to hospice programs with cap liabilities in one fiscal year are 5.8 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 potential effect on market structure of reducing the cap.

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

# II. Context

## A. 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, Alzheimer's disease and related dementias ("ADRD," hereafter), 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 (10$^{th}$ percentile), to 18 days (50$^{th}$ percentile), or to 287 days or more (90$^{th}$ percentile) (MedPAC, 2022).

[9] Medicare provider agreements are terminated when a provider exits the Medicare market. They are also terminated when an institutional provider experiences a change of ownership and the new owner does not accept the institution's existing provider agreement. However, 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 AIV.C for more information.

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 patient-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 ($10^{\text{th}}$ percentile), to 166 patients ($50^{\text{th}}$ percentile), or to 830 patients or more ($90^{\text{th}}$ 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).

### B. Hospice payments and the cap

Hospice programs' cap liabilities depend on measures of their annual payments and patient volumes. For each program $j$ and each FY $t$, let $\text{Payment}_{jt}$ be $(j, t)$'s gross Medicare payment, let $\text{Census}_{jt}$ be its measure of patient volume, and let $\text{Cap}_t$ be its cap.[10] Its average annual payment

[10]Within a given fiscal year, the cap is fixed across $j$ except for new hospice programs. Our calculations account for this source of variation. See appendix AI for details. However, we omit the $j$ subscript for ease of exposition.

per patient is then $\text{PPP}_{jt} := \text{Payment}_{jt}/\text{Census}_{jt}$ and its cap liability is:

$$\text{Liability}_{jt} := \max\Big\{\big(\text{PPP}_{jt} - \text{Cap}_t\big) \cdot \text{Census}_{jt}, 0\Big\} = \max\{\text{Payment}_{jt} - \text{Cap}_t\text{Census}_{jt}, 0\} \quad (1)$$

Within a given fiscal year, each hospice program is paid 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 level of hospice care. There are four levels of hospice care: routine home care ("RHC," hereafter), continuous home care ("CHC," hereafter), inpatient respite care ("IRC," hereafter), and general inpatient care ("GIC," hereafter).[11] The base payment is lowest for RHC and IRC and highest for GIC and CHC.[12] It is otherwise largely fixed.[13] Virtually all patient-days are associated with RHC. The wage index adjusts the base payment in accordance with geographic variation in labor costs.[14] Programs operating below the 10th percentile of the wage index earned \$142 per patient-day on average in 2018. Programs operating above the 90th percentile of the wage index earned \$204 per patient-day on average contemporaneously. Since the cap is fixed nationally, this means that programs with low wage index values can provide more days of care per patient and remain below the cap. Each program's gross Medicare payment in each fiscal year is the sum of the daily payments made to that program for patient-days that fall within that fiscal year.

The patient volume measure ("cap census," hereafter) is more complex. It accounts for the fact that patients may utilize the hospice benefit during several fiscal years and with several hospice programs. Since FY 1984, it has been calculated using two different formulas, or "counting methods:" the streamlined method and the proportional method. For a given $(j, t)$, the counting methods specify how patients are counted toward $\text{Census}_{jt}$ within a census counting period that sometimes—but not always—coincides with FY $t$.[15] All programs used the streamlined method until FY 2011. Since FY 2012, almost all programs used the proportional method.[16] We therefore

[11] The levels of hospice care vary according to their purpose and resource intensity. 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.

[12] In 2012, base payments for RHC, CHC, GIC, and IRC were respectively \$151, \$881, \$672, and \$156.

[13] See appendix AI for details about other sources of variation in base payment rates.

[14] To see where the wage index appears in the cap liability formula, note that $\text{Payment}_{jt}$ varies with $j$ in part through $j$'s wage index value. The wage index is pegged to approximately 1 nationally. Each program's wage index deviates from 1 based on how its region's hospital labor costs deviate from the national average. See 87 FR 45669 for details.

[15] This means that for a given $(j, t)$, the patient-days used to determine $\text{Census}_{jt}$ may not coincide with the patient-days used to determine $\text{Payments}_{jt}$.

[16] Only 486 hospice programs used the streamlined method in FY 2013. Since then, this number has weakly decreased. See appendix AI for details.

refer to fiscal years prior to 2011 as the "streamlined method era" and fiscal years after 2012 as the "proportional method era."

Under the streamlined method, patients are counted in one of two ways. If they are only ever affiliated with one hospice program, then they are counted toward that program's cap census only in the first census counting period that they are enrolled in hospice care. Their contributions to the program's cap census do not depend on their lifetime LOS in hospice care: they contribute "1" in the first census counting period and "0" thereafter. If they are ever affiliated with at least two hospice programs, then their contribution to each $\text{Census}_{jt}$ is that fraction of their lifetime LOS in hospice care spent at $(j, t)$. During the streamlined method era, each fiscal year $t$ began on November 1 of calendar year $t-1$ and ended on October 31 of calendar year $t$. However, the census counting period for patients who were only ever affiliated with one hospice program spanned September 28 of calendar year $t-1$ to September 27 of calendar year $t$. Consequently, patients who first enrolled in hospice care with a program $j$ on September 27 of calendar year $t$ during the streamlined method era and who were subsequently only ever affiliated with program $j$ raised $\text{Census}_{jt}$ by 1 and contributed at most 35 days of payments to $\text{Payments}_{jt}$. The census counting period for patients who were ever affiliated with at least two hospice programs coincided with the fiscal year. Under the proportional method, patients contribute to each $\text{Census}_{jt}$ that fraction of their lifetime LOS in hospice care spent at $(j, t)$ regardless of their lifetime number of hospice program affiliations. We use the term "primary census counting period" to refer to the fiscal year during the proportional method era. We use it to refer to the span between September 28 and September 27 during the streamlined method era because most patients are only ever affiliated with one hospice program. Table A1 presents a few illustrative examples of these counting methods.

A given fiscal year's cap liabilities may not be finalized at the end of that fiscal year because the counting methods rely on measures of each patient's lifetime hospice utilization. In practice, CMS finalizes $\text{Liability}_{jt}$ at the end of fiscal year $t+3$ using all available claims data at that time. Therefore, our definitions of cap-related variables such as $\text{Liability}_{jt}$, $\text{Census}_{jt}$, and $\text{PPP}_{jt}$ are with respect to this three-year lookback period. In each fiscal year $t$, hospice programs must repay an estimate of their cap liabilities within five months of the end of $t$.[17] Their cap liabilities will be weakly larger than this estimate as some patients who were counted in year $t$ continue to use hospice through year $t+3$. They may be subsequently asked to repay the difference.[18]

We have simplified the foregoing summary for the sake of brevity. For instance, the start and end dates of the fiscal years have changed over time, the transition from the streamlined method

[17]See 42 CFR 418.308.

[18]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.

era to the proportional method era created a gap in cap census calculations in fall 2011, and RHC payments have been a piecewise function of lifetime LOS in hospice care since 2016. We account for these and other details in our empirical exercises and we discuss them in appendix AI.

### C. Theoretical predictions

The cap may be rationalized by a concern that provider-induced demand or moral hazard would lead to excessive hospice care in the absence of a cap—that is, the social cost of the marginal unit of hospice care would exceed its social benefit (Arrow, 1963). The provider-induced demand theory suggests that financially motivated health care providers may encourage marginally eligible Medicare beneficiaries to initiate hospice care too early or remain enrolled in hospice care too long after their condition improves.[19] Moral hazard can magnify the effects of provider-induced demand because hospice patients are insulated from the monetary cost of hospice care.[20,21] Under these circumstances, in theory, a cap on average Medicare payments to hospice programs can raise welfare by reducing hospice programs' financial incentives to treat patients for too long. Recently, some scholars have argued that higher hospice utilization rates may be welfare increasing because they reduce individuals' overall health care consumption (e.g., Gruber et al., 2023; Kelley et al., 2013). We instead use the cap as an opportunity to study health care providers' responses to a payment program with sharp, nonlinear financial incentives: a limit on hospice programs' average annual revenue.

To understand the financial incentives created by the cap, consider a financially-motivated hospice program $j$ in fiscal year $t$ that will exceed the cap but for some adjustment. For concreteness, assume that its daily payment rate is \$200, $\text{Cap}_t = \$20{,}000$, and in the absence of a response, $\text{Census}_{jt}$ will be 50 and $\text{Payments}_{jt}$ will be \$1,200,000. Therefore, $\text{PPP}_{jt}$ is on track to be $\frac{\$1{,}200{,}000}{50} = \$24{,}000$ and $\text{Liability}_{jt}$ is on track to be $50 \times (\$24{,}000 - \$20{,}000) = \$200{,}000$. We hypothesize that the

[19] 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.) Whistleblower lawsuits filed against other hospice programs have made similar allegations (Kofman, 2022; Rao, 2011).

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

[21] The provider-induced demand theory suggests providers' scope for providing inefficiently high levels of 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). Death is highly unpredictable among Medicare beneficiaries (e.g., Einav et al., 2018), and it is difficult for health care providers to determine when hospice care is needed most (e.g., Sack, 2007). However, concerns about overutilization arising from these phenomena may be dampened by the fact that CMS requires a patient's regular doctor to certify that their life expectancy is six months or less before initiating hospice care and the fact that hospice patients must forgo curative care for their terminal illnesses. See the Medicare Hospice Benefit Manual.

program has a financial incentive to reduce its average annual payments per patient by adjusting its census before the end of the fiscal year. Specifically, we hypothesize that it may adjust its enrollment rates, live discharge rates, and utilization of RHC, CHC, GIC, and IRC.

First, we examine program $j$'s incentives to adjust enrollment rates. Consider its choice to enroll a Medicare beneficiary $i$ during the streamlined method era during $t$'s primary census counting period. Assume that this beneficiary had not previously received hospice care. If this beneficiary were to enroll, remain enrolled at $(j, t)$ for $D_{ijt}$ days, and not subsequently enroll with another hospice program within the three-year lookback period, then she would contribute to $(j, t)$'s cap liability $\$200 D_{ijt} - \$20{,}000$. To make an extreme example: if $i$ were to enroll at $j$ on September 27 of calendar year $t$ and pass away on October 31 after 35 days in hospice care, then she would reduce Liability$_{jt}$ by \$13,000 because Census$_{jt}$ would increase by 1 and Payments$_{jt}$ would increase by only $\$200 \times 35 = \$7{,}000$. If she were to pass away on the evening of September 27, then she would reduce Liability$_{jt}$ by \$19,800. This reasoning may motivate program $j$ to enroll patients who have a low $D_{ijt}$. For instance, it may do so by enrolling patients near the end of FY $t$'s primary census counting period who would not have enrolled otherwise; who would have enrolled sooner and therefore, potentially, spent more time at $(j, t)$; or who would have enrolled during $(j, t+1)$'s primary census counting period (e.g., September 28), when their contribution to hospice $j$'s cap census would have come too late.

Now consider its choice to enroll $i$ during the proportional method era. If this beneficiary were to enroll, remain enrolled at $(j, t)$ for $D_{ijt}$ days, and be enrolled in hospice care for $D_i$ days through the end of the three-year lookback period, then she would contribute to $(j, t)$'s cap liability $\$200 D_{ijt} - \$20{,}000 \frac{D_{ijt}}{D_i}$. This reasoning may motivate program $j$ to enroll patients who have $(D_{ijt}, D_i)$ pairs such that $D_{ijt}$ is small and $\frac{D_{ijt}}{D_i}$ is large. For instance, it may do so by enrolling patients near the end of the fiscal year who have short expected lifetime LOS in hospice care. Note that this proportional method era (2012 and later) incentive to enroll patients was smaller than the corresponding streamlined method era (2011 and earlier) incentive because $\$200 D_{ijt} - \$20{,}000 \leq \$200 D_{ijt} - \$20{,}000 \frac{D_{ijt}}{D_i}$; that is, each enrollment had a smaller downward impact on Liability$_{jt}$ during the proportional method era.[22]

Second, we consider program $j$'s incentives to adjust live discharge rates. Consider its choice to live discharge a Medicare beneficiary $i$ during the streamlined method era. Assume that this beneficiary had not previously received hospice care elsewhere. Let $D_{ijt}$ be her LOS in hospice care at $(j, t)$ but for a live discharge and let $D'_{ijt}$ be her LOS in hospice care at $(j, t)$ if she were

[22]Under the streamlined method, program $j$'s incentives to enroll Medicare beneficiaries who had previously been enrolled at another hospice program or who will subsequently enroll at another hospice program are similar to its incentives to enroll Medicare beneficiaries during the proportional method era.

live discharged. If she will not enroll with another hospice program within the three-year lookback period, then the effect of her live discharge on $\text{Liability}_{jt}$ is \$200$(D'_{ijt} - D_{ijt})$. In other words, on any given day during FY $t$, program $j$ would earn zero net Medicare revenue for continuing to treat $i$. This reasoning may motivate program $j$ to live discharge patients who have a high remaining LOS in hospice care at $(j, t)$ but for their live discharge.

Now consider its choice to live discharge $i$ during the proportional method era. As before, let $D_{ijt}$ be her total days at $(j, t)$ but for a live discharge and let $D'_{ijt}$ be her total days at $(j, t)$ if she were live discharged. Likewise, let $D_i$ be her total days in hospice care through the end of the three-year lookback period but for a live discharge and let $D'_i$ be her total days in hospice care through the end of the three-year lookback period if she were live discharged. Then the effect of her live discharge on $\text{Liability}_{jt}$ is \$200$(D'_{ijt} - D_{ijt})$−\$20,000$(D'_{ijt}/D'_i - D_{ijt}/D_i)$. This reasoning may motivate program $j$ to live discharge patients who have $(D_{ijt}, D_i, D'_{ijt}, D'_i)$ pairs such that $D'_{ijt} - D_{ijt}$ is low or $D'_{ijt}/D'_i$ is large relative to $D_{ijt}/D_i$. For instance, it may do so by live discharging patients for whom the live discharge would significantly reduce their lifetime LOS in hospice care or significantly reduce their LOS in hospice care at $(j, t)$.[23]

Thus far, we have assumed that daily payments are fixed (at \$200, in our running example). 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 to reduce its average annual payments per patient because GIC and CHC base payments are 4-6 times higher than RHC and IRC base payments.

These cap-related financial incentives to adjust utilization rates 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 whether or not they will exceed the cap 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 financial incentives by making FY $t$'s cap liabilities more salient than FY $t + 1$'s cap liabilities during FY $t$'s last weeks.

[23]Under the streamlined method, program $j$'s incentive to live discharge a patient who had not previously been enrolled at another hospice program is moderated by the possibility that their live discharge may cause them to subsequently resume hospice elsewhere. Otherwise, under the streamlined method, program $j$'s incentives to live discharge Medicare beneficiaries who had previously been enrolled at another hospice program or who will subsequently enroll at another hospice program are similar to its incentives to live discharge Medicare beneficiaries during the proportional method era.

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 from the outgoing fiscal year to the next fiscal year. We examine them separately during the streamlined method era and the proportional method era. 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.

## III. 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.[24] We assigned to each (program, day) realization a corresponding fiscal year (see appendix AII) 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 streamlined or proportional counting methods. In this step, we assumed that all programs used the proportional method in FY 2012 and onward. We assumed that claims spanning 2000-2019 are sufficient to observe all hospice utilization for beneficiaries who were enrolled in hospice during FY 2001 – FY 2018.[25] 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 $\text{PPP}_{jt}$ and $\text{Liability}_{jt}$ for each program $j$ and FY $t$ between FY 2001 and FY 2018.[26] We also calculated $\text{PPP}_{jtd}$ 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 $t$

[24]Almost all (patient, day) observations (99.97%) are associated with at most one program. Patients may be associated with multiple programs on days that they switch from one hospice program to another. Such patient-days count toward both programs' cap censuses. See Medicare hospice transmittal 156.

[25]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.

[26]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 AIII.

through day $d$.

We also rely on additional data. We analyzed live discharges (see appendix AIV.A), patient demographics (see appendix AIV.B), hospice program business records (see appendix AIV.C), the wage index and daily payment rates (see appendix AIV.D), nursing home spells (see appendix AIV.E), hospice staff visits (see appendix AIV.F), each program $j$'s proximity to other programs that exceeded the cap in year $t$ (see appendix AIV.G), hospitalizations (see appendix AIV.H), levels of hospice care (see appendix AIV.I), and ADRD diagnoses (see appendix AIV.J). 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.

## IV. 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, 2,212 (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 $497,000. They earned $148 per patient-day on average; but only $117 per patient-day net of their cap liabilities.[27]

Table 2 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 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

[27]These descriptive statistics 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 $406,000 among 13.8% 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 II.

cap contemporaneously. Table 3 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 705,000 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 indicate that cap risk is geographically clustered and autocorrelated. Figure A1 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 A2 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.

Our cap liability estimates also enable us to examine the distribution of average annual payments per patient relative to the cap. Figure 1 plots the distribution of $\text{PPP}_{jt}/\text{Cap}_t$. There is no visual indication of bunching around 1.[28] 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.[29]

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 A6 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 A7 plots trends in its $\text{PPP}_{jt}/\text{Cap}_t$. It shows that between 2006-2008, Vitas consolidated its

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

[29] 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 A3-A5. 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.

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.

Nevertheless, figures 1 and A6-A7 suggest that hospice programs do not generally equilibrate their average annual payments per patient with the cap.[30] 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 $166,000 on average (see table 1)—this finding implies that programs' marginal adjustment costs are high.

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 4 reports estimates from several models relating 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 4.7% 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 0.32% higher gross daily payments and 0.29% 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 5 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 21.3 percentage points more likely to exceed the cap again and their cap liabilities are 243% higher on average. They do not experience a statistically significant

[30]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).

change to their gross payments or their number of unique patients on average. However, their cap censuses are 10.3% lower and their total number of patient-days are 9.7% higher on average. CCNs associated with programs that exceed the cap are 5.8 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.

# V. Does the cap affect enrollment or live discharge rates?

## A. 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 minimizing their cap liabilities. In this section, we leverage variation in cap-related financial incentives generated by the policy's non-linear 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," hereafter). The transitions are between primary census counting periods for some outcomes (such as enrollments) and fiscal years for others (such as live discharges), as noted in the tables and figures below. In the remainder of the main text, we say that the transitions are between fiscal years for brevity. We compare average outcome trends among hospice programs that began the event windows 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. We average the trend differences across events.

Figure 2 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 rate trends 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 enrollment rates move seasonally. But the figure also shows that on average programs with higher average annual payments per patient have higher differential enrollment rates in the weeks preceding the end of the outgoing fiscal year than programs with lower average annual payments per patient. We measure this difference-in-differences with the following regression analysis.

Mathematically, let $e$ index events. As before, let $j$ index programs, $t$ index fiscal years, and $\text{Cap}_t$ 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 $W := \{..., -2, -1, 1, 2, ...\}$ 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 $\text{PPP}_{ej}^O$ 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:

$$f_{ejw}^{\text{S}} := 1[(e, j) \in \mathcal{T}]1[w < 0]\beta + \text{FE}_{ej} + \text{FE}_{ewg_{ej}} + \text{FE}_{ewg_{ej}} \times \text{WI}_{jt_e^O} \tag{2}$$

$$f_{ejw}^{\text{D}} := \sum_{w' \in W} 1\left[(e, j) \in \mathcal{T}\right]1[w = w']\beta_{w'} + \text{FE}_{ej} + \text{FE}_{ewg_{ej}} + \text{FE}_{ewg_{ej}} \times \text{WI}_{jt_e^O} \tag{3}$$

where S and D are mnemonics for static and dynamic difference-in-differences, respectively, $\text{FE}_{ej}$ is a program fixed effect, $g_{ej}$ (a mnemonic for "group") indexes $(j, t_e^O)$'s state and ownership type, $\text{FE}_{ewg_{ej}}$ is a week fixed effect, and $\text{WI}_{jt_e^O}$ is the wage index value for $(j, t_e^O)$. We related $f_{ejw}^{\text{S}}$ and $f_{ejw}^{\text{D}}$ to the conditional expectations of binary outcomes $Y_{ejw}$ to estimate $\beta$ and $(\beta_w : w \in W)$ using ordinary least squares ("OLS," hereafter). We also related $\exp(f_{ejw}^{\text{S}})$ and $\exp(f_{ejw}^{\text{D}})$ to the conditional expectations of other non-negative outcomes $Y_{ejw}$ to estimate $\beta$ 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 differed between the streamlined method era and the proportional method era.

The parameters $\beta$ 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 near the end of $e$'s outgoing fiscal year and at the start of $e$'s incoming fiscal year 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.[31]

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 $\text{PPP}^{O}_{ej}/\text{Cap}_{t^{O}_{e}} \in [0.9, 1]$. As we discuss below, excluding these programs does not significantly change our estimates. Second, programs $(e, j) \in \mathcal{T}$ may respond 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.

### B. Results

First, we examine trends in the daily number of patients enrolling in hospice care for the first time. Table 6 and figure 3 present the corresponding estimates of $\beta$ and $(\beta_w : w \in W)$. The estimates show that regression-adjusted average enrollment rate differences between the outgoing

[31]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.

fiscal year's last three months and the incoming fiscal year's first three months are 0.055 log points (5.7%) 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.[32] 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 three months, before suddenly differentially decreasing by 0.151 log points (16.3%) in the first week of the incoming fiscal year on average. The magnitudes of these difference-in-differences are higher in the pre-2011 sub-sample than in the post-2012 sub-sample (0.093 versus 0.035 log points).

Second, we examine trends in the new enrollees' characteristics.[33] Tables A3-A8 and figures A8-A17 present the corresponding estimates of $\beta$ and $(\beta_w : w \in W)$. The estimates show that programs on track to exceed the cap in a given fiscal year differentially enroll patients in the last three months of the fiscal year with 0.02 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, 1.0 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 0.058 log point (6.0%) higher remaining life expectancies 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.

Third, we examine trends in daily live discharge rates. Table 7 and figure 4 present the corresponding estimates of $\beta$ and $(\beta_w : w \in W)$. The estimates show that regression-adjusted average live discharge rate differences between the outgoing fiscal year's last three months and the incoming fiscal year's first three months are 0.042 log points (4.3%) higher at hospice programs on track to exceed the cap in the outgoing fiscal year than at programs on track to remain below the cap on average. The magnitudes of these difference-in-differences are higher in the pre-2011 sub-sample than in the post-2012 sub-sample (0.067 versus 0.023 log points).

Fourth, we examine trends in the discharged patients' characteristics.[34] Tables A9-A10 and figures A18-A22 present the corresponding estimates of $\beta$ and $(\beta_w : w \in W)$. The estimates show that programs on track to exceed the cap in a given fiscal year differentially live discharge

[32]Throughout the paper, we convert log points to percent changes using the formula: Percent = $\left(\exp(\text{Log})-1\right)\times 100$.
[33]In these specifications, each $(e, j, w)$ observation is weighted by the number of new enrollees.
[34]In these specifications, each $(e, j, w)$ observation is weighted by the number of live discharged patients.

patients in the last three months of the fiscal year who would take 0.047 log point (4.8%) 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.

Fifth, we examine trends in treatment patterns for active patients.[35] Tables A11-A13 and figures A23-A29 present the corresponding estimates of $\beta$ and $(\beta_w : w \in W)$. The estimates 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.[36] The estimates 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.

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 AV.A. 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 AV.B. 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 streamlined method era. We did not find other evidence of significant heterogeneity along these dimensions.

In sum, our estimates support the idea that the cap influences hospice programs' enrollment and live discharge rates. With respect to enrollments, they indicate that programs on track to exceed the cap in an outgoing fiscal year increase enrollment rates in the fiscal year's last three months, especially when each enrollment could reduce their cap liability by tens of thousands of dollars during the streamlined method era. They also indicate that these 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 have poorer outcomes on average (i.e., they experience more lifetime live discharges and are less likely to ultimately die in hospice care). With respect to live discharges, our estimates indicate that programs on track to

[35] In these specifications, each $(e, j, w)$ observation is weighted by the number of active patients. Figure A32 shows that the number of active patients differentially decreases at programs on track to exceed the cap throughout the event window on average.

[36] In this analysis, we excluded programs $(e, j)$ that provided no patient-days of RHC, CHC, IRC, or GIC, respectively, in either $t^O_e$ or $t^I_e$. However, including these programs does not significantly change our results.

exceed the cap in an outgoing fiscal year increase live discharge rates in the fiscal year's last three months on average, especially when each marginal hospice patient-day contributes nothing to their net revenues or their cap censuses, as was often the case during the streamlined method era.

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 1.55 additional enrollments and 0.36 additional live discharges throughout the outgoing fiscal year's last three months on average.[37] 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 (6.9%) on average in the last three months of an outgoing fiscal year, but their cap liabilities remain at approximately $497,000 on average. (See table 1 and figure A30.) That hospice programs do not further reduce their cap liabilities by enrolling more patients or live discharging 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.

## VI. Conclusion and policy implications

Health policy intended to cut costs arising from overutilization may raise social surplus—if it reduces utilization. In this paper, we document evidence that hospice programs make limited intensive margin responses to the aggregate payment cap in the Medicare hospice benefit. We find that programs that exceed the cap have an approximately $500,000 cap liability on average per year and that the wage index—a significant, visible, and administratively set determinant of daily payment rates—is nevertheless a significant predictor of cap liabilities. We do not find evidence of bunching in programs' average annual payments per patient around the cap. We also find that programs on track to exceed the cap in an outgoing fiscal year increase their enrollment and live discharge rates by 5.7% and 4.3% respectively during the fiscal year's last three months on average. But these estimates amount to only 1.55 additional enrollees and 0.36 additional live discharges on average. Together, our estimates suggest that hospice programs face barriers to adjusting their census to minimize their cap liabilities. While our estimates—especially as they pertain to enrollment—support the idea that provider-induced demand exists, they also suggest that its magnitude is small in this

[37] 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 0.252 and 0.156, respectively, among programs that were on track to exceed the cap in the outgoing fiscal year. We computed $7 \times 0.252 \sum_{w<0} \big(\exp(\hat{\beta}_w) - 1\big)$ 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 tables 6 and 7.

context.

Our work has several policy implications. First, that hospice programs incur larger cap liabilities when the wage index raises their daily payment rates supports MedPAC (2022)'s suggestion 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 in one fiscal year are 5.8 percentage points more likely to be terminated in the next fiscal year on average. We caution that causal inference with respect to CCN terminations is complicated by the possibility that unobserved factors—such as poor management or decreasing market-level 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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| | All | All | 10% of cap | | 20% of cap | All |
|---|---|---|---|---|---|---|
| | | Above-cap | | Below-cap | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Patient volume and cap census** | | | | | | |
| Unique patients | 353 | 178 | 249 | 376 | 360 | 376 |
| Patient-days | 23,492 | 20,745 | 26,387 | 36,423 | 33,888 | 23,849 |
| Cap census | 270 | 105 | 156 | 248 | 242 | 2,912 |
| Patient-days per unique patient | 71 | 122 | 107 | 101 | 97 | 65 |
| Cap census contr. per unique patient | 0.76 | 0.56 | 0.62 | 0.64 | 0.66 | 0.78 |
| Stl. method fraction of patient-days (pre-'11) | 0.85 | 0.66 | 0.71 | 0.74 | 0.76 | 0.87 |
| Prop. method fraction of patient-days (pre-'11) | 0.15 | 0.34 | 0.29 | 0.26 | 0.24 | 0.13 |
| **Gross Medicare payments** | | | | | | |
| Payments ($K) | 3,640 | 3,017 | 4,009 | 5,829 | 5,293 | 3,721 |
| Payments per patient-day ($) | 146 | 148 | 150 | 149 | 149 | 146 |
| Payments per unique patient ($) | 10,306 | 17,649 | 15,771 | 14,891 | 14,263 | 9,353 |
| Payments per cap census unit (PPP) ($) | 15,239 | 33,595 | 26,393 | 23,826 | 22,353 | 12,855 |
| **Cap liabilities and net Medicare payments** | | | | | | |
| Cap ($) | 24,047 | 24,930 | 25,215 | 25,136 | 25,092 | 23,932 |
| PPP/Cap | 0.63 | 1.35 | 1.05 | 0.95 | 0.89 | 0.53 |
| Cap liability ($K) | 57 | 497 | 166 | 0.00 | 0.00 | 0.00 |
| Payments net of cap liability ($K) | 3,583 | 2,520 | 3,843 | 5,829 | 5,293 | 3,721 |
| Net payments per patient-day ($) | 143 | 117 | 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) | 57,413 | 6,598 | 2,017 | 2,925 | 6,820 | 50,815 |
| Unique programs | 5,685 | 2,212 | 1,278 | 1,603 | 2,517 | 5,300 |

**Tab. 1.** This table reports descriptive statistics about the (program, fiscal year)-level sample, especially as they pertain to the cap. Among other things, it shows that programs that exceed the cap have substantial cap liabilities on average. It also shows that they treat fewer unique patients, their patients contribute less to their annual cap censuses, their patients have longer LOS in hospice care that year, and their daily payments net of their cap liabilities are 21% less than their gross daily payments ($117 vs. $148) on average. See the discussion near page 13. Columns (3) and (4) describe hospice program-years near the cap. Column (5) describes the hospice program-years in the range of average annual payments per patient targeted by MedPAC (2020)'s proposal.

| | | Above-cap | | | Below-cap | |
|---|---|---|---|---|---|---|
| | All | All | 10% of cap | | 20% of cap | All |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Age and ownership** | | | | | | |
| Age | 12.27 | 6.19 | 7.26 | 8.28 | 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 | 105 | 157 | 249 | 242 | 293 |
| Live discharges | 56 | 57 | 62 | 77 | 72 | 56 |
| % hospitalized within 7 days of enrollment | 0.35 | 0.24 | 0.27 | 0.29 | 0.30 | 0.37 |
| % in a NH within 7 days of enrollment | 0.27 | 0.19 | 0.24 | 0.28 | 0.30 | 0.28 |
| % elsewhere within 7 days of enrollment | 0.46 | 0.62 | 0.55 | 0.51 | 0.49 | 0.44 |
| **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 | 0.982 | 0.992 | 0.992 | 0.990 | 0.990 | 0.980 |
| Fraction of patient-days with CHC | 0.001 | 0.002 | 0.001 | 0.002 | 0.002 | 0.000 |
| Fraction of patient-days with IRC | 0.002 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 |
| Fraction of patient-days with GIC | 0.012 | 0.004 | 0.003 | 0.005 | 0.005 | 0.014 |
| **Other characteristics** | | | | | | |
| 1[Patient-day at a NH] | 0.23 | 0.14 | 0.19 | 0.23 | 0.25 | 0.25 |
| 1[At least one NH patient] | 0.95 | 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) | 57,413 | 6,598 | 2,017 | 2,925 | 6,820 | 50,815 |
| Unique programs | 5,685 | 2,212 | 1,278 | 1,603 | 2,517 | 5,300 |

