Dying or Lying? For-Profit Hospices and End of Life Care

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August, 2024

The Medicare hospice program is intended to provide palliative care to terminal patients, but patients with long stays in hospice are highly profitable, motivating concerns about overuse among the Alzheimer's and Dementia (ADRD) population in the rapidly growing for-profit sector. We provide the first causal estimates of the effect of for-profit hospice on patient spending using the entry of for-profit hospices over twenty years. We find hospice has saved money for Medicare by offsetting other expensive care among ADRD patients. As a result, policies limiting hospice use including revenue caps and anti-fraud lawsuits are distortionary and deter potentially cost-saving admissions.

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We are very grateful for the feedback from Amy Finkelstein, Ashvin Gandhi, Tal Gross, Riley League, Ryan McDevitt, Jack Mountjoy, James Poterba, Alan Sorensen, Maggie Shi, Andrei Shleifer, and Dr. Timothy Murphy. We thank participants of the NBER Public Economics group meeting, the NBER Aging group meeting, the Harvard-MIT-BU Health Economics Seminar, the National Tax Association health group meeting, the ASHEcon conference, the American Economic Association Long Term Care session, the Boston University Applied Microeconomics Seminar, the West Virginia University economics seminar, the Carnegie Mellon Heinz College seminar, the Bates White Life Sciences Conference, and the MIT Public Finance Lunch. We benefited greatly from research assistance by Alexia Witthaus-Viñé. Research reported in this publication was supported by the National Institute on Aging of the National Institutes of Health under Award Number P30AG012810 and by the National Institutes of Health under grant T32-AG000186. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

1. Introduction

The intensive and costly treatment of patients near the end of life is a persistent source of criticism of the US healthcare system (Porter, 2012). Hospice provides an alternative to traditional medical care: it allows patients with a life expectancy of less than 6 months to receive palliative care at home in return for agreeing to forgo curative therapy, potentially improving the experience of dying while reducing Medicare spending (Davis, 1988). Since its inception in 1983, hospice use has grown enormously, accounting for more than $20 billion in federal spending by 2019 or $500 per Medicare beneficiary.

While hospice is an attractive option in theory, there is little evidence on its impact on health care costs. There are competing factors to consider: while hospice patients may forgo other expensive forms of care, hospice providers are paid hundreds of dollars per patient per day for their services. In addition, patient eligibility for hospice is uncertain: eligibility is based on prognosis as certified by a physician, but predicting life expectancy is challenging, and the greatest end-of-life costs are incurred by patients who die unexpectedly (Einav, Finkelstein, Mullainathan, & Obermeyer, 2018).

The structure of the hospice program, and the growth of its for-profit sector, has led to concerns that hospice care is overutilized. Hospice care is provided by private providers, and these private providers face incentives to admit profitable patients. Hospices are paid a daily rate, but their costs of providing care highest at admission and near death (Huskamp, Newhouse, Norcini, & Keating, 2008; MedPAC, 2006); therefore, patients with longer lengths of stay are most profitable. Relatedly, the for-profit hospice sector has grown rapidly. From 2000 to 2019, the number of for-profit hospice firms quintupled while the number of non-profit firms was roughly unchanged. Concurrently, Medicare spending on the hospice program increased from roughly $2.5 billion in 1999 to over $20 billion in 2019 (MedPAC, 2004) (MedPAC, 2021).

Many for-profit firms have been investigated for admitting ineligible patients. In particular, for-profit entry has coincided with a large increase in the number of patients admitted with a diagnosis of ADRD, who tend to have long hospice lengths-of-stay and a particularly uncertain prognosis. Between 1999 and 2019, the share of ADRD patient-years including a hospice stay rose from 4.4% to nearly 15%. Moreover, since 1999, dozens of the

largest for-profit hospices have collectively paid hundreds of millions to the Department of Justice to settle allegations that they admitted ineligible patients, a form of health care fraud.[1]

In this paper, we study the effects of for-profit hospice use on Medicare spending in the ADRD population and evaluate the impact of policies designed to curtail overuse of the hospice benefit. We begin by providing the first causal estimates of the impact of for-profit hospice enrollment for the marginal patient. To identify this estimate, we exploit the rapid entry of for-profit hospices, which exposes Medicare beneficiaries to varying levels of hospice access over time and by location. Specifically, we use a standard distance-based instrument with locality fixed effects to estimate the impact of for-profit hospice care. The entry of for-profit hospices changes the likelihood of hospice use among ADRD patients residing in the same zip code but diagnosed at different times.

We find striking evidence that, despite concerns about inappropriate hospice use for ADRD patients, for-profit hospice for the marginal ADRD patient saves money, mostly due to large reductions in the use of skilled nursing facilities (SNF) and home health care. On average, we estimate a savings of about $29,000 to Medicare for each marginally admitted ADRD for-profit hospice patient over years 0-5 post diagnosis. Our results suggest that, on the margin, expanding hospice access would reduce Medicare costs, even if it meant admitting patients who could potentially live longer than 6 months.

In light of our finding that hospice for the marginal patient reduces Medicare spending, we also examine the impact of hospice care on patient outcomes. Using the same instrumental variables design, we find that admission to for-profit hospice increases mortality by 9 percentage points for the marginal ADRD patient. The welfare implications are unclear, however, given that hospice patients agree to forgo life-saving care. We show that hospice appears to improve quality of life by reducing the frequency of surgeries, the incidence of pressure ulcers, and the number of infection-related stays.

[1] The ability of the government to enforce eligibility standards is unclear: in one high-profile case, the court sided with the hospice on the grounds that claims about patients' life expectancy cannot be "objectively false" given the inherent uncertainty in predicting survival. See: United States vs Aseracare, Inc.

The entry of for-profit hospices affects two distinct groups of patients: patients who would otherwise not have gone to hospice and patients who would have otherwise gone to non-profit hospice. Typically, distance-based instrumental variable strategies lump these groups together, even though marginal effects may be quite different. We apply the empirical strategy of Mountjoy (2022) to decompose the effects along these two margins. We find that for-profit hospice savings and mortality effects are concentrated among patients whose outside option was no hospice. This strategy also allows us to evaluate the patients who are diverted from non-profit care to for-profit care, which reflects on quality differences between firms of different profit types. We find no evidence of major quality or treatment differences between these firm types. We further characterize differences between for-profit and nonprofit firms; nonprofits are generally smaller and take more acutely ill patients.

The finding that for-profit hospice exposure saves money for ADRD patients suggests that policies designed to curtail hospice use ought to be carefully scrutinized. We therefore provide new evidence on the impact of two important policies -- an aggregate revenue cap and antifraud litigation -- on patient costs and outcomes. The aggregate cap on hospice revenues is designed to limit long stays. The cap equals a fixed dollar amount multiplied by the number of patients admitted in a given fiscal year, computed at the firm-year level. Hospices must refund any revenues in excess of this amount, thereby counteracting hospices' incentives to admit long-stay patients. Compared to non-profit hospices, for-profit hospices have a considerably longer average duration of stay and consequently face higher cap pressure. We find that when facing pressure from the cap, hospices change how they treat patients. Among all hospice patients, (not just the ADRD cohort), patients in hospices facing cap pressure are more likely to be discharged from hospice alive and experience higher mortality rates. We show that cap-induced discharges from hospice disrupt health care use, and many discharged patients eventually return to hospice, indicating that the cap induces costly care transitions near the end of life. The cap also lowers patient-level spending, but only by roughly $2,300 over 12 months.

The government also uses the False Claims Act, a federal anti-fraud statute, to penalize hospices suspected of admitting ineligible patients. Using new data from a Freedom of Information Act Request, we examine the effect of False Claims Act litigation on firm behavior

with a difference-in-difference design. We find that defendant firms admit fewer long-staying patients and fewer ADRD patients. We show that these effects hold throughout the ADRD spending distribution, i.e., that the lawsuits do not accomplish a targeted reduction in use among patients for whom hospice is unlikely to be cost saving. Moreover, because marginal patients save money by going to hospice, federal litigation appears to discourage hospices from admitting cost-saving patients. Hospice use is an unusual case where federal anti-fraud initiatives potentially increase costs because the marginal admittee saves money.

Our study makes several contributions to the prior literature on the impact of hospice care, which we review in detail in Appendix A. Hospice improves quality of care, including among dementia patients (Harrison, Cenzer, Ankuda, Hunt, & Aldridge, 2022). Studies of spending effects typically begin by identifying a sample of decedents and then looking back in time to compare spending between decedents who were or were not in hospice at the time of death (for example, (Kelley, Deb, Du, Aldrige Carlson, & Morrison, 2013) (Campbell, Lynn, Louis, & Shugarman, 2004). This approach is tantamount to selecting on the outcome, because patients who are discharged from hospice while alive are excluded, and estimates may be biased by differences in unobserved characteristics between groups (Aldridge, Moreno, & McKendrick, 2022). In contrast, our intent to treat approach considers the full population of ADRD patients and does not select on outcomes.

Our work is also related to a literature on health care fraud and the effect of for-profit care on patient health. O'Malley *et al*. (2021) discuss fraud in Medicare home health care provision, documenting a rise in fraudulent care by for-profit firms. Leder-Luis (2023) reports that hospice cases account for a large share of False Claims Act lawsuits, and Howard (2020) discusses the legal issues surrounding medical necessity and fraud in hospice care, but neither measure the effects of hospice use or hospice fraud. Gupta *et al.* (2021) and Gandhi *et al.* (2022) study the implications of private-equity ownership of nursing homes for patient care and reach conflicting conclusions about the welfare consequences of ownership. Gonda & Song (2019) and a recent MedPAC report (2021) consider the implications of private equity in health care and discuss the tradeoff between increased productive efficiency versus reductions in the quality of care. Studies have documented the rise of for-profit care (Braun, Stevenson, & Unruh,

2021) and the its impact on quality and access (Dalton & Bradford, 2019) (Wachterman, Marcantonio, & Davis, 2011). Our work also speaks directly to questions about the differential treatment effects of for-profit and non-profit hospices.

This paper proceeds as follows. Section 2 discusses the institutional context of hospice and anti-fraud litigation against hospices and reviews the existing literature on hospice care. Section 3 presents our data and descriptive statistics, and Section 4 describes the instrumental variables design and its results. Sections 5 addresses the hospice cap and its policy implications with empirics. Section 6 discusses hospice litigation and presents empirical evidence on the effect of hospice fraud lawsuits, and Section 7 concludes.

2. Background: The Medicare Hospice Program

2.1 Hospice Program Overview

Medicare beneficiaries with a life expectancy of less than 6 months are eligible for hospice care. While hospice patients retain Medicare coverage for other conditions, such as injuries, Medicare does not cover curative treatment for the condition for which they are admitted to hospice. Hospices are responsible for ensuring the comfort of dying patients. They provide counseling, nursing visits, help with activities of daily living (*e.g*, bathing), chaplaincy, and pain management, which may entail the administration of opioids. Routine Home Care, conducted at the patient's place of residence, accounts for over 98% of hospice care days (National Hospice and Palliative Care Organization, 2020). Routine care is paid at a fixed daily rate that is adjusted regionally in proportion to average wages. The daily payment rate for routine-home care in 2020 was $199.25 for days 1-60, before regional adjustment. Before 2015, the daily rate was constant. Since 2015, Medicare pays about $150 per day on or after day 61. Payment is not adjusted for patient diagnosis. Hospices can also provide inpatient and respite care in rare circumstances of acute patient need.

Hospice payments and costs differ in their structure. While hospices face a near-constant daily payment rate, their costs are non-linear: the costs of hospice are highest at enrollment, when hospices incur the upfront costs of patient acquisition and enrollment and at the end of life, when patients need the greatest care (Huskamp, Newhouse, Norcini, & Keating, 2008). Hospices therefore earn the largest profits on patients with long lengths of stay.

To combat the incentive to admit long-stay patients, Medicare has imposed an aggregate cap on hospice payments per firm. The formula for the cap takes an annual constant and multiplies it by the number of new patients the hospice admits in a given year. The constant is adjusted annually (but not regionally) and in 2019 it was $29,205. All revenue over this cap amount must be returned, producing a cliff in reimbursement. The cap applies at the firm-year level, not at the patient level. For example, if a hospice had two patients who incurred spending of $40,000 and $10,000 (for an average of $25,000), the hospice would fall below the cap. We empirically analyze the effects of the cap in Section 5.

Since 1996, there have been dozens of False Claims Act anti-fraud lawsuits filed against hospice firms for enrolling patients who were not terminal or for recertifying non-terminal patients for continued hospice care. Many of the patients in question had Alzheimer's or dementia. The False Claims Act allows whistleblowers to file lawsuits against firms that defraud the federal government. Whistleblowers, often hospice employees, alleged that management pressured clinical staff to meet admissions targets and that hospice physicians inappropriately certified patients as eligible.

Use of the False Claims Act to target hospices for admitting ineligible patients is controversial. Hospices have argued that their physicians' assessments of patient life expectancy are inherently subjective and thus cannot be considered "false" under the Act. Federal appellate circuit courts have reached conflicting opinions on the matter, and litigants have asked the Supreme Court to weigh in. Our study provides evidence both on the effect of these admissions on federal spending and on the value of the application of the False Claims Act to hospices' admission decisions.

3. Data and Descriptive Statistics

3.1 Data

We use 100% samples of Medicare Fee-for-Service claims data from 1999 through 2019,[2] including hospice claims, beneficiary enrollment files, chronic conditions indicators, inpatient claims, and cost and use files. The hospice claims data allow us to identify patient-

[2] As is standard in the health economics literature, we cannot observe patients who enroll in Medicare Advantage (Part C). We only observe 20% samples for Medicare Part D drug claims and Part B physician's office visits.

level hospice use, providers, and payments. The Medicare beneficiary summary files include patients' zip codes and death dates, and the Chronic Conditions Warehouse files identify patients diagnosed with ADRD. We use the Cost and Use files to identify annual spending in different categories of care, such as inpatient, outpatient, and SNF care. We supplement information on the profit status and zip code of providers from the Provider of Service Files, which we can match to the hospice claims data. When constructing patients' exact 12-month spending after each month to analyze the cap in Section 5, we use claims data from each type of Medicare spending, e.g. inpatient claims, outpatient claims, durable medical equipment claims, etc.

To study hospice litigation, we use data from the Department of Justice on fraud cases. We filed a Freedom of Information Act (FOIA) request that identified 163 lawsuits against hospice companies and chains. Many lawsuits contain multiple defendants. We pair the FOIA data with substantive information from Department of Justice press releases and the Public Access to Court Electronic Records system. We combine our FOIA request, which contains defendant firm's names, with data from the Medicare Provider of Service files to identify which providers in the Medicare data were subject to litigation. We supplemented our understanding through numerous interviews with Department of Justice attorneys who litigated hospice fraud cases.

Finally, to assess the impact of hospice care on quality-of-life outcomes, we collect data on treatment and diagnoses. The Medicare claims contain Diagnosis Related Group codes for inpatient stays and nursing visits, as well as National Drug Codes for pharmaceutical prescriptions, which we use to describe types of care. We supplement the Medicare data with data from the state of California to assess visit rates by hospices, which are not available during our sample in the Medicare claims. For our analysis of pressure ulcers, a common and painful condition resulting from extended bed rest, we use data from the Minimum Data Set from 1999 through 2016, which contains data on all patients in nursing facilities nationwide.

3.2 Descriptive Statistics on Hospice Use

We begin by documenting trends in the hospice industry that highlight concerns about overuse. The left panel of Figure 1 shows trends in the number of for-profit and not-for-profit

hospices in our data. Between 1999 and 2019, the number of for-profit hospice firms quintupled, from 624 firms to more than 3,300. The right panel of Figure 1 shows the use of hospice care by ADRD patients. In 1999, 4.4% of ADRD patient-years included a hospice claim. By 2019, that number more than tripled to 14.7%. Appendix Figure A1 shows trends in the geographic density of hospices between 2000 and 2014. The growth in hospice density was concentrated in the American South and Midwest.

The growth of for-profit hospices has coincided with a decline in the share of hospice episodes for which the patients died within six months, from 86.4% in 2000 to 79.2% in 2018. Only 73.4% of 2018 for-profit hospice patients died within 6 months. These trends are consistent with allegations that for-profit hospices do not rigorously restrict admission to eligible patients.