**Tab. 2.** This table reports descriptive statistics about the (program, fiscal year)-level sample. Among other things, it shows that 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. It also shows that they enroll fewer patients, live discharge a larger fraction of patients, and enroll fewer patients with a recent hospital or nursing home stay on average. However, it is unclear how much of these differences are attributable to the cap versus other program or regional factors. We isolate variation attributable to the cap in our difference-in-differences analysis below. Finally, this table shows that programs that exceed the cap are more likely to close next year. See the discussion near page 14. Columns (3) and (4) describe hospice program-years near the cap. Column (5) describes the hospice program-years in the range of average annual payments per patient targeted by MedPAC (2020)'s proposal.

| | | Above-cap | | | Below-cap | |
|---|---|---|---|---|---|---|
| | All | All | 10% of cap | | 20% of cap | 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 | 0.83 | 0.82 | 0.84 | 0.88 |
| 1[Black] | 0.08 | 0.13 | 0.10 | 0.10 | 0.10 | 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 | 81.71 | 81.64 | 82.27 | 82.39 | 82.26 | 81.71 |
| **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 | 0.94 | 0.96 | 0.97 | 0.97 | 0.98 |
| Age at death (decedents) | 82.11 | 82.89 | 83.14 | 83.06 | 82.90 | 82.08 |
| Remaining days of life (decedents) | 133 | 349 | 257 | 210 | 201 | 123 |
| Remaining days of life | 175 | 433 | 316 | 253 | 243 | 162 |
| 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, K) | 15,627 | 705 | 319 | 731 | 1,660 | 14,922 |

**Tab. 3.** This table reports descriptive statistics about the sample of hospice patients. It shows that patients enrolling in program-years that exceed the cap have longer average lifetime LOS in hospice care, are treated at more hospice programs, and are live discharged more frequently. It also shows that they have longer remaining lifetimes and are less likely to ultimately die in hospice. 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 then assigned to a column based on the program's cap liability in that day's fiscal year. Decedents are identified by a non-missing date of death. For non-decedents, remaining days of life is calculated through the end of our sample of claims data (i.e., 12/31/2019). See the discussion near page 14. Columns (3) and (4) describe patients who enrolled in program-years near the cap. Column (5) describes the patients who enrolled in program-years in the range of average annual payments per patient targeted by MedPAC (2020)'s proposal.

| | 1[Over cap] | Liability | Liability per unique patient | Gross Medicare payments | PPP |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Log(WI) | 0.112*** | 4.647*** | 2.870** | 0.221 | 0.406*** |
| | (0.022) | (1.049) | (1.154) | (0.171) | (0.062) |
| 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 | 1.80e+05 | 3,110 | 3.67e+06 | 15,160 |
| $N$ | 56,201 | 17,514 | 17,444 | 56,210 | 56,201 |
| Clusters | 5,247 | 2,080 | 2,073 | 5,247 | 5,247 |

| | Medicare payments per patient-day | | | |
|---|---|---|---|---|
| | Gross | Net | Gross | Net |
| | (6) | (7) | (8) | (9) |
| Log(WI) | 0.320*** | 0.293*** | 0.340*** | 0.197*** |
| | (0.038) | (0.036) | (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 |
| $N$ | 56,210 | 56,210 | 18,389 | 18,389 |
| Clusters | 5,247 | 5,247 | 2,231 | 2,231 |

| | Annual cap census contribution per patient | Cap census | Number of unique patients | Number of patient-days |
|---|---|---|---|---|
| | (10) | (11) | (12) | (13) |
| Log(WI) | -0.003 | -0.105 | -0.085 | -0.046 |
| | (0.009) | (0.084) | (0.089) | (0.127) |
| 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 | - | - | - | - |
| $\bar{Y}$ | 0.759 | 273 | 357 | 23,616 |
| $N$ | 56,208 | 56,210 | 56,210 | 56,210 |
| Clusters | 5,247 | 5,247 | 5,247 | 5,247 |

**Tab. 4.** 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 $\beta$ using ordinary least squares. We relate $\exp(f_{jt})$ to the conditional expectations of other non-negative outcomes $Y_{jt}$ to estimate $\beta$ using the Poisson pseudo-maximum likelihood estimator (Wooldridge, 1999). Program-level cluster-robust SEs in parentheses. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. See the discussion near 15.

| | 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*** | 1.233*** | 0.725*** | 0.072 | 0.162*** | 0.056*** |
| | (0.010) | (0.057) | (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 | 1.95e+05 | 2,989 | 3.91e+06 | 15,257 | 0.025 |
| $N$ | 51,210 | 15,463 | 15,417 | 51,217 | 51,210 | 52,926 |
| Clusters | 4,879 | 1,891 | 1,885 | 4,880 | 4,879 | 5,376 |

| | 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*** | -0.078*** | -0.109** | -0.027 | 0.093** |
| | (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 | 0.753 | 286 | 376 | 25,050 |
| $N$ | 51,217 | 51,217 | 51,217 | 51,217 | 51,217 | 51,217 |
| Clusters | 4,880 | 4,880 | 4,880 | 4,880 | 4,880 | 4,880 |

**Tab. 5.** 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 $\beta$ using ordinary least squares. We relate $\exp(f_{jt})$ to the conditional expectations of other non-negative outcomes $Y_{jt}$ to estimate $\beta$ using the Poisson pseudo-maximum likelihood estimator (Wooldridge, 1999). Program-level cluster-robust SEs in parentheses. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. See the discussion near 16.

| | Daily new enrollments (log diff.) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| **Static model: Year-end average DID** | | | |
| $\beta$ | 0.055*** | 0.093*** | 0.035*** |
| | (0.007) | (0.012) | (0.008) |
| **Dynamic model: DID relative to week 0** | | | |
| $\beta_{-4}$ | 0.061*** | 0.109*** | 0.035 |
| | (0.020) | (0.029) | (0.026) |
| $\beta_{-3}$ | 0.059*** | 0.111*** | 0.029 |
| | (0.020) | (0.035) | (0.024) |
| $\beta_{-2}$ | 0.084*** | 0.150*** | 0.046** |
| | (0.017) | (0.031) | (0.020) |
| $\beta_{-1}$ | 0.151*** | 0.256*** | 0.088*** |
| | (0.019) | (0.035) | (0.021) |
| $\beta_0$ | - | - | - |
| $\beta_1$ | 0.030* | 0.025 | 0.032 |
| | (0.016) | (0.028) | (0.020) |
| $\beta_2$ | -0.009 | -0.009 | -0.010 |
| | (0.017) | (0.030) | (0.020) |
| $\beta_3$ | -0.000 | -0.001 | 0.001 |
| | (0.017) | (0.029) | (0.021) |
| Estimator | PPML | PPML | PPML |
| Event range | 01-18 | 01-11 | 12-18 |
| Hospice FE | Y | Y | Y |
| Period FE | Y | Y | Y |
| B-line $Y$ | 0.252 | 0.259 | 0.249 |
| $N$ | 1,407,556 | 734,951 | 672,605 |
| Clusters | 5,554 | 3,788 | 4,983 |
| $\lvert\mathcal{T}\rvert$ | 5,137 | 1,826 | 3,311 |
| $\lvert\mathcal{U}\rvert$ | 49,010 | 26,446 | 22,564 |

**Tab. 6.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) in our difference-in-differences analysis. 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. See the discussion near page 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. Baseline $Y$ is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Estimates of the remaining $\beta_w$ are excluded from the table for space; they are presented in figure 3.

| | Daily live discharges (log diff.) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| **Static model: Year-end average DID** | | | |
| $\beta$ | 0.042*** | 0.067*** | 0.023* |
| | (0.010) | (0.016) | (0.013) |
| **Dynamic model: DID relative to week 0** | | | |
| $\beta_{-4}$ | 0.036 | 0.068* | 0.011 |
| | (0.029) | (0.036) | (0.043) |
| $\beta_{-3}$ | 0.010 | 0.007 | 0.012 |
| | (0.028) | (0.038) | (0.040) |
| $\beta_{-2}$ | 0.036 | 0.068* | 0.012 |
| | (0.028) | (0.040) | (0.039) |
| $\beta_{-1}$ | 0.053* | 0.033 | 0.068* |
| | (0.028) | (0.040) | (0.037) |
| $\beta_0$ | - | - | - |
| $\beta_1$ | -0.013 | -0.046 | 0.013 |
| | (0.026) | (0.037) | (0.034) |
| $\beta_2$ | -0.045* | -0.026 | -0.059 |
| | (0.027) | (0.038) | (0.039) |
| $\beta_3$ | -0.052* | -0.040 | -0.062 |
| | (0.029) | (0.041) | (0.040) |
| Estimator | PPML | PPML | PPML |
| Event range | 01-18 | 01-11 | 12-18 |
| Hospice FE | Y | Y | Y |
| Period FE | Y | Y | Y |
| B-line $Y$ | 0.156 | 0.210 | 0.125 |
| $N$ | 1,372,156 | 713,279 | 658,877 |
| Clusters | 5,530 | 3,768 | 4,970 |
| $\|\mathcal{T}\|$ | 5,163 | 1,878 | 3,285 |
| $\|\mathcal{U}\|$ | 47,533 | 25,502 | 22,031 |

**Tab. 7.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge more patients in the weeks leading up to the end of the fiscal year. See the discussion near page 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. Baseline $Y$ is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Estimates of the remaining $\beta_w$ are excluded from the table for space; they are presented in figure 4.

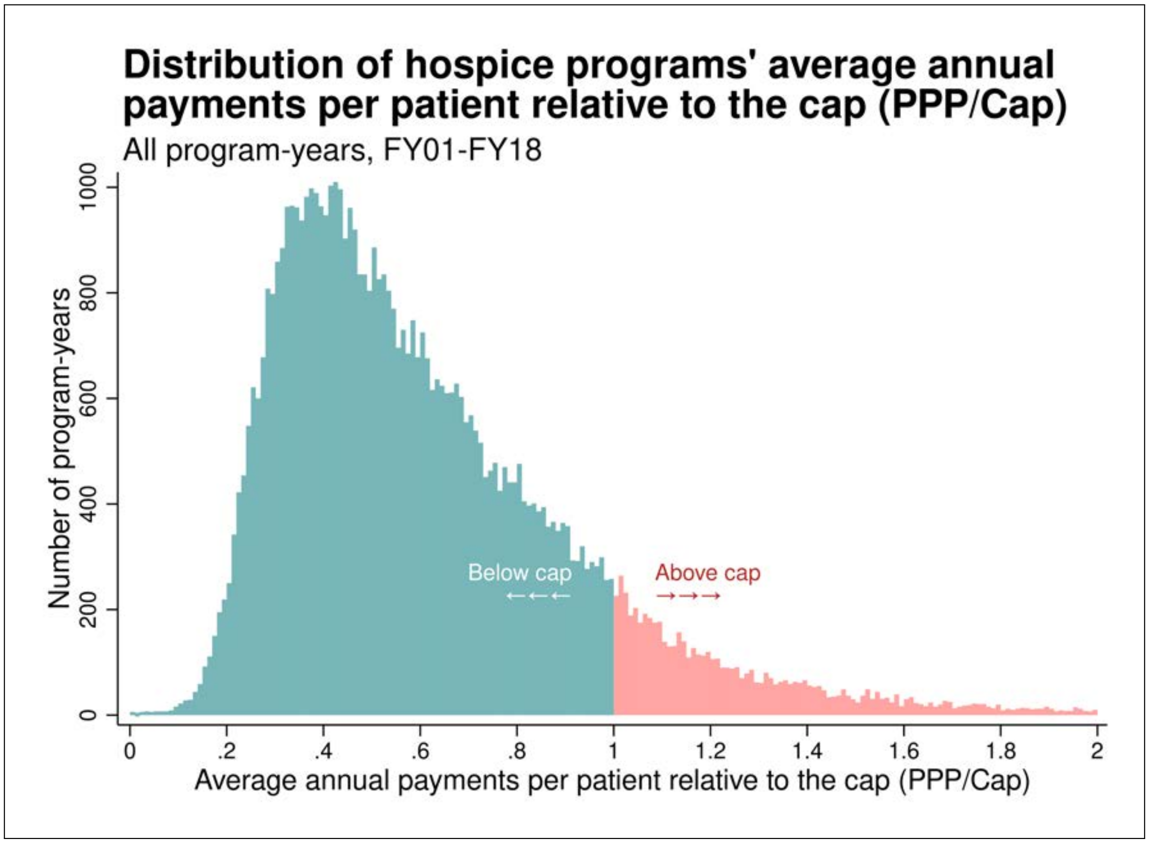


**Fig. 1.** This figure plots the distribution of $\text{PPP}_{jt}/\text{Cap}_{jt}$—i.e., hospice programs' average annual payments per patient relative to the cap. The figure is censored at $\text{PPP}_{jt}/\text{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See the discussions near page 15 and table A2.

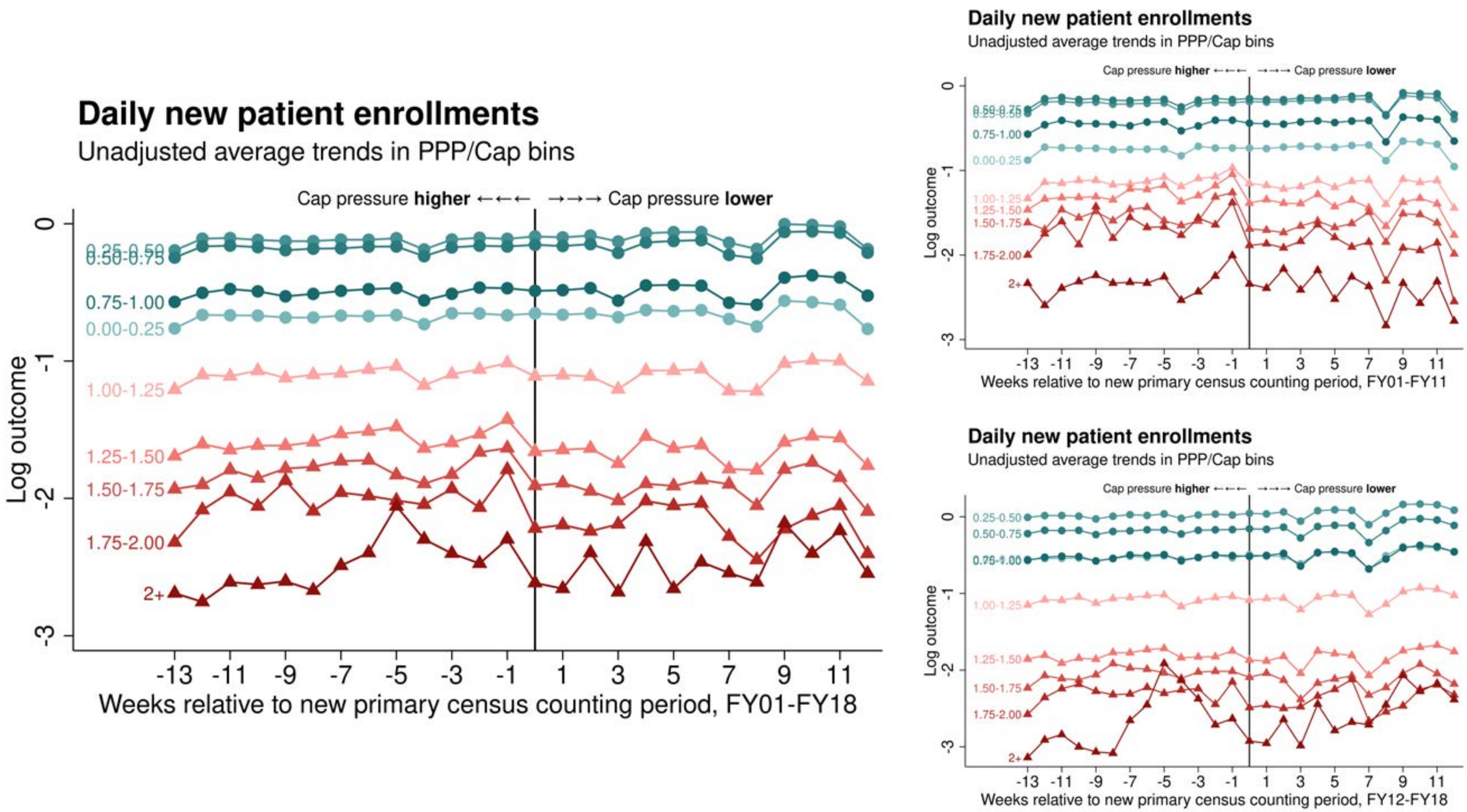


**Fig. 2.** In each panel, this figure plots raw trends in average enrollment rates for hospice programs grouped into nine bins of rolling average annual payments per patient as of the beginning of the 180-day event window. It illustrates the challenges with identifying the cap's effect on enrollment rates—that is, the level differences between programs on track to exceed the cap and programs on track to remain below the cap, and seasonality. But it also shows the variation that is generated by cap-related financial incentives and isolated by our difference-in-differences research design. In particular, it shows that programs on track to exceed the cap in a given fiscal year differentially enroll more patients during the fiscal year's final weeks than programs on track to remain below the cap. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom). See the discussions near page 17. Figure 3 plots the difference-in-differences estimates corresponding to this outcome.

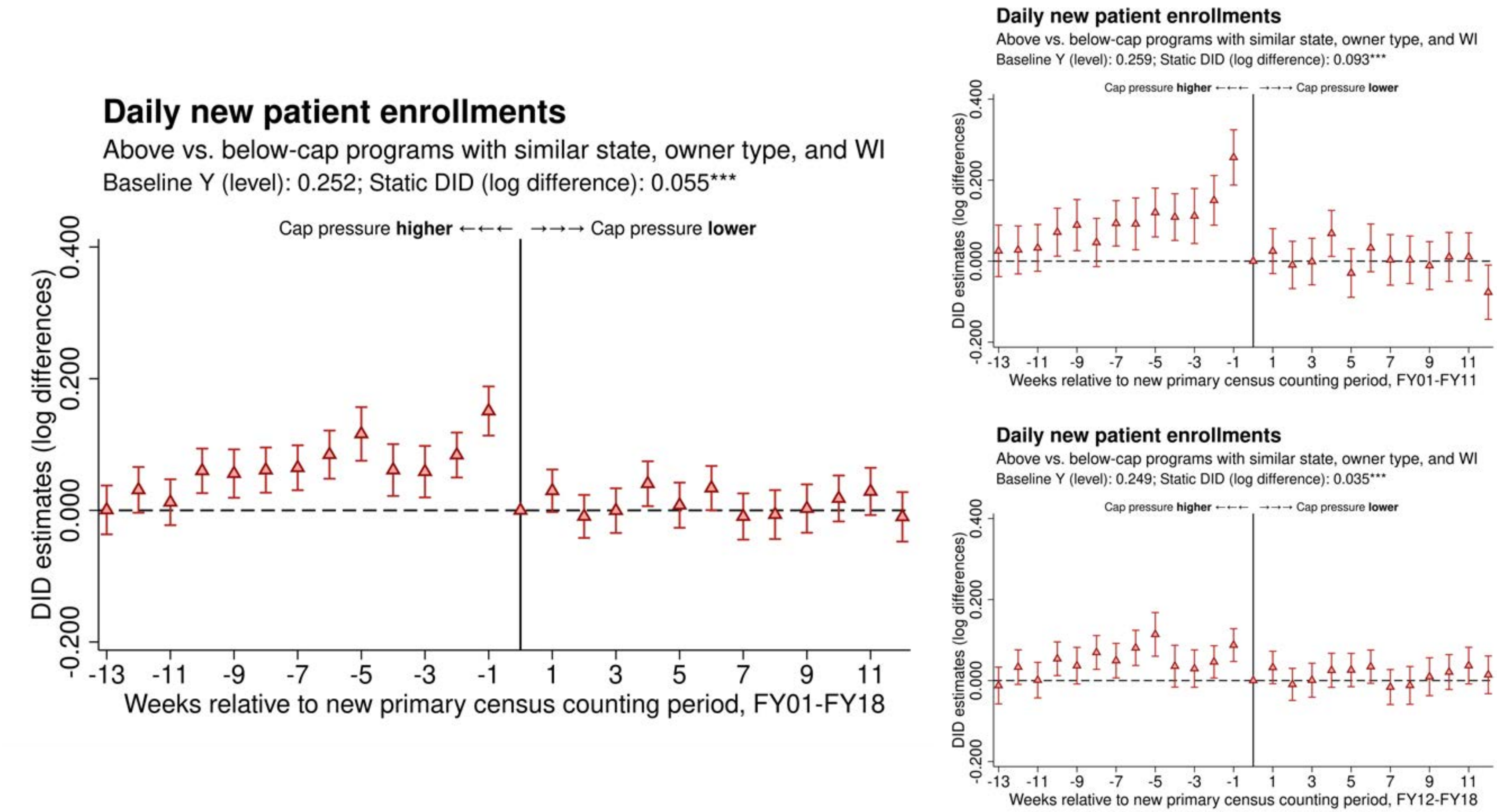


**Fig. 3.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year. See table 6 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. Baseline $Y$ is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

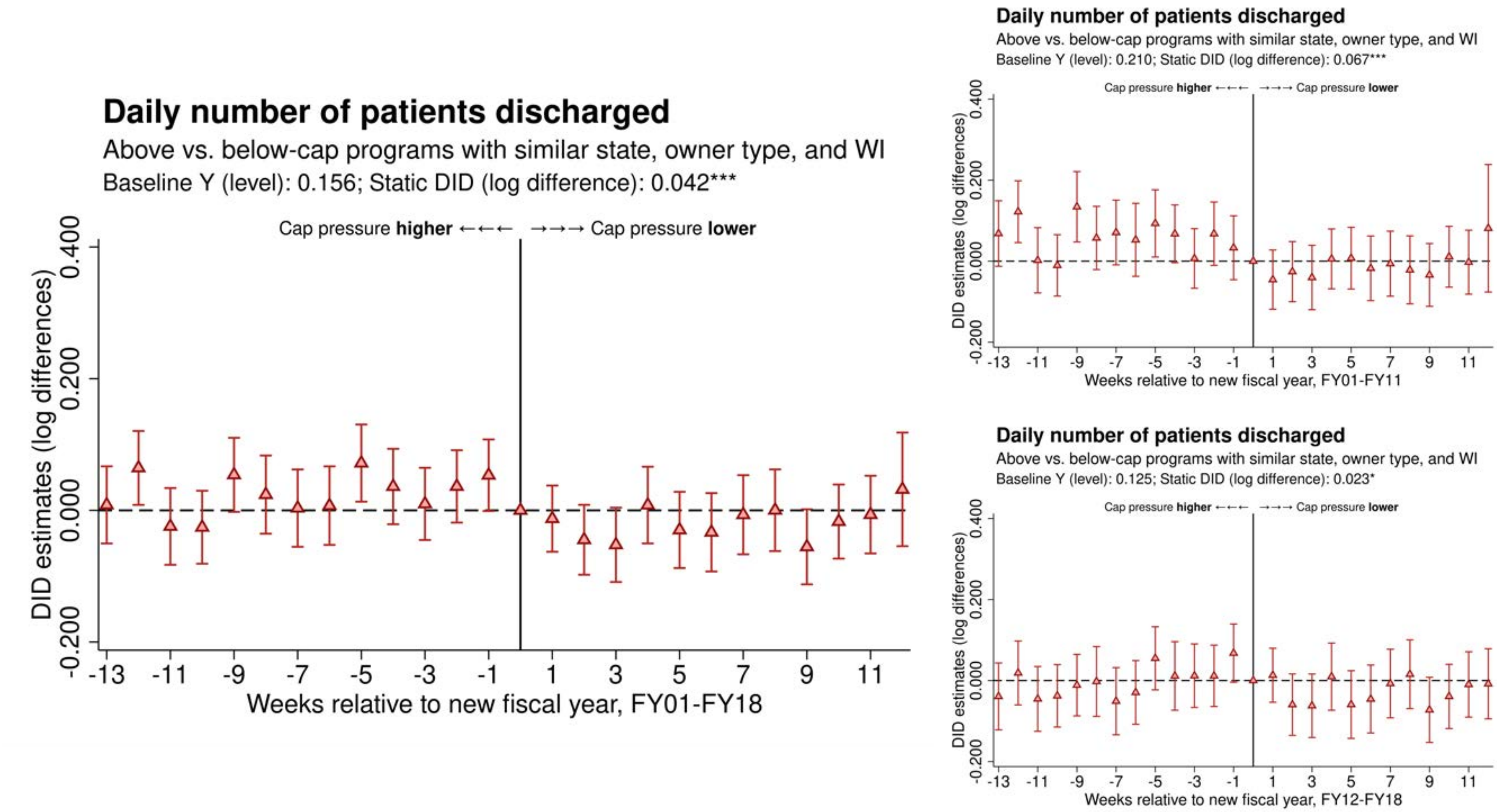


**Fig. 4.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge more patients in the weeks leading up to the end of the fiscal year. See table 7 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. Baseline $Y$ is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

Provider payment incentives: evidence from the U.S. hospice industry
By Norma B. Coe and David A. Rosenkranz.
September 8, 2023

Appendix

# AI. Application of the payment cap

## A. 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.[38] The cap has grown from $6,500 at the inception of the hospice benefit to $32,487 in FY 2023.

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.[39]

## B. 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 $t$.

## C. 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.

[38]Federal Register, vol. 80(151): 47207.
[39]Medicare hospice transmittal 156.

### D. 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 $\mathrm{PD}(i, j, d)$ be the per diem payment made to $j$ for beneficiary $i$'s care on $d$. Then for every $(j, t)$, total payments were:

$$\text{Payment}_{jt} := \sum_{d:t(d)=t} \sum_{i:a(i,j,d)=1} \mathrm{PD}(i, j, d) \tag{4}$$

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.[40]

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 $k(i, d) \in \{\mathrm{RHC}, \mathrm{CHC}, \mathrm{IRC}, \mathrm{GIC}\}$ indicate whether beneficiary $i$ received RHC, CHC, IRC, or GIC on day $d$. Let $\mathrm{BP}_k(i, j, d)$ be the beneficiary's base payment

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

rate on day $d$ at program $j$ for treatment type $k$. (Recall that for a given $(j, d)$, $\mathrm{BP}_k(i, j, d)$ does not vary with $i$ unless $k = \mathrm{RHC}$.) Let $\mathrm{LS}_k$ be the labor share for treatment type $k$. Finally, let $\mathrm{WI}(j, t)$ be the wage index adjustment for program $j$ in fiscal year $t$. Then the per diem rates were:

$$\mathrm{PD}(i, j, d) := \sum_k 1[k(i, d) = k]\Big(\mathrm{BP}_k(i, j, d)(1 - LS_k) + \mathrm{BP}_k(i, j, d)\mathrm{LS}_k\mathrm{WI}(j, t(d))\Big) \qquad (5)$$

### E. 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 $t \in \{2001, ..., 2016\}$ 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 $(j, t)$.[41] 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. 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.[42]

[41]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.

[42]Medicare hospice transmittal 156.

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 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.[43]

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.[44]

Only 486 hospice programs used the streamlined method in FY 2013.[45] 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

[43]Medicare hospice transmittal 156.
[44]Medicare hospice transmittal 156.
[45]Federal Register, vol. 80(151): August 6, 2015

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.[46]

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 $t + 3$.

## AII. 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.)

[46] Medicare hospice transmittal 156.

## AIII. 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.[47] 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%.

## AIV. Data

### A. 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."

[47] 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.")

### B. 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 A31 reports difference-in-differences estimates of equations (2) and (3) 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 13.

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.

### C. 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 identified the programs' earliest observed Medicare certification dates to determine their ages.[48]

We also used the hospice claims data to identify the first and last dates a hospice program's CCN

[48]When certification dates were missing or contradicted claims data, we used the claims data to determine approximate certification dates. See appendix AII.

is associated with a hospice claim. See appendix AII 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. 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.

### E. Nursing home stays

We constructed nursing home spells using the Minimum Dataset ("MDS," hereafter). 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. There were approximately 135.1M unique (patient, nursing home, day) observations in the MDS corresponding to 9.99M patients who appeared in the hospice claims between 2000 and 2019. 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. After applying such exclusions, there were 133.9M unique observations corresponding to 9.90M hospice patients.

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.

## F. 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.

## G. 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:

$$D_{jzt} := \sum_{j' \in J_{zt} \setminus \{j\}} 1[\text{Over the cap}]_{j't} \left( \frac{|I_{j'zt}|}{\sum_{j' \in J_{zt} \setminus \{j\}} |I_{j'zt}|} \right) \tag{6}$$

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:

$$D_{jt} := \sum_{z:j\in J_{zt}} D_{jzt}\left(\frac{|I_{jzt}|}{\sum_{z:j\in J_{zt}} |I_{jzt}|}\right) \tag{7}$$

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.

### H. 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. We determined days that hospice patients spent in the hospital using the admission and discharge dates associated with each hospital 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.

### I. 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.

### J. 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.

## AV. Difference-in-differences

### A. 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.[49] 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 (2) and (3) with $\mathrm{FE}_{ew}$. 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.

### B. 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 (2) for covari-

[49] 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.

ates $X_{ej}^O$ measured at the start of the event windows. Likewise, we substituted $1[(e,j) \in \mathcal{T}]1[w = w']\beta_{w'}$ with $1[w = w']X_{ej}^O\beta_{w'}^{\mathrm{X}} + 1[(e,j) \in \mathcal{T}]1[w = w']\beta_{w'}^{\mathrm{T}} + 1[(e,j) \in \mathcal{T}]1[w = w']X_{ej}^O\beta_{w'}^{\mathrm{XT}}$ in equation (3). In order to examine heterogeneity by profit status, we defined $X_{ej}^O$ as an indicator for whether hospice $j$ was for-profit in fiscal year $t_e^O$. In order to examine heterogeneity across cap census, we defined $X_{ej}^O$ as the log of program $j$'s cumulative cap census in FY $t_e^O$ at the beginning of $e$'s event window. In order to examine heterogeneity across proximity to other hospice programs on track to exceed the cap, we defined $X_{ej}^O$ 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 AIV.G for details. In order to examine heterogeneity by association with a nursing home, we defined $X_{ej}^O$ as an indicator for whether hospice $j$ shared any patient-day with a nursing home in fiscal year $t_e^O$.