Appendix B provides additional details about hospice firm dynamics. Upon entry, non-profit and for-profit hospices start with similar patient volumes. Over time, both grow larger, but for-profit hospices expand more rapidly, so that by 10 years post-entry, they are about 67% larger. The average age of for-profit hospices in our sample is 6.4 years, and the average age among non-profit firms is 8.7 years, reflecting greater entry by non-profits. The average length-of-stay is about 30 days longer at for-profit hospices, and the difference does not vary greatly with hospice age. Using supplementary data from California on visits provided by hospices (because Medicare claims do not report visit frequency for most years in our sample), we calculate that non-profit and for-profit hospices provide similar numbers of visits on average, 0.5 visits per patient-day, but there is greater variability among for-profit hospices. The distribution of the specialty of the referring physician (i.e., the physician who certifies that a patient is eligible for hospice) is similar between non-profit and for-profit hospices, though non-profit hospices tend to admit more patients with recent hospital stays, reflecting their general focus on more acutely ill patients.

4. The Effects of Hospice Use on Patient Spending and Outcomes

4.1 Empirical Design

Our first analysis evaluates the effect of for-profit hospice usage on patient spending and health outcomes. This is motivated by concerns among policymakers about the

proliferation of for-profit care and admission of ineligible patients, as well as the use of antifraud litigation against for-profit providers for these admissions.

Our strategy for estimating the effects of for-profit hospice uses variation in patients' exposure to for-profit hospices based on where they live and the timing of their diagnosis among beneficiaries ever diagnosed with ADRD. We used the chronic conditions file to identify patients with ADRD and their comorbid conditions. We obtained patients' zip code and demographic characteristics from the enrollment file. We focus on the ADRD population because these are the "marginal" patients of most interest to policy makers and relevant to questions about uncertain eligibility and anti-fraud enforcement. Moreover, within this population, hospice use is sufficiently frequent that we can use an intent-to-treat design to address selection in who does and does not enroll in hospice.[3]

Hospice use may change the length of time a patient spends in our sample (for example, if hospice use impacts death). Therefore, we design a cohort-based study where, for each patient, we consider the patient's health and spending outcomes in a fixed period following ADRD diagnosis. The choice of a time window entails a trade-off between observing outcomes but restricting our data to years with sufficient post-period. We consider a window following diagnosis of [*t, t+5*] years, as the majority of patients are deceased five years after diagnosis. We also use a shorter window, [t, t+2], as a robustness check. The [t, t+5] window includes beneficiaries who were first flagged as having ADRD between 2000 and 2014.

Table 1 shows descriptive statistics for our main sample of ADRD patients. Our cohort consists of about 10.9 million patients. The mean age at diagnosis is 81. Sixty two percent of patients are female and 86% are white. The patient population is relatively sickly: 59% have hypertension, 27% have diabetes at baseline, and 67% percent of patients die within 5 years.

We use a distance-based IV strategy to address selection into for-profit hospice, following a large literature in health economics (McClellan & Newhouse, 1997) (Einav,

[3] An alternative strategy would be to focus on all those likely to use hospice, or to have long hospice stays, but as we discuss throughout, hospice use and longevity after hospice enrollment are incredibly hard to predict. Appendix Table A1 presents the results of a logistic regression that predicts hospice admission and long hospice spells as a function of a patient's chronic conditions, using a random sample of about 10 million Medicare beneficiaries. The pseudo-R^2 of this regression is only about 8%, and ADRD is the strongest predictor of hospice use and of long hospice episodes.

Finkelstein, & Mahoney, 2022). A concern with distance-based IVs is the endogeneity of provider location. Hospices, which face low entry costs, may enter markets with more profitable patients. We therefore augment our distance-based IV strategy by including location (zip code) specific fixed effects, so that we compare individuals in the same zip code before and after a for-profit hospice enters or exits. This allows us to control for for-profit hospices' selection of markets based on fixed area factors. We present tests of IV validity in section 4.5.

We rule out endogenous patient mobility after diagnosis by considering each individual's zip code in the year before they first have an ADRD diagnosis flag, so that our estimates are identified only by for-profit hospice entry/exit and not by patient movement. Our identification comes from comparing patients who live in the same zip code and who are diagnosed with ADRD in different years, where there is entry or exit of a for-profit hospice between patients' diagnosis dates. We also control for diagnosis cohort fixed effects, to account for trends in both hospice entry and patient outcomes, and for distance to a non-profit hospice. Appendix C.1 presents more details about the distance calculations. We also show balanced trends before and after hospice entry below.

We use two-stage least squares estimates to implement the instrumental variables design. For the first stage, we estimate the effect of exposure to for-profit hospice on for-profit hospice use:

$$FPHospice_{icz} = a_0 + \beta D_{FP,cz} + \eta_z + T_c + \delta X_{icz} + \zeta D_{NP,cz} + e_{icz}, \quad (1)$$

for patient i in cohort c in zip code z, where $D_{FP,cz}$ is the zip code's distance to a for-profit hospice for patients in cohort c; η_z is a zip-code fixed effect; T_c is the diagnosis cohort fixed effect; $D_{NP,cz}$ is distance to a non-profit hospice; and X_{icz} is a vector of patient characteristics including age at diagnosis, sex, race, and indicators of other chronic conditions at baseline. $FPHospice_i$ is an indicator that equals 1 if the patient goes to for-profit hospice within 5 years. We also include a control for distance to a non-profit hospice, which we use later when decomposing the overall effect into its different margins (Mountjoy, 2022). Controlling for non-profit distance also ensures that our empirical design isolates the effect of changes in for-profit distance. We also present estimates of the impact of distance on measures

of for-profit hospice use that capture both intensive and extensive margin effects: length of stay and hospice spending (where both are 0 for hospice non-users).

We then estimate the effect of hospice use on 5-year patient spending and mortality. We estimate:

$$Y_{icz} = a_1 + \gamma\, \widehat{FPHospice}_{icz} + \eta_z + T_c + \delta X_{icz} + \zeta D_{NP,cz} + e_{icz}. \qquad (2)$$

where Y_i is spending on different categories of care, indicators for death, or quality-of-life related outcomes.

This design estimates the Local Average Treatment Effect for a population of compliers, for whom our instrument, exposure to for-profit hospice, increases the probability of for-profit hospice uptake. Our results rely on the standard IV monotonicity and exclusion assumptions, which in our circumstance mean that patients who are closer to for-profit hospices are weakly more likely to attend and that distance to a for-profit hospice, conditional on zip fixed effects and distance to non-profit hospice, affects outcomes like spending and mortality only through its impact on enrollment in for-profit hospice. In Section 4.4 below, we further explore substitution between non-profit and for-profit hospice as a function of entry by for-profit hospices. Section 4.5 presents robustness estimates to alternative specifications as well as tests of our assumptions.

4.2 Spending Results

Appendix Table A2 presents the first-stage estimates of the coefficient β from Equation (1). The coefficient represents the marginal effect of a 10-mile increase in distance to the nearest for-profit hospice. Being 10 miles closer to a for-profit hospice increases extensive margin hospice use by 1 percentage point from a baseline of 14.7% and length of stay (coded 0 for non-goers) increases by 0.85 days from a baseline of 15 days. For each 10 miles a patient is closer to a for-profit hospice, for-profit hospice spending increases by $100 from a baseline mean of $2,300. These estimates apply to the whole ADRD population of 10.86 million individuals and are very precise, with *p < 0.01* for each estimate and an *F*-statistic of 707 for the extensive margin.

Appendix Table A3 characterizes the complier population of ADRD patients induced into for-profit hospice by for-profit entry and compares them to the entire ADRD sample and to

ADRD patients enrolled in for-profit hospice. Compliers tend to be older and are more likely to have comorbidities than the general population, as would be expected given that they are entering hospice, but are quite similar to the population of all for-profit hospice enrollees. Compliers live somewhat further away from non-profit hospices than the general population, also as expected, but the average complier appears to have access to both hospice types: 43.9% of compliers live within 10 miles of a non-profit hospice.

Table 2 presents OLS and two-stage-least-squares estimates of the effect of for-profit hospice on a patient's spending among different categories of care within 5 years of diagnosis, γ from Equation (2). OLS estimates (first panel, column 1) suggest that use of for-profit hospice increases spending, but these are biased upward because sicker patients enroll in hospice.

The two-stage-least-squares estimates in Table 2 can be interpreted as the effect on the complier population, for whom exposure to for-profit hospice leads to enrollment. For-profit hospice reduces 5-year spending among ADRD patients by $29,000 on net, or 36% from a base of $81,100.[4] These results do not include additional savings to Medicaid and Social Security.

Next, we decompose Medicare cost savings by spending on different categories of care. Not surprisingly, for-profit hospice use increases spending on for-profit hospices by about $10,200. Spending on non-profit hospices decreases by $2,800. The net effect is a $7,400 increase in total hospice spending. Entry by for-profit hospices shift patients away from non-profit hospices as well as increasing overall hospice use. We decompose these effects in Section 4.4 below, where we examine multiple treatment margins.

Although hospice use increases hospice spending, it substantially decreases spending on two other expensive forms of care: skilled nursing (SNF) and home health care. Among compliers, for-profit hospice enrollment reduces SNF spending by $12,600 from a baseline mean of $12,700. Enrollment reduces home health expenditures by about $7,000 from a

[4] Total spending is drawn from the 100% Beneficiary Summary Cost and Use files and is the sum of all the Medicare payment variables, including all hospital payments, ambulatory surgical centers, Part B spending including drugs, testing, imaging and physicians, Part D drugs, skilled nursing, home health, hospice, and Durable Medical Equipment.

population mean of $5,600. The large reductions indicate that for-profit hospice use reduces spending on SNF and home health among a relatively expensive set of patients.

For-profit hospice use leads to a shift from inpatient to outpatient care. We estimate that enrollment reduces 5-year spending on inpatient care by $8,700 from a base mean of $31,100. In contrast, enrollment increases spending on hospital outpatient care by about $3,600 from a mean of $6,700. While hospice patients forfeit curative treatment for their terminal condition, they are still eligible to receive hospital care for other conditions. Hospice patients are also closely monitored by the hospice staff, who may refer patients for physician and hospital outpatient care for conditions unrelated to their terminal diagnosis.

Finally, for-profit hospice substantially decreases expenditures on Part D pharmaceuticals; spending decreases by $7,000 over 5 years from a baseline mean of $5,600. While Medicare does not broadly cover pharmaceutical therapies for ADRD, hospice patients are less likely to receive other expensive drugs near the end of life.

To validate our finding that for-profit hospice patients receive less SNF and home health care, we conduct a supplementary analysis to examine the discharge destination of ADRD patients following hospitalization. Using the universe of hospitalizations of ADRD patients discharged from 2000 to 2018, we regress the share of patients discharged into different types of care on an indicator for whether patients were concurrently in hospice. Discharge categories include SNF, home health, discharged home without care discharged into hospice care, or died in the hospital. Appendix Table A4 presents these results. Consistent with our IV findings, ADRD patients hospitalized with concurrent hospice are 11 percentage points less likely to be discharged to home health from a baseline of 15 percentage points. These patients are also substantially less likely to be discharged home without further care. In contrast, patients are 23 percentage points more likely to be discharged from the hospital to hospice care. These results are consistent with our finding that for-profit hospice reduces the use of SNF and home health care. Patients in hospice are also more likely to die in the hospital, reflecting differences in health status between hospice and non-hospice patients.

Appendix Figure A2 presents results from an event study analysis as a robustness check (see Appendix D for details). Because the “event” in our case – a change in distance – is

continuous, we use methods for creating event studies for continuous treatments (Schmidheiny & Siegloch, 2023). This approach has been shown to be equivalent to a two-way fixed effects model with binned endpoints. As with our IV design, we consider patient spending in each category from years 0 to 5 post diagnosis. Therefore, patients' 5-year exposure to hospice entry depends on the timing of their diagnosis relative to entry. For example, a patient diagnosed four years before nearby hospice entry would be untreated in years one to four and treated in year five.

Appendix Figure A2 shows results that are consistent with our IV effects and also allow us to rule out pre-trends before for-profit hospice entry or exit. Five-year for-profit use begins to rise 5 years before entry (the first vertical dashed line) as each newly diagnosed cohort is exposed to entry for successively longer periods. Usage then peaks and levels off once the cohort is fully exposed (the second vertical dashed line). Appendix Figure A2 also shows a parallel analysis for spending categories. There is little evidence of pre-trends. Total spending declines after a cohort is initially exposed then decreases steadily over time. In this case, the reduction in spending continues even after full exposure, presumably reflecting longer-run impacts of hospice entry.

4.3 Patient Care and Health Effects

Table 3 presents the two-stage-least-squares and reduced-form estimates of the effect of for-profit hospice on mortality within 5 years of diagnosis. For this analysis, we use cumulative mortality in periods after the patient's exact date of ADRD diagnosis. For-profit hospice enrollment increases 1-year-post diagnosis mortality by 6.8 percentage points from a baseline of 26.3% and 5-year post-diagnosis mortality by 8.6 percentage points from a baseline of 66.6%. We also find that for-profit hospice increases 90-day mortality by 4 percentage points from a baseline of 12.7%. The increase may be due to ADRD hospice patients immediately forgoing life-prolonging care. These estimates are all statistically significant at the 1% level.

Table 4 presents the effects of hospice on types of care likely to affect quality of life. Generally, for-profit hospice seems to eliminate potentially disruptive or harmful care and also changes the types of care patients do receive. For-profit hospice enrollment reduces inpatient surgeries by 0.94 on a baseline mean of 3.88, with a small corresponding increase in outpatient

surgeries. Patients with limited life expectancies are unlikely to benefit from most surgeries. Using data from the Minimum Data Set (MDS), which tracks patient health status in long term care facilities and rehab nursing homes, we estimate that hospice use leads to a statistically significant reduction in pressure ulcers, a common and painful condition that often results from bed rest (Agency for Healthcare Research and Quality, 2024). This result persists even after we restrict our sample to patients with at least one MDS observation (i.e., have a long-term care or rehabilitation nursing home stay) within the diagnosis year 0-5 window.

To better understand how hospice affects health care use, we examine the impact of hospice on broad clinical categories of inpatient care and prescription drugs. Each MedPAR event (inpatient short or long hospital stay or SNF visit) falls into one of 26 Major Diagnostic Categories (MDC), which generally correspond to different organ systems. Table 4 shows IV estimates of the impact of for-profit hospice use on spending among some particularly relevant MDCs, and Appendix Figure A3 shows the full distribution of stays by MDC, analyzing both visit counts and spending. We find that hospice use reduces spending on respiratory, circulatory, musculoskeletal, and infectious disease stays. We find that hospice patients are more likely to be admitted for kidney-related stays but that spending on kidney stays declines, suggesting that hospice leads to more frequent but less severe hospitalizations for conditions such as urinary tract infections. Infectious disease stays and spending also decline. These results are consistent with less intensive treatment within a hospital and SNF setting, echoing the reduction in surgeries.

Appendix Figure A4 presents estimates of the impact of hospice use on prescription drug classes, defined by Anatomical Therapeutic Chemical (ATC) class. Like MDCs, these generally correspond to organ systems. The results are consistent with a shift from curative care towards palliative care. We find a substantial reduction in the use of respiratory, cardiovascular, and musculoskeletal drugs. Many drugs in these classes are associated with side effects (Sevilla-Sanchez, et al., 2017) and are considered inappropriate at the end of life (De Schreye, Houttekier, Deliens, & Cohen, 2017). In contrast, there is an increase in nervous system drugs, the category containing painkillers and opioids commonly used by hospices for management of symptoms near death. One limitation of this analysis is that hospices may

provide drugs to patients directly, without submitting Part D claims, which limits our ability to observe prescribing behavior.

4.4 Decomposing Treatment Margins

For-profit hospice entry has two distinct margins along which it affects patients: patients can be "diverted" from non-profit to for-profit hospice or they can be induced into for-profit hospice as opposed to no hospice. The estimates presented above combine the effects in these two populations, but understanding the separate effect in each group is important for policy. We are especially interested in the effect in patients for whom the alternative is no hospice. We adopt the methodology used by Mountjoy (2022) to disentangle these marginal treatment effects. In line with this method, we can write the marginal treatment effect of for-profit hospice as a convex combination across two sets of patient types:
$MTE_{FP} = \omega MTE_{FP\leftarrow 0} + (1-\omega) MTE_{FP\leftarrow NFP}$ where ω is the share of compliers who are induced along the no-hospice margin, and $(1-\omega)$ is the share of patients diverted from the non-profit hospice margin. $MTE_{FP\leftarrow 0}$ reflects the marginal treatment effect along the no-hospice inducement margin, and $MTE_{FP\leftarrow NFP}$ reflects the marginal treatment effect along the non-profit diversion margin. The share of compliers along the no-hospice to for-profit hospice margin can be computed as a ratio of first-stages:

$$\omega = \frac{\text{First Stage Effect of For-Profit Distance on Any Hospice Use}}{\text{First Stage Effect of For-Profit Distance on For-Profit Hospice Use}}$$

Intuitively, suppose exposure to a for-profit hospice increases the probability of going to a for-profit hospice by 1% but increases the probability of going to any hospice by only 0.4%. Then, the other 0.6% must be diverted from non-profit hospice, and the share of compliers from each margin are 0.4%/1% = 40% and 0.6%/1% = 60%, respectively.

Estimation of the marginal treatment effects of interest $MTE_{FP\leftarrow 0}$ and $MTE_{FP\leftarrow NFP}$ are further described by Mountjoy (2022) using a combination of the two instruments, distance to a non-profit hospice and distance to a for-profit hospice. We adopt this methodology, which relies on the standard linearity assumptions as well as a "comparable compliers assumption," which in our case implies that the marginal patient deterred from non-profit hospice by a marginal increase in non-profit distance, or induced to for-profit hospice by a marginal

decrease in for-profit distance, are alike in the limit. Appendix C.2 gives the estimating equations used for this exercise.

This approach requires within-zip code variation in the distance to a non-profit hospice. While there was no net change in the *number* of non-profit hospices, there was substantial variation over the study period in patients' distance to a non-profit due to entry and exit. Appendix Figure A5 shows a histogram of these zip-level distance changes; 57% of zip codes experienced a change in non-profit distance over our sample period. Moreover, the Wald first stage F statistic using non-profit distance as an instrument for for-profit hospice use is 206.

Table 5 presents the results of this decomposition exercise. We estimate that $\omega = 0.58$, i.e. that 58% of our compliers are patients who would otherwise not use hospice, and 42% of patients are diverted from non-profit hospices. We find reductions in spending for both groups. Spending for patients induced to hospice who would otherwise not attend hospice declines by $44,000 and by $8,000 for patients induced from non-profit hospice. For patients who would otherwise not enroll in hospice, we can reject the null of $0 savings at a *p = 0.05* level using bootstrap estimates. For patients diverted from non-profit hospice, we cannot reject the null of $0 savings. This finding is reasonable given that for-profit and non-profit hospices provide similar services.

Much like the savings effects, the effects of for-profit hospice admission on 5-year mortality are concentrated among patients who would not have gone to any hospice in the absence of for-profit entry. Among these patients, there is a 15 percentage point increase in 5-year mortality. Mortality effects for patients induced from non-profit hospice are, not surprisingly, near 0. Patients who would otherwise attend non-profit hospice would also forgo curative care.

Table 5 also presents estimates of the effect of for-profit hospice on days in hospice and months of survival. The marginal treatment effect of for-profit hospice on length of stay is an increase of 61.5 days, which reflects an increase of 69 days among those who would otherwise not enroll in hospice and 52 days among those who are diverted from non-profit hospice. The increased stay length among patients who would otherwise enroll in non-profit hospice indicates that patients in for-profit hospice enter earlier in their disease course. This finding is

consistent with media reports and False Claims Act litigation highlighting for-profit hospices' aggressive admissions tactics in the ADRD population.

For-profit hospice could also affect spending among patients diverted from non-profit hospice via its impact on the timing of death, even though there is no effect on total five-year mortality for patients diverted from non-profit hospice. We find that for-profit hospice reduces survival by 5 months (in a 5-year period). This estimate combines the effect of for-profit hospice on patients induced from no-hospice (a reduction of 7 months) and patients diverted from non-profit hospice (a non-significant reduction of 2 months).

An analysis of the different categories of spending shows other margins along which for-profit and non-profit hospice differ, reflecting differences in treatment choices. Patients induced from non-profit to for-profit hospice spend *more* on Part D pharmaceutical drugs, although the total effect of for-profit hospice on drugs is negative, driven by savings among patients whose outside option is no hospice. In contrast, spending on both skilled nursing and home health care decline for patients induced into for-profit instead of non-profit care. Patients in for-profit hospice are often enrolled earlier in their disease course, reducing the use of close substitutes. For-profit hospice reduces the use of inpatient care and increases the use of outpatient care, both for patients whose alternative is no hospice and also patients induced from non-profits.

A final question relates to differences in patient characteristics along these two margins. Appendix Table A5 shows the ω statistic – that is, the share of patients along the no-hospice to for-profit hospice margin – computed within each demographic and chronic condition, among our ADRD sample. There are only small differences by race and by age. Greater differences appear by chronic condition: patients with lung cancer and AMI have a low ω values of 0.314 and 0.328 respectively, indicating these patients are largely diverted from non-profit hospice, which aligns with our understanding that nonprofit hospices treat acutely ill patients.

Our results show an interesting new application of the multiple treatment effects margin literature and indicate there are small differences between for-profit and nonprofit hospices. In Section 4.6 below, we discuss welfare concerns related to these estimates.

4.5 Robustness

Appendix Figure A6 describes the distribution of the first stage effects, which appear roughly linear between 0 and 50 miles. While the linearity of the relationship between the instrument and first stage outcome is not necessary for instrumental validity, the figure shows that the effect of distance on hospice use (a 1% increase per 10 miles) is constant throughout the distance distribution.

We used the window [t, t+5] years after ADRD diagnosis in our main specification so that we had a sufficiently long time period to observe the spending and mortality effects of for-profit hospice. Appendix Table A6 presents parallel estimates using the window [t, t+2] years after diagnosis. The sample includes patients diagnosed with ADRD from 2000 to 2017. The results are quite similar: for-profit hospice saves $22,100 over this period, driven by reductions in skilled nursing, home health, inpatient care and Part D, which offset increases in hospice spending. Similar to our main result, for-profit hospice usage in the ADRD population increases 2-year post-diagnosis mortality by 8.6 percentage points.

Our main specification uses patients' zip code to compute the distance to for-profit hospice in the year before they first have an ADRD flag in our data. To ensure the use of pre-diagnosis distance is not a source of measurement error, particularly given that patients may move, we repeat our main specification among non-movers. Appendix Table A7 presents results on the non-mover sample. Our results are very similar under this specification check.

We present specification checks to test the validity of our instrument (the distance to a for-profit hospice with zip fixed effects). Appendix Table A8 shows the covariate balance across patients above and below 25 miles. Means are quite similar along most dimensions, including sex, age, and chronic conditions, although patients who live nearer to for-profit hospices are somewhat more likely to be black and less likely to be white.

The exclusion restriction underlying our IV strategy would be violated if hospices enter in response to or in anticipation of changes in market characteristics correlated with ADRD patients' spending. For example, if hospices entered in response to increases in the number of beneficiaries with less severe ADRD, then our analysis could erroneously show that entry reduces spending for beneficiaries with ADRD. Appendix Table A9 presents estimates of the impact of the number, share, and severity (as proxied by quintile of national spending) of ADRD

patients on the distance to a for-profit hospice. Regressions are conducted at the zip-year level and include zip and year fixed effects. The zip-code level prevalence of ADRD among Medicare beneficiaries has a small, negative correlation with distance to a for-profit hospice. For example, zip codes at the 75th percentile of the prevalence distribution are 0.05 miles further from a for-profit hospice (from a base of 30.8 miles) compared the median zip code. The share of ADRD patients in the top spending quintile has a miniscule but significant association with distance, but the effect is positive, indicating that hospices are slightly more likely to enter markets where the share of patients with more severe ADRD is increasing. These patterns of entry would bias our IV analysis *against* finding that entry reduces spending. Overall, these results indicate that hospice entry does not respond endogenously to changes in ADRD prevalence of spending in a way that invalidates our IV design.

We also apply our methods to beneficiaries with common cancers (breast, colorectal, prostate, lung, or endometrial cancer). Patients with these cancers are likely to be admitted to hospice (Table A1). We repeat the same cohort-based design and follow patients for years 0-5 post diagnosis. Appendix Table A10 displays the effects of for-profit hospice on spending and mortality in this period. The exposure of cancer patients to for-profit hospice increases for-profit hospice usage, reduces five-year spending by $24,800, and increases mortality by 9 percentage points. The effects on spending by category are similar to those among ADRD patients, though for-profit hospice leads to an especially large reduction in Part D pharmaceutical spending among cancer patients. Overall, these results indicate that for-profit hospice has similar cost-saving effects among Medicare beneficiaries with cancer, although the eligibility of cancer patients for hospice is less questionable and therefore not our main focus.

4.6 Discussion

Our results provide the first causal estimates of the impact of the $20 billion hospice program on total health care costs for marginal enrollees. We find that hospice admission reduces spending but increases mortality rates. If hospice were a normal medical intervention, we could compare the change in spending to the change in survival to calculate its cost-effectiveness. But when patients enter hospice, they or their caregivers must sign a form indicating they understand that they will forgo curative care, in effect agreeing to accept a

higher risk of death in return for potential improvements in quality of life. If hospice patients are well-informed, then hospice may help patients and reduce spending.

However, prosecutors in hospice fraud lawsuits allege that, in some circumstances, patients' families were not made aware that their relative would have to forgo life-prolonging care following hospice enrollment. If patients or their families did not understand that hospice patients face higher mortality risks, the welfare implications from expanding hospice are less clear. There are no data on the share of hospice enrollees who do not understand the implications of enrollment. However, a bounds analysis can help quantify the welfare effects of hospice given the differing valuations of mortality effects for patients who do and do not understand that hospice will lead to the cessation of life-prolonging care. As shown by Table 5, for-profit hospice enrollment for the marginal enrollees who would otherwise not attend hospice saves $44,082 and increases mortality by 15% over a five-year period. On average, compliers lose roughly 7.2 months (0.6 years) in this window. If we are willing to consider death as a welfare cost only for those patients who were misinformed, the efficiency of for-profit hospice inducement of patients is governed by the tradeoff:

$$\$44{,}082 \geq 0.6 \times \text{Value of LifeYear} \times \text{Share Uninformed.} \qquad (3)$$

Appendix Figure A7 shows the tradeoff between these parameters and displays the regions where expanded hospice enrollment is efficient or inefficient. The value of life year varies between $15,000 and $150,000, where the upper bound is in line with standard life-year estimates (ICER, 2020). As shown by Appendix Figure A7, for most reasonable ranges of the value of a life-year for end-of-life ADRD patients, a very high share of patients would need to be uninformed about the mortality effects of hospice – despite signing paperwork agreeing to forgo curative care – for this regime to be inefficient.

Quality of life for patients with late-stage ADRD is low, possibly below the cost-savings of $44,082. Hospice also improves quality of life, as we describe above. Therefore, hospice enrollment may be efficient even if we value the lost 0.6 life-years of life for patients who knowingly consent to forgo curative care. Our welfare calculations, while rudimentary, show that under a range of assumptions about the proportion of patients who are uninformed and

the value of life for ADRD patients, hospice enrollment may be welfare-improving from a societal perspective.

5. The Hospice Cap

The estimates presented above address the broad question of whether the government should adopt a more or less permissive approach to hospice use by ADRD patients. But the government has only a limited set of tools at its disposal to affect hospice use, and the types of patients affected by these policies may differ from the set of patients induced to enroll in hospice by the entry of for-profit firms. Thus, it is important to evaluate these policies in their own right. Below, we focus on two: the hospice cap and antifraud litigation.

The cap, an aggregate limit on hospices' Medicare revenues, is a longstanding policy designed to limit the overuse of hospice. In 2016, the cap was $27,820 per patient. However, the cap is applied at the firm level, not the patient level, and so short stay and long staying patients can balance each other out. For example, a hospice that served 100 patients would face a cap of $27,820 $\times$ 100. The cap imposes a 100% tax rate: hospices must refund all payments received from Medicare that exceed this amount. Payments to hospices are measured over the cap year, which runs from November 1 to October 31 the following year. Appendix E presents institutional details about the cap calculation.

5.1 Cap and Firm Profit Status

The cap is designed to reduce hospices' incentives to treat long-stay patients, and we show that it binds more strictly for for-profit hospice firms. Using the universe of hospice claims for Medicare beneficiaries from 1999 to 2019, we create a dataset at the hospice-year level. Our data contain about 31,200 for-profit hospice years and 28,700 non-profit hospice years. We exclude hospices with an average annual census of ten or fewer patients during the period in which they are present in data. We also exclude hospices' first and last years in business for hospices that entered or exited during the study period, as they might not have had a full cap year with which to compute revenues.

For each hospice-year, we calculate the ratio of revenues to the hospice's cap (the per-patient cap multiplied by the number of patients admitted). Figure 2 shows the histogram of the cap ratio by ownership status. For-profit hospices are much more likely to exceed the cap

(19.8%) compared to non-profit hospices (2.9%). Half of for-profit hospices (2,182 out of 4,359) and 14.6% of non-profit hospices (374 out of 2,568) exceed the cap at least once during the twenty-year period we study.

Figure 2 also reveals a distinct lack of "bunching" at the cap threshold. Hospices' inability to maintain revenues just below the cap may reflect the difficulty of making short-term adjustments to their average length of stay and of predicting future revenues and patient length of stays. Appendix Table A11 shows the inability of firms to predict patient stay length. The R^2 from a regression of an indicator for whether patients survive 180 days following hospice admission on the patients' chronic condition indicators, patient demographics, and year of admission fixed effects is between 0.02 and 0.03, illustrating the difficulty hospices face trying to predict long stays.

5.2 Effects of Cap on Spending and Patient Care

In light of our findings that for-profit hospice enrollment saves federal money among potentially long-staying patients, we evaluate the spending and health effects of the cap. We begin with a sample of all patient-months in hospice from 2000 through 2019 (N = 53 million) and consider patient spending, care, and health outcomes in the 12-month period following each patient-month in hospice as a function of patients' hospices' proximity to the cap in that month. We consider all patients, rather than just ADRD patients, because the cap policy that targets overuse by long-staying ADRD patients can affect any hospice patient. Appendix E details the sample construction.

A primary threat to identification is that hospices which admit long-staying patients, and are thus closer to the cap, may be different along many dimensions than those that do not. Therefore, we consider a *within-hospice-year* regression, conducted at the patient-month level:

$$Y_{imLk} = a + \beta OverCap_{kLm} + \eta_{kL} + \gamma_{Lm} + Staylength_{im} + \epsilon_{imk}. \quad (4)$$

Here, Y_{imLk} includes outcome variables such as patient spending and care in the subsequent 12 months for patient i in month m of year L at hospice k. $OverCap_{kLm}$ is hospice *k*'s predicted probability of exceeding the cap in year *L*, as observed in a given month *m* in year L, based on the cumulative level of spending per patient up to that month. We use a logit model on the universe of hospice months to estimate a firm's probability of exceeding a cap based on

its revenue and patient count in that month (see Appendix E for details). The inclusion of hospice-year fixed effects allows us to compare patients from within the same firm in the same year, controlling for seasonal trends with year-month fixed effects and patient length-of-stay fixed effects $Staylength_{im}$. Standard errors are clustered at the hospice firm level. This specification identifies the effect of quasi-random cap pressure driven by within-year variation in patient longevity and length of stay, *not* by long-term admissions patterns.

Table 6A presents estimates of β from equation (4), with spending outcomes measured over a 12-month period following each patient-month. When a firm faces the cap, patient spending declines by $2,300 over the subsequent 12 months. This effect is nearly entirely driven by a reduction in hospice spending. There is a small but statistically significant increase in home health spending, reflecting the substitutability of home health and hospice care. There are small effects on other categories of spending.

Table 6B presents estimates from Equation 4 for different hospice care choices and health measures that may respond to cap pressure. When facing cap pressure, patients are 1 percentage point (24%) more likely to be discharged alive from a baseline mean of 4.4%. Patients are also less likely to receive inpatient hospice: spending on inpatient hospice decreases by $4.26 from a baseline mean of $41 over 12 months. Inpatient hospice is an infrequently used short-term option for patients facing acute crises.

Secondly, Table 6B shows that twelve-month patient mortality increases by 2 percentage points from a baseline of 75%. Deaths caused by cap pressure can be due either to changes in care within the hospice – such as shirking on care – or as a consequence of harmful care transitions that occur when patients are discharged alive from hospice. Unlike the ambiguous interpretation of our earlier mortality results, these mortality increases are welfare-decreasing, as patients do not consent to changes in care due to cap pressure.

We further evaluate changes in health care use among patients who were discharged alive from hospices facing cap pressure (in a month where the probability of exceeding the cap was above 90%) to provide added context for our spending and mortality estimates. We compare use of hospitals and specialists in the year before these patients were admitted to hospice and in the year following discharge. Appendix F presents the results of this analysis. We

find that inpatient admissions and visits to specialists decline significantly, even conditional on surviving 12-months post hospice. These results indicate that this patient population does not simply return to their normal pre-hospice spending and care patterns. The transitions into and out of hospice appear to disrupt patients' connections with care providers. Post-discharge disruptions to care may explain why our estimates of the impact of hospice discharge do not mirror our estimates of the impact of hospice admission: patients who attend hospice do not return to their normal, pre-hospice patterns after live discharge.