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

| Obs. num. | (1) Patient ID | (2) Provider ID | (3) Fiscal year | (4) Days | (5) Provider's census counting method | (6) Cap census contribution |
|---|---|---|---|---|---|---|
| 1 | 1 | A | 2009 | 2 | S | 1 |
| 2 | 1 | A | 2010 | 1 | S | 0 |
| 3 | 2 | A | 2009 | 1 | S | 0.33 |
| 4 | 2 | B | 2009 | 1 | S | 0.33 |
| 5 | 2 | B | 2010 | 1 | S | 0.33 |
| 6 | 3 | A | 2012 | 2 | P | 0.67 |
| 7 | 3 | A | 2013 | 1 | P | 0.33 |

**Tab. A1.** This table presents illustrative examples of the census counting methods for three hypothetical patients. Each patient's lifetime LOS in hospice care is three days. Patient 1 is only ever enrolled with program A while program A uses the streamlined method. She contributes to program A's cap census only in her first fiscal year of hospice care. Patient 2 is enrolled with programs A and B while both programs use the streamlined method. She contributes to each program's cap census 1/3 in each fiscal year. Finally, patient 3 is enrolled with program A while program A uses the proportional method. She contributes to program A's cap census 1/3 on each patient-day as well. See the discussion near page 8.

| | Samples | | | |
|---|---|---|---|---|
| | Full | For-profit | Cap census above annual median | Ever over the cap |
| | (1) | (2) | (3) | (4) |
| **Estimates** | | | | |
| Test statistic | 0.0855 | 0.1621 | -0.9555 | 1.9665 |
| $p$-value | 0.9319 | 0.8712 | 0.3393 | 0.0492 |
| **Upper bandwidth** | | | | |
| Range | 0.147 | 0.156 | 0.158 | 0.135 |
| Observations | 6,598 | 5,791 | 1,430 | 6,598 |
| Effective observations | 2,666 | 2,410 | 913 | 2,499 |
| **Lower bandwidth** | | | | |
| Range | 0.204 | 0.187 | 0.228 | 0.151 |
| Observations | 50,815 | 23,687 | 27,275 | 12,417 |
| Effective observations | 7,002 | 5,124 | 3,696 | 3,522 |

**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 1 plots this distribution for column (1) (i.e., the full distribution). Figures A3-A5 plot the distributions for the sub-samples corresponding to columns (2)-(4). See the discussion near page 15.

| | 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** | | | | | | |
| $\beta$ | 0.020*** | 0.021* | 0.019** | 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** | | | | | | |
| $\beta_{-4}$ | 0.026 | 0.022 | 0.029 | -0.004 | -0.004 | -0.004 |
| | (0.026) | (0.043) | (0.033) | (0.007) | (0.011) | (0.008) |
| $\beta_{-3}$ | 0.008 | -0.013 | 0.022 | -0.008 | -0.006 | -0.009 |
| | (0.026) | (0.044) | (0.033) | (0.007) | (0.012) | (0.008) |
| $\beta_{-2}$ | 0.029 | -0.019 | 0.064** | 0.001 | 0.000 | 0.001 |
| | (0.026) | (0.042) | (0.032) | (0.007) | (0.011) | (0.008) |
| $\beta_{-1}$ | 0.043* | 0.043 | 0.042 | 0.003 | 0.005 | 0.001 |
| | (0.026) | (0.040) | (0.035) | (0.007) | (0.011) | (0.008) |
| $\beta_0$ | - | - | - | - | - | - |
| $\beta_1$ | 0.003 | -0.021 | 0.020 | -0.007 | -0.020* | 0.000 |
| | (0.027) | (0.044) | (0.034) | (0.007) | (0.011) | (0.008) |
| $\beta_2$ | 0.017 | 0.001 | 0.028 | 0.003 | -0.008 | 0.009 |
| | (0.026) | (0.043) | (0.033) | (0.007) | (0.012) | (0.008) |
| $\beta_3$ | 0.012 | 0.005 | 0.015 | -0.000 | -0.001 | 0.000 |
| | (0.026) | (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 | 217 | 162 | 1.220 | 1.282 | 1.184 |
| $N$ | 1,142,877 | 601,897 | 540,980 | 1,142,877 | 601,897 | 540,980 |
| Clusters | 5,534 | 3,782 | 4,965 | 5,534 | 3,782 | 4,965 |
| $\|\mathcal{T}\|$ | 3,041 | 1,130 | 1,911 | 3,041 | 1,130 | 1,911 |
| $\|\mathcal{U}\|$ | 41,192 | 22,239 | 18,953 | 41,192 | 22,239 | 18,953 |

**Tab. A3.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A8 and A9.

| | 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** | | | | | | |
| $\beta$ | 0.019$^{**}$ | 0.028$^{**}$ | 0.012 | -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** | | | | | | |
| $\beta_{-4}$ | -0.024 | -0.025 | -0.023 | -0.001 | 0.005 | -0.005 |
| | (0.027) | (0.041) | (0.037) | (0.006) | (0.011) | (0.006) |
| $\beta_{-3}$ | 0.002 | 0.032 | -0.021 | -0.007 | -0.019 | -0.001 |
| | (0.027) | (0.041) | (0.037) | (0.006) | (0.012) | (0.006) |
| $\beta_{-2}$ | -0.006 | -0.013 | 0.001 | 0.006 | 0.003 | 0.008 |
| | (0.029) | (0.047) | (0.036) | (0.006) | (0.011) | (0.006) |
| $\beta_{-1}$ | 0.015 | 0.039 | -0.005 | -0.011$^{**}$ | -0.018$^{*}$ | -0.006 |
| | (0.027) | (0.039) | (0.037) | (0.005) | (0.011) | (0.006) |
| $\beta_0$ | - | - | - | - | - | - |
| $\beta_1$ | -0.039 | -0.091$^{**}$ | 0.001 | -0.003 | -0.000 | -0.005 |
| | (0.027) | (0.039) | (0.037) | (0.005) | (0.011) | (0.006) |
| $\beta_2$ | -0.028 | -0.068 | 0.001 | 0.000 | 0.003 | -0.001 |
| | (0.028) | (0.045) | (0.036) | (0.005) | (0.011) | (0.006) |
| $\beta_3$ | 0.013 | 0.019 | 0.007 | -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 | 0.865 | 0.781 | 0.915 |
| $N$ | 1,123,833 | 591,515 | 532,318 | 1,139,018 | 604,221 | 534,797 |
| Clusters | 5,513 | 3,766 | 4,951 | 5,508 | 3,787 | 4,942 |
| $\lvert\mathcal{T}\rvert$ | 3,022 | 1,124 | 1,898 | 2,886 | 1,116 | 1,770 |
| $\lvert\mathcal{U}\rvert$ | 40,491 | 21,827 | 18,664 | 41,223 | 22,352 | 18,871 |

**Tab. A4.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A10 and A11.

| | 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** | | | | | | |
| $\beta$ | -0.010*** | -0.020*** | -0.004 | -0.006*** | -0.010*** | -0.004 |
| | (0.002) | (0.004) | (0.003) | (0.002) | (0.004) | (0.002) |
| **Dynamic model: DID relative to week 0** | | | | | | |
| $\beta_{-4}$ | -0.021*** | -0.047*** | -0.007 | -0.011* | -0.014 | -0.009 |
| | (0.007) | (0.012) | (0.009) | (0.007) | (0.011) | (0.008) |
| $\beta_{-3}$ | -0.010 | -0.023* | -0.003 | -0.010 | -0.014 | -0.007 |
| | (0.007) | (0.012) | (0.009) | (0.007) | (0.012) | (0.008) |
| $\beta_{-2}$ | -0.016** | -0.034*** | -0.006 | -0.022*** | -0.021* | -0.023*** |
| | (0.007) | (0.012) | (0.009) | (0.007) | (0.011) | (0.008) |
| $\beta_{-1}$ | -0.024*** | -0.042*** | -0.014 | -0.001 | -0.005 | 0.001 |
| | (0.007) | (0.012) | (0.009) | (0.007) | (0.011) | (0.008) |
| $\beta_0$ | - | - | - | - | - | - |
| $\beta_1$ | -0.005 | -0.008 | -0.004 | -0.011* | -0.013 | -0.010 |
| | (0.007) | (0.012) | (0.009) | (0.007) | (0.011) | (0.008) |
| $\beta_2$ | -0.014* | -0.023* | -0.009 | -0.011 | -0.005 | -0.014 |
| | (0.007) | (0.013) | (0.009) | (0.007) | (0.011) | (0.008) |
| $\beta_3$ | -0.015** | -0.037*** | -0.002 | -0.010 | -0.010 | -0.010 |
| | (0.008) | (0.013) | (0.010) | (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 | 0.271 | 0.284 | 0.229 | 0.225 | 0.232 |
| $N$ | 1,150,445 | 606,409 | 544,036 | 1,150,445 | 606,409 | 544,036 |
| Clusters | 5,540 | 3,788 | 4,974 | 5,540 | 3,788 | 4,974 |
| $\lvert\mathcal{T}\rvert$ | 3,044 | 1,132 | 1,912 | 3,044 | 1,132 | 1,912 |
| $\lvert\mathcal{U}\rvert$ | 41,485 | 22,419 | 19,066 | 41,485 | 22,419 | 19,066 |

**Tab. A5.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A12 and A13.

| | 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** | | | | | | |
| $\beta$ | 0.001 | 0.004 | -0.000 | 0.058$^{***}$ | 0.094$^{***}$ | 0.023$^{**}$ |
| | (0.001) | (0.003) | (0.002) | (0.010) | (0.017) | (0.010) |
| **Dynamic model: DID relative to week 0** | | | | | | |
| $\beta_{-4}$ | 0.003 | 0.002 | 0.003 | 0.068$^{**}$ | 0.094$^{*}$ | 0.042 |
| | (0.005) | (0.009) | (0.006) | (0.030) | (0.050) | (0.033) |
| $\beta_{-3}$ | 0.010$^{*}$ | 0.013 | 0.008 | 0.056$^{*}$ | 0.099$^{**}$ | 0.013 |
| | (0.006) | (0.013) | (0.005) | (0.029) | (0.048) | (0.034) |
| $\beta_{-2}$ | 0.003 | 0.004 | 0.002 | 0.050$^{*}$ | 0.071 | 0.031 |
| | (0.005) | (0.010) | (0.005) | (0.031) | (0.050) | (0.033) |
| $\beta_{-1}$ | 0.005 | 0.006 | 0.004 | 0.057$^{*}$ | 0.111$^{**}$ | -0.002 |
| | (0.005) | (0.009) | (0.006) | (0.029) | (0.046) | (0.035) |
| $\beta_0$ | - | - | - | - | - | - |
| $\beta_1$ | 0.002 | -0.002 | 0.004 | 0.000 | 0.001 | 0.000 |
| | (0.005) | (0.009) | (0.005) | (0.031) | (0.049) | (0.034) |
| $\beta_2$ | 0.003 | -0.002 | 0.006 | 0.018 | 0.007 | 0.027 |
| | (0.005) | (0.009) | (0.005) | (0.030) | (0.050) | (0.034) |
| $\beta_3$ | 0.006 | 0.011 | 0.003 | 0.019 | 0.035 | 0.002 |
| | (0.005) | (0.009) | (0.006) | (0.030) | (0.048) | (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 | 403 | 598 | 292 |
| $N$ | 1,150,445 | 606,409 | 544,036 | 1,142,688 | 601,770 | 540,918 |
| Clusters | 5,540 | 3,788 | 4,974 | 5,534 | 3,782 | 4,965 |
| $\lvert\mathcal{T}\rvert$ | 3,044 | 1,132 | 1,912 | 3,041 | 1,130 | 1,911 |
| $\lvert\mathcal{U}\rvert$ | 41,485 | 22,419 | 19,066 | 41,187 | 22,239 | 18,948 |

**Tab. A6.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A14 and A15

| | $\text{PPP}_{ijt}$ among enrollees counted proportionally in their first $(j,t)$ (log diff.) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| **Static model: Year-end average DID** | | | |
| $\beta$ | 0.012 | 0.027 | 0.011 |
| | (0.008) | (0.027) | (0.009) |
| **Dynamic model: DID relative to week 0** | | | |
| $\beta_{-4}$ | 0.017 | 0.084 | 0.011 |
| | (0.029) | (0.100) | (0.031) |
| $\beta_{-3}$ | 0.005 | -0.030 | 0.007 |
| | (0.030) | (0.101) | (0.032) |
| $\beta_{-2}$ | 0.027 | 0.046 | 0.025 |
| | (0.029) | (0.098) | (0.030) |
| $\beta_{-1}$ | 0.016 | 0.020 | 0.015 |
| | (0.030) | (0.093) | (0.032) |
| $\beta_0$ | - | - | - |
| $\beta_1$ | 0.028 | 0.142 | 0.016 |
| | (0.030) | (0.095) | (0.031) |
| $\beta_2$ | 0.029 | 0.082 | 0.023 |
| | (0.029) | (0.090) | (0.031) |
| $\beta_3$ | 0.006 | -0.066 | 0.012 |
| | (0.030) | (0.102) | (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 $Y$ | 28,466 | 55,131 | 26,039 |
| $N$ | 634,392 | 93,438 | 540,947 |
| Clusters | 5,392 | 2,982 | 4,965 |
| $\lvert\mathcal{T}\rvert$ | 2,283 | 372 | 1,911 |
| $\lvert\mathcal{U}\rvert$ | 22,326 | 3,373 | 18,953 |

**Tab. A7.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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—either because they enrolled during the streamlined method era and were ever associated with multiple hospice programs or because they enrolled during the proportional method era—with much the same $\text{PPP}_{ijt}$ in their first $jt$. See the discussion near page 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figure A16.

| | Fraction of enrollees with ADRD (% point diff.) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| **Static model: Year-end average DID** | | | |
| $\beta$ | 0.003 | 0.000 | 0.003 |
| | (0.002) | (0.004) | (0.002) |
| **Dynamic model: DID relative to week 0** | | | |
| $\beta_{-4}$ | 0.008 | 0.001 | 0.008 |
| | (0.008) | (0.014) | (0.008) |
| $\beta_{-3}$ | 0.018** | 0.009 | 0.018** |
| | (0.008) | (0.014) | (0.008) |
| $\beta_{-2}$ | 0.004 | -0.011 | 0.004 |
| | (0.008) | (0.013) | (0.008) |
| $\beta_{-1}$ | 0.008 | -0.011 | 0.008 |
| | (0.008) | (0.013) | (0.008) |
| $\beta_0$ | - | - | - |
| $\beta_1$ | 0.008 | -0.009 | 0.008 |
| | (0.008) | (0.014) | (0.008) |
| $\beta_2$ | 0.015* | -0.009 | 0.015* |
| | (0.008) | (0.014) | (0.008) |
| $\beta_3$ | -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 |
| $N$ | 1,150,445 | 606,409 | 1,150,445 |
| Clusters | 5,540 | 3,788 | 5,540 |
| $\lvert\mathcal{T}\rvert$ | 3,044 | 1,132 | 3,044 |
| $\lvert\mathcal{U}\rvert$ | 41,485 | 22,419 | 41,485 |

**Tab. A8.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 19. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figure A17.

| | 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** | | | | | | |
| $\beta$ | 0.014 | 0.012 | 0.015 | 0.047** | 0.058** | 0.032 |
| | (0.008) | (0.013) | (0.011) | (0.019) | (0.028) | (0.024) |
| **Dynamic model: DID relative to week 0** | | | | | | |
| $\beta_{-4}$ | -0.020 | -0.030 | -0.012 | 0.013 | -0.058 | 0.103 |
| | (0.027) | (0.040) | (0.037) | (0.068) | (0.103) | (0.083) |
| $\beta_{-3}$ | -0.006 | 0.004 | -0.014 | 0.124* | 0.156 | 0.081 |
| | (0.028) | (0.040) | (0.038) | (0.067) | (0.100) | (0.084) |
| $\beta_{-2}$ | -0.002 | -0.013 | 0.007 | 0.090 | 0.186* | -0.046 |
| | (0.028) | (0.041) | (0.040) | (0.065) | (0.097) | (0.084) |
| $\beta_{-1}$ | 0.010 | 0.042 | -0.014 | -0.012 | -0.099 | 0.092 |
| | (0.027) | (0.038) | (0.036) | (0.063) | (0.093) | (0.082) |
| $\beta_0$ | - | - | - | - | - | - |
| $\beta_1$ | -0.054* | 0.017 | -0.105*** | 0.003 | -0.005 | 0.014 |
| | (0.028) | (0.039) | (0.039) | (0.068) | (0.100) | (0.089) |
| $\beta_2$ | -0.012 | -0.012 | -0.012 | 0.013 | 0.052 | -0.045 |
| | (0.028) | (0.040) | (0.038) | (0.067) | (0.100) | (0.085) |
| $\beta_3$ | 0.005 | 0.030 | -0.013 | -0.017 | -0.032 | 0.000 |
| | (0.030) | (0.043) | (0.040) | (0.068) | (0.102) | (0.086) |
| 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 | 246 | 332 | 160 |
| $N$ | 676,730 | 359,089 | 317,641 | 498,656 | 249,125 | 249,531 |
| Clusters | 5,458 | 3,718 | 4,904 | 5,299 | 3,597 | 4,775 |
| $\|\mathcal{T}\|$ | 2,400 | 1,015 | 1,385 | 1,954 | 838 | 1,116 |
| $\|\mathcal{U}\|$ | 23,697 | 12,898 | 10,799 | 17,178 | 8,652 | 8,526 |

**Tab. A9.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 20. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A18 and A19.

| | 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** | | | | | | | | | |
| $\beta$ | -0.003 | -0.005 | -0.002 | 0.003 | 0.003 | 0.003 | -0.003 | -0.003 | -0.003 |
| | (0.003) | (0.005) | (0.004) | (0.004) | (0.006) | (0.006) | (0.004) | (0.006) | (0.006) |
| **Dynamic model: DID relative to week 0** | | | | | | | | | |
| $\beta_{-4}$ | -0.016 | 0.006 | -0.034** | -0.004 | 0.022 | -0.024 | 0.004 | -0.022 | 0.024 |
| | (0.011) | (0.016) | (0.016) | (0.015) | (0.024) | (0.020) | (0.015) | (0.024) | (0.020) |
| $\beta_{-3}$ | -0.009 | 0.004 | -0.019 | 0.004 | 0.004 | 0.004 | -0.004 | -0.004 | -0.004 |
| | (0.011) | (0.017) | (0.015) | (0.015) | (0.022) | (0.020) | (0.015) | (0.022) | (0.020) |
| $\beta_{-2}$ | -0.023** | -0.008 | -0.035** | -0.007 | -0.006 | -0.009 | 0.007 | 0.006 | 0.009 |
| | (0.011) | (0.016) | (0.015) | (0.015) | (0.023) | (0.020) | (0.015) | (0.023) | (0.020) |
| $\beta_{-1}$ | -0.008 | 0.010 | -0.021 | -0.025* | -0.008 | -0.039** | 0.025* | 0.008 | 0.039** |
| | (0.011) | (0.016) | (0.015) | (0.014) | (0.020) | (0.020) | (0.014) | (0.020) | (0.020) |
| $\beta_0$ | - | - | - | - | - | - | - | - | - |
| $\beta_1$ | -0.023** | -0.009 | -0.034** | -0.011 | -0.017 | -0.007 | 0.011 | 0.017 | 0.007 |
| | (0.011) | (0.017) | (0.015) | (0.016) | (0.023) | (0.021) | (0.016) | (0.023) | (0.021) |
| $\beta_2$ | -0.027** | -0.027* | -0.027* | -0.010 | 0.009 | -0.025 | 0.010 | -0.009 | 0.025 |
| | (0.011) | (0.016) | (0.015) | (0.015) | (0.023) | (0.020) | (0.015) | (0.023) | (0.020) |
| $\beta_3$ | -0.017 | -0.003 | -0.029* | -0.016 | -0.005 | -0.024 | 0.016 | 0.005 | 0.024 |
| | (0.012) | (0.017) | (0.016) | (0.016) | (0.024) | (0.022) | (0.016) | (0.024) | (0.022) |
| 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 | 0.448 | 0.497 | 0.401 | 0.552 | 0.503 | 0.599 |
| $N$ | 682,375 | 362,290 | 320,085 | 507,234 | 254,134 | 253,100 | 507,234 | 254,134 | 253,100 |
| Clusters | 5,469 | 3,734 | 4,918 | 5,355 | 3,660 | 4,822 | 5,355 | 3,660 | 4,822 |
| $\|\mathcal{T}\|$ | 2,406 | 1,018 | 1,388 | 1,963 | 841 | 1,122 | 1,963 | 841 | 1,122 |
| $\|\mathcal{U}\|$ | 23,905 | 13,023 | 10,882 | 17,515 | 8,842 | 8,673 | 17,515 | 8,842 | 8,673 |

**Tab. A10.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 20. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A20, A21, and A22.

| | 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** | | | | | | |
| $\beta$ | -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** | | | | | | |
| $\beta_{-4}$ | 0.000 | -0.000 | 0.000 | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{-3}$ | 0.000 | -0.000 | 0.000 | 0.000 | 0.000** | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{-2}$ | 0.000 | -0.000 | 0.000 | 0.000 | 0.000** | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{-1}$ | 0.000 | -0.000 | 0.000 | 0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_0$ | - | - | - | - | - | - |
| $\beta_1$ | 0.000 | -0.000 | 0.000 | 0.000 | 0.000** | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | 0.000 | 0.000 | 0.000 | -0.000 | 0.000** | -0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3$ | -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 |
| $N$ | 1,419,860 | 741,650 | 678,210 | 456,248 | 254,436 | 201,812 |
| Clusters | 5,558 | 3,790 | 4,993 | 3,384 | 2,189 | 2,450 |
| $\|\mathcal{T}\|$ | 5,257 | 1,910 | 3,347 | 2,330 | 849 | 1,481 |
| $\|\mathcal{U}\|$ | 49,353 | 26,615 | 22,738 | 15,218 | 8,937 | 6,281 |

**Tab. A11.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 20. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A23 and A24. 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** | | | | | | |
| $\beta$ | -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** | | | | | | |
| $\beta_{-4}$ | 0.000 | -0.000 | 0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{-3}$ | -0.000 | -0.000* | -0.000 | -0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{-2}$ | -0.000*** | -0.000** | -0.000* | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_{-1}$ | -0.000 | -0.000 | -0.000 | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_0$ | - | - | - | - | - | - |
| $\beta_1$ | -0.000 | 0.000 | -0.000 | -0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_2$ | -0.000** | -0.001*** | -0.000 | -0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3$ | -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 | 987,246 | 554,242 | 433,004 |
| Clusters | 4,214 | 3,004 | 3,766 | 4,045 | 3,108 | 3,433 |
| $\|\mathcal{T}\|$ | 2,464 | 946 | 1,518 | 2,249 | 1,029 | 1,220 |
| $\|\mathcal{U}\|$ | 35,035 | 17,912 | 17,123 | 35,722 | 20,288 | 15,434 |

**Tab. A12.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, ..., 3\})$ from equations (2) and (3) 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 20. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A25 and A26. 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** | | | | | | | | | |
| $\beta$ | 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** | | | | | | | | | |
| $\beta_{-4}$ | 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) |
| $\beta_{-3}$ | 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) |
| $\beta_{-2}$ | 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) |
| $\beta_{-1}$ | -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) |
| $\beta_0$ | - | - | - | - | - | - | - | - | - |
| $\beta_1$ | 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) |
| $\beta_2$ | 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) |
| $\beta_3$ | 0.003** | 0.005* | 0.002* | -0.001 | 0.001 | -0.002 | 0.001* | -0.001 | 0.002*** |
| | (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 |
| $N$ | 999,648 | 321,438 | 678,210 | 999,648 | 321,438 | 678,210 | 999,648 | 321,438 | 678,210 |
| Clusters | 5,246 | 3,474 | 4,993 | 5,246 | 3,474 | 4,993 | 5,246 | 3,474 | 4,993 |
| $\|\mathcal{T}\|$ | 4,350 | 1,003 | 3,347 | 4,350 | 1,003 | 3,347 | 4,350 | 1,003 | 3,347 |
| $\|\mathcal{U}\|$ | 34,098 | 11,360 | 22,738 | 34,098 | 11,360 | 22,738 | 34,098 | 11,360 | 22,738 |

**Tab. A13.** This table reports estimates of $\beta$ and $(\beta_w : w \in \{-4, \ldots, 3\})$ from equations (2) and (3) 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 20. Program-level cluster robust SEs are in parenthesis. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. 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 the remaining $\beta_w$ are excluded from the table for space; they are presented in figures A27-A29.

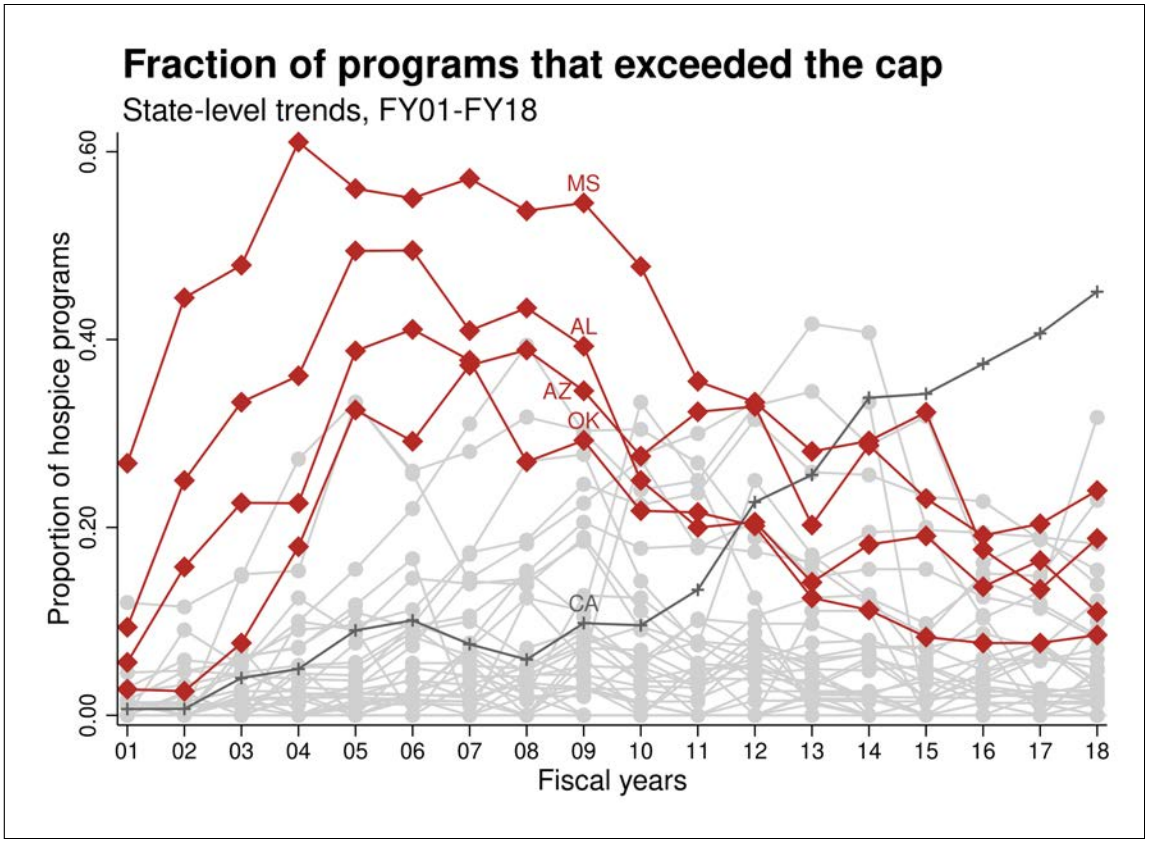


**Fig. A1.** This figure plots trends in the proportion of each state's hospice programs that exceeded the cap in each fiscal year between 2001 and 2018. It shows that cap liabilities were particularly prevalent in MS, AL, OK, AZ, and CA during this period. See the discussions near page 14.

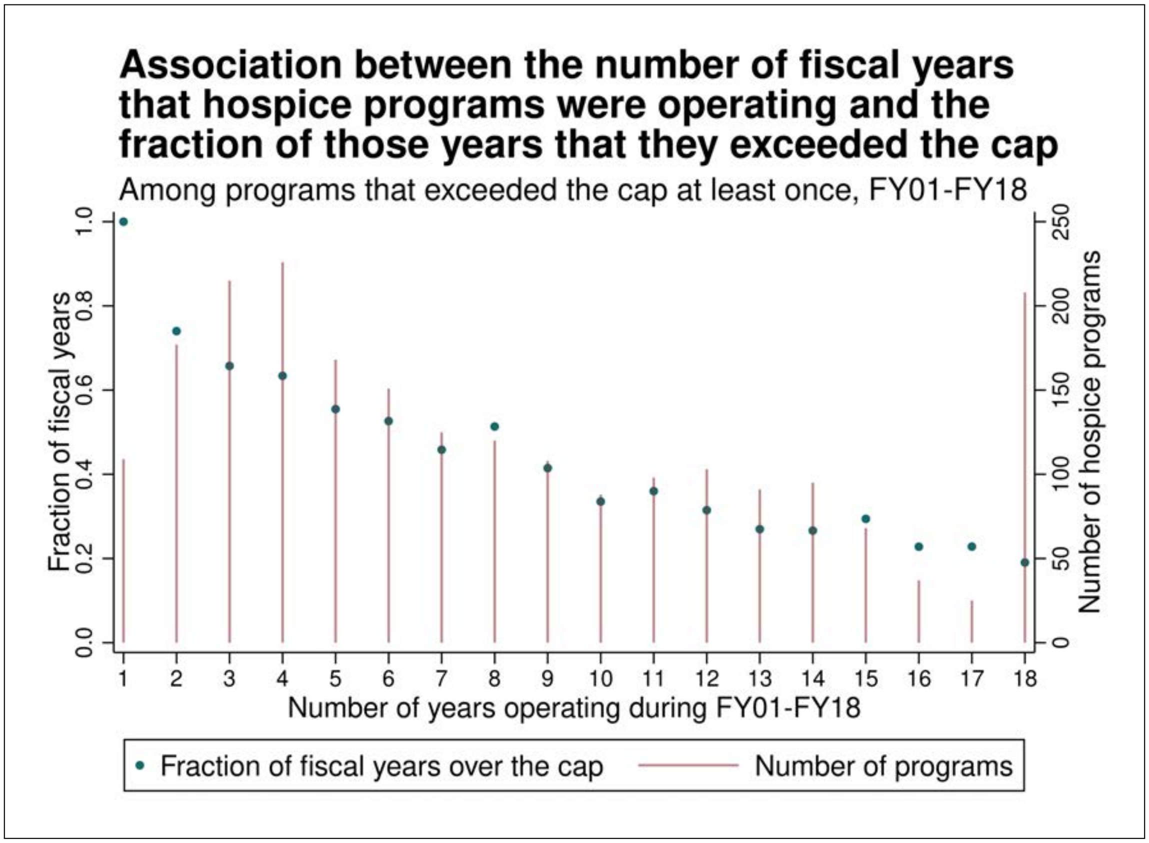


**Fig. A2.** This figure plots the joint distribution between the number of years hospice programs operated between FY 2001 and FY 2018 and the fraction of those years that they exceeded the cap. It is limited to those programs that exceeded the cap at least once. It shows that hospice programs that exceed the cap at least once often exceed it multiple times. See the discussions near page 14.