An analysis of the same cohort shows a further worrying trend: 70% of patients who are discharged alive return to hospice after discharge, with a median return time of 28 days. Thirty eight percent of those patients return to the same provider, suggesting that some hospices may be gaming the cap. Moreover, many of these patients due quickly: 32.5% die within 6 months of the live discharge, indicating that they would have remained eligible for hospice.

In summary, the hospice aggregate cap distorts patient care. The cost of these distortions, including disruptive care transitions and cycling through hospices, may outweigh any savings to the Medicare program. While we cannot directly examine the deterrence effects of the cap, our earlier results suggest that by deterring admissions of marginally-eligible patients, the cap could actually increase Medicare spending. The effects are important to consider as a Congressional advisory panel, MedPAC, recently suggested *lowering* the hospice cap based on concerns about excess admissions (MedPAC, 2021).

Our findings that for-profit entry reduces spending but that cap-induced discharge does not increase spending are not contradictory. For-profit hospice entry saves Medicare money for the *marginal patients who are induced to enroll*. Our cap analysis instead shows the effects of patients' continued enrollment in hospice *at the margin where the cap binds*. These analyses fundamentally address different policy-relevant questions; the former is about access to hospice, and the latter is about what happens to patients who are already admitted and, in some cases, have received hospice for a long time. Further policy innovations in the hospice market should be sensitive when distinguishing between these *ex-ante* eligible versus *ex-post* questionable populations.

6. Anti-Fraud Lawsuits and Hospice Behavior

Another major policy used to combat "overuse" of hospice is the federal False Claims Act, an anti-fraud statute that levies civil penalties on firms that violate Medicare coverage rules. False Claims Act lawsuits have targeted hospice firms – mainly, though not exclusively, for-profit firms – for admitting non-terminal patients or, at the 6-month mark, recertifying these patients as terminal for another 6 months of eligibility. These lawsuits are often settled out of court, because if they lose, defendants face large penalties equal to treble the amount of fraudulent billings plus a fine of roughly $11,000 per claim. For a deeper treatment of the economics of the False Claims Act, see Leder-Luis (2023).

The over-admission of ADRD patients has been a major source of litigation against hospice companies. For example, a False Claims Act lawsuit against Evercare, a multi-state hospice chain, alleged that the hospice admitted patients with conditions that, "while serious were not likely to lead to the death of the patient within six months." This lawsuit settled for $18 Million in 2016. Similar allegations have been made in dozens of other FCA cases.

Appendix Table A12 provides descriptive statistics about these cases from a Freedom of Information Act request we filed with the Department of Justice. Appendix G describes the matching process between the FOIA and the Medicare data to identify prosecuted firms. Of the 163 cases, 37% have been settled for a total of $351 million. Lawsuits have occurred from 1998 through 2021, spanning our entire sample period. Most defendants are large chains with multiple hospice locations.

The use of anti-fraud litigation against hospice firms has been a source of major controversy. Different federal appellate courts have established varying standards for determining whether admissions are fraudulent. At issue is the inherent subjectivity of determining whether patients have less than 6 months left to life and whether hospices' certification of eligibility can ever be "false" given that life expectancy is an error-prone prediction, not a concrete fact (West, 2021). This unresolved case law highlights the importance of understanding the effect of hospice use on the ADRD and hospice population.

6.1 Effect of Litigation on Firm Behavior

We consider the effects of False Claims Act civil anti-fraud lawsuits on firm behavior. Lawsuits could deter hospices from admitting long-staying patients and ADRD patients. This

could unintentionally increase Medicare costs if they inhibit the use of hospice care by patients for whom hospice care would be cost saving.

There is a strong relationship between ADRD diagnosis and long stays: 50% of hospice episodes over 180 days are among patients with an ADRD diagnosis at time of admission. While hospices may not be able to accurately predict patient stay length, as shown in Table A11 and discussed in Section 5.1, ADRD diagnosis is a highly predictive criteria for long stays, as shown in Table A1. As such, reductions in long-staying patients to comply with regulatory pressure may entail costly reductions in ADRD hospice usage.

We use a sample of all hospice years from 2000 to 2019 and create a firm-year level dataset. We evaluate the impact of litigation on hospices' share of patients who stay above 180 days, the share of days from patients with an ADRD diagnosis in the year before coming to hospice, hospices' mean length of stay, and live discharge rates. For each hospice year, we identify whether and when the hospice was sued based on the FOIA request. We restrict our sample to 10 years before and after a lawsuit is filed for sued firms and use the full panel for untreated firms. Our sample contains about 66,600 hospice years.

We employ a difference-in-difference identification strategy that exploits the differences in timing of when hospice firms are sued. We estimate:

$$Y_{ht} = \alpha + \sum_{\tau \in [-5,5], \tau \neq -1} \beta_\tau D_{h\tau} + \gamma_h + \eta_{tm} + \varepsilon_{ht}. \qquad (5)$$

where Y_{ht} is an outcome for hospice h at year t; D_{ht} is an indicator for whether hospice h at year t had been sued; and γ_h and η_t are provider and year-month fixed effects. Our control group includes hospices that are not sued. We estimate dynamic effects in the 5 years before and after the hospice is sued, and we include firm and year-month fixed effects. The coefficient of interest is β_τ, which captures the effect of being sued on the hospice-level outcome in year τ relative to the lawsuit.

Figure 3 shows the estimates of β_τ as an event study, where the outcome is the share of long-staying patients and ADRD patients. The share of Alzheimer's patient days is measured by calendar year, and the share of patients discharged alive is measured by patient admission year. The results show that the proportions of long-stay patients and ADRD patients decline following lawsuits and that there are no pre-trends. Appendix Figure A8 presents event study figures for

additional outcomes including the average length of stay and share of patients live discharged, measured by patient admission year, which also decline and do not exhibit pre-trends. Appendix Figure A9 repeats this specification to account for modern critiques of two-way fixed effects designs, following Sun and Abraham (2021). Our results are robust to this alternative approach.

For completeness, we also estimate the static difference-in-differences specification and present the results in Appendix Table A13, Panel A. Being sued causes hospices to decrease the share of patients staying over 180 days by 1.3 percentage points from a mean of 13.5%, and average length of stay falls by 6.5 days from a mean of 84 days. Sued firms reduce their share of ADRD patient days by 1.2 percentage points from a baseline mean of 41% in the years following their lawsuit. Interestingly, the proportion of patients who are discharged alive declines by 1.5 percentage points from a mean of 21.5%. After being sued, hospices may admit fewer patients with uncertain eligibility who could ultimately be live discharged.

The results from our analysis show that, following a lawsuit, firms are less likely to accept ADRD and long-staying patients. Given that enrolling ADRD patients reduces spending on the margin, lawsuits that are not well-targeted could discourage enrollment of ADRD patients for whom hospice would be cost saving.

We conduct a heterogeneity analysis to understand the types of patients for whom lawsuits discourage hospice admission. We group ADRD hospice patients by their spending in the year before hospice admission and repeat the static difference-in-difference design. Appendix Table A13, Panel B presents the results. Lawsuits reduce hospice use evenly throughout the spending distribution, even among patients in the top quintile of pre-hospice spending. These results indicate that anti-fraud lawsuits against hospice firms deter hospice usage even among patients for whom hospice has the greatest opportunity for cost savings.

6.3 Discussion

Our results show that anti-fraud lawsuits inhibit the use of hospice for long-staying patients and ADRD patients, for whom we estimate that hospice enrollment reduces Medicare spending. Sued firms increase compliance with eligibility rules, decreasing the share of patients who stay over 180 days and admitting fewer ADRD patients. They appear to reduce admissions

of ADRD patients across the spending distribution, rather than only restricting enrollment of ADRD patients with the best prognoses, as indicated by low pre-enrollment spending. This result should be interpreted cautiously, however, because pre-hospice spending may be only a weak signal of life expectancy.

Our results caution against aggressive civil prosecution of purportedly fraudulent behavior without consideration of its effects on health spending. Hospice litigation is a case where the government's anti-fraud crackdowns potentially increased spending by deterring cost-effective care. These results stand in contrast to existing work documenting large savings from fraud enforcement in health care (Howard & McCarthy, 2021) (Leder-Luis, 2023).

Our estimates do not measure spillover effects of litigation on firm behavior across the hospice industry. To the extent that some firms that were sued may have already adjusted their behavior in response to previous suits, our results will understate the effects of False Claims Act litigation. Moreover, we fail to quantify general deterrence effects, wherein never-sued firms respond to the threat of a lawsuit by altering their admission practices and admitting fewer ADRD patients. Overall, lawsuits that deter hospice use by ADRD patients, whether directly or indirectly, may result in higher Medicare spending.

7. Conclusion

More than 50% of Medicare decedents use hospice services every year. Over the past 20 years, there has been extensive growth in the market for hospice, largely driven by the entry of for-profit hospice firms and the use of hospice by patients with ADRD. Using patient exposure to for-profit hospice as an instrument, we provide the first causal evidence on the effects of for-profit hospice use by ADRD patients, a group whose eligibility has been controversial.

We estimate that for-profit hospice enrollment of the marginal patient reduces costs by about $29,000 over 5 years, driven by large reductions in inpatient, skilled nursing, home health, and pharmaceutical spending that far offset the increased spending on hospice. Decomposing our effects along two treatment margins, we find these effects are concentrated among compliers induced into for-profit hospice use instead of no hospice. While enrollment also reduces patient longevity, it appears to be welfare-improving for reasonable values of the willingness-to-pay for an ADRD quality-adjusted life year. However, a full treatment of the

relevant ethical questions is beyond the scope of this paper. Future work could further quantify the impact of hospice on quality of life.

If hospice enrollment is welfare-improving, then policies that limit hospice use on the margin may be inefficient. We find that the aggregate cap on hospice revenues distorts patient care, increasing live discharges and patient mortality in return for minimal savings. Cap-related discharges appear to disrupt patient care, and many of the patients discharged are near death. We also find that anti-fraud lawsuits against firms for potentially inappropriate hospice use end up reducing hospice use by long-staying patients and ADRD patients. While the admission of ADRD patients who are not terminally ill may be fraudulent under current coverage rules, our results suggest that the problem may lie not with firm behavior but with the rules themselves.

More generally, our findings raise a host of interesting policy questions for the hospice program. Given the flaws we find in the current system, how should the government encourage the use of hospice for well-informed patients who are at the end of life while ensuring that there is not overuse on the margin? Would a different cap structure, or different standards for fraudulent firm behavior, be more efficient? These are important topics for future research.

Our results provide lessons beyond the $20 billion hospice industry. While recent studies have largely found negative effects of for-profit care, the hospice industry demonstrates that for-profit care can, in fact, save money if it is a substitute for even more expensive alternatives. This underscores the importance of measuring general equilibrium effects like total expenditure when evaluating the impact of a particular form of medical care. More broadly, hospice serves as a model for where expanding access can reduce spending by providing alternatives to expensive, invasive care.

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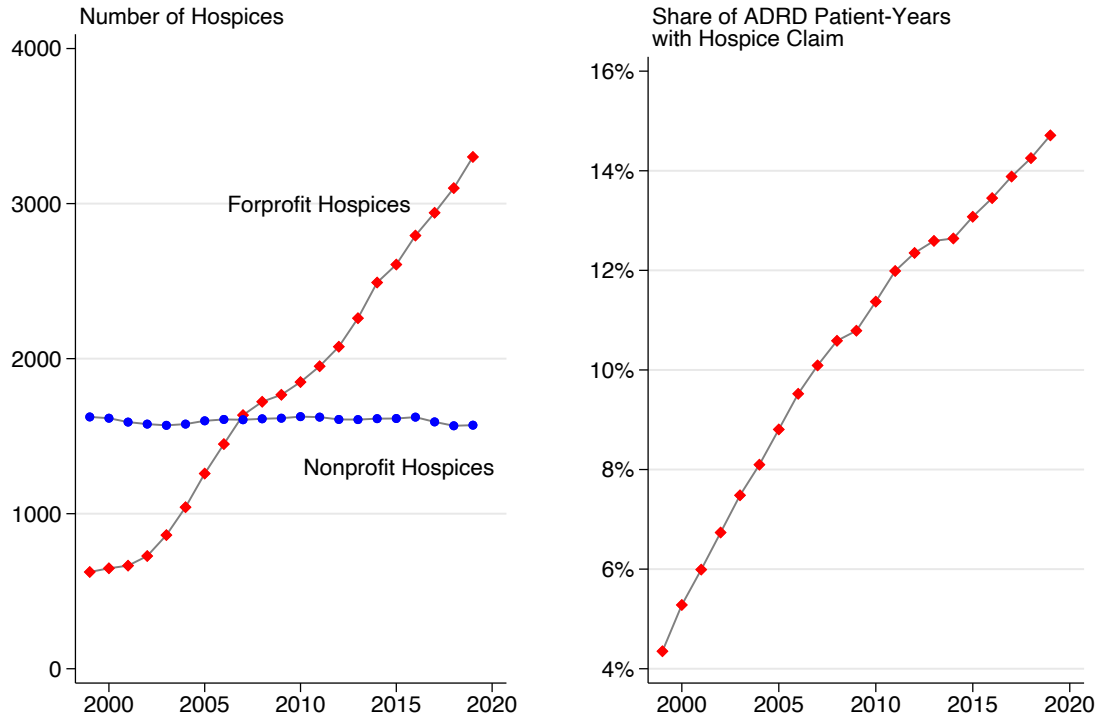
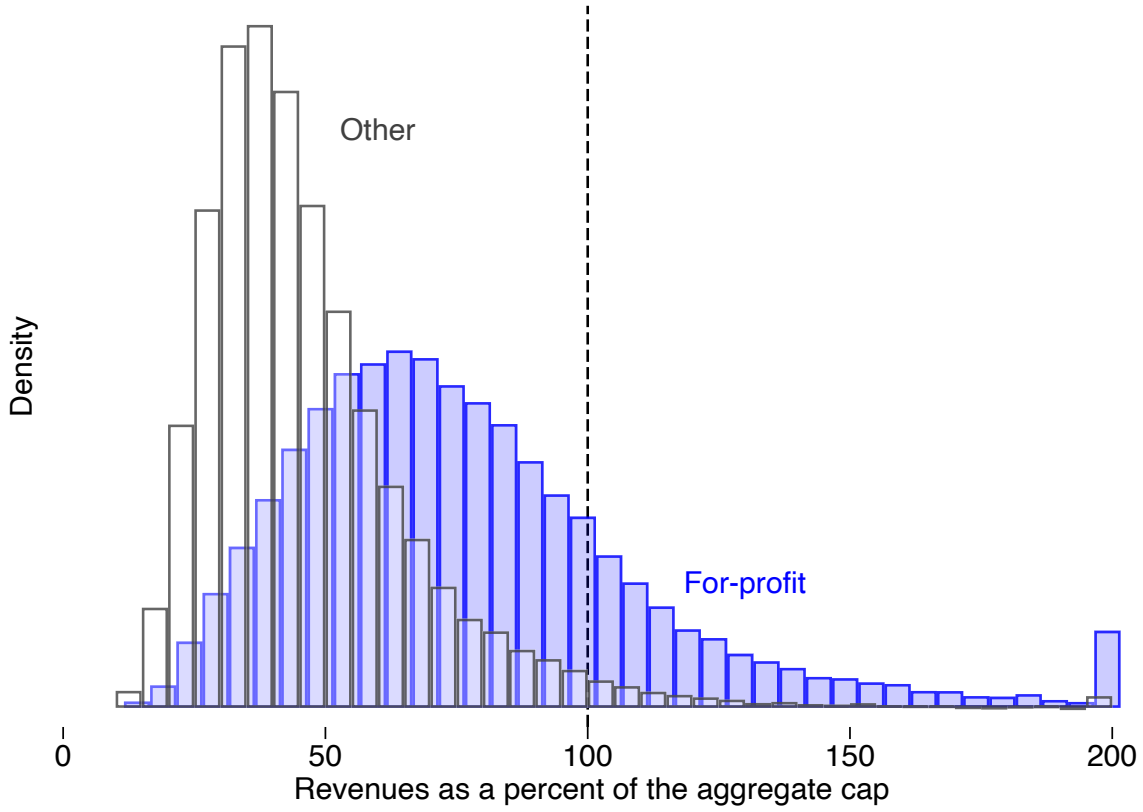
Tables and Figures

Figure 1: Proliferation of Hospice Over Time



Notes: This figure shows the expansion of hospice over time using Medicare Provider of Service data matched to Medicare claims. The left panel shows the number of hospices that serve Medicare patients, by profit status and year. The right panel shows the share of Alzheimer's and Dementia patient-years that contain at least one hospice claim over time.

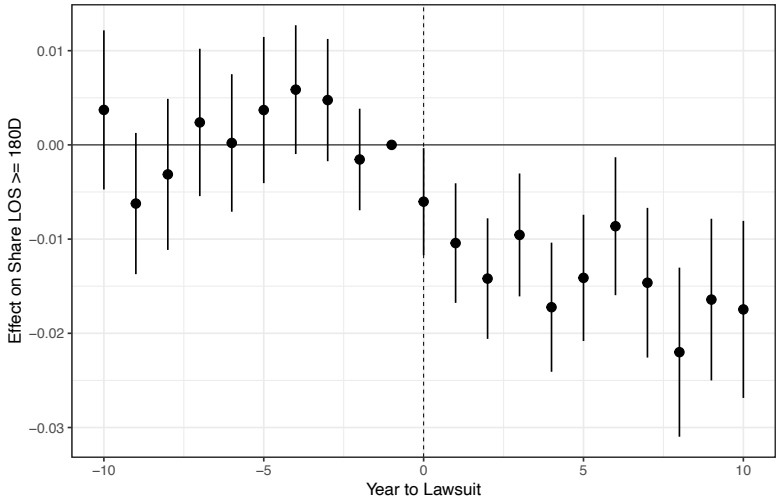
Figure 2: Histogram of hospice Revenue Relative to the Cap by Ownership Type



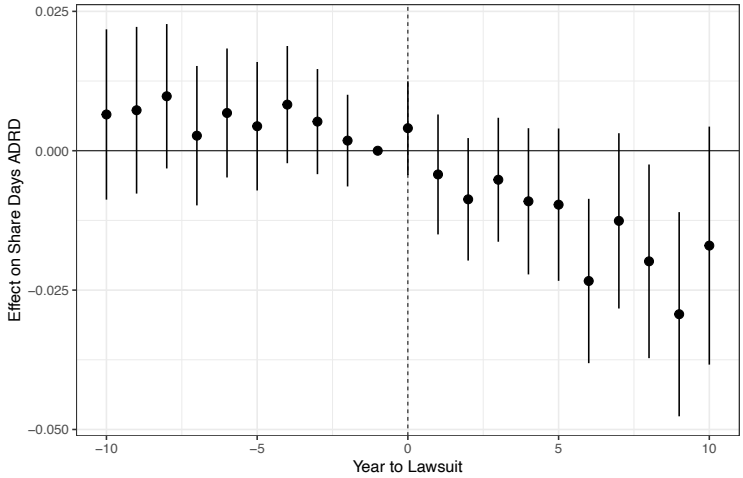
Notes: The graph shows histograms of hospices' annual cap-year revenues as a percent of the aggregate cap, by for-profit status. The aggregate cap was calculated by multiplying the number of admissions during the cap year by the per patient cap in a given year. Data were winsorized at 200%. Appendix E provides additional details of the cap calculation.

Figure 3: Event-Study Estimates of Impact of Lawsuits

3A: Effect of Lawsuit on Patients Staying Over 6 Months



3B: Effect of Lawsuit on Share ADRD Days



Notes: These figures show outcomes of the event study described in equation (5). Specifically, the figures show the dynamic effects of a lawsuit in year 0 on the share of patients staying over 6 months (Panel A) and the share of days from patients with an ADRD diagnosis (Panel B). Error bars correspond to 95% confidence intervals. Each event study is normalized such that the coefficient corresponding to year -1 is 0.

Table 1: Descriptive Statistics for ADRD Patient Sample

		Mean	Std. Dev.
Total Pmt		81,134.48	85053.94
Year of DX		2007	4.38
Age at DX		81.03	9.75
5Y Mortality		0.67	0.47
Any Hospice		0.33	0.47
Forprofit Hospice		0.15	0.35
Nonprofit Hospice		0.19	0.39
Acute Myocardial Infarction		0.01	0.11
Atrial Fibrillation		0.12	0.33
Cataracts		0.22	0.42
Chronic Kidney Disease		0.14	0.35
COPD		0.15	0.36
Heart Failure		0.26	0.44
Diabetes		0.27	0.45
Glaucoma		0.11	0.32
Hip Fracture		0.02	0.13
Ischemic Heart Disease		0.39	0.49
Depression		0.17	0.37
Osteoperosis		0.09	0.28
Rheumatoid Arthritis		0.31	0.46
Stroke / Transient Ischemic Attack		0.09	0.28
Breast Cancer		0.03	0.16
Colorectal Cancer		0.02	0.13
Prostate Cancer		0.04	0.19
Lung Cancer		0.01	0.09
Endometrial Cancer		0.00	0.05
Anemia		0.31	0.46
Asthma		0.04	0.20
Hyperlipidemia		0.34	0.47
Benign Prostatic Hyperplasia		0.06	0.24
Hypertension		0.59	0.49
Acquired Hypothyroidism		0.10	0.30
		N	Pct.
Sex	Female	6,696,327	61.7
	Male	4,159,827	38.3
Age at DX	<65	503,787	4.6
	65-74	1,816,710	16.7
	75-84	4,266,341	39.3
	85-94	3,737,041	34.4
	95+	532,275	4.9
Race	Black	1,008,814	9.3
	Hispanic	203,135	1.9
	Other	316,497	2.9
	White	9,327,708	85.9
ESRD	ESRD	162,187	1.5
	Not ESRD	10,693,967	98.5

N = 10856154

Notes: This table describes the characteristics of ADRD patients in our sample. For binary variables, the mean is the share of the sample that matches that description. Chronic conditions are measured in the year prior to ADRD diagnosis.

Table 2: IV Results for Medicare Spending Outcomes

Dependent Variables:	Total		Inpatient	Outpatient	Home Health
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	17,965.2***	-29,027.6***	-8,718.6***	3,550.6***	-7,039.7***
	(95.51)	(4,606.6)	(2,260.9)	(807.1)	(1,138.1)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	10,856,158	10,856,158	10,856,158	10,856,158	10,856,158
R^2	0.21668	0.18241	0.14650	0.22820	0.06570
Within R^2	0.00635	-0.03711	-0.00754	-0.00974	-0.05005
Dependent variable mean	81,134.5	81,134.5	31,078.4	6,668.2	5,623.9
Wald (1st stage), FP Hospice Admission		707.55	707.55	707.55	707.55

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	SNF	Part D	Hospice	Forprofit Hospice	Nonprofit Hospice
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	-12,603.1***	-7,040.0***	7,405.3***	10,164.1***	-2,773.1***
	(1,328.6)	(1,374.4)	(870.3)	(548.2)	(691.2)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	10,856,158	10,856,158	10,856,158	10,856,158	10,856,158
R^2	0.00703	0.11194	0.11211	0.21688	0.02648
Within R^2	-0.07191	-0.01461	0.08122	0.18855	-0.00147
Dependent variable mean	12,701.8	5,633.3	4,484.6	2,331.4	2,141.9
Wald (1st stage), FP Hospice Admission	707.55	707.55	707.55	707.55	707.55

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports 2SLS estimates of equation (2) for Medicare spending outcomes. Column 1 presents OLS estimates for total spending, for contrast. The dependent variables are categories of Medicare spending between years 0-5 of ADRD diagnosis. The endogenous variable is whether the patient went to for-profit hospice in years 0-5 of ADRD diagnosis, which is instrumented using distance to for-profit hospice in the 2SLS regressions. Each regression includes controls for zip code, diagnosis year cohort, and patient characteristics (age, sex, race, chronic conditions) and non-profit distance in the year before diagnosis.

Table 3: IV Results for Mortality Outcomes

Dependent Variables: Model:	30D Mortality (1)	90D Mortality (2)	1Y Mortality (3)	2Y Mortality (4)	5Y Mortality (5)
Variables					
FP Hospice Admission	0.0127	0.0402***	0.0679***	0.0722***	0.0861***
	(0.0109)	(0.0140)	(0.0188)	(0.0214)	(0.0208)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	10,856,158	10,856,158	10,856,158	10,856,158	10,856,158
R^2	0.02935	0.04679	0.09120	0.12703	0.17823
Within R^2	-0.00170	-0.00475	-0.00481	-0.00167	0.01703
Dependent variable mean	0.06868	0.12715	0.26315	0.39000	0.66576
Wald (1st stage), FP Hospice Admission	707.55	707.55	707.55	707.55	707.55

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports 2SLS estimates of equation (2) for patient health outcomes. The dependent variables are mortality in different periods after ADRD diagnosis. The endogenous variable is whether the patient went to hospice in years 0-5 of ADRD diagnosis, which is instrumented using distance to for-profit hospice in the 2SLS regressions. Each regression includes controls for zip code, diagnosis year cohort, patient characteristics (age, sex, race, chronic conditions) in the year before diagnosis, and distance to non-profit hospice.

Table 4: Quality of Life Effects of For-Profit Hospice Enrollment

Dependent Variables:	IP Surgeries	OP Surgeries	Pressure Ulcers	
Model:	(1)	(2)	(3)	(4)
Variables				
Forprofit Hospice	-0.9350**	0.2514**	-0.3280***	-0.2943***
	(0.3844)	(0.1143)	(0.0510)	(0.0619)
Fixed-effects				
Demographics Controls	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	10,856,158	10,856,158	8,902,303	5,784,221
R^2	0.16574	0.05133	0.01140	0.02460
Within R^2	-0.00269	-0.00567	-0.03868	-0.02491
Dependent variable mean	3.8854	0.45974	0.40435	0.62232
Wald (1st stage), Forprofit Hospice	707.55	707.55	600.18	516.34

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	MDC 5: Circulatory	MDC 4: Respiratory	ATC R: Respiratory	ATC N: Nervous
Model:	(1)	(2)	(3)	(4)
Variables				
Forprofit Hospice	-3,953.8***	-3,039.0***	-168.5***	289.8**
	(668.8)	(626.1)	(35.67)	(131.9)
Fixed-effects				
Demographics Controls	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	10,856,158	10,856,158	2,144,876	2,144,876
R^2	0.08669	0.05744	0.10863	0.19744
Within R^2	-0.00852	-0.00769	-0.02308	-0.01165
Dependent variable mean	5,913.6	4,860.5	90.022	582.90
Wald (1st stage), Forprofit Hospice	707.55	707.55	496.99	496.99

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents IV results on the effects of for-profit hospice use on quality-of-life-related care for ADRD patients. Data on hospitalizations comes from MedPAR files available for a 100% sample, and data on drug usage comes from the Medicare 20% Part D files. Data on surgical counts comes from the Beneficiary Cost and Use Summary Files, and data on pressure ulcers come from the Minimum Data Set. All files are available from 1999 through 2019, except the Minimum Data Set which is not available after 2016. Appendix Figures A3 and A4 further detail complete usage of Major Diagnostic Categories (MDCs) to categorize hospitalizations and Anatomical Therapeutic Classes (ATCs) to categorize pharmaceuticals.

Table 5: Decomposition of For-Profit Hospice Treatment Effects

Outcome	MTE_{FP}	$MTE_{FP \leftarrow NP}$	$MTE_{FP \leftarrow 0}$
Hospice Length of Stay (Days)	61.5 [50.1, 72.4]	51.5 [19.2, 81.8]	68.7 [50.5, 90.7]
Total Payment	-29028 [-36855, -21769]	-7933 [-19801, 6983]	-44082 [-58391, -30875]
Inpatient Payment	-8,719 [-12933, -4946]	-5300 [-10829, -96]	-11158 [-18722, -5112]
Outpatient Payment	3551 [2172, 5097]	2585.3 [419, 5664]	4240 [2228, 6886]
Home Health Payment	-7040 [-9474, -4907]	-4379 [-6455, -2382]	-8939 [-11841, -5748]
SNF Payment	-12603 [-15125, -10470]	-3088 [-5870, -175]	-19393 [-24085, -15869]
Part D Payment	-7040 [-9287, -4933]	2964 [707, 6658]	-14179 [-18227, -9843]
Hospice Payment	7405 [5712, 9002]	5536 [1647, 10873]	8739 [5878, 11342]
FP Hospice Payment	10164 [8972, 11040]	13701 [11571, 16290]	7640 [4990, 10125]
NP Hospice Payment	-2773 [-4042, -1424]	-8143 [-10874, -5094]	1059 [49, 1510]
30D Mortality (pp)	1.3 [-0.9, 3.6]	4.0 [-0.6, 7.5]	-0.7 [-4.9, 3.5]
90D Mortality (pp)	4.0 [1.3, 7.0]	7.7 [1.0, 14.2]	1.4 [-4.3, 8.1]
1Y Mortality (pp)	6.8 [3.3, 10.2]	8.1 [-5.2, 17.7]	5.9 [-4.0, 16.3]
2Y Mortality (pp)	7.2 [3.2, 11.5]	5.3 [-13.0, 16.0]	8.6 [-2.6, 20.3]
5Y Mortality (pp)	8.6 [4.1, 13.5]	-0.7 [-7.9, 3.2]	15.3 [6.4, 22.7]
Life in Years 1-5 (Months)	-5.0 [-7.2, -2.6]	-1.9 [-6.4, 6.2]	-7.2 [-12.6, -1.7]
ω (Share $FP \leftarrow 0$)	0.58 [0.54, 0.66]		

Notes: This table decomposes the spending effects of for-profit hospice from Table 2 and the mortality effects from Table 3 along two dimensions of treated patients: patients who are induced to use for-profit hospice from no hospice and patients who are diverted to for-profit hospice from non-profit hospice. Spending is by category for which we can observe 100% samples, including yearly spending, but we omit the physician office visits (Carrier File) category for which only 20% are available. ω is the share of patients induced from no hospice. For-profit hospice decreases spending, increases time in hospice, and decreases months alive for patients induced from no hospice. Overall 5-year mortality is also concentrated among compliers who would otherwise not use hospice. 95% confidence intervals, block bootstrapped at the zip level, are presented in brackets. Appendix C.2 discusses the calculation of these estimates.

Table 6: Impact of Cap Proximity on Patient Spending and Care

6A: Effect on Patient Spending

Dependent Variables:	Total	Outpatient	Inpatient	SNF	Hospice	HHA	DME
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Pr(Over Cap at EOY)	-2,306.5***	-24.22***	-46.38**	-0.2509	-2,273.8***	44.61***	-6.545**
	(102.4)	(5.738)	(22.92)	(10.20)	(98.09)	(6.130)	(2.561)
Fixed-effects							
Hospice-Cap Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months in Hospice	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	52,905,828	52,905,828	52,905,828	52,905,828	52,905,828	52,905,828	52,905,828
R^2	0.17497	0.02679	0.02937	0.02058	0.18460	0.03890	0.01723
Within R^2	8.02×10^{-5}	1.19×10^{-6}	3.19×10^{-7}	4.32×10^{-11}	9.86×10^{-5}	5.6×10^{-6}	3.75×10^{-7}
Dependent variable mean	18,700.5	266.59	1,088.9	383.35	16,669.3	199.30	93.026

Clustered (Hospice) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

6B: Effect on Patient Care

Dependent Variables:	Live Discharge	Died w/in 1Y	Hospice: Inpatient
Model:	(1)	(2)	(3)
Variables			
Pr(Over Cap at EOY)	0.0104***	0.0236***	-4.258***
	(0.0009)	(0.0013)	(0.7674)
Fixed-effects			
Hospice-Cap Year	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes
Months in Hospice	Yes	Yes	Yes
Fit statistics			
Observations	52,905,828	52,905,828	52,905,828
R^2	0.01673	0.12191	0.03120
Within R^2	1.51×10^{-5}	1.95×10^{-5}	1.25×10^{-6}
Dependent variable mean	0.04381	0.74786	40.775

Clustered (Hospice) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Notes: This table presents estimates from Equation (4), which measures the effect of a firm's probability of exceeding the hospice revenue cap on patient spending outcomes over the subsequent 12 months. This regression is estimated at the patient-month level, with provider-year, year-month and stay length fixed effects. Standard errors are clustered at the hospice provider level. Total spending is computed from the other categories listed, but omits Part D and Carrier (physician's office visit) spending, which are not available in the 100% sample at a monthly level.