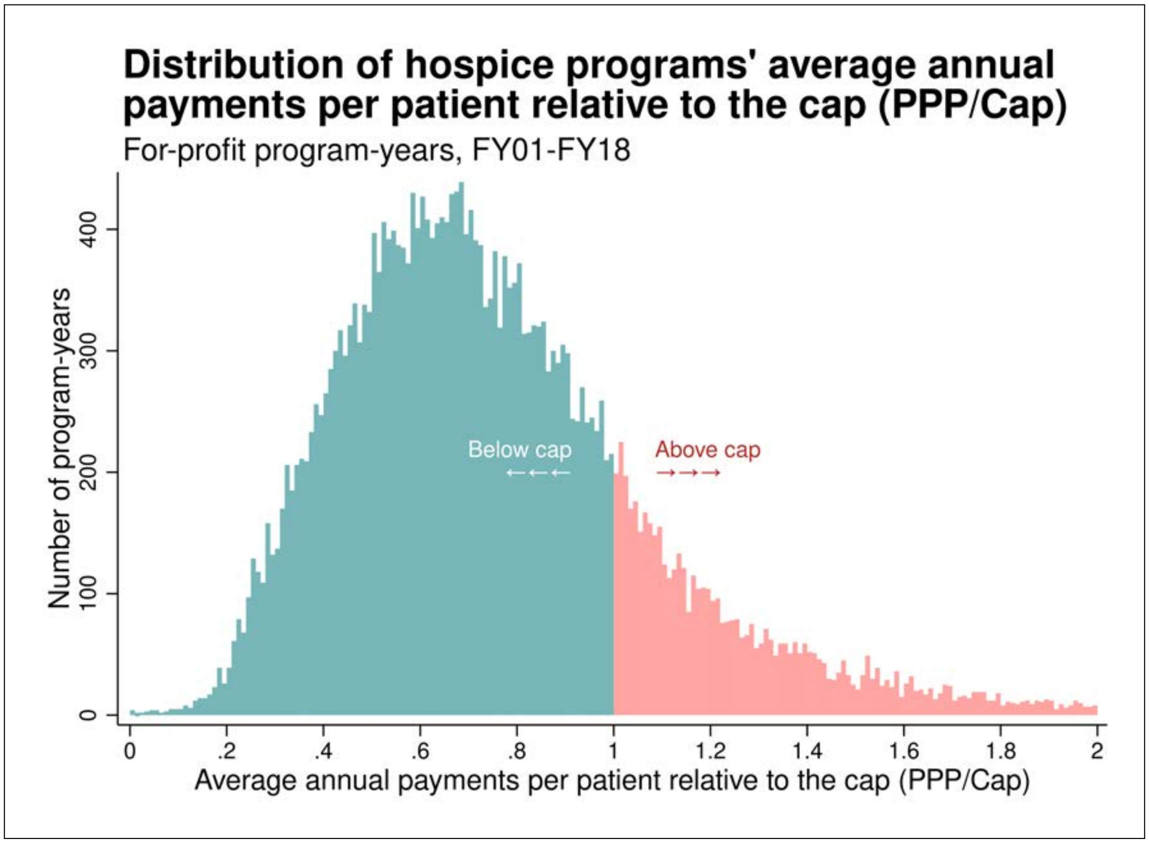


**Fig. A3.** This figure plots the distribution of $\text{PPP}_{jt}/\text{Cap}_{jt}$—i.e., hospice programs' average annual payments per patient relative to the cap. The figure is censored at $\text{PPP}_{jt}/\text{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See the discussions near page 15 and table A2.

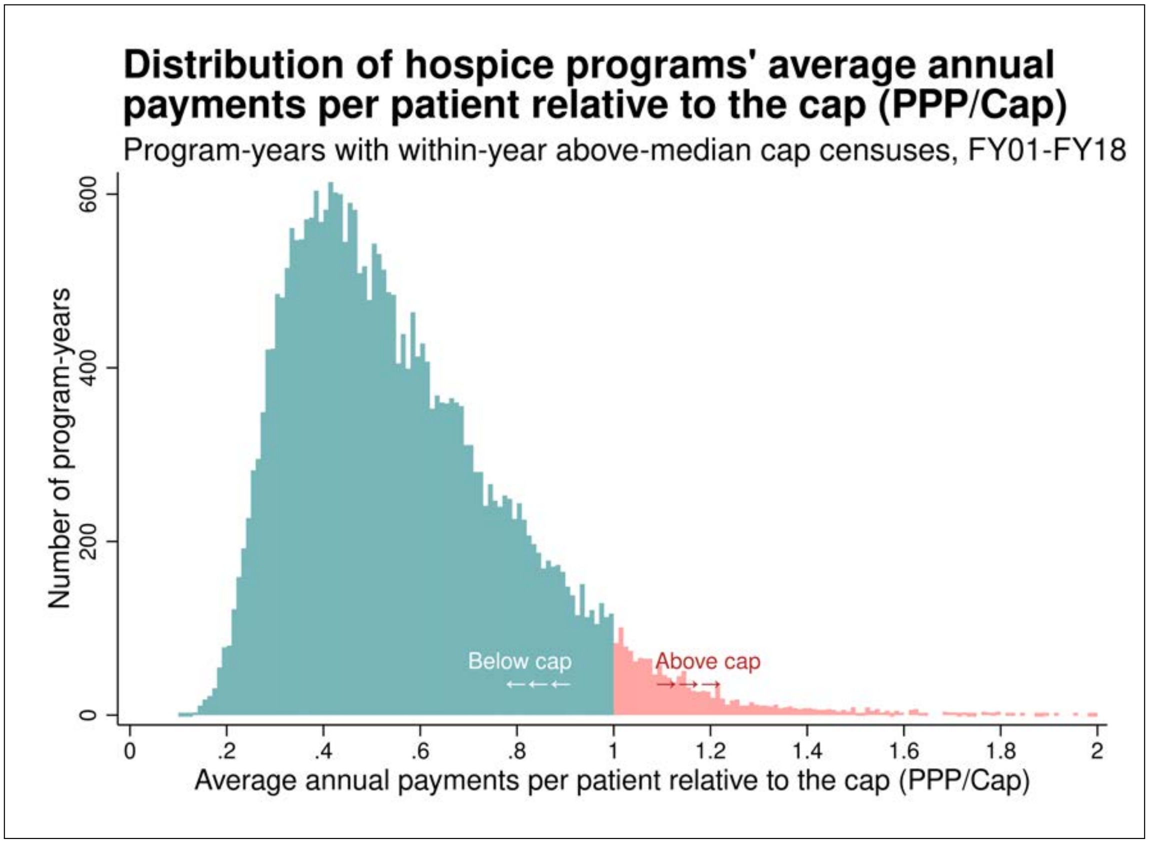


**Fig. A4.** This figure plots the distribution of $\mathrm{PPP}_{jt}/\mathrm{Cap}_{jt}$—i.e., hospice programs' average annual payments per patient relative to the cap. The figure is censored at $\mathrm{PPP}_{jt}/\mathrm{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See the discussions near page 15 and table A2.

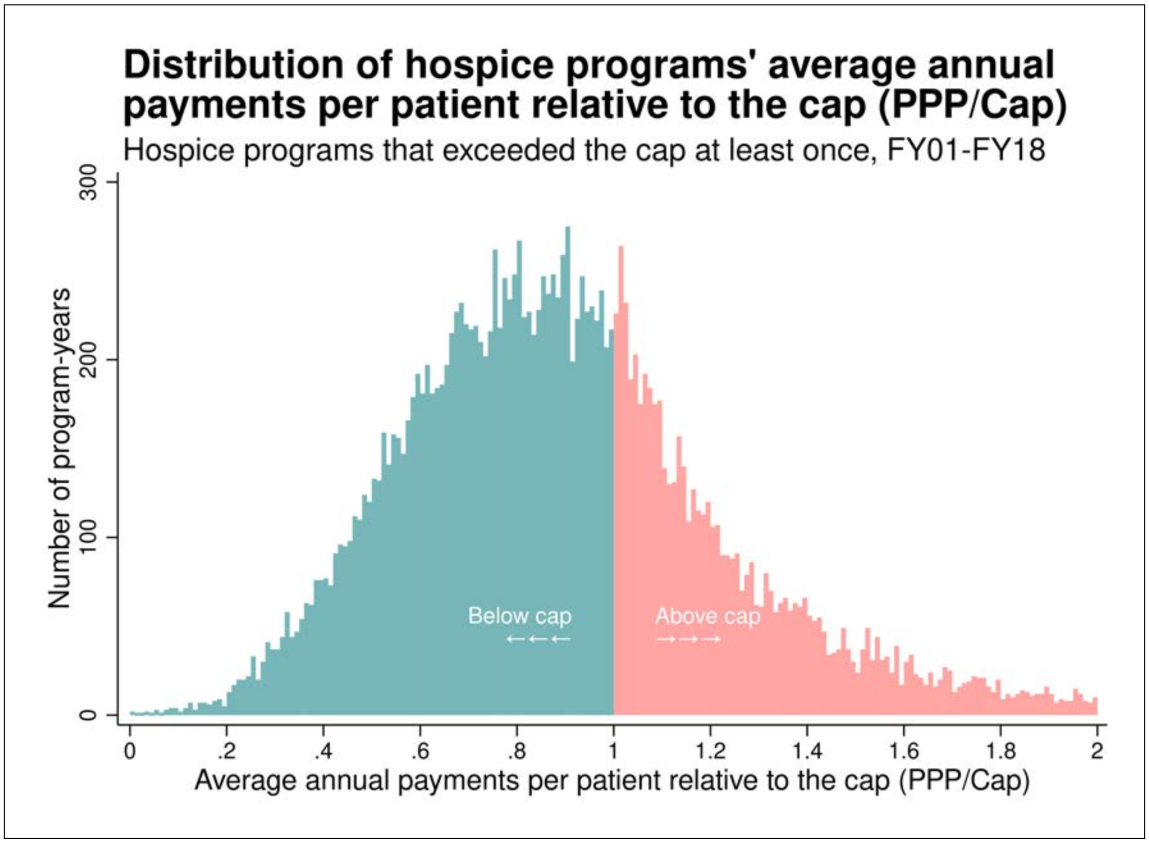


**Fig. A5.** This figure plots the distribution of $\text{PPP}_{jt}/\text{Cap}_{jt}$—i.e., hospice programs' average annual payments per patient relative to the cap. The figure is censored at $\text{PPP}_{jt}/\text{Cap}_{jt} = 2$ for visual clarity. There is no visual indication that hospice programs' average annual payments per patient bunch around the cap. See the discussions near page 15 and table A2.

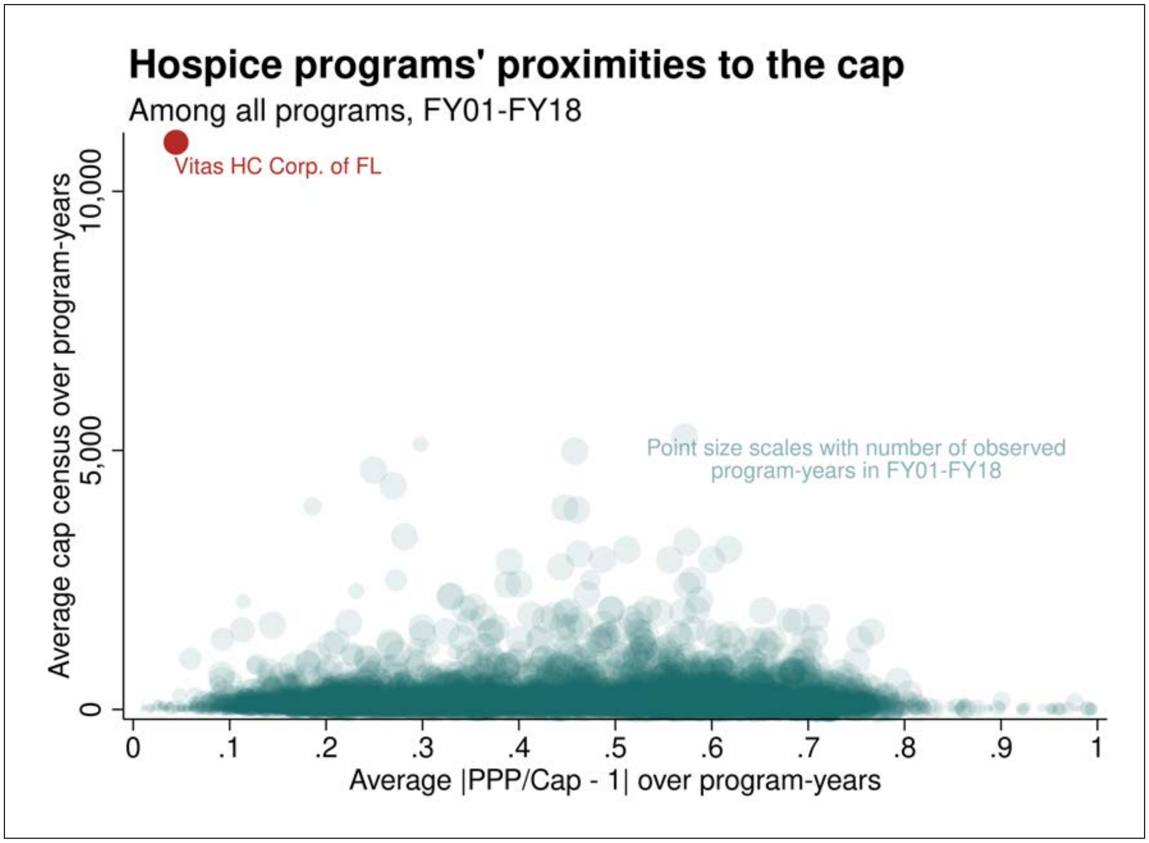


**Fig. A6.** This figure plots the joint distribution between the number of years that hospice programs in our sample are observed between FY 2001 and FY 2018, and their average annual cap censuses and proximities to the cap during this time. It supports the idea that most hospice programs do not persistently 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 near page 15.

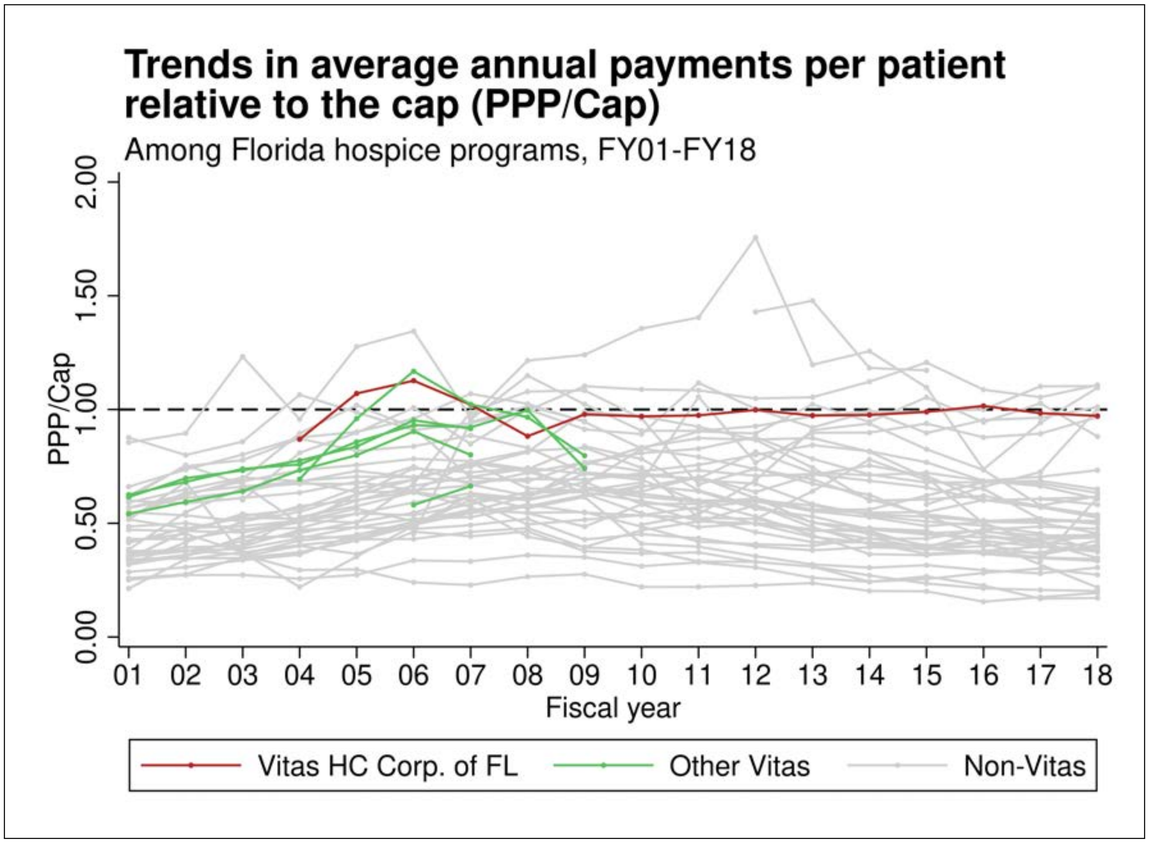


**Fig. A7.** This figure plots trends in $\text{PPP}_{jt}/\text{Cap}_{jt}$—i.e., hospice programs' average annual payments per patient relative to the cap—among Florida hospice programs. It shows that Vitas Healthcare Corporation of Florida has nearly equilibrated its average annual payments per patient with the cap since 2009. Other Vitas hospice programs were identified by the word "Vitas" in their facility name. See the discussions near page 15.

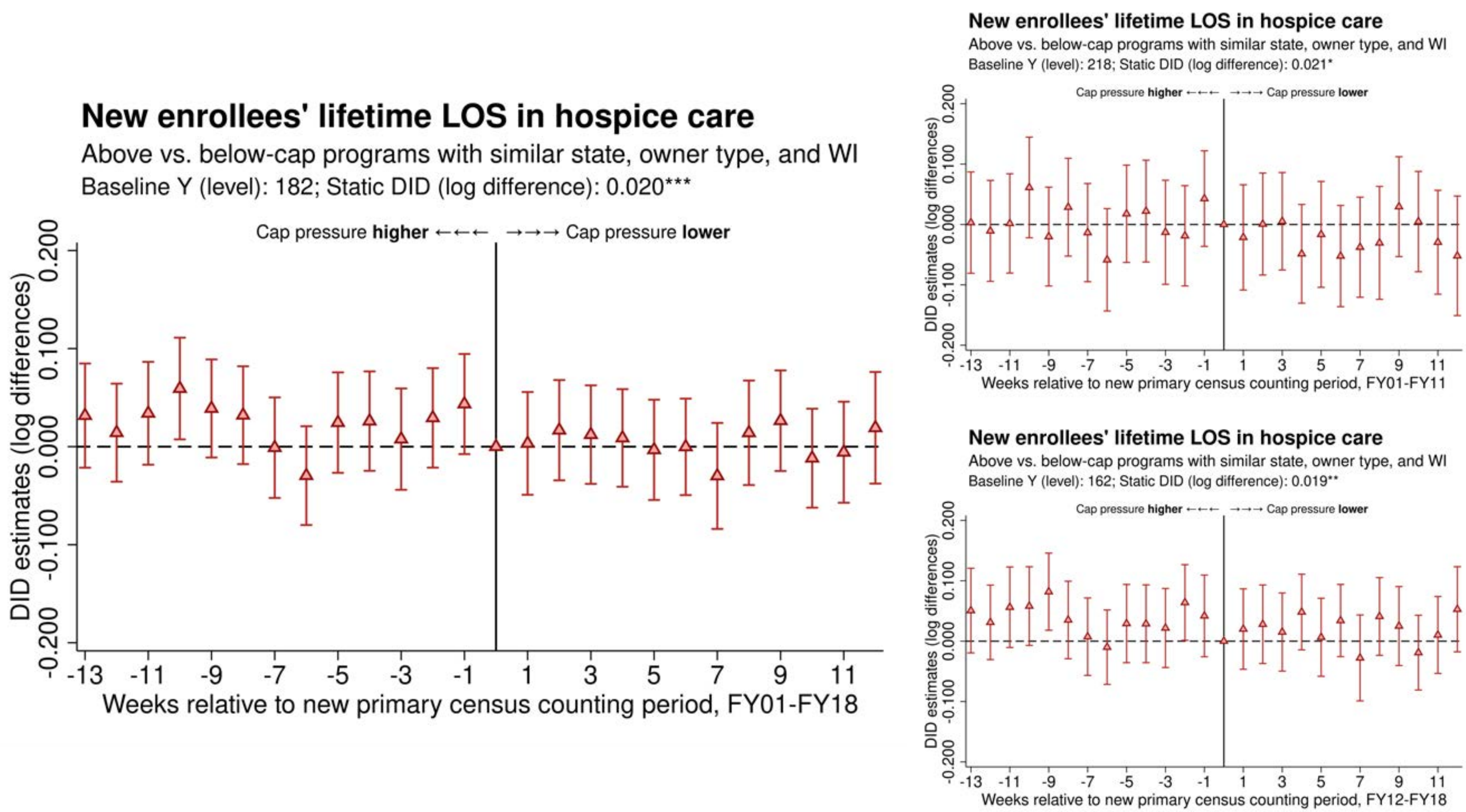


**Fig. A8.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who ultimately have longer average lifetime LOS in hospice care. See table A3 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

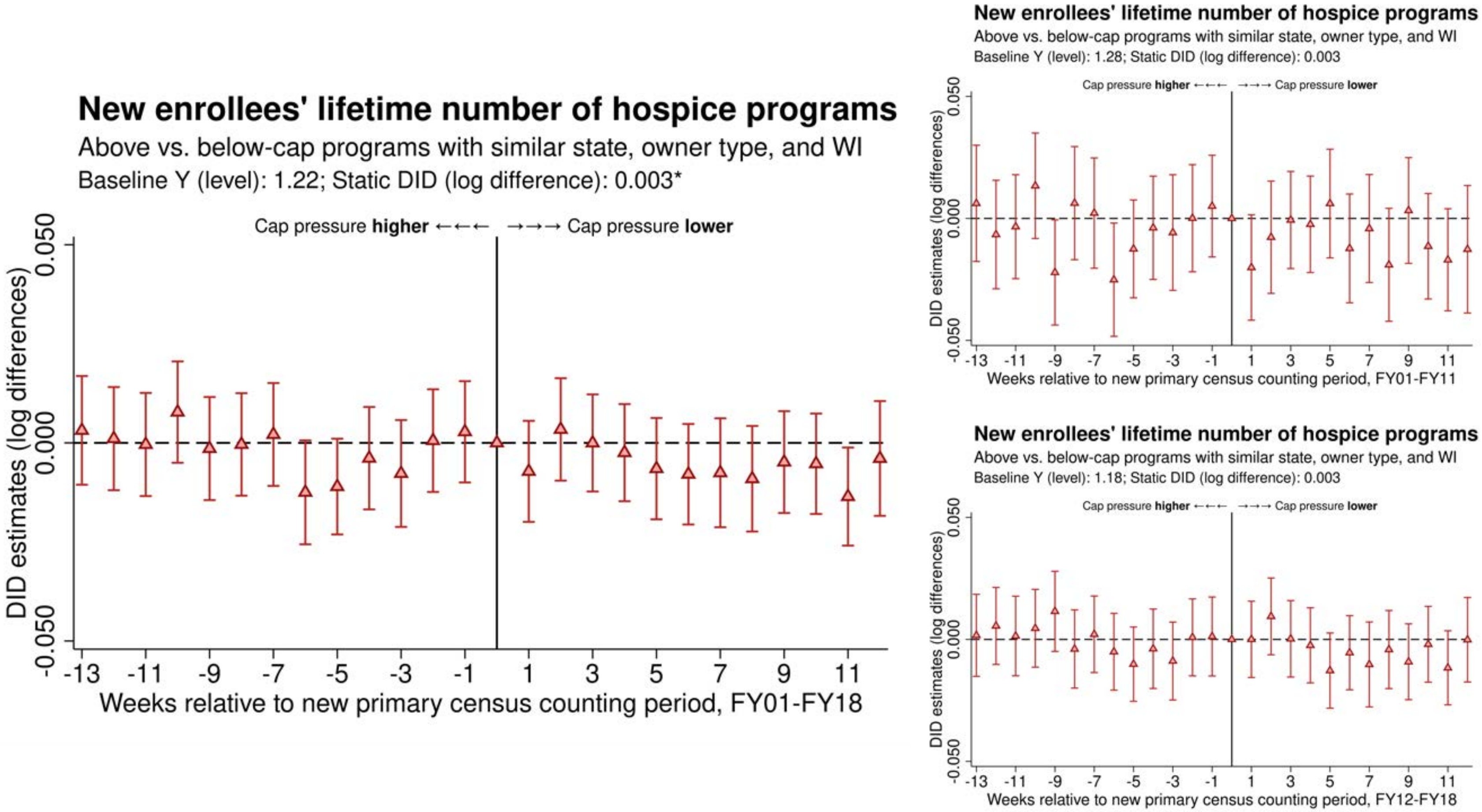


**Fig. A9.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who subsequently receive care at much the same number of unique hospice programs. See table A3 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^*p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

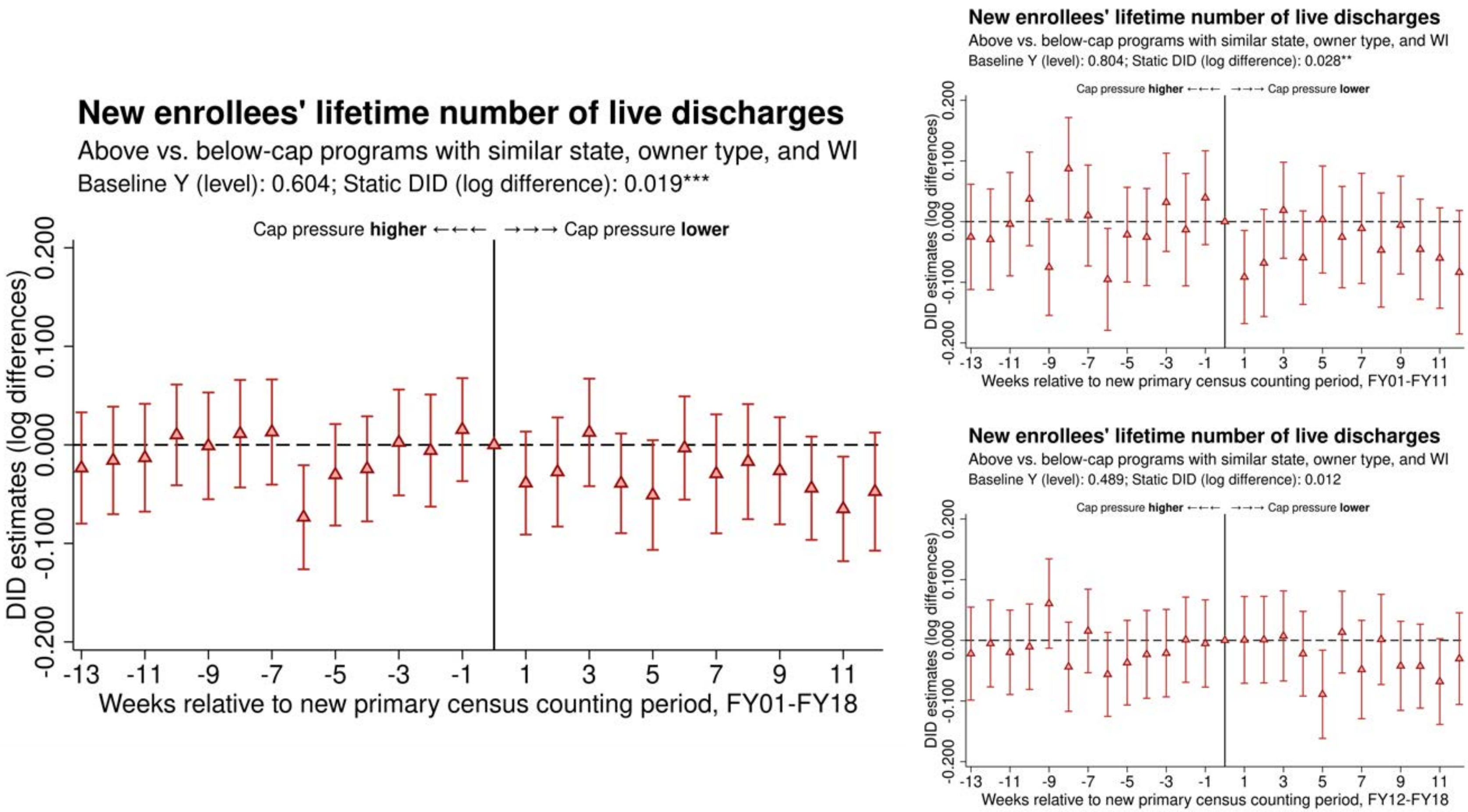


**Fig. A10.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who subsequently experience more lifetime live discharges. See table A4 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

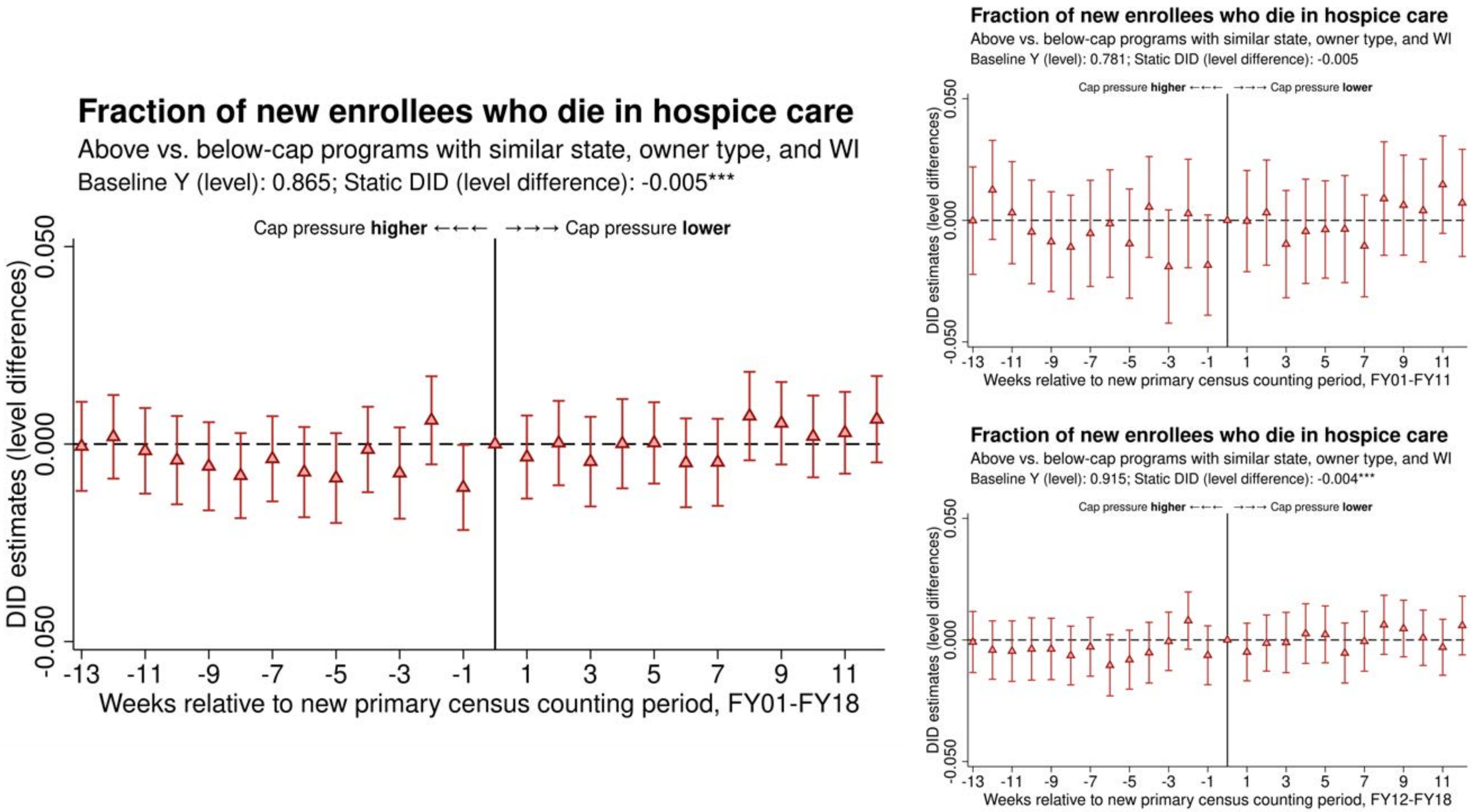


**Fig. A11.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are less likely to ultimately die in hospice care. See table A4 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

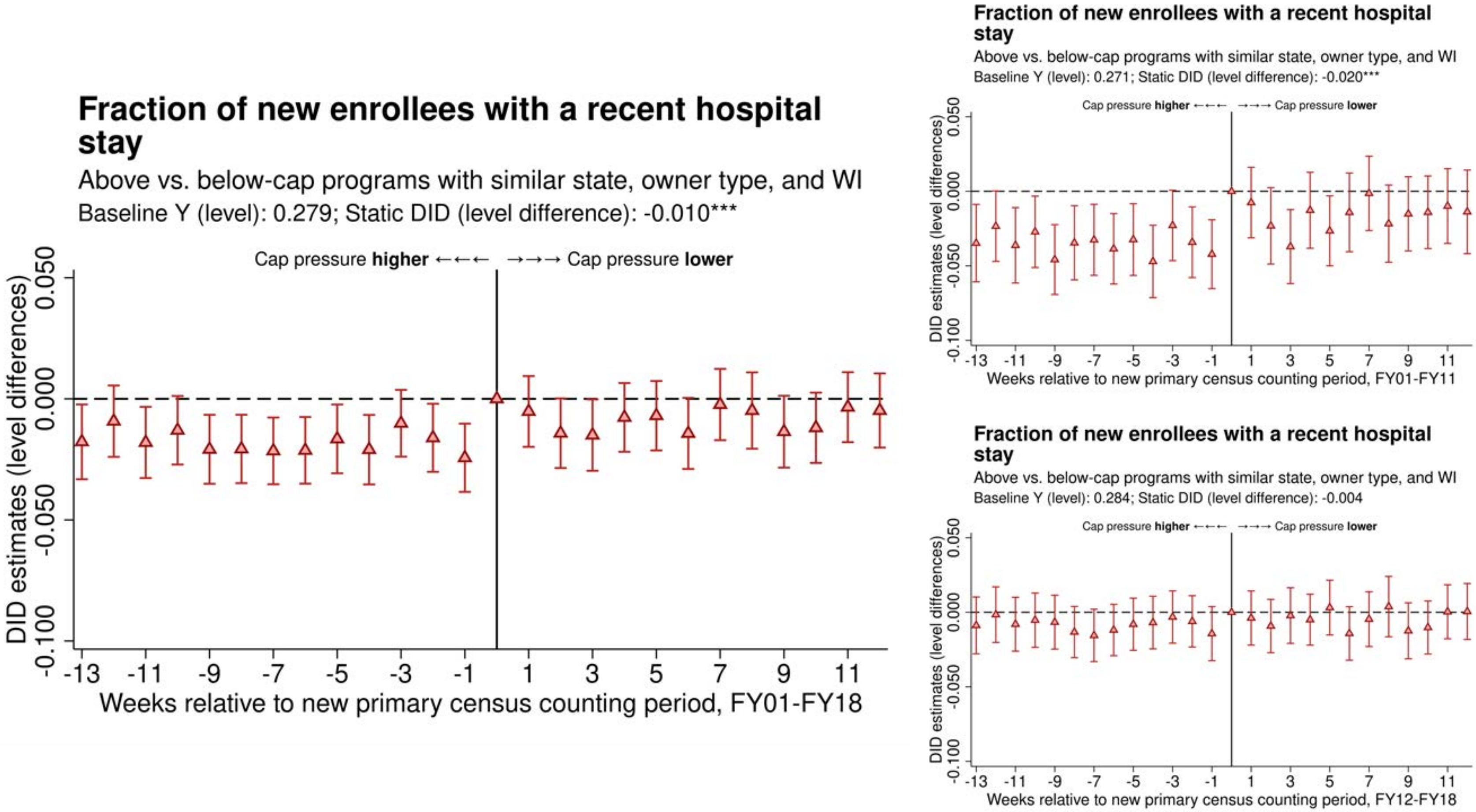


**Fig. A12.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are less likely to have had a hospital stay in the week prior to enrollment. See table A5 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

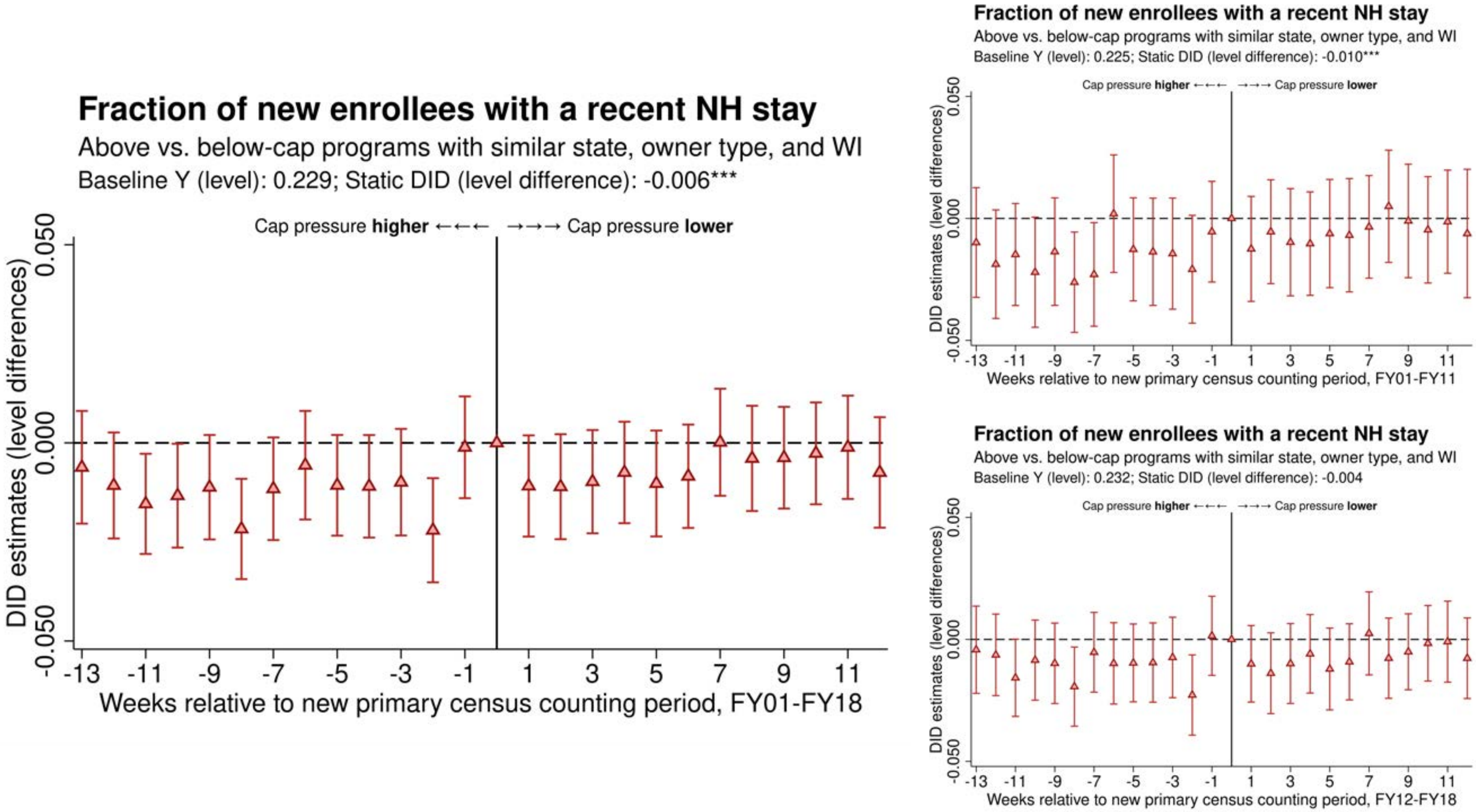


**Fig. A13.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are less likely to have had a nursing home stay in the week prior to enrollment. See table A5 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^*p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

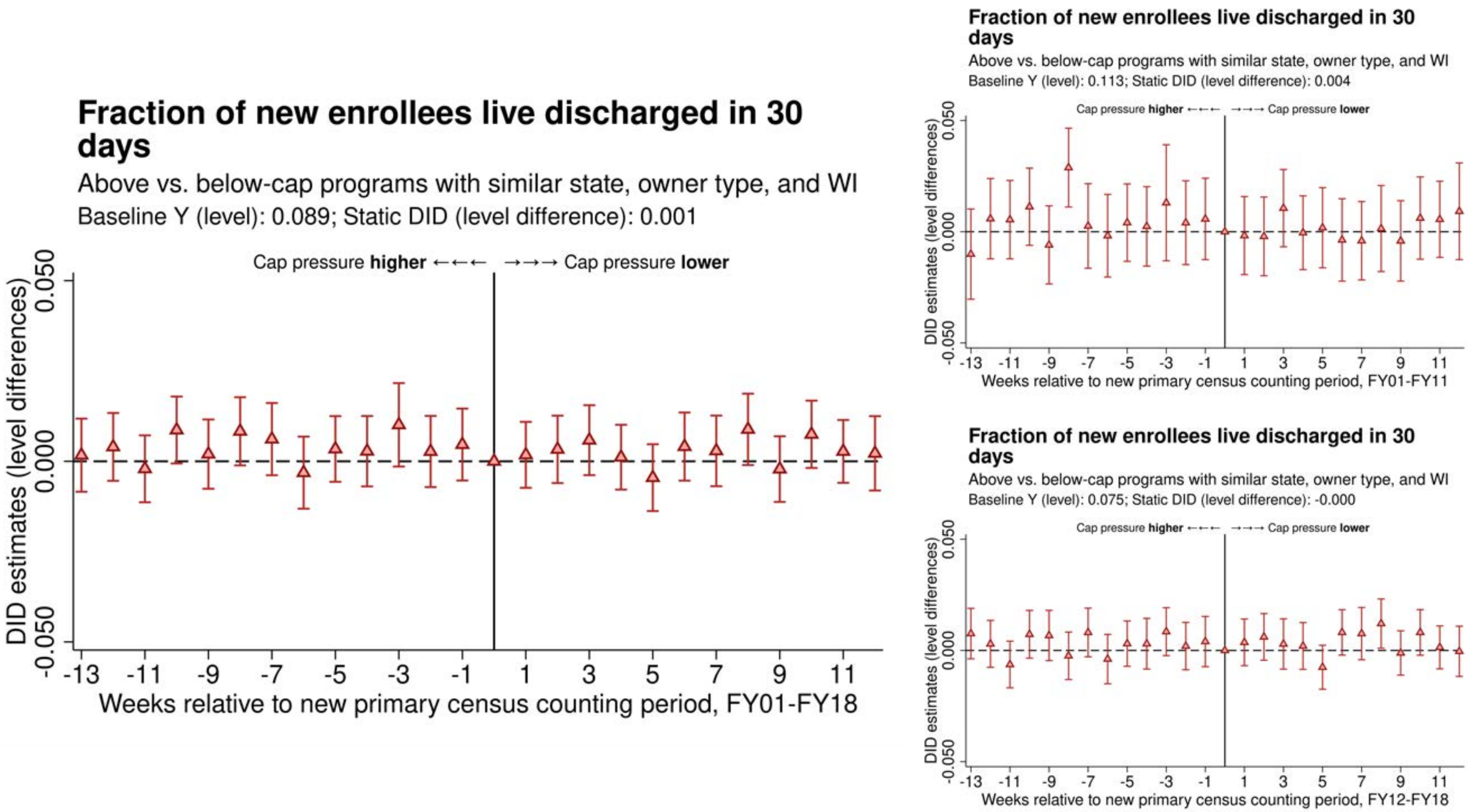


**Fig. A14.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who are live discharged within 30 days enrollment at much the same rate. See table A6 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

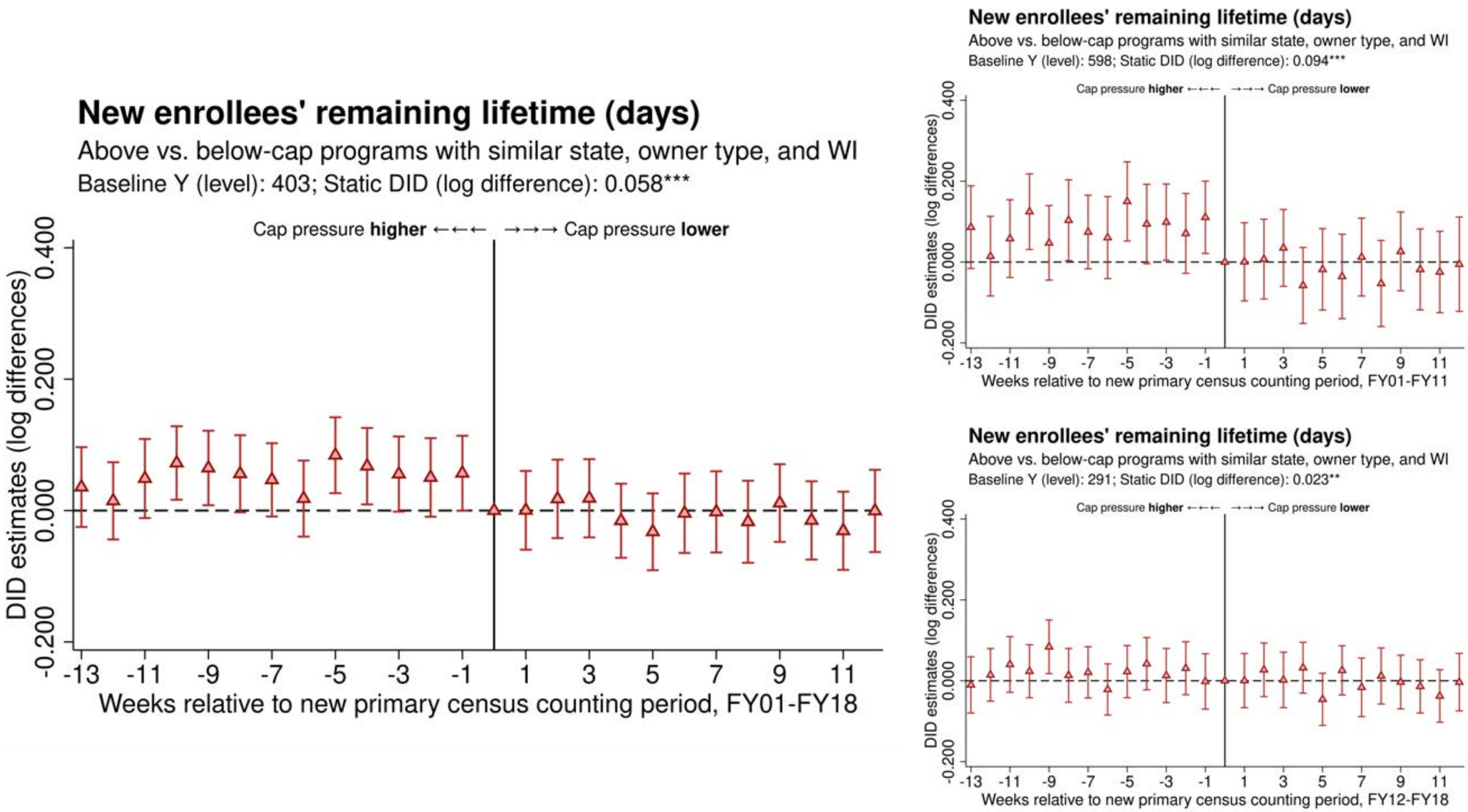


**Fig. A15.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year who have longer remaining lifetimes. See table A6 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

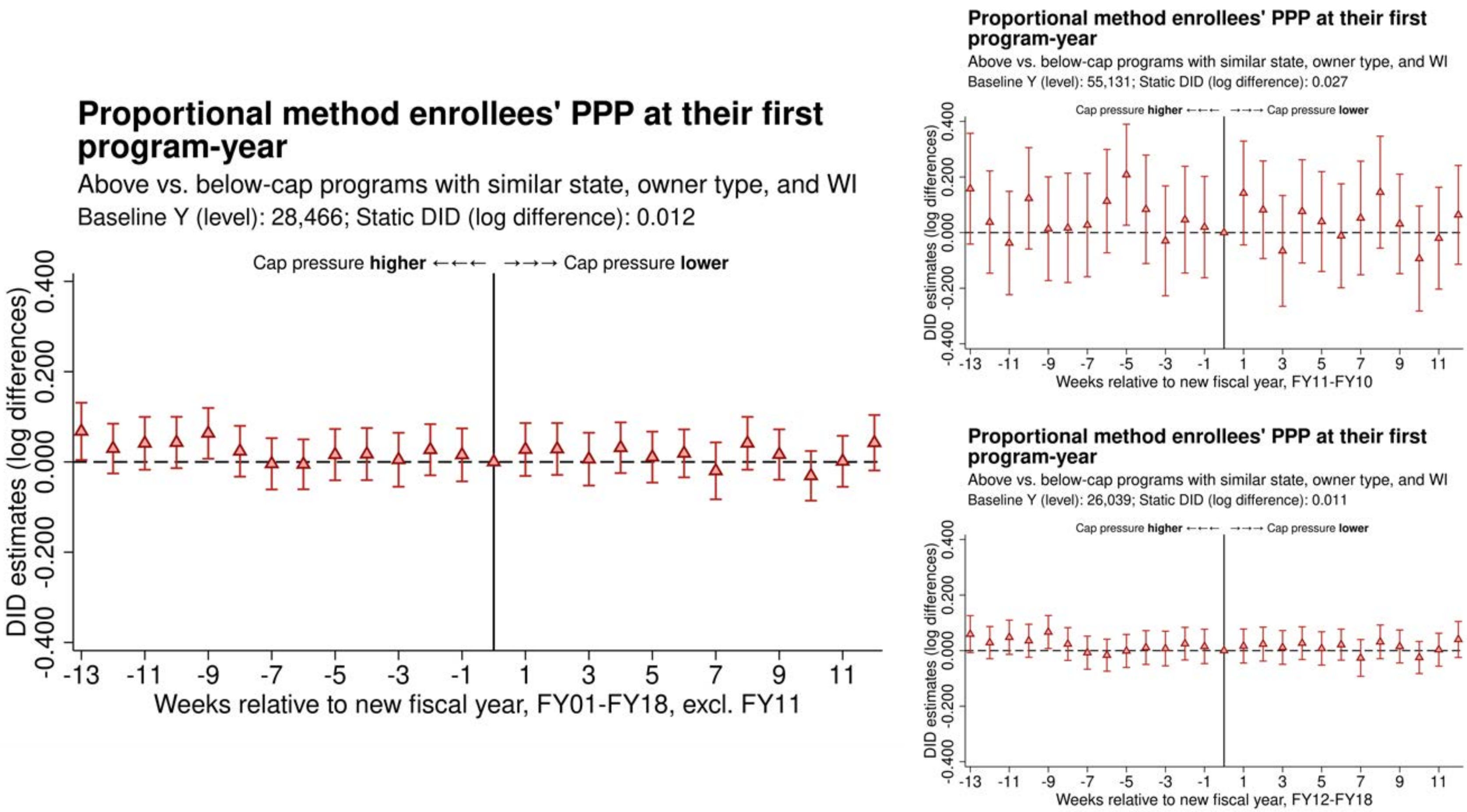


**Fig. A16.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients counted toward a cap census in proportion to their lifetime LOS in hospice care—either because they enrolled during the streamlined method era and were ever associated with multiple hospice programs or because they enrolled during the proportional method era—with much the same $\text{PPP}_{ijt}$ in their first $(j, t)$. See table A7 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom). Observations are weighted by the number of enrollees counted toward cap censuses in proportion to their lifetime LOS in hospice care.

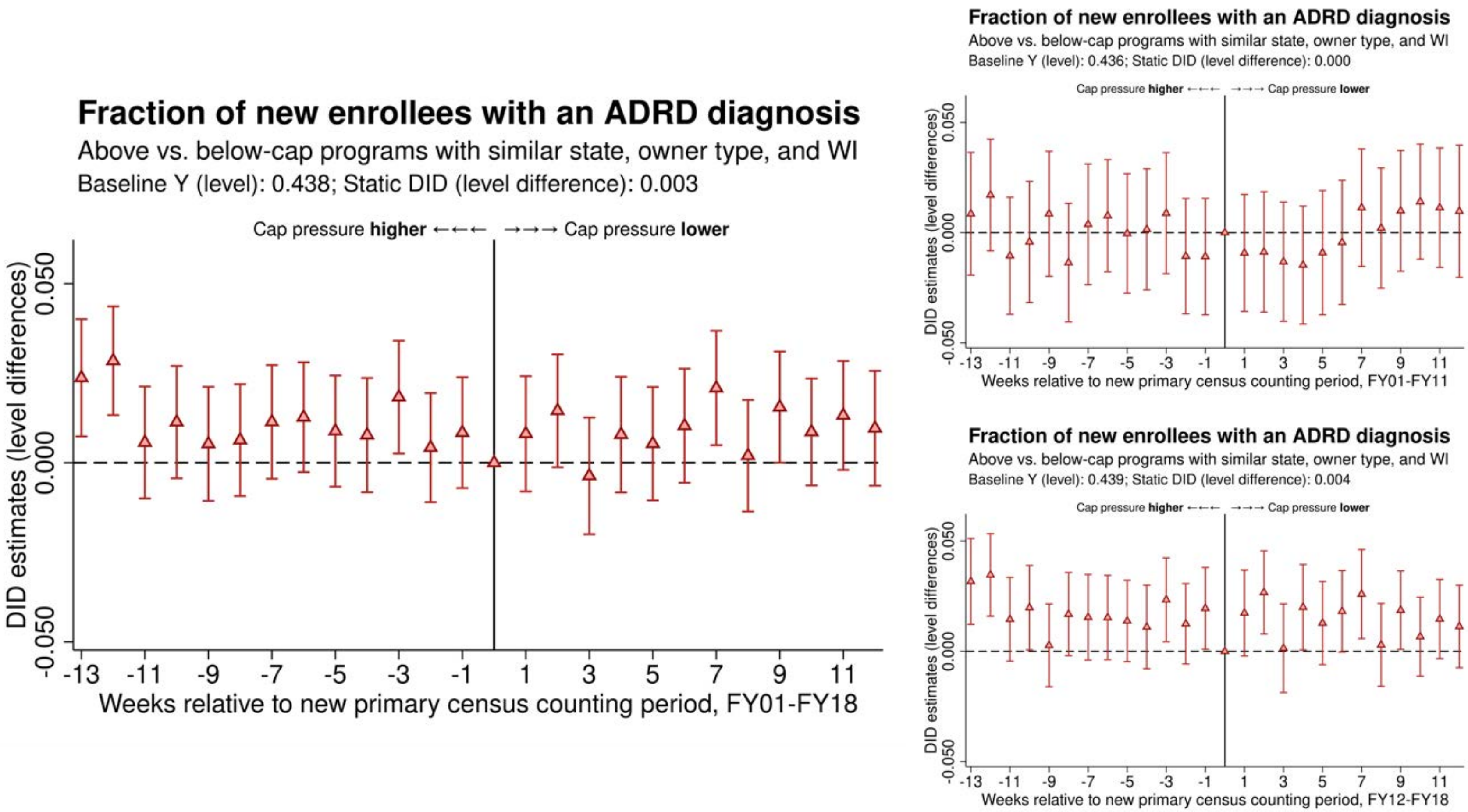


**Fig. A17.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap enroll patients in the weeks leading up to the end of the fiscal year with much the same rates of ADRD. See table A8 and the discussion near page 19. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

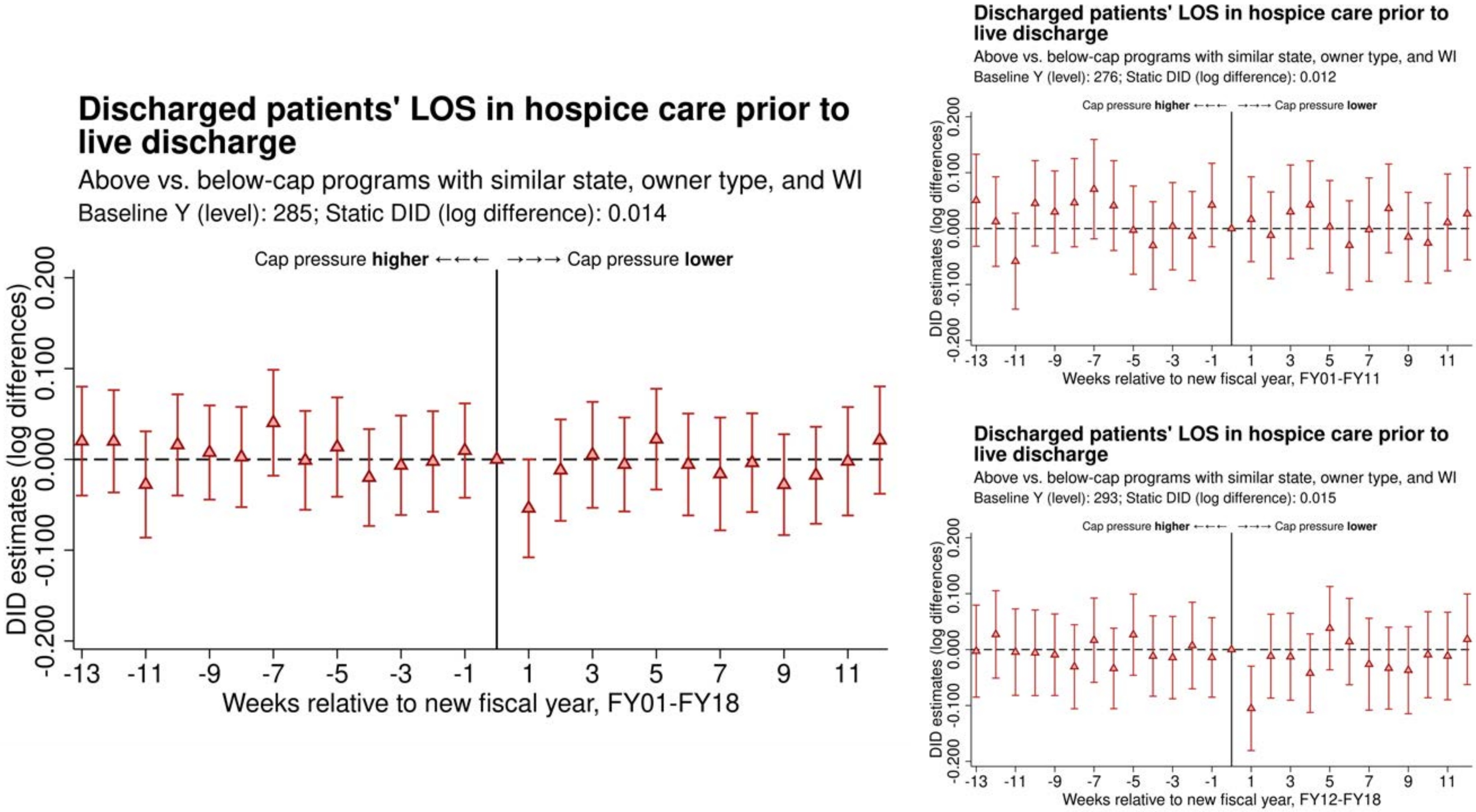


**Fig. A18.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who previously had much the same average LOS in hospice care. See table A9 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^*p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