Appendix for Online Publication

Appendix A: Related Literature

A large literature, primarily in public health, has examined various aspects of the use and expansion of hospice, although our paper is the first to examine its causal impact on patients and the effect of policies designed to limit hospice use.

Early supporters hoped to demonstrate that hospice is the rare instance of a medical innovation that improves patient welfare while simultaneously reducing costs (Krant, 1978). The 1980s National Hospice Study evaluated the impact of the nascent hospice movement by comparing spending and quality-of-life between terminal cancer patients treated in hospice and patients treated in conventional settings. The study found that hospice care reduced Medicare spending, but savings were concentrated in the last month of life (Greer, et al., 1986). More recently, studies have compared costs and other outcomes between decedents treated in hospice and matched non-hospice decedents (Harrison, Cenzer, Ankuda, Hunt, & Aldridge, 2022) (Kelley, Deb, Du, Aldrige Carlson, & Morrison, 2013) (Leibowitz, Tan, & Gildner, 2020) (Taylor Jr, Ostermann, Van Houtven, Tulsky, & Steinhauser, 2007) (Emanuel, et al., 2002) (Campbell, Lynn, Louis, & Shugarman, 2004) (Zuckerman, Stearns, & Sheingold, 2016). Estimates based on a fixed time period (e.g., the last year of life) tend to find that costs are similar, while those that analyze costs from the date of hospice enrollment onward tend to find substantial savings (Hogan, 2015).

These studies suffer from two key empirical limitations. First, by focusing on decedents or on fixed end-of-life windows, they exclude or misclassify long-stay patients and/or patients discharged alive from hospice. In 2018, 15.5% of those admitted to hospice were discharged alive, and they may be particularly relevant to assessing the net cost implications of hospice use. Second, these studies generally do not address the bias arising from the fact that patients who select into hospice have unobserved preferences for less intensive treatment. One paper that attempts to address the later concern is Hogan (2015), who use a long panel to estimate end-of-life costs among decedents as a function of market-level hospice penetration with region fixed-effects. He finds that end-of-life costs increased more rapidly in markets that

experienced more rapid growth in hospice enrollment and that the effect was concentrated among non-cancer patients.

More recently, researchers have investigated whether the benefits associated with increased hospice enrollment, particularly among non-cancer patients, justify potentially increased spending. Harrison et al. (2022) found that hospice improved quality of care among dementia patients in their last month of life, which suggests that increased hospice enrollment improves patient well-being, regardless of spending effects. But no studies address the impact of hospice care on the "marginal" patient, i.e., patients for whom eligibility is uncertain and whose use of hospice is affected by antifraud enforcement and related policies.

A handful of papers in the industrial organization literature have modeled hospice entry and competition, but they do not estimate the effects of hospice on spending or patient welfare. Chung and Sorensen (2018) build a model of market expansion among for-profit hospices and discuss the impacts on hospice use among cancer and dementia patients. These authors find that for-profit hospices engage in business stealing, particularly among cancer patients, but less so among dementia patients. This aligns with our finding that a large share of ADRD patients who attend for-profit hospice have an outside option of no hospice, which we discuss in Section 4.4. Ho (1991) studied the role of local wage variation and firm profit status in the expansion of Medicare hospice benefit. Alam (2022) models hospices' choice of quality under reputation effects.

The rapid entry of for-profit hospices and, more recently, acquisitions of hospices by other providers (e.g., home health agencies and nursing homes) (Gozalo, Mlotzke, Mor, Miller, & Teno, 2015; Stevenson, Sinclair, Zhang, Meneades, & Huskamp, 2020; Fowler, Grabowski, Gambrel, Huskamp, & Stevenson, 2017) and private equity firms (Braun, Stevenson, & Unruh, 2021) has spurred interest in the impact of hospice ownership on firm behavior. For-profit hospices admit more patients with a primary diagnosis of dementia, have longer average lengths of stay (Dalton & Bradford, 2019; Lindrooth & Weisbrod, 2007; Wachterman, Marcantonio, & Davis, 2011), and receive more referrals from nursing homes (Gandhi S. O., 2012). Differences in behavior are generally attributed to differences in the weight for-profit and non-profit hospices assign to patient welfare but may also arise from non-profit hospices'

dependence on charitable donations. If revenue from donations depends on the number of patients served rather than the duration of service, non-profit hospices will face a stronger incentive to admit short-stay patients (Dalton & Bradford, 2019). Hospices can influence enrollment by cultivating referral relationships with other providers (e.g., case managers at hospitals) and by setting admission standards (for example, will the hospice accept patients receiving transfusions). For-profit hospices are more likely to impose restrictions on the patients they will accept (Aldridge Carlson, Barry, Cherlin, McCorkle, & Bradley, 2012).

As a result of the cap on their payments, discussed in Section 5, hospices' incentives to admit and discharge patients may vary throughout the year (Ata, Killaly, Olsen, & Parker, 2012). Dolin *et al.* (2018) find that hospices with longer lengths of stay tend to have higher live discharge rates, and Plotzke *et al.* (2015) find that live discharge rates increase throughout the cap year, especially in hospices that exceed the cap.

Appendix B: Firm Dynamics

For-profit and non-profit firms differ in other ways beyond their profit status. While the main paper focuses on the fact that for-profit firms are more likely to take ADRD patients than non-profit firms are, these firms also adopt different approaches to scale, treatment, and patient acquisition, which we describe in this Appendix.

For-profit hospices adopt a larger scale than non-profit hospices. Appendix Figure A10 shows the census – that is, average patients per month – by for-profit and non-profit hospices. Because firms take time to grow, this is plotted as a function of firm age. In order to ensure firms are observed for equal amounts of time – that is, older firms do not have more years in our data – we consider the first 5 years and 10 years of firm age, which requires sample restrictions to 2000 through 2014, and 2000 through 2009 respectively. We see that upon entry, non-profit and for-profit hospices start with similar patient volumes. Over time, both grow larger, but for-profit hospices expand more rapidly, so that by 10 years post-entry, they are about 67% larger. Relatedly, the average age of for-profit hospices in our sample is 6.14 years, and the average age among non-profit firms is 8.87 years, reflecting greater entry by non-profits.

Appendix Figure A11 performs a similar study of average length of stay by profit status, across the first 5 and 10 years that we see firms open. The average length-of-stay is about 40 days longer at for-profit hospices, but the difference does not vary greatly with hospice age. This reflects the main descriptive fact of the paper, which is that for-profit hospices take patients with less acute illnesses, which drives the longer stays.

A persistent policy question is whether for-profit hospices potentially provide lower-quality care than non-profit hospices. The major input to this care is frequency of visits. Appendix Figure A12 addresses this question. Medicare claims do not report visit frequency for most years in our sample, as they were not required to do so until at least 2010. Instead, we use supplementary data from the state of California on visits provided by hospices. These data are mandated by the state and are available from the years 2002 through 2019. Hospices in California report visits per patient; however, as shown in the main, paper, for-profit hospices take patients that stay much longer on average. Therefore, we compute average visits per patient-day by dividing the average visits per patient by length of stay, where length of stay is computed from the Medicare claims data among all for-profit and non-profit hospices in California, separately. We find that non-profit and for-profit hospices provide similar numbers of visits per patient-day on average, 0.5 visits per patient-day, but there is greater variability among for-profit hospices. Figure A12 plots the histogram of the distribution of visits per patient day by hospice profit status at a hospice-year level.

A final set of analyses show how for-profit and non-profit hospices differ in the way that they acquire patients. Hospice claims are required to list the referring physician and their specialty, although these data are only available from 2015 through 2019. Appendix Table A14 characterizes the frequency of referring physician, by hospice profit status. The distribution of the specialty of the referring physician specialty is quite similar between non-profit and for-profit hospices. Second, Appendix Figure A13 counts the rate at which hospice patients have a precipitating hospitalization, by matching inpatient hospital stays from the MedPAR files to the timing of a patient's hospice claim. We find that non-profit hospices tend to admit more patients with recent hospital stays, reflecting their general focus on more acutely sick patients.

Appendix C: Distance metric and instrumental variables design details

C.1: Computation of the Distance Metric

Distance is measured as the miles between the centroid of a patient's home zip code to the centroid of the nearest for-profit hospice's zip code. When there is a for-profit hospice in a patient's zip code, this distance is 0. Because marginal miles above a certain distance are unlikely to matter, we truncate distance at 50 miles: i.e., those that do not have any for-profit hospice within 50 miles are coded as having a distance of 50. We apply the same measurement restriction similarly for non-profit hospices. Zip codes that are not in the NBER zip-to-zip database are counted as a distance of 50 miles.

C.2 Treatment Effect Margin Calculations

Mountjoy (2022) shows how to decompose the effect of a treatment when the compliers are driven from 2 groups. His context is the rise of community colleges, where access to a 2-year college "diverts" students from a 4-year college, but also "democratizes" students who would otherwise not go to college.

In the context of this study, the relevant margins of interest are attending no hospice, attending a for-profit (FP) hospice, or attending a non-profit (NFP) hospice. Non-profits are all hospices that have a non-profit, government, church, or "other" status in the provider of service files. Compliers are induced by the change in distance to a for-profit hospice. The introduction of FP hospice both "democratizes" hospice among those who would not go, and also "diverts" patients from NP hospice.

Mountjoy (2022) shows, in its Eq. 15, applied to our setting:

$$MTE_{FP} = \omega MTE_{FP\leftarrow 0} + (1-\omega) MTE_{FP\leftarrow NFP}$$

Where MTE_{FP} is the net effect of for-profit entry; ω is the share of compliers along the democratization margin; $MTE_{FP\leftarrow 0}$ is the "democratization" effect, i.e. the marginal treatment effect among patients who would otherwise not enroll in hospice; and $MTE_{FP\leftarrow NFP}$ is the

"diversion" effect, i.e. the marginal treatment effect among patients who would otherwise enroll in for-profit hospice.

Mountjoy (2022) estimates these effects using a partial derivative related to the 2SLS equivalent, evaluated at the mean of the instrument, computed using a kernel density estimation. The kernel density estimator is used in order to avoid making the "common" IV restriction that control variables, necessary for the validity of the instrument, are linear in their effect on the treatment and outcome variables. Making that assumption, we can use simple first stage, reduced form, and 2SLS estimates to directly compute the parameters of interest.

Call D_{FP} , D_{NP}, and D_0 treatment at a for-profit, non-profit, or no hospice respectively. Similarly, call Z_{FP} and Z_{NP} distance to a for-profit and non-profit hospice respectively, our instruments. Mountjoy introduces the notation YD_{FP} to mean the value of Y among those treated in For-Profit, or 0 otherwise, a critical outcome variable used in the estimation, as well as the equivalent notation YD_0 and YD_{NP} . All regressions include controls for baseline characteristics described in our main specification. Regressions instrumented with for-profit distance control for non-profit distance and vice-versa.

Adapting the Mountjoy equations to a standard IV design, and suppressing expectation functions for simplicity:

$$MTE_{FP} = \frac{\frac{\partial Y}{\partial Z_{FP}}}{\frac{\partial D_{FP}}{\partial Z_{FP}}} = \text{2SLS Effect of For-Profit Distance on } Y$$

$$\omega = \frac{-\frac{\partial D_0}{\partial Z_{FP}}}{\frac{\partial D_{FP}}{\partial Z_{FP}}} = \frac{\text{First Stage Effect of For-Profit Distance on Any Hospice Use}}{\text{First Stage Effect of For-Profit Distance on For-Profit Hospice Use}}$$

$$MTE_{FP \leftarrow NP} = \frac{\frac{\partial YD_{FP}}{\partial Z_{NP}}}{\frac{\partial D_{FP}}{\partial Z_{NP}}} - \frac{\frac{\partial YD_{NP}}{\partial Z_{FP}}}{\frac{\partial D_{NP}}{\partial Z_{FP}}}$$

=2SLS of FP Outcome on FP Treatment, Instrumented with NP Distance

− 2SLS of NP Outcome on NP Treatment, Instrumented with FP Distance

This is sufficient for solving for the two marginal treatment effects, because we can estimate a single margin treatment effect and the relative weights of the two effects, ω and 1 – ω.

We use this same procedure for each outcome variable of interest. Note that when producing months of life calculations, we start counting on January 1 of the year following ADRD diagnosis, to account for patients with missing exact diagnosis dates, but for whom their diagnosis year can be observed.

To estimate 95% confidence intervals, we follow Mountjoy (2022) by block-bootstrapping the point estimate over zip codes and taking the 2.5^{th} and 97.5^{th} percentile.

Finally, we note that for the purposes of this analysis, we count months alive starting in month 1 of year 1, where diagnosis happens in year 0. That is necessary to include our full sample, because we are missing exact diagnosis dates for some individuals.

Appendix D: Continuous Event Study Details

The goal of the Continuous Event Study presented in Figure A2 is to re-structure the effects of hospice spending due to changes in firm distance as an event study. The value of the event study is that it allows us to evaluate pre-trends, to ensure that, for example, spending isn't declining in the period prior to hospice opening, which could conflate secular trends with treatment effects.

However, changes in distance take on continuous values, which inhibits traditional event studies, which would focus on discrete events such as large changes in distance. Instead, we use a continuous event study, which allows us to estimate the average effect of every 10-mile change in for-profit distance. This mechanism was first proposed in Schmidheiny and Siegloch (2023), which uses a distributed lags model to estimate "continuous difference-in-difference" effects. Specifically, following this work, we estimate coefficients for a set of lags and leads of the continuous treatment – that is, all changes in distance to a for-profit hospice –

on the outcome, and then accumulate these estimates to compute the effect of a one-unit change in treatment at time periods before and after that change. Schmidheiny and Siegloch (2023) prove that this procedure is equivalent to a standard TWFE model (with binned endpoints) when treatment is binary and that the lag and lead coefficients can be interpreted analogously to a standard TWFE event study.

We implement this method on our hospice data. The result is a set of difference-in-difference style graphs, which show the marginal effect of every 10-mile reduction in distance to a for-profit hospice on patients by the cohort in which they are diagnosed, relative to the timing of the distance changed.

The event studies are set up in parallel to our main IV results. Figure A2 shows the effect on first stage usage and categories of spending. For each variable, we consider the effect on each cohort, and measure the outcome in years 0-5 post diagnosis, as we do in our main specification. The horizontal (time) axis is in terms of cohort years, parallel to the IV analysis. We use changes in zip-code distance from 2002 to 2013 to have sufficient lags and leads to compute the distributed lags continuous event study. Beginning in 2002 and ending in 2013 allows us to observe spending in patients 5 years after diagnosis.

There are two relevant events in each graph. First, 5 years before the opening of the hospice, we begin to see patients whose 0-5 year post-diagnosis window overlaps with the hospice being open (for example, the 0-5 year spending for patients diagnosed in 2007 will have one year of overlap with a for-profit hospice that enters in 2012). That is, since we are using a year 0-5 spending window, hospice entry will affect spending over a six-year period starting five years before entry. The second event is the opening of the hospice, after which all cohorts are fully treated. Therefore, each graph has 3 segments: the pre-trend effects, the phase-in effect, and the effects on the fully treated cohorts.

The results of this continuous difference in difference match those of our main results. They show, consistently, minimal pre-trends, as well as signs and magnitudes that align with our IV results: use of for-profit hospice reduces total spending and site-specific spending (inpatient, SNF, home health, etc.), except for outpatient care, which appears noisier. Total and for-profit hospice spending increases, but non-profit hospice spending falls.

Appendix E: Additional Cap Details

E.1 Computing the Cap

Hospices are permitted to use varying methods for computing their cap, and the rules have changed over time. Under the "streamlined" method, hospices count the number of new patients admitted from September 28 in one year to September 27 the following year. Under the "proportional" method, hospices count patients fractionally based on the proportion of the stay at that hospice during the cap period. Our data do not report which method hospices use. Hospices exclusively used the streamlined method before 2011, when the proportional method was introduced and made the default. By 2013, only 486 hospices used the streamlined method (Centers for Medicare & Medicaid Services, 2015). Because the streamlined method is simpler than the proportional method and because the streamlined method was the only method used for the majority of our study period, we use the streamlined method to estimate hospices cap usage. Using this method, our estimates of the proportion of hospices that exceed the cap matches other sources closely, e.g., Cuppett & Forster (2014).

Because we consider how each hospice's proximity to the cap changes within each cap year, we measure Medicare payments to the hospice at the monthly rather than yearly level. To that end, for each hospice claim, we distribute the Medicare payment amount evenly across the months covered in that claim. For example, if a claim is for a hospice stay that lasts between January and March and has a Medicare payment amount of $900, we assign a $300 Medicare payment to January, February, and March for that hospice. Then, we aggregate payments at the hospice-month level to measure monthly Medicare payments.