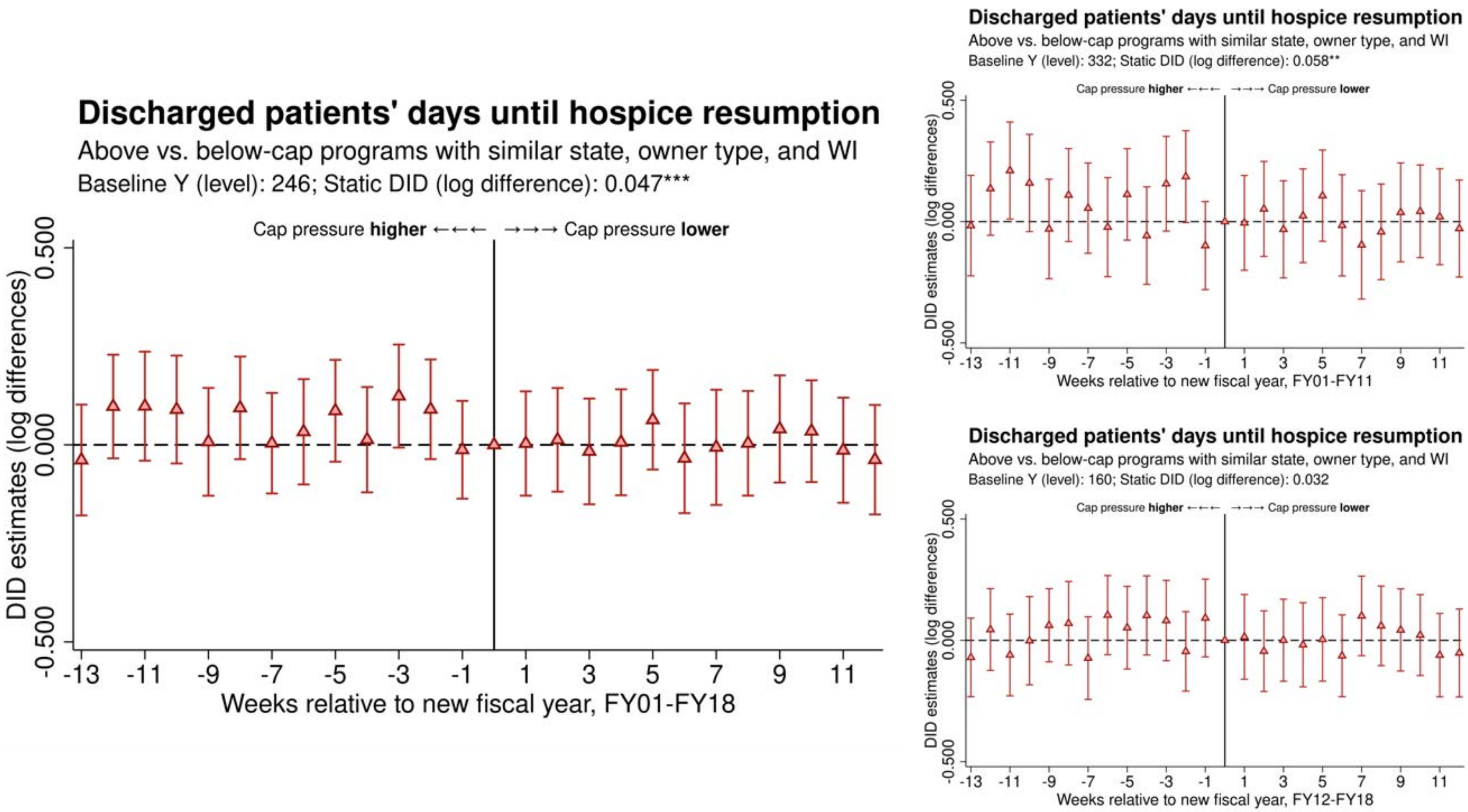


**Fig. A19.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently experience a longer spell without hospice care. See table A9 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

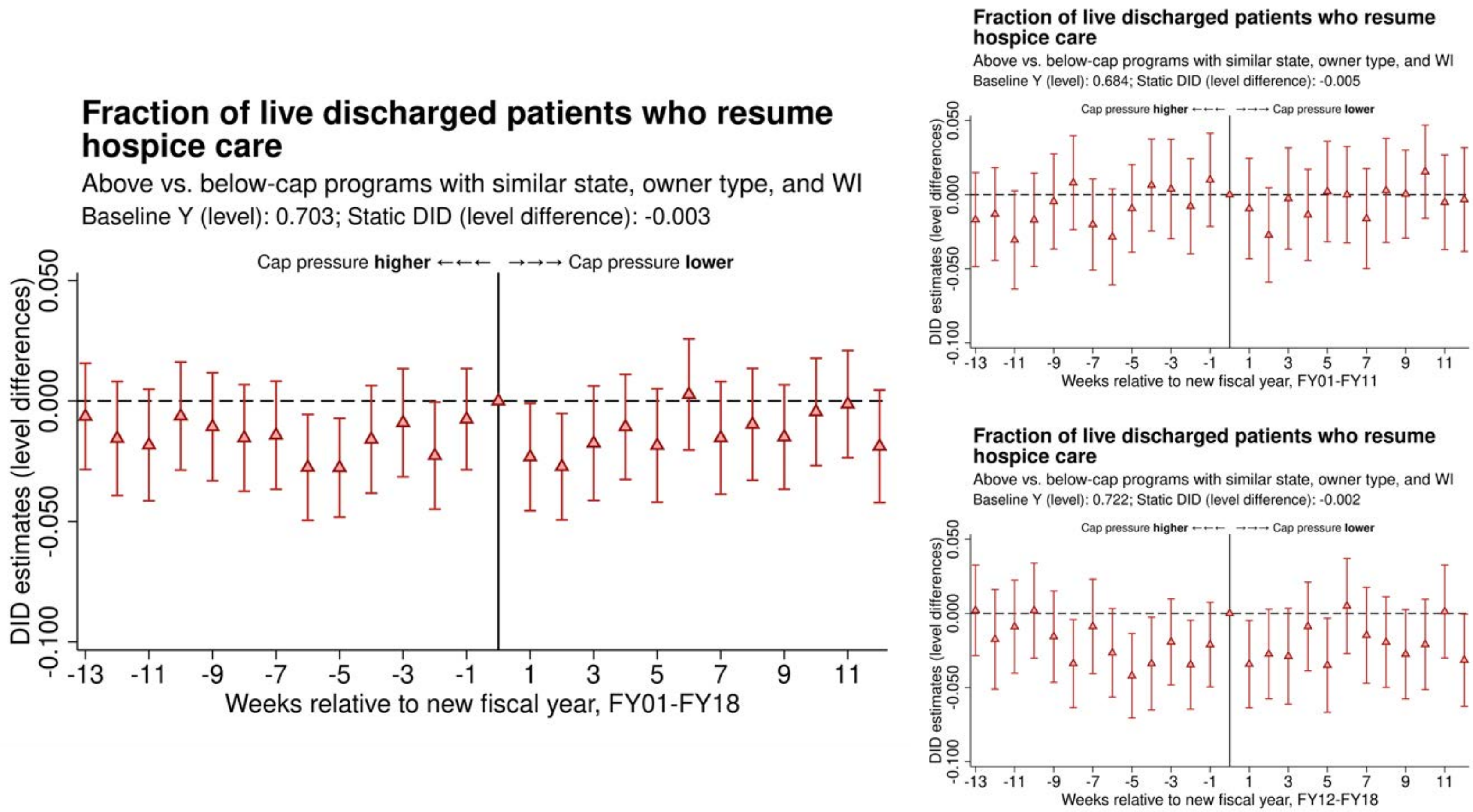


**Fig. A20.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently resume hospice care anywhere at much the same rates. See table A10 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

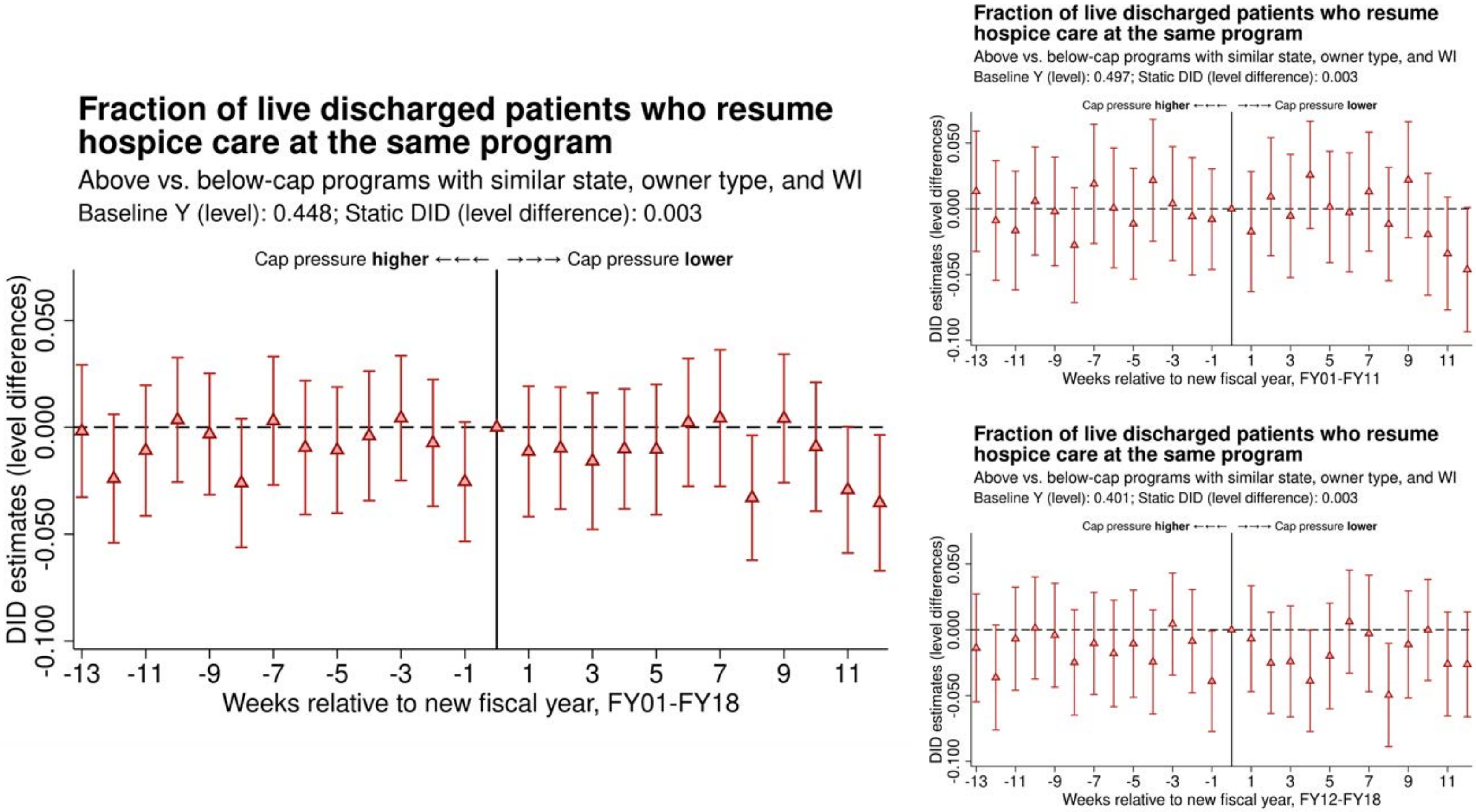


**Fig. A21.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently resume hospice care at the same program at much the same rates. See table A10 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

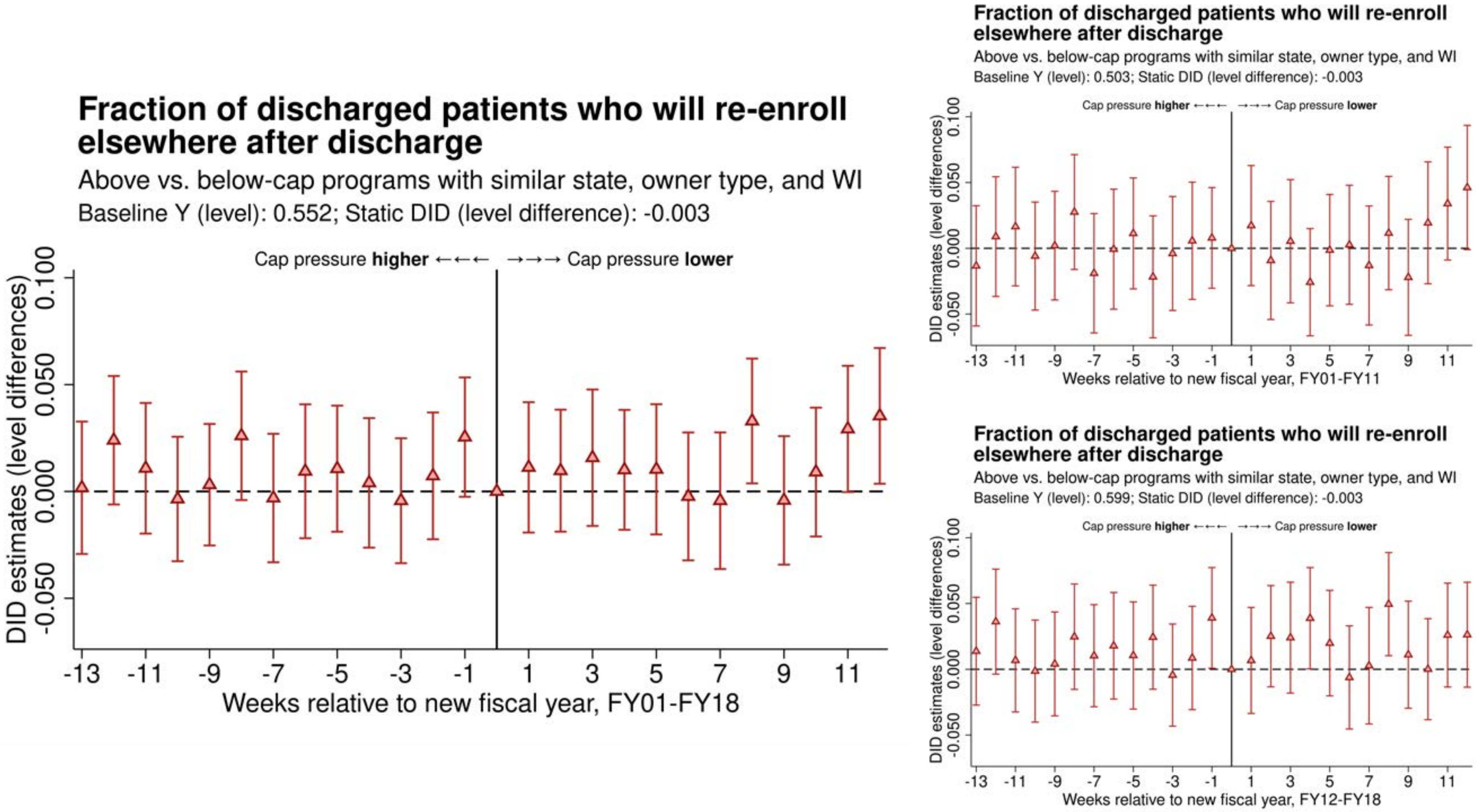


**Fig. A22.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap live discharge patients in the weeks leading up to the end of the fiscal year who subsequently resume hospice care at a different program at much the same rates. See table A10 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

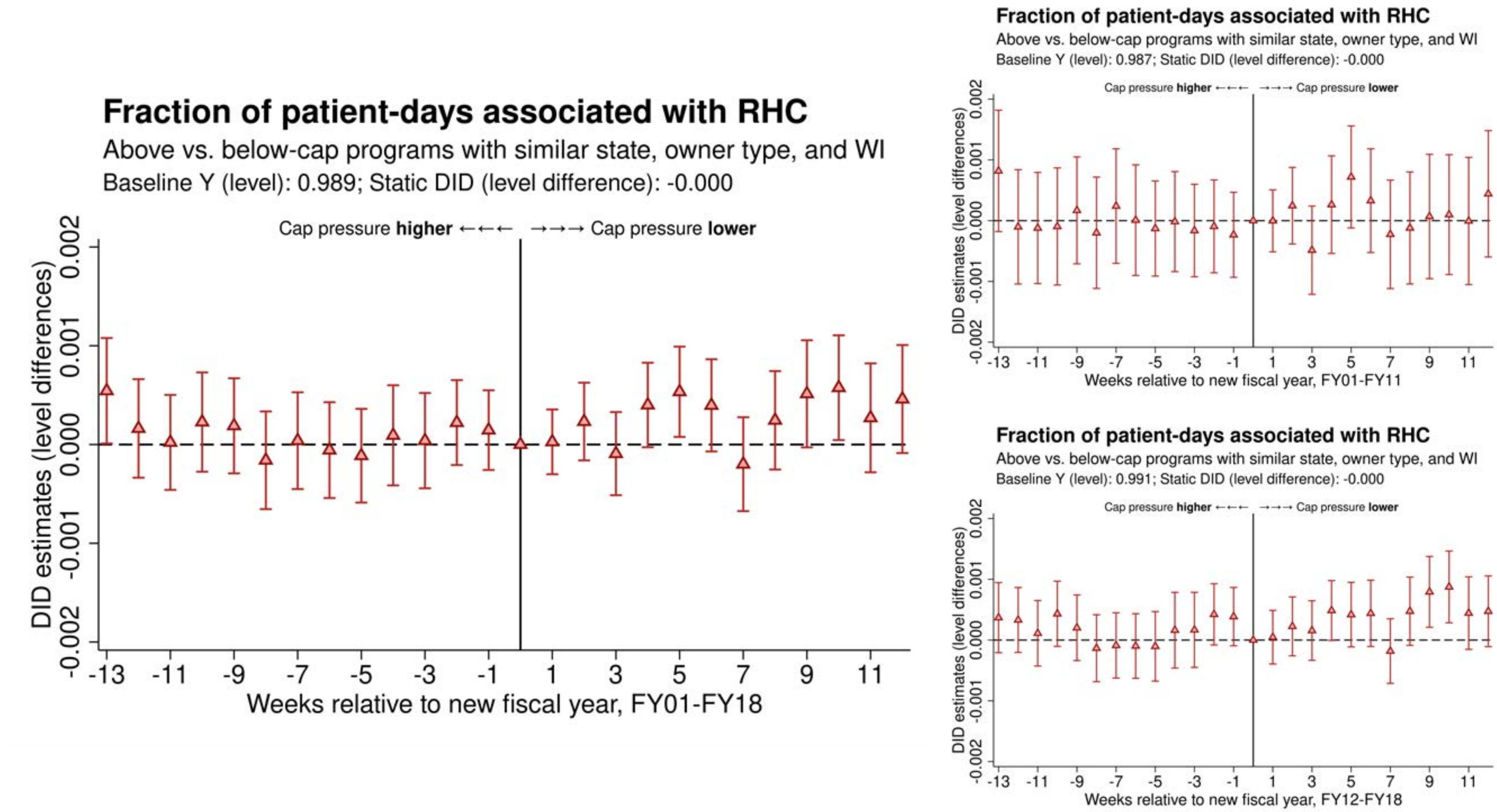


**Fig. A23.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' RHC rates in the weeks leading up to the end of the fiscal year. See table A11 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

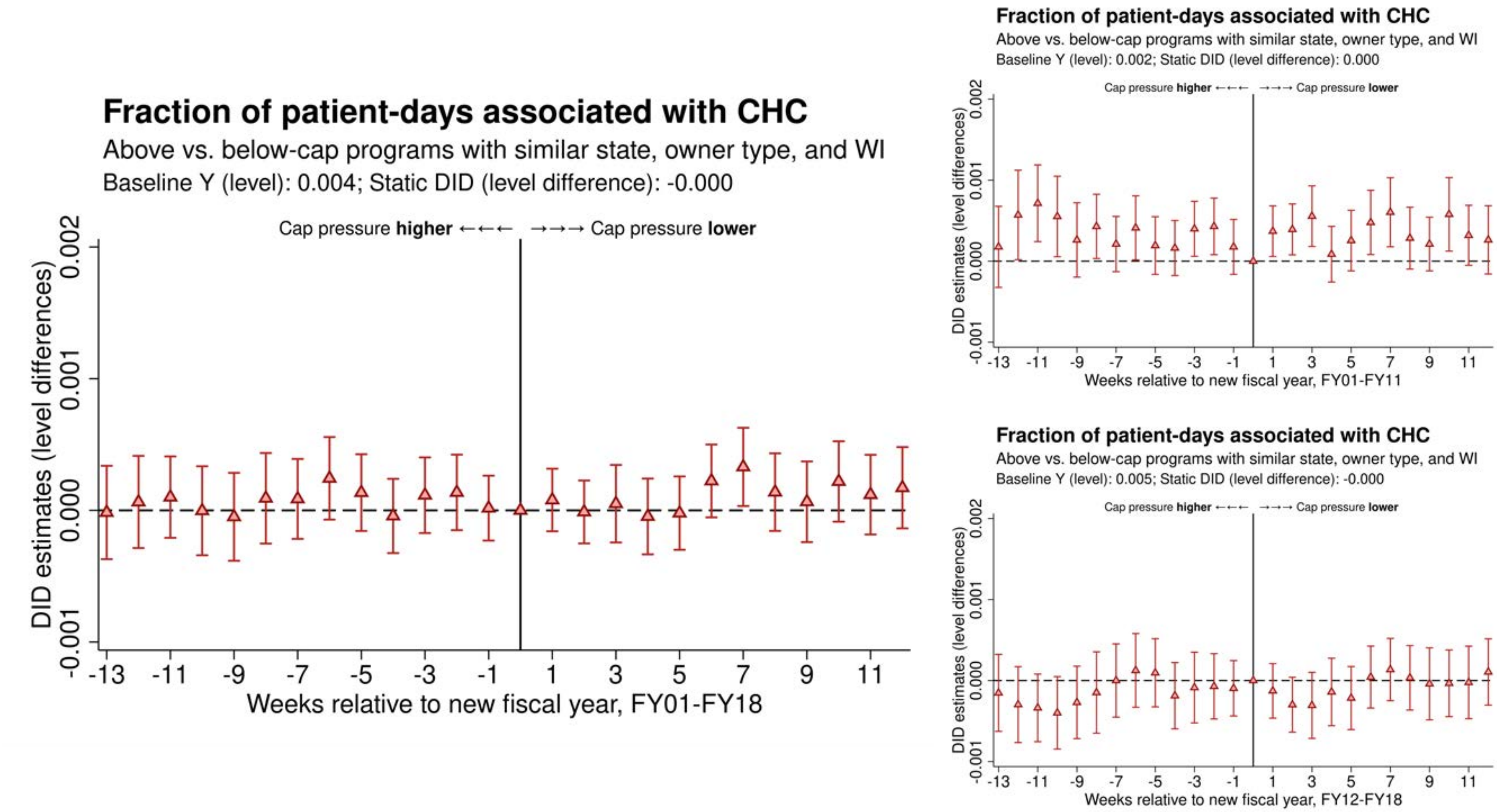


**Fig. A24.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' CHC rates in the weeks leading up to the end of the fiscal year. See table A11 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

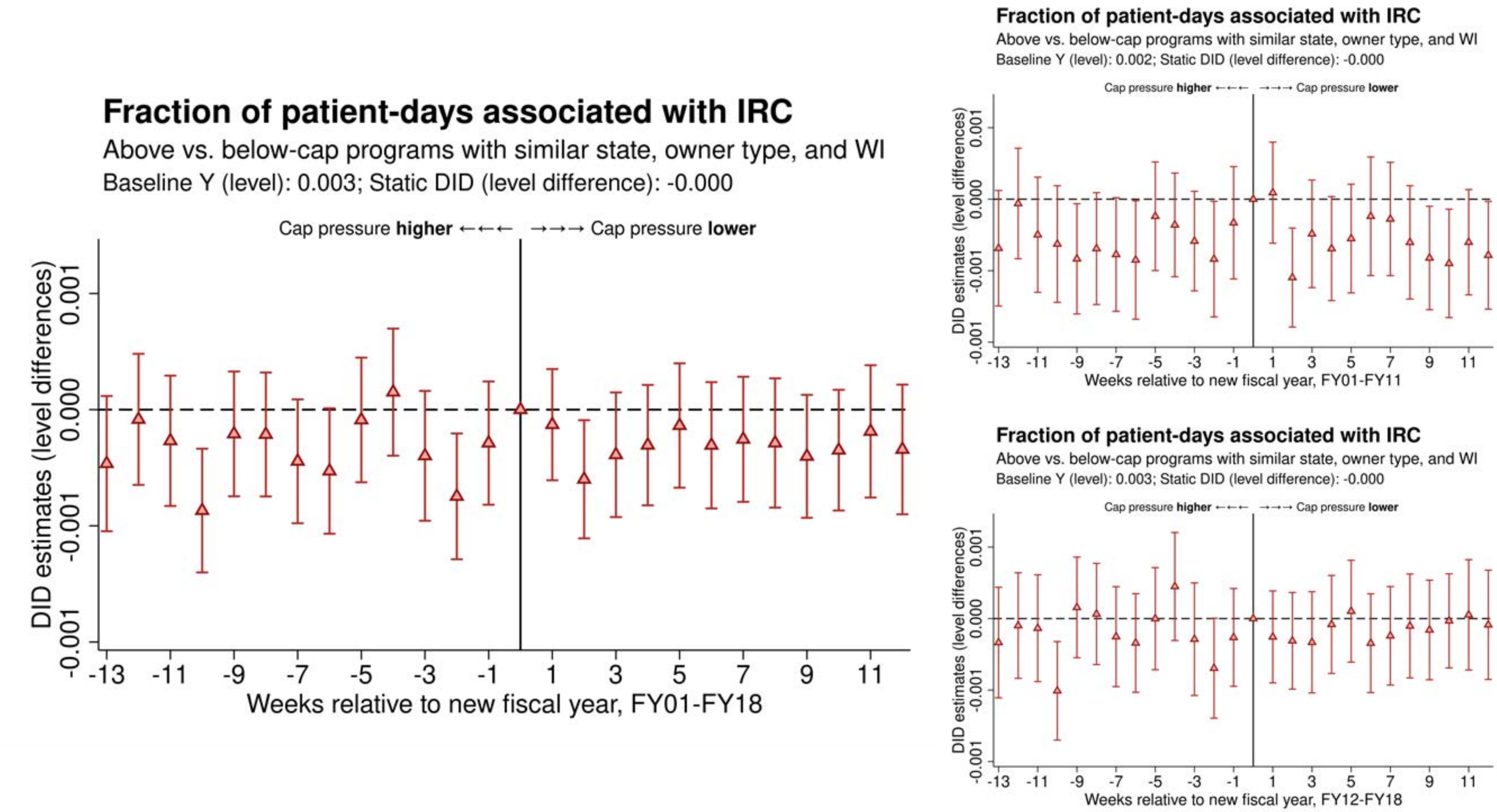


**Fig. A25.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' IRC rates in the weeks leading up to the end of the fiscal year. See table A12 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

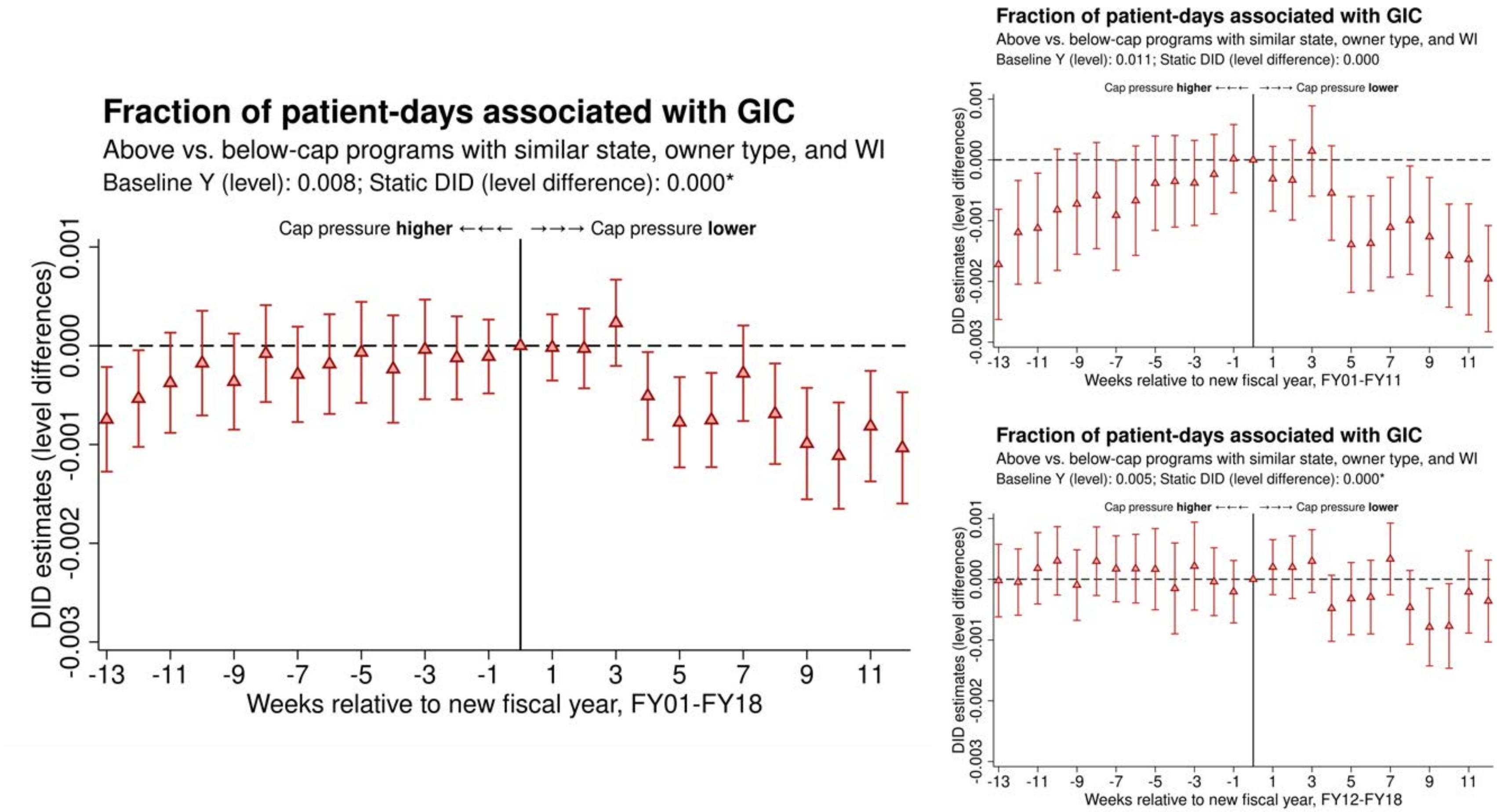


**Fig. A26.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their active patients' GIC rates in the weeks leading up to the end of the fiscal year. See table A12 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

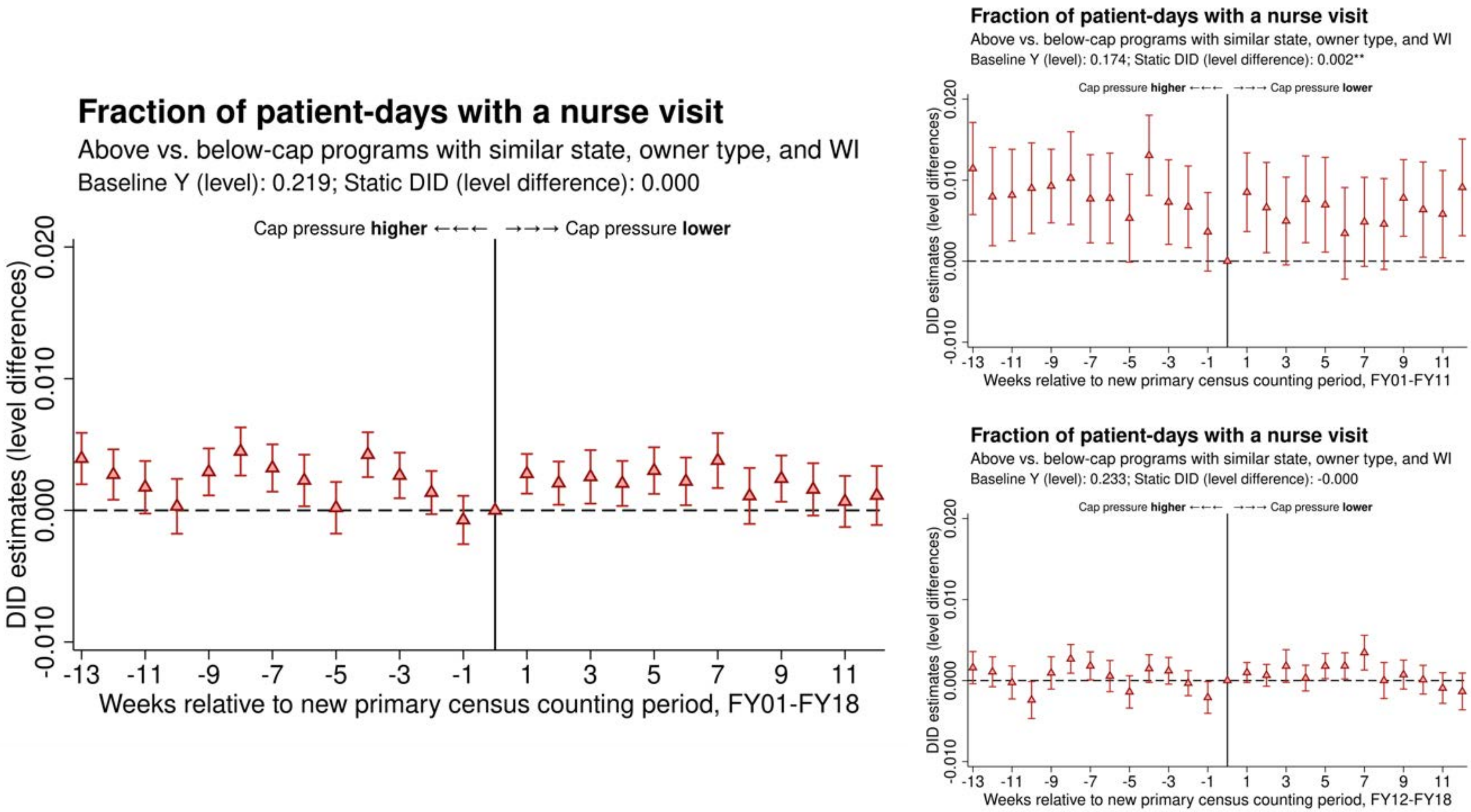


**Fig. A27.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their nurse visit rates in the weeks leading up to the end of the fiscal year. See table A13 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

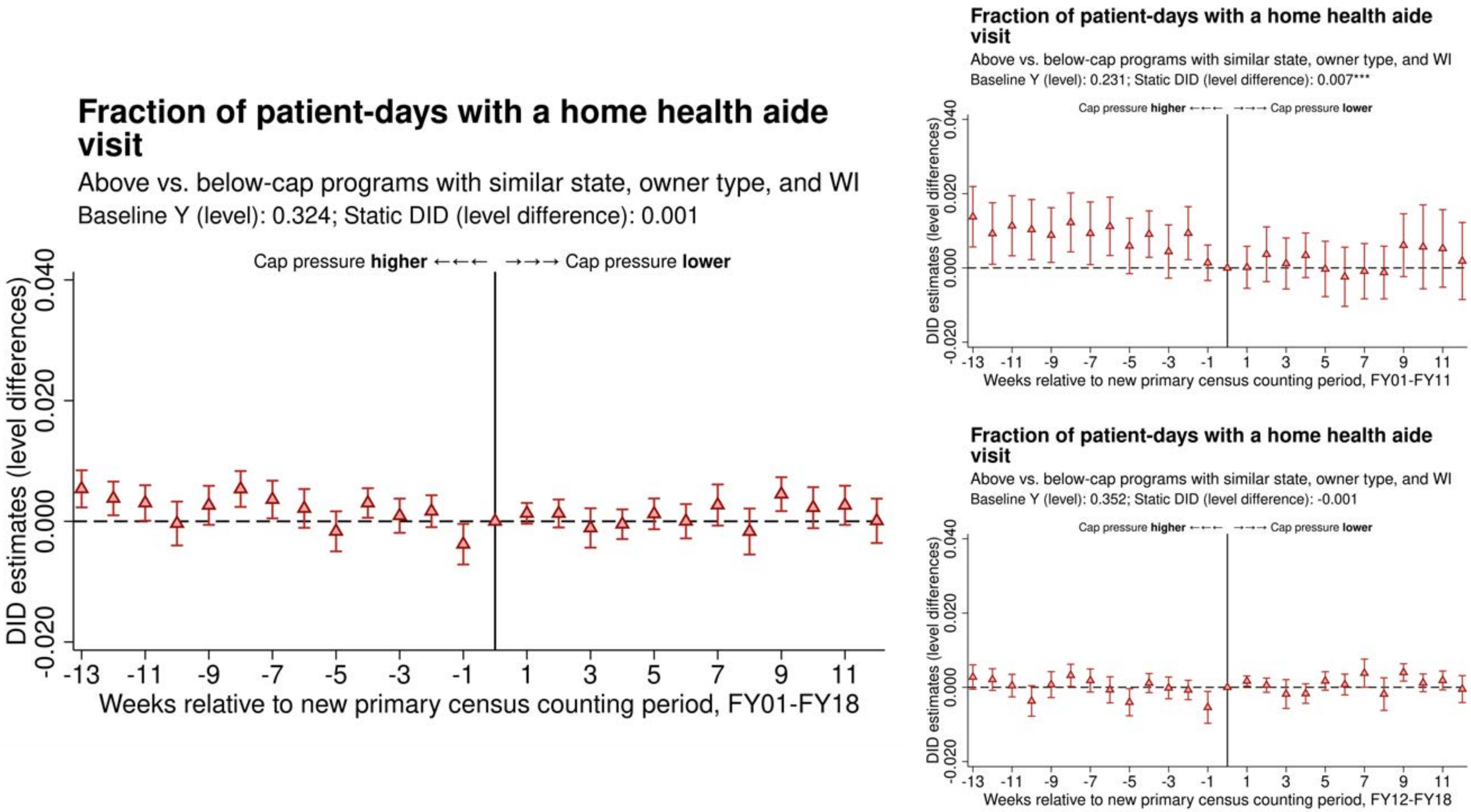


**Fig. A28.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their home health aid visit rates in the weeks leading up to the end of the fiscal year. See table A13 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

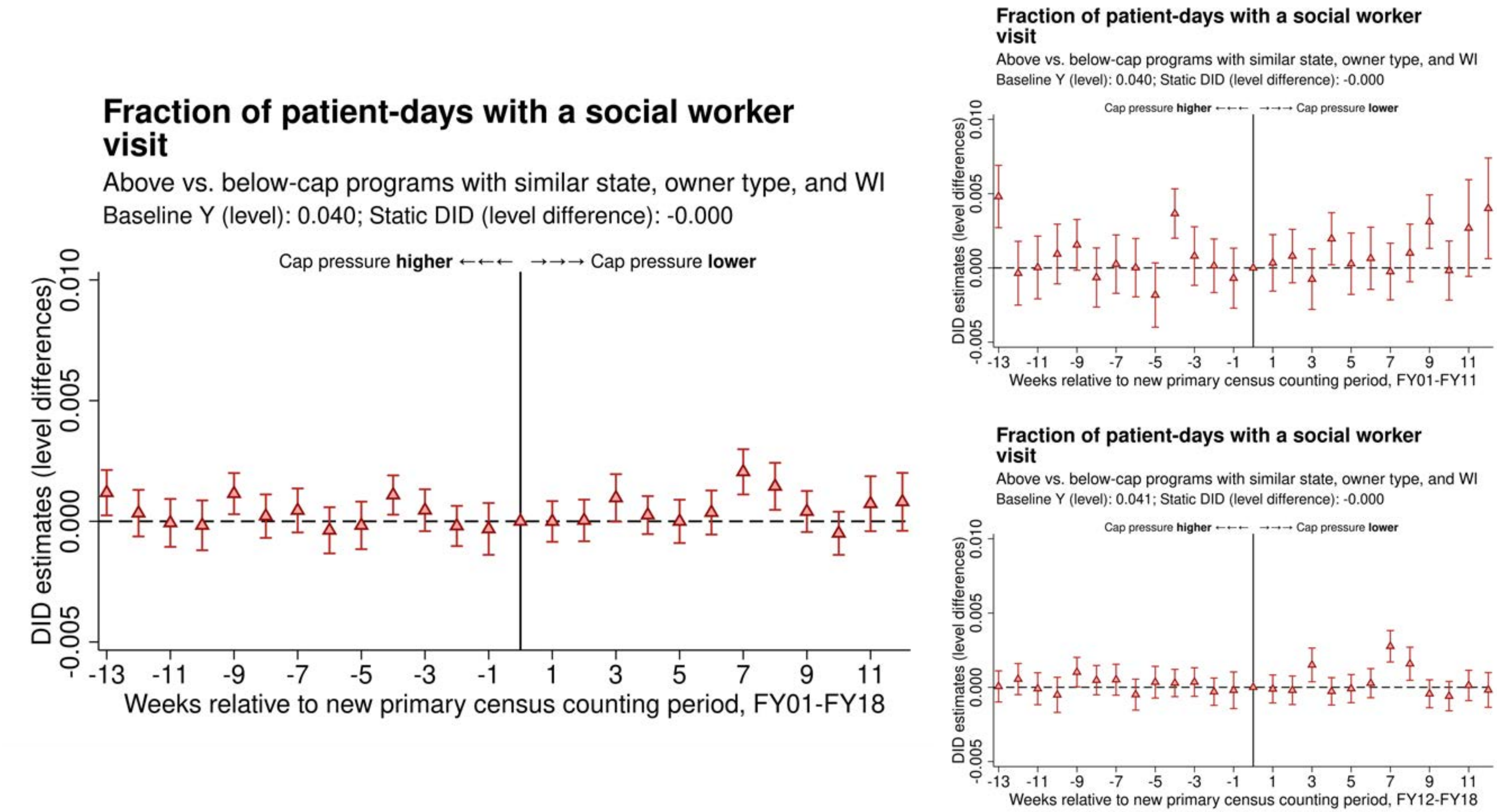


**Fig. A29.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap do not adjust their social worker visit rates in the weeks leading up to the end of the fiscal year. See table A13 and the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. 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. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

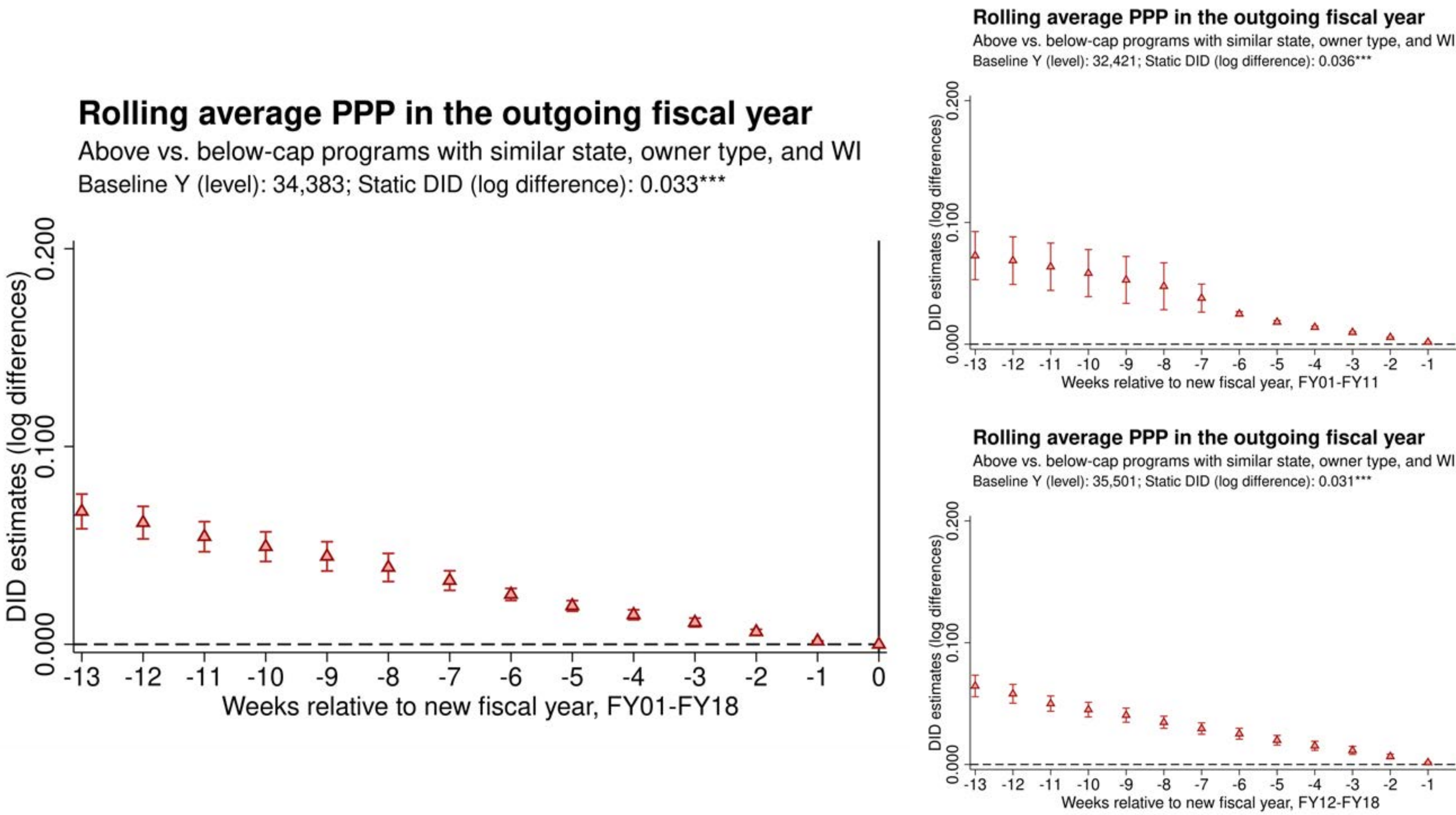


**Fig. A30.** In each panel, this figure plots estimates of $(\beta_w : w \in W, w \leq 0)$ from equation (3) in our difference-in-differences analysis. Estimates corresponding to $w > 0$ are excluded because average annual payments per patient are fixed after the end of the fiscal year. The figure supports 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 21. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. Baseline $Y$ is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

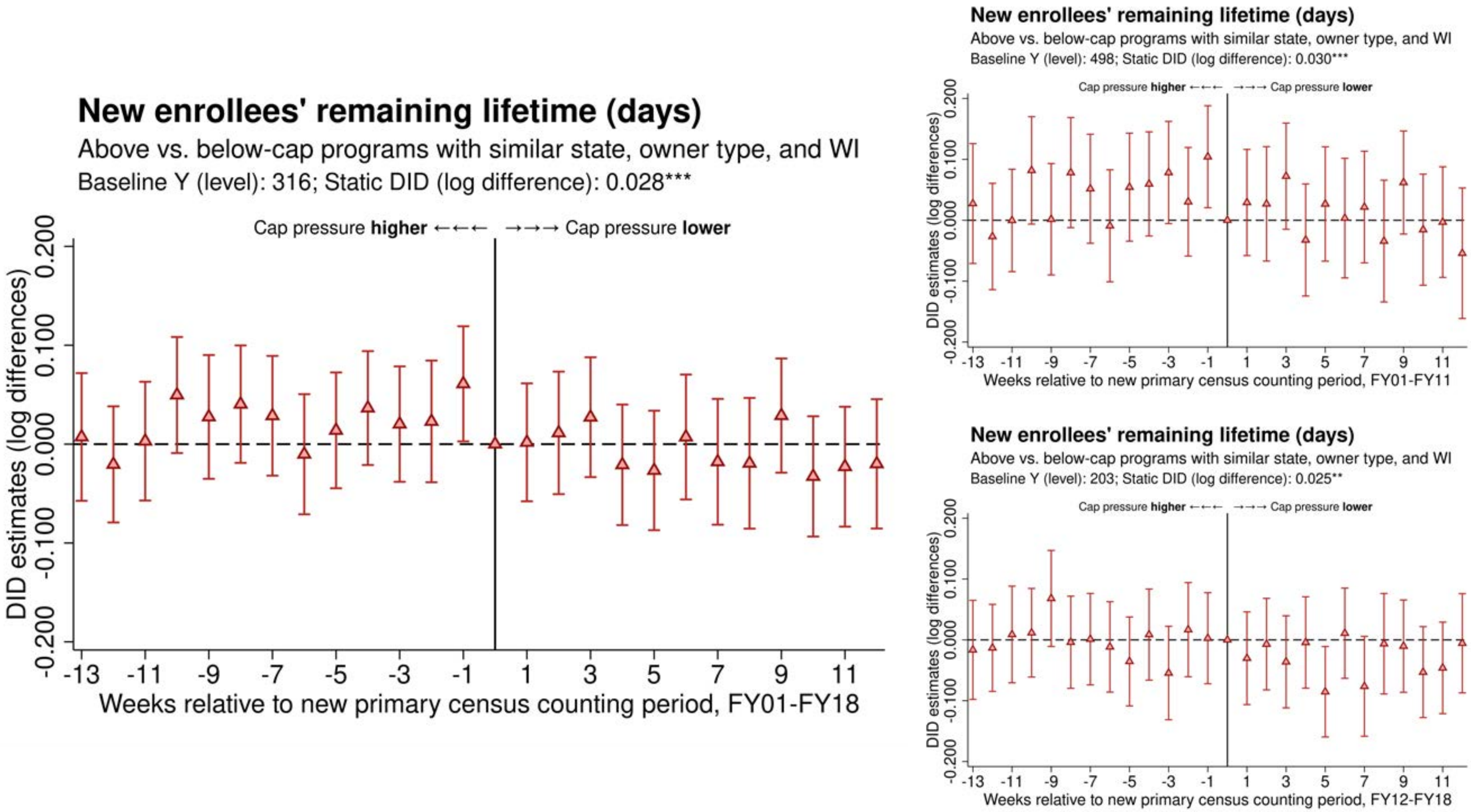


**Fig. A31.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) for the alternative definition of remaining lifetime discussed in appendix AIV.B. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. Baseline $Y$ is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Observations are weighted by the number of enrollees. Static DID is an estimate of $\beta$ from equation (2). $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$. The primary census counting periods are described in appendix AI. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

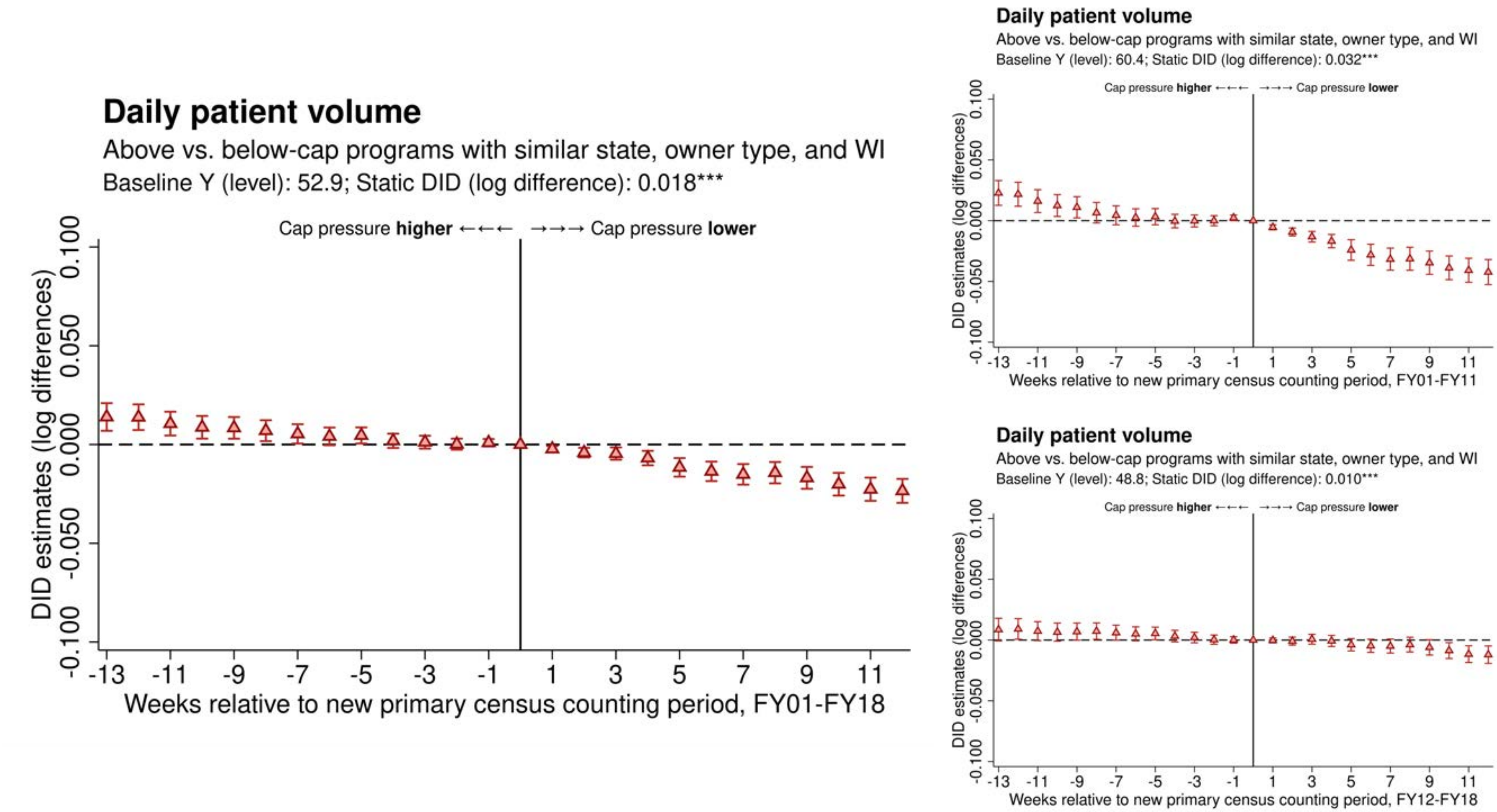


**Fig. A32.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from equation (3) in our difference-in-differences analysis. It supports the idea that programs on track to exceed the cap differentially decrease their active patient volume throughout the event window. See the discussion near page 20. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. Baseline $Y$ is the average value of the outcome during relative time 0 among programs in $\mathcal{T}$. Static DID is an estimate of $\beta$ from equation (2). $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

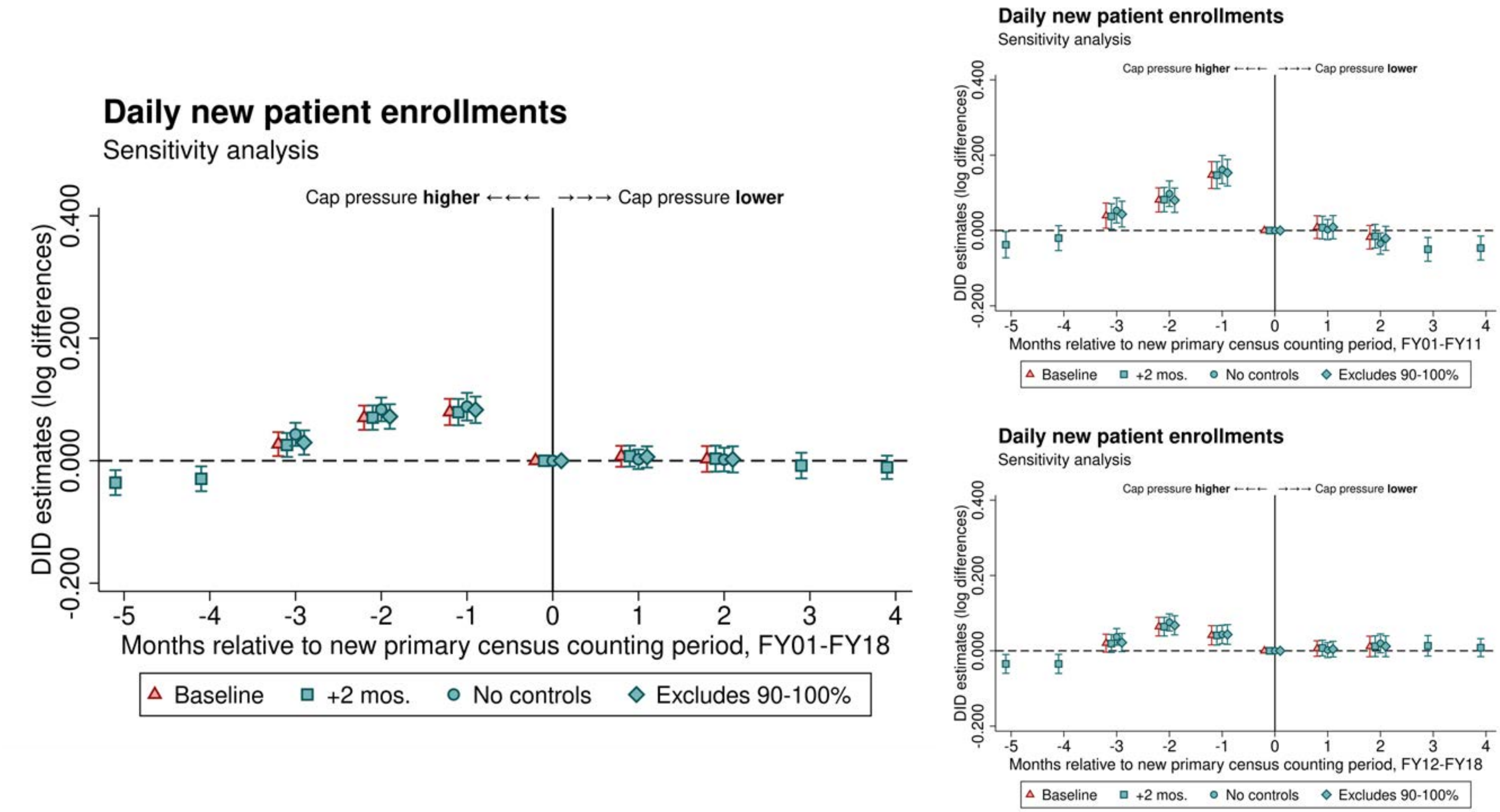


**Fig. A33.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from a monthly version of equation (3) in our difference-in-differences analysis. It also plots corresponding estimates from the robustness checks discussed in section AV.A. It supports the idea that programs on track to 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 V. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

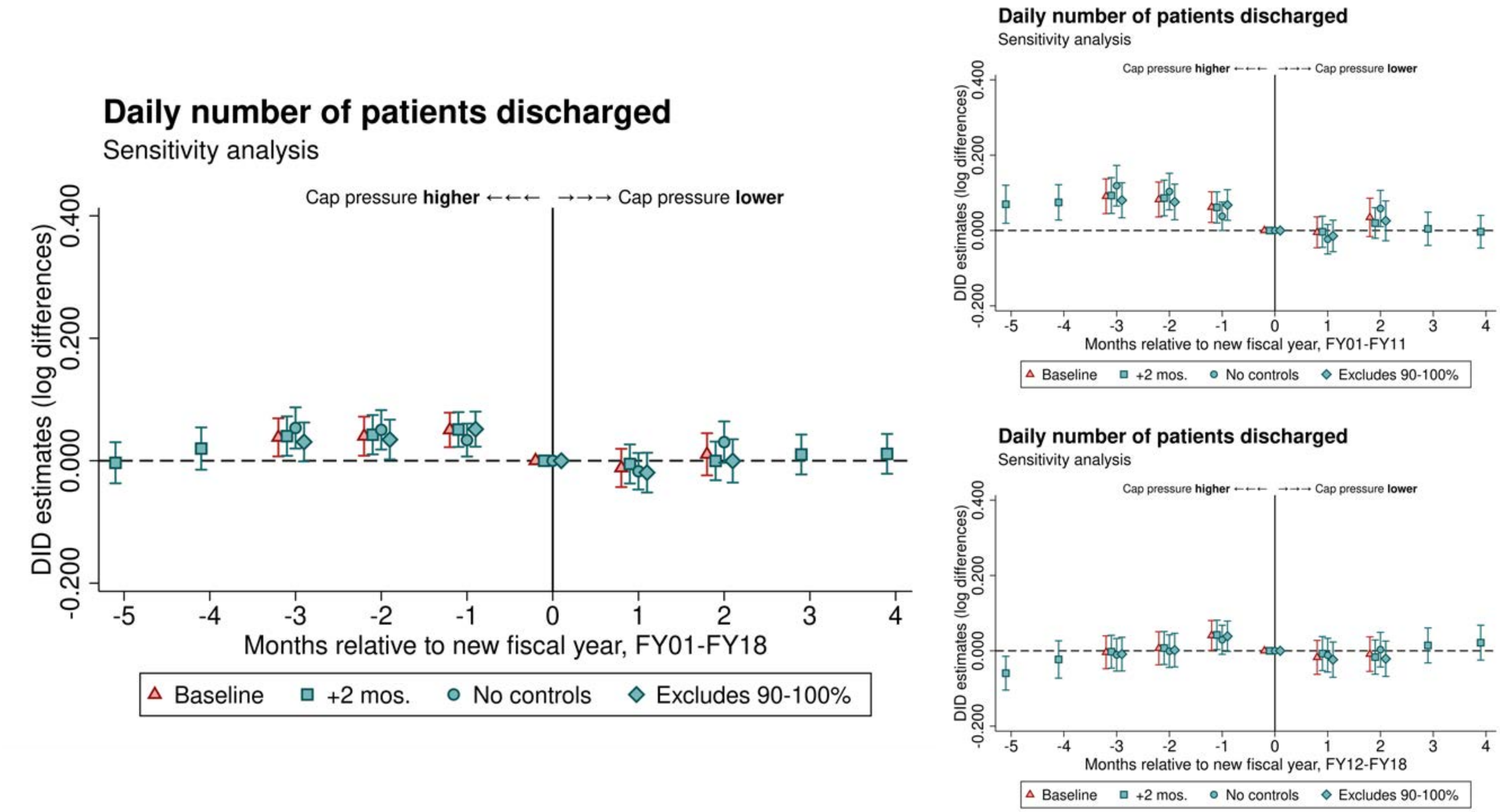


**Fig. A34.** In each panel, this figure plots estimates of $(\beta_w : w \in W)$ from a monthly version of equation (3) in our difference-in-differences analysis. It also plots corresponding estimates from the robustness checks discussed in section AV.A. It supports the idea that programs on track to 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 V. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