E.2 Patient-Month Estimates

To construct the patient-month sample that estimates Equation (4), we use the following criteria. We start with cap years 2001 through 2019, where cap year 2001 began in October 2000 and cap year 2019 began in October 2018. The sample ends in December 2018 to ensure we can observe 12 months after a given month for spending and care outcomes. We restrict the sample to hospices not in their first cap year, because partial years distort the cap calculation. We consider a patient's first visit to hospice; patients who are live discharged and

ever re-enter hospice are excluded (though subsequent hospice episodes are included in the aggregate cap payment). We also exclude patients whose death date is before the first of that month.

E.3 Probability of Exceeding the Cap

We use a logistic regression to calculate, for each hospice in each month, the probability that a hospice will be over the cap at the end of the year based upon all interactions between the month of the year and the ratio of payments to the cap in that month. Specifically, we estimate the following logistic regression:

$$Y_i = \alpha + \phi Share\ of\ Cap + \sum_{i=1}^{12} \beta_i Month_i + \sum_{i=1}^{12} \gamma_i Month_i \times Share\ of\ Cap + e_i$$

Where, because this is a logistic regression, Y is the log odds ratio that the hospice will be over the cap at the end of the year, and the Share of Cap variable is the ratio of cumulative payments to the hospice up until that month to their cap allotment at that time, and Month is the calendar month. If there are no patients in a given month that count toward the hospice's patient total, but the hospice accrues revenue, the share of the cap is undefined (due to a divide by zero) and is therefore dropped. The regression is estimated on all hospice-months where the hospice is not in its first cap year. We use this regression to predict fitted values for the probability that the hospice will be over the cap.

Appendix F: Care for Patients Discharged During High Cap Pressure Months

To further analyze the consequences of the cap admission, we conduct a supplementary analysis of the care of patients who are discharged alive from hospices in months with high cap pressure, specifically where the probability of exceeding the cap is greater than 0.9. We follow these patients for the year following their discharge and compare their care to the year prior to entering hospice. In doing so, we can understand how hospice live discharge changes care as compared to the way in which patients were treated before entering. To ensure we can observe patients for the year before and after hospice, we limit our sample to the years 2000 to 2018, i.e. one year after the start and before the end of our data. Because patients may attend hospice more than once, we define our sample from the first live discharge for clarity.

Appendix Figure A14 shows the distribution of hospitalizations among this sample, comparing the 12 months before hospice to the 12 months post hospice. The leftmost histogram is the pre-hospice distribution; the center panel is the full distribution among patients live-discharged (including patients who died shortly following discharge), and the rightmost panel is the distribution among patients who are live-discharged and survive 12 months. The third panel is included to differentiate between patients who die within 12 months of live discharge, which produces a mechanical reduction in utilization, versus those who live but receive less care. Overall, we see a major reduction in care for patients following hospice discharge. Following a live discharge, there is a substantial reduction in hospitalization as compared to the pre-period, and patients are nearly 50% more likely to have 0 hospitalizations as opposed to the pre-hospice period. We see that this pattern persists even in this subsample of patients who survive 12 months, indicating it is not driven by mortality.

Appendix Table A15 shows the rate at which patients who experience live discharge have interactions with outpatient physicians, by the specialty of the physician, before or after hospice. As in the figure above, the third panel includes only patients who live for 12 months. Note that, due to limited availability of the specialty code among the outpatient claims, we use 2015-2019 data for this analysis. We see that there is a large decrease in the use of physician services between the pre-admission and post-discharge periods across all specialties. For example, patients have 70% fewer interactions with hematologists/oncologists. The rate at which they see emergency medicine specialists is roughly halved, as is the rate at which they see urologists, cardiologists, and orthopedists. These effects persist *even* when we consider patients who survive all 12 months, indicating that hospice-ending live discharge strongly diminishes the rate at which patients receive care.

A major factor driving the reduction in care is that many patients who are live discharged return to hospice. Among our sample patients live-discharged with a high cap value, 70% will ever return to hospice. The median time to hospice after live discharge is 28 days, and 38% of those who return to hospice will be treated by the same provider. These statistics are consistent with gaming behavior – wherein hospices cycle patients in and out of hospice to avoid the cap. Moreover, it may speak to a taste for hospice, where patients who have begun

palliative care prefer to continue it, which also indicates that live discharge is costly to the patients.

Finally, we consider mortality among this sample, and find that live-discharged patients experience high mortality rates. Among the same live discharge sample, we find 5.5% of patients die within a week, 13.9% die within 30 days, and 32.5% die within six months. Notably, Medicare hospice coverage regulations includes a provision for "re-certification," wherein a patient who is on hospice can stay longer than 6 months if they still have a less than 6 month life expectancy. With roughly 1/3 of these patients dying within 6 months, it appears hospices are discharging many patients who are eligible for continued hospice care.

Overall, while there is evidence that some patients are appropriately live-discharged from hospice during high cap periods, a substantial share of patients die very quickly post-live-discharge. For these, disruptions to normal care, as well as lack of access to palliative care because hospice has been removed, suggests that the cap leads to low-quality end-of-life care. Ultimately, the sum of this analysis supports our main findings in the paper and provides additional mechanisms by which we see the cap's distortionary effects.

Appendix G: Matching FOIA Data into Medicare Claims

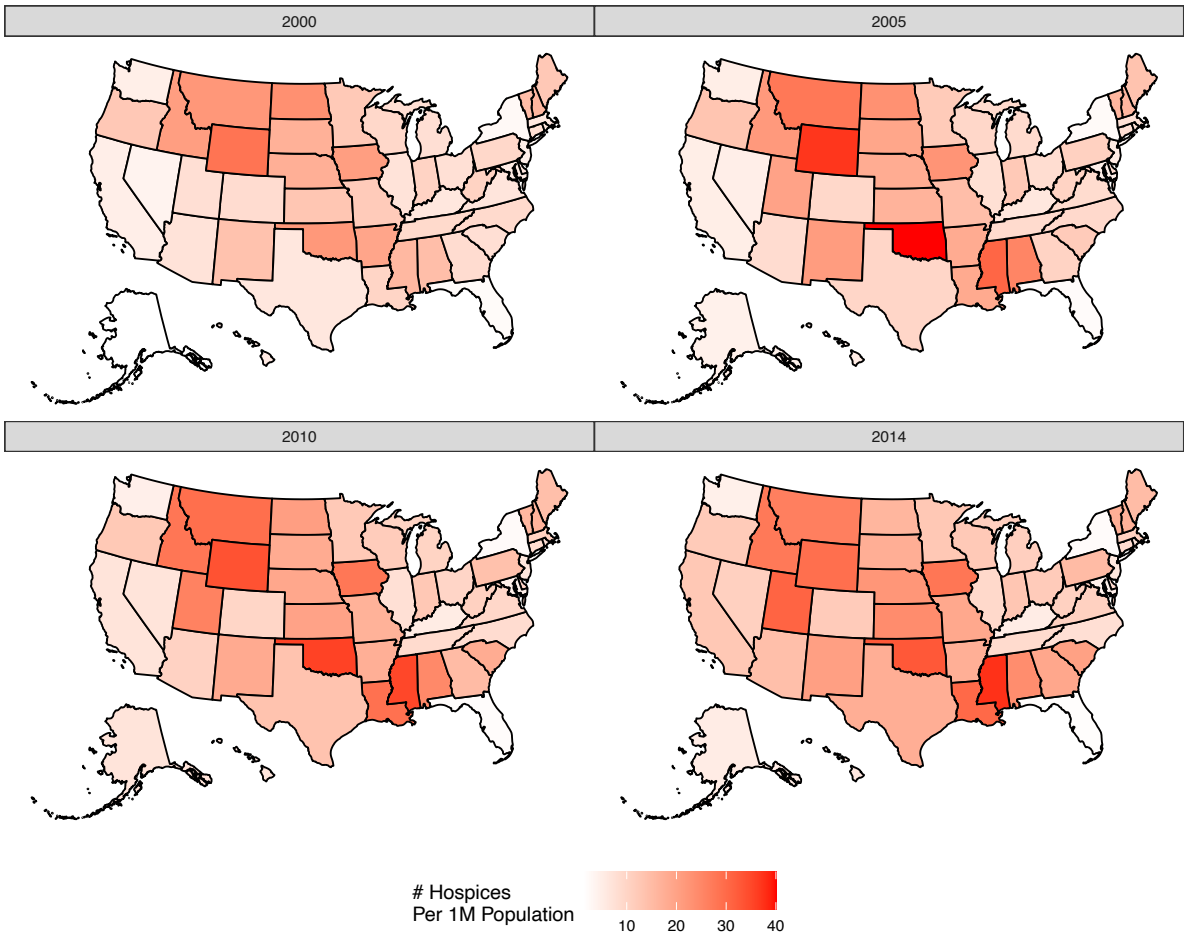
This appendix describes the steps we took to identify hospices that were defendants in False Claims Act lawsuits in the Medicare data.

We began with a list of hospice names from the Freedom of Information Act (FOIA) request, and hospice names from the Provider of Services File. The Provider of Service files include Medicare provider numbers that can be merged to claims, but the FOIA does not. Multiple defendants can be listed in a single lawsuit, and these were separated into individual hospice names from the Freedom of Information Act data. We manually cleaned the hospice names to remove common words like "hospice", "care", and "LLC", leaving behind the brand names like "Vitas" or "Aseracare". We merged the defendant name and Provider of Service data on the basis of hospice names – if the defendant name appears within the hospice name, we call this a match.

The Freedom of Information Act request from the Department of Justice gives details about the timing of the lawsuit. We use the “date received” variable to identify the year in which the lawsuit was filed. This is roughly the filing date of the lawsuit.

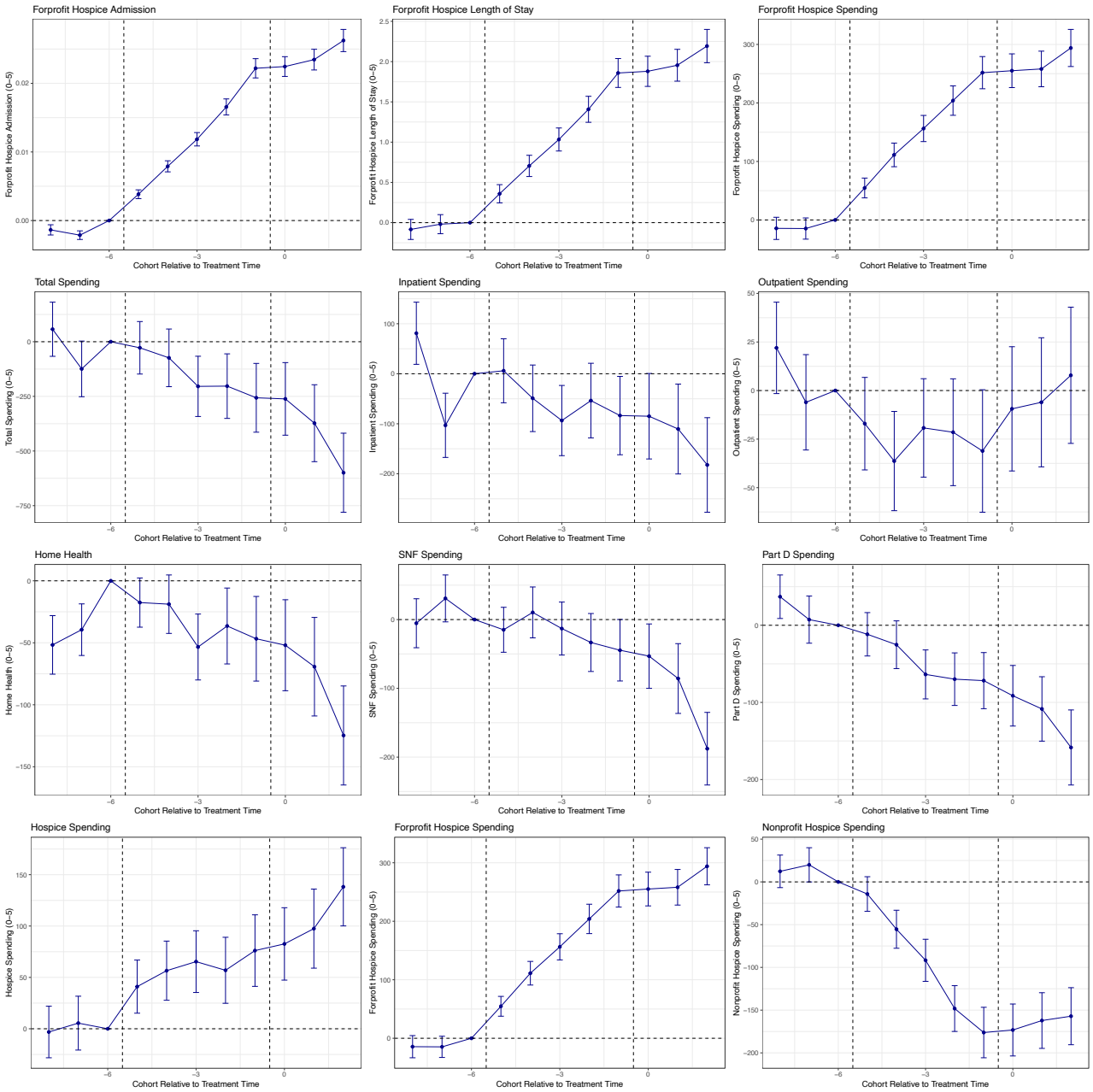
Appendix Tables and Figures

Figure A1: Geographic Trends in Hospices



Notes: This figure shows the number of hospices per 1 million residents in each of the 50 states in 2000, 2005, 2010, and 2014. The number of hospices is calculated from the Medicare Claims files, and state population is extracted from the St. Louis Federal Reserve annual State Population estimates.

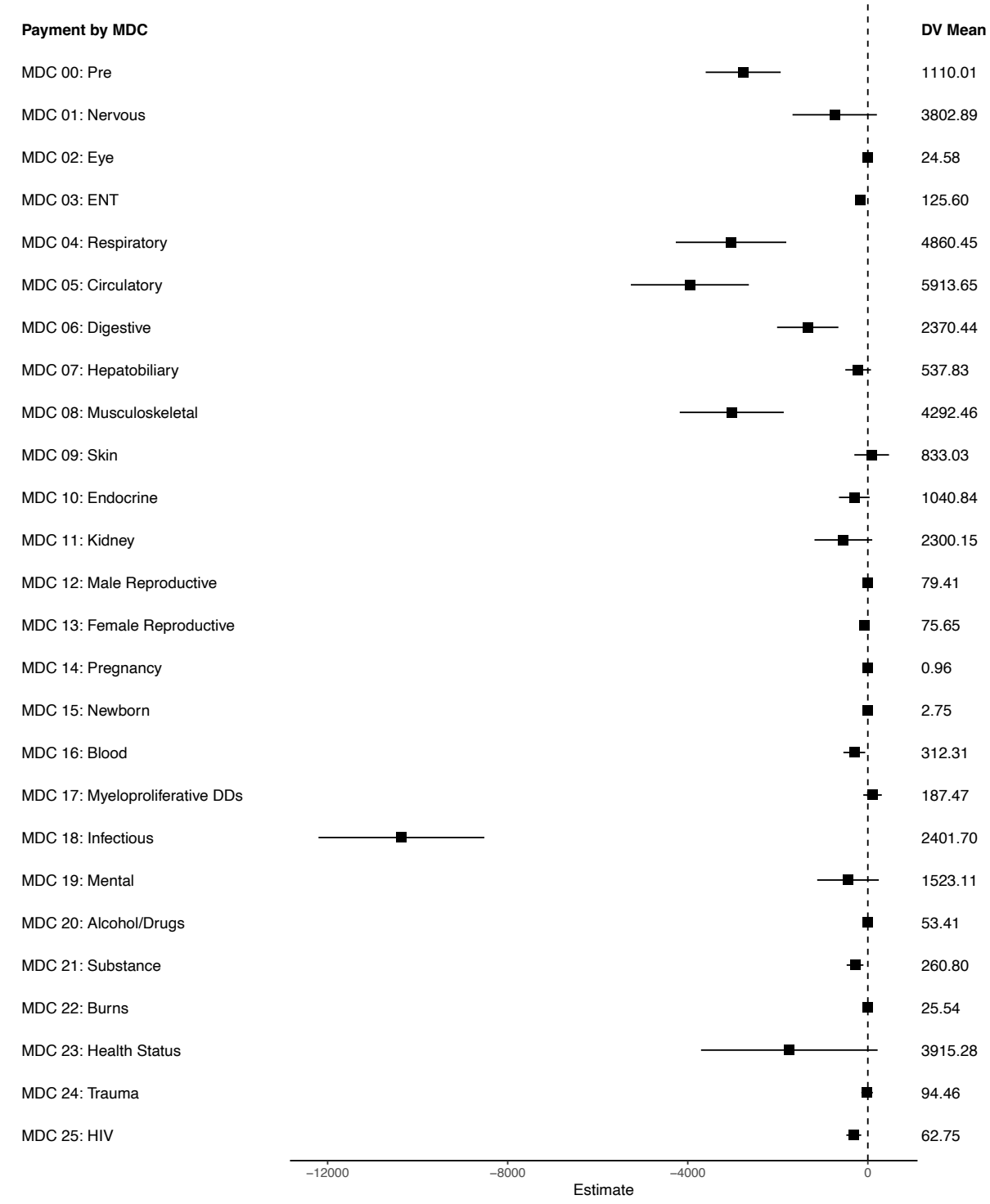
Figure A2: Continuous Event Study Design