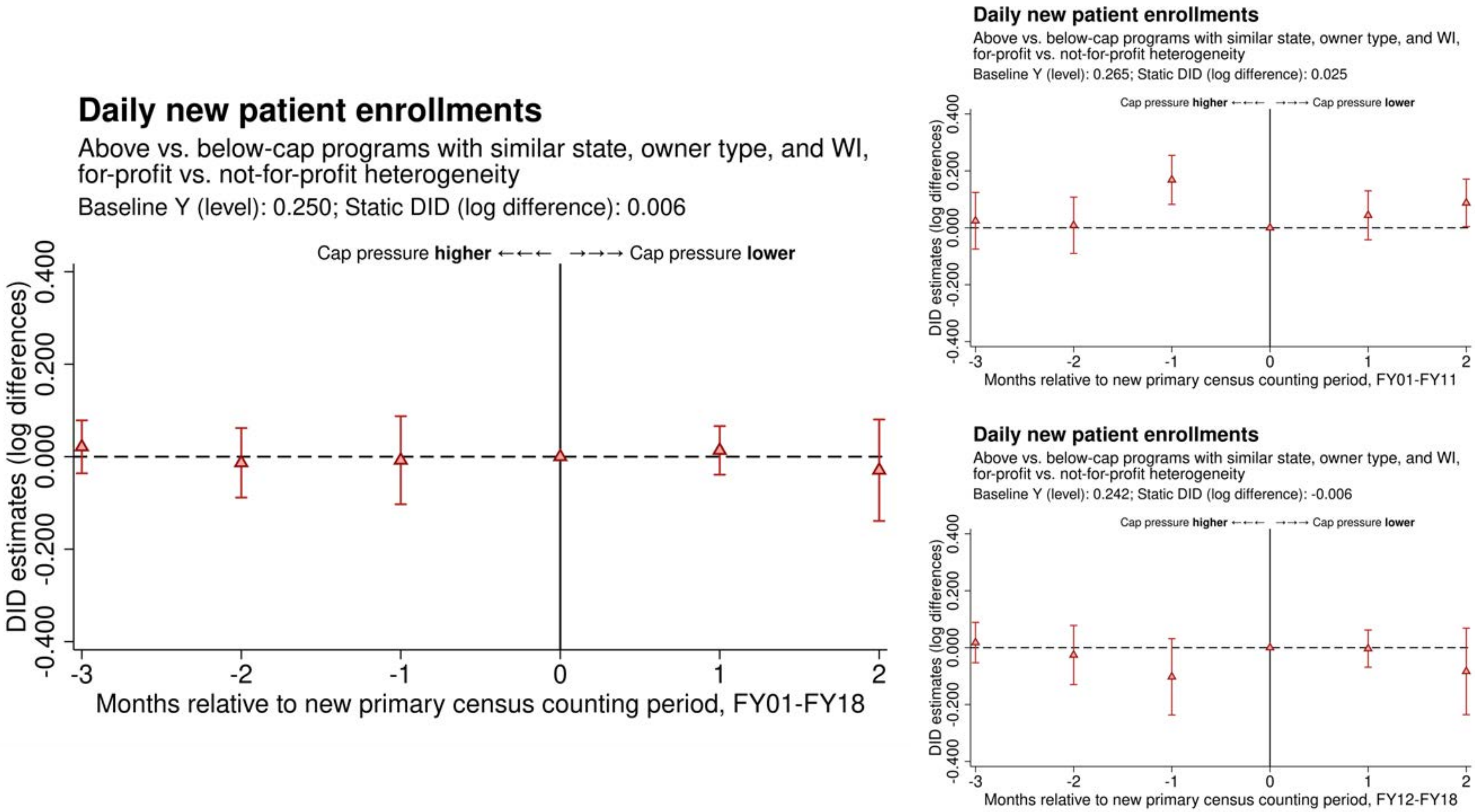


**Fig. A35.** In each panel, this figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that for-profit and not for-profit programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

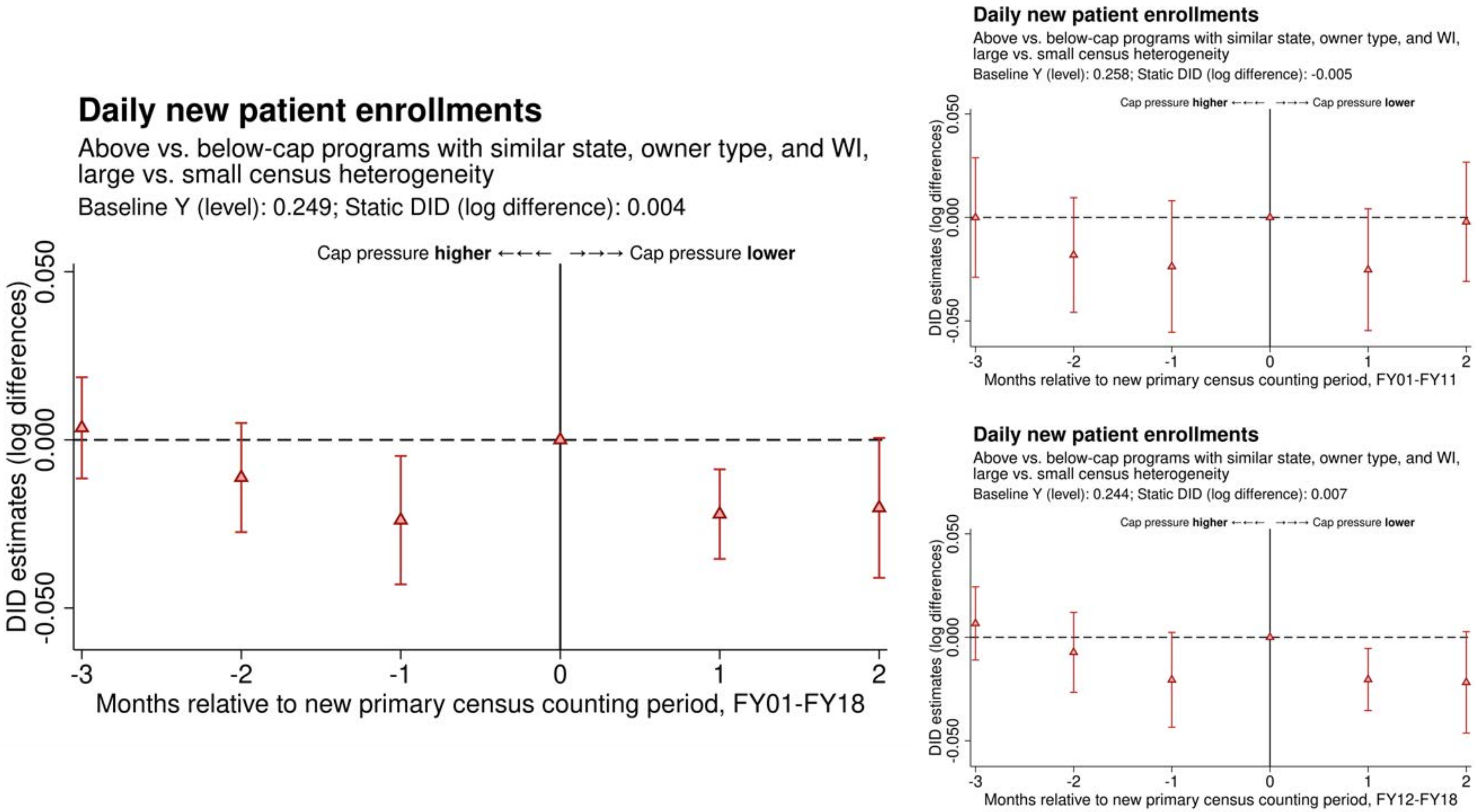


**Fig. A36.** In each panel, this figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that large and small programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

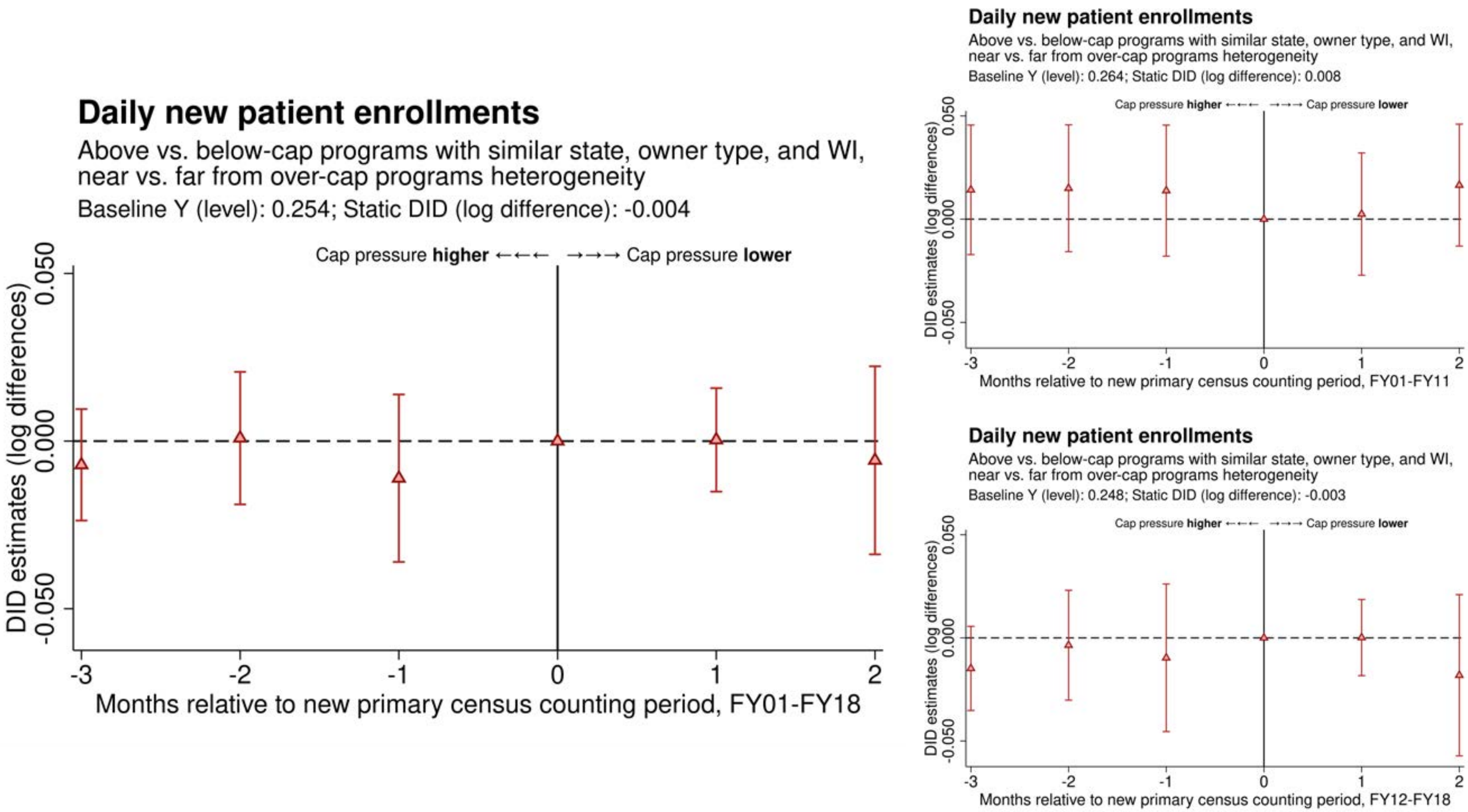


**Fig. A37.** In each panel, this figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates whether they are near or far from other programs that are also on track to exceed the cap contemporaneously. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

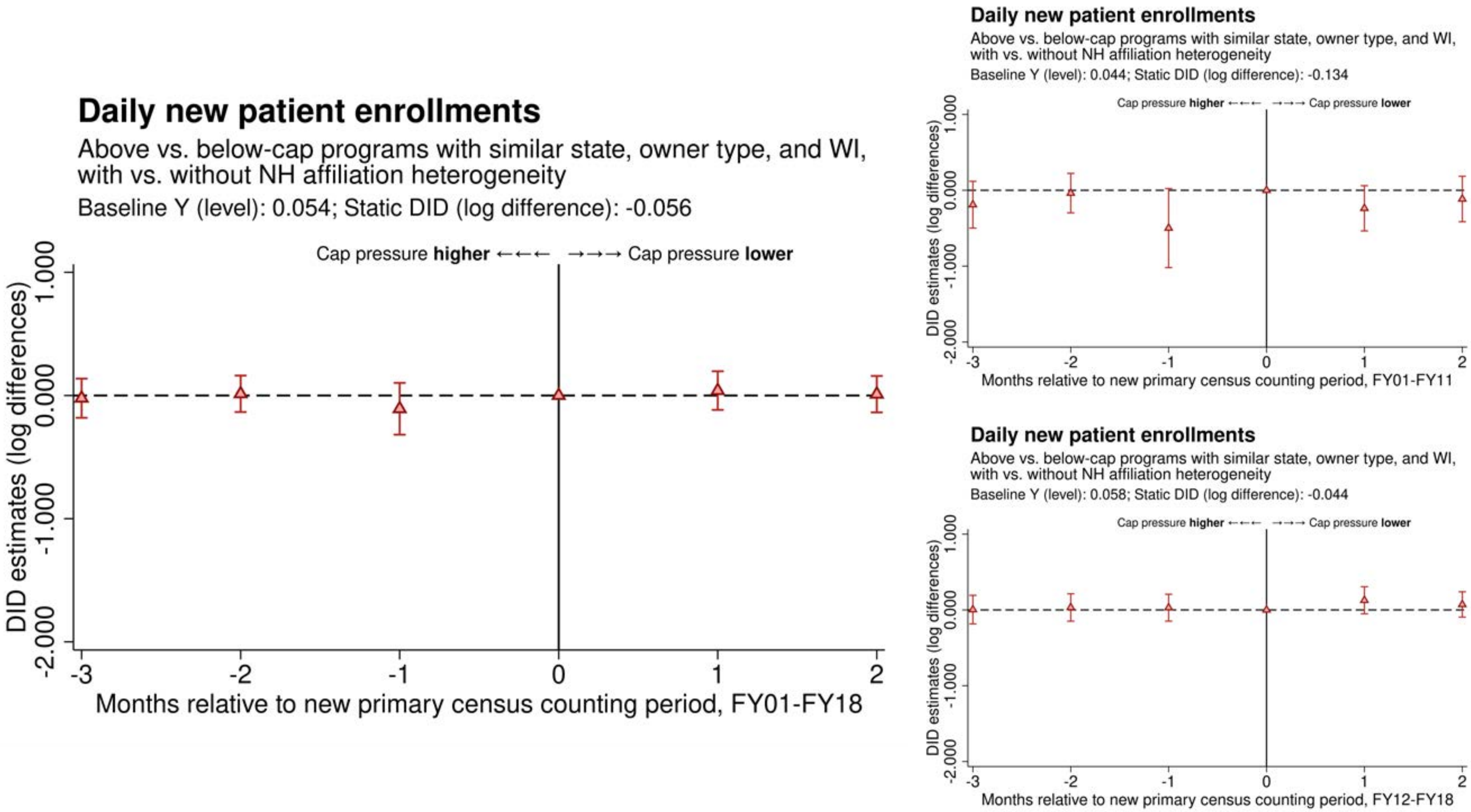


**Fig. A38.** In each panel, this figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that programs on track to exceed the cap raise enrollment rates in the weeks leading up to the end of the fiscal year at much the same rates whether they are affiliated with a nursing home or not. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

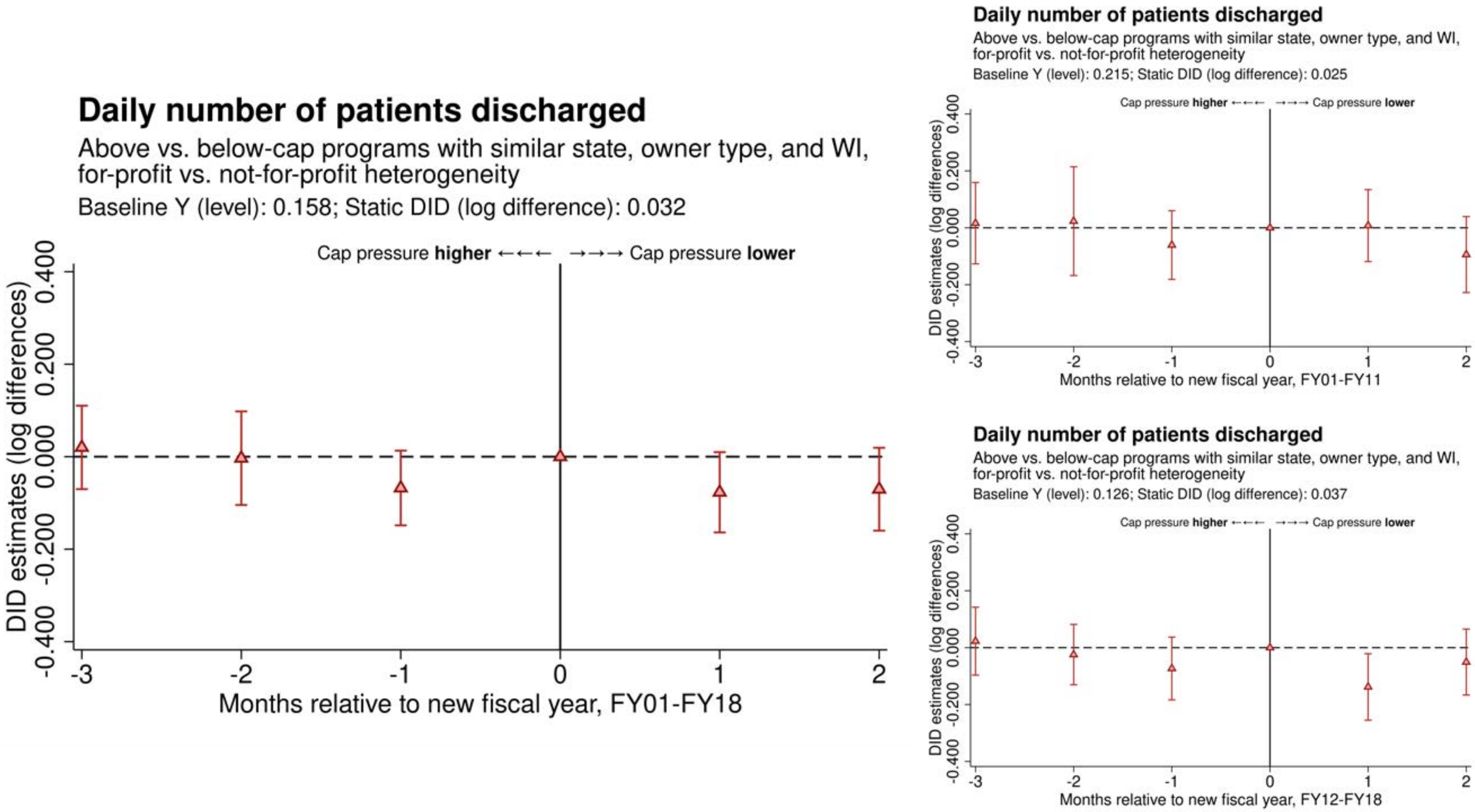


**Fig. A39.** In each panel, this figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that for-profit and not for-profit programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at much the same rates. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

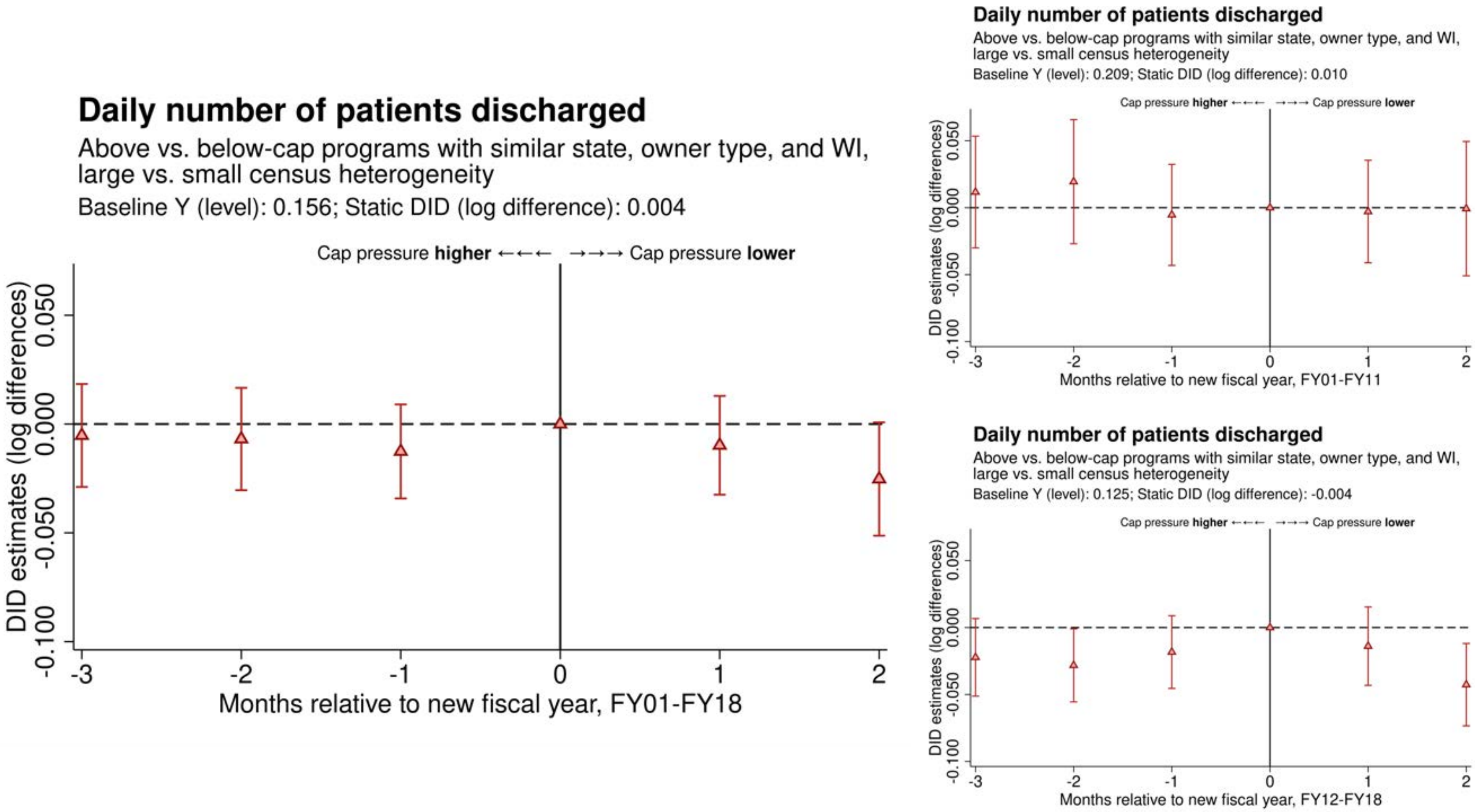


**Fig. A40.** In each panel, this figure plots estimates of $(\beta^1_w : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that large and small programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at much the same rates. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

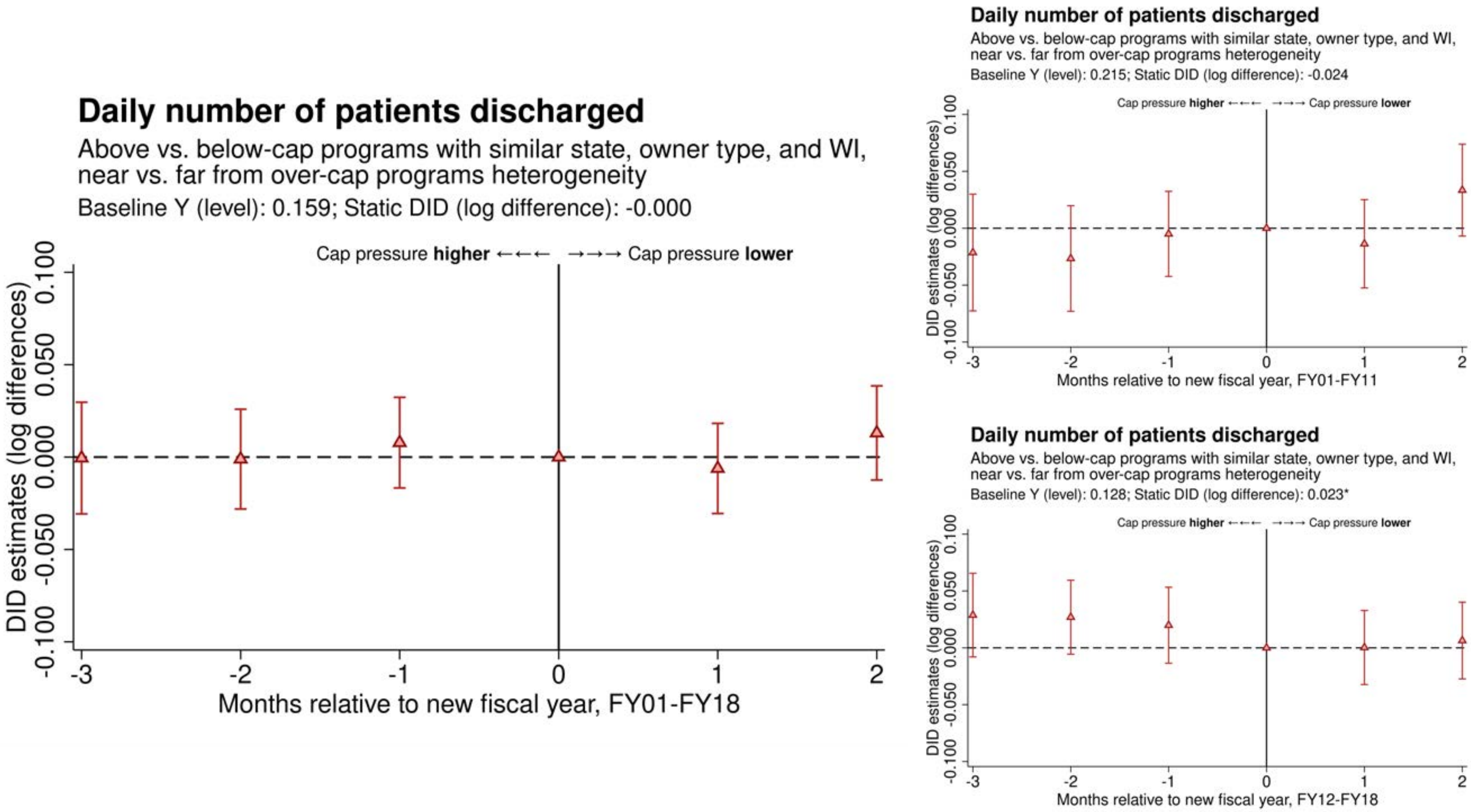


**Fig. A41.** In each panel, this figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at much the same rates whether they are near or far from other programs that are also on track to exceed the cap contemporaneously. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).

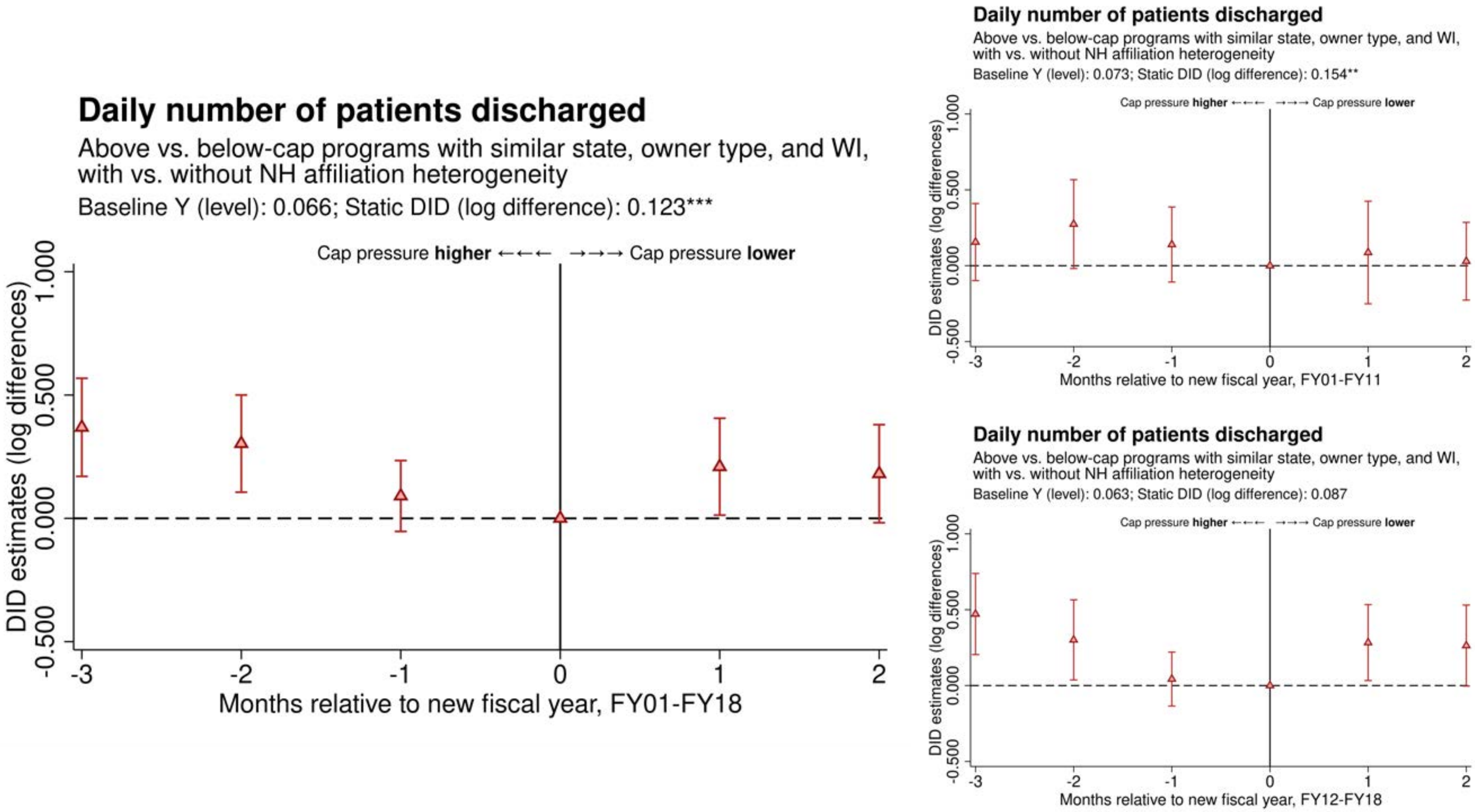


**Fig. A42.** In each panel, this figure plots estimates of $(\beta_w^1 : w \in W)$ from the version of equation (3) described in appendix AV.B. It supports the idea that programs on track to exceed the cap raise live discharge rates in the weeks leading up to the end of the fiscal year at higher rates when they are affiliated with a nursing home. Program-level cluster robust SEs are are used to construct the 95% confidence intervals. The panels examine the overall average (left), streamlined method era (top), and proportional method era (bottom).