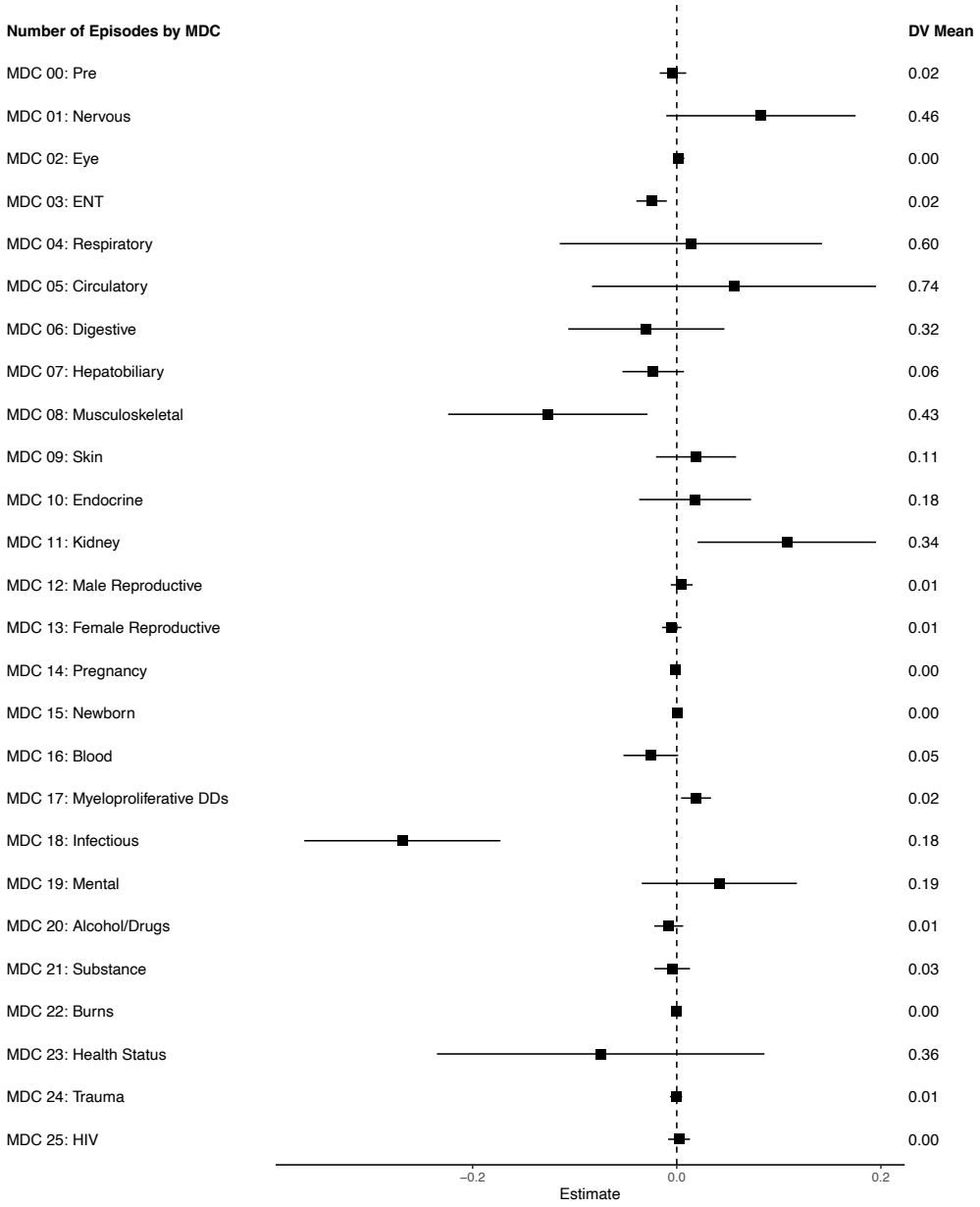
Notes: The figure shows the coefficient estimates and 95% confidence intervals for a continuous event study specification, following Scmidheiny and Siegloch (2023). Treatment is where a zip code experiences a change in distance to a for-profit hospice, with a one unit change corresponding to a 10 mile decrease. Each outcome is measured for the cohort of individuals diagnosed in the relative year, over the period 0-5 years following that diagnosis, and therefore shows a phase-in effect. As indicated by the first vertical line, 5 years before the hospice is opened, 5-year hospice usage rises and 5-year spending falls. These effects continue for the cohorts with greater exposure throughout the phase-in period (between the vertical lines) until the opening of the hospice at the second vertical line.

Figure A3: Spending and Visits by Major Diagnostic Category (Hospitalization & Nursing)

A3.A: Spending by MDC



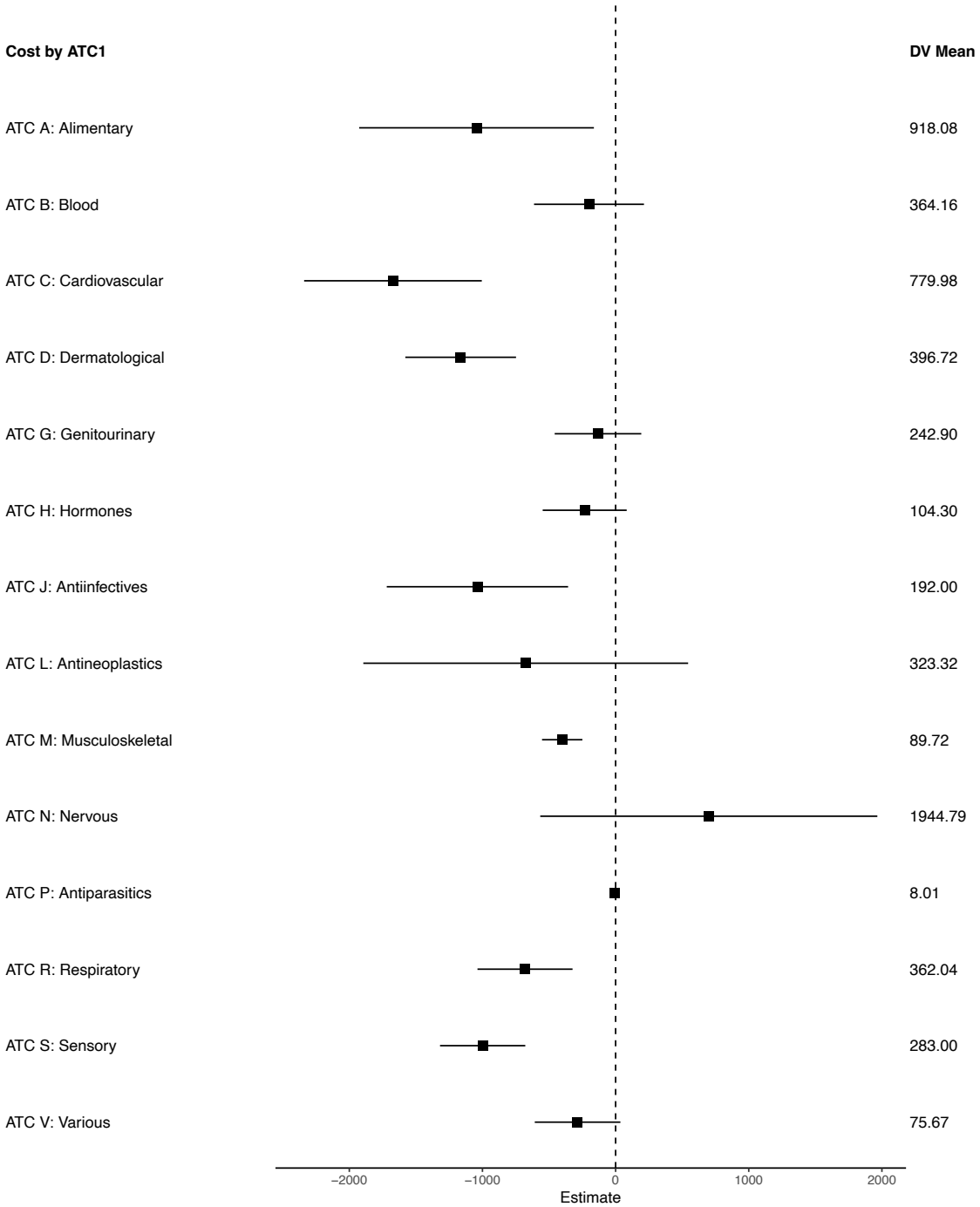
A3.B: Visit Count by MDC



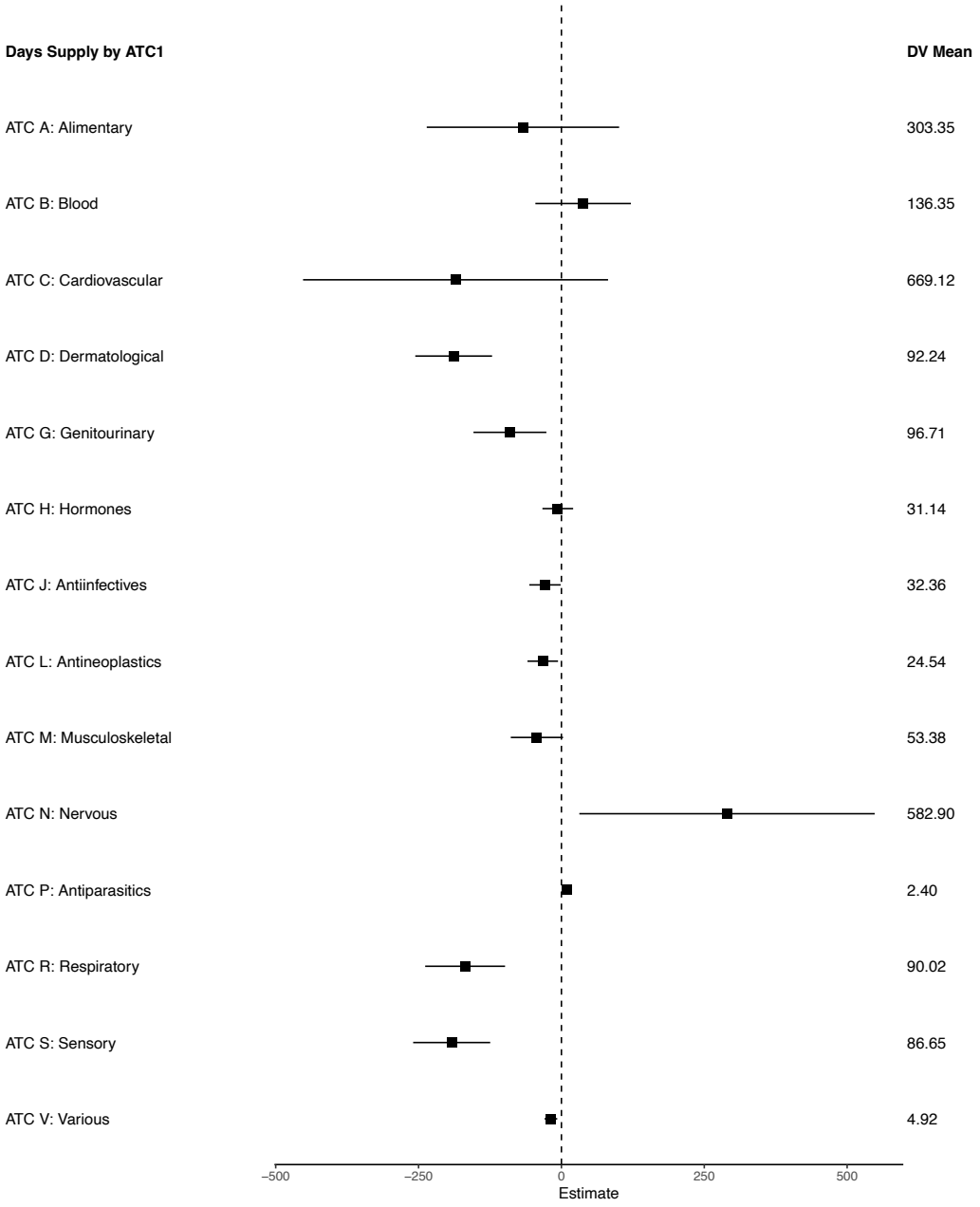
Notes: This figure shows the effect of for-profit hospice use on spending and visit counts by Major Diagnostic Category (MDC). Panel A shows spending within each MDC, while Panel B shows visit counts within each MDC. Data are taken from a 100% sample of MedPAR, which contains hospitalizations and Skilled Nursing Facility visits. Mapping into MDCs is performed using the NBER Diagnosis-Related Group Major Diagnostic Category Crosswalk. Each point estimate and confidence interval are drawn from an instrumental variables regression as in our main specification. Means of each category are presented on the right. Spending on many types of hospitalizations fall, but number of visits is slightly positive for some categories, such as kidney-related stays.

Figure A4: Spending and Days Supply by Anatomical Therapeutic Code of Drug (ATC1)

A4.A: Spending by ATC1 Group

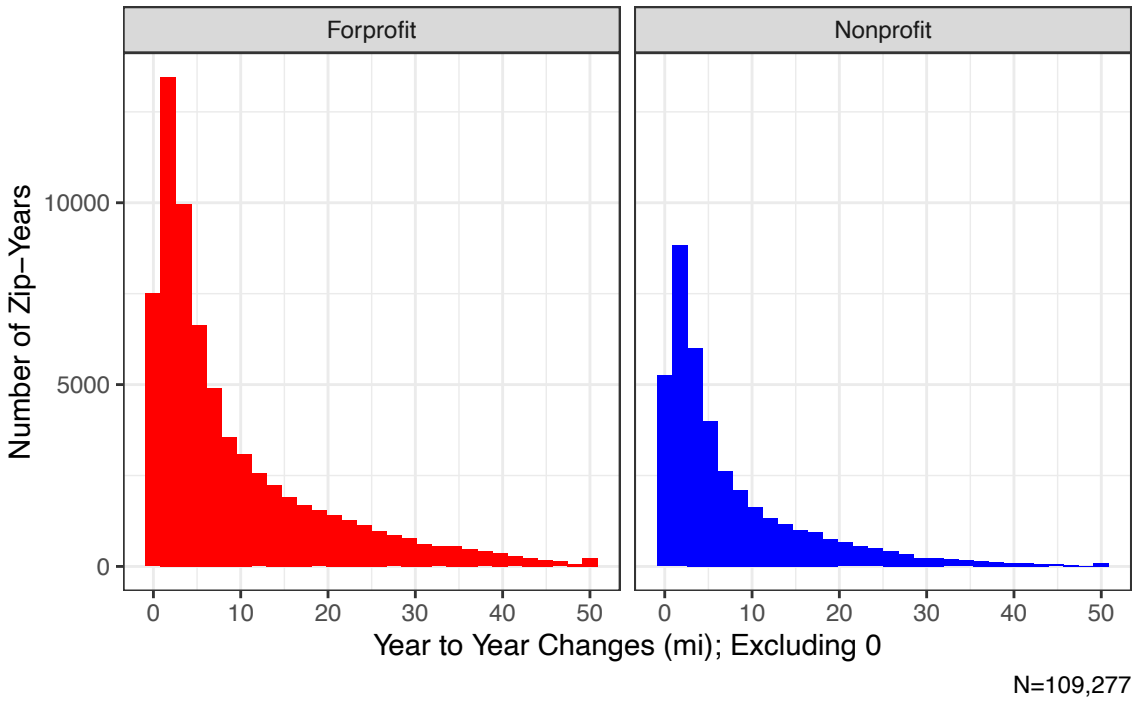


A4.B: Days Supply of Drugs by ATC1 Code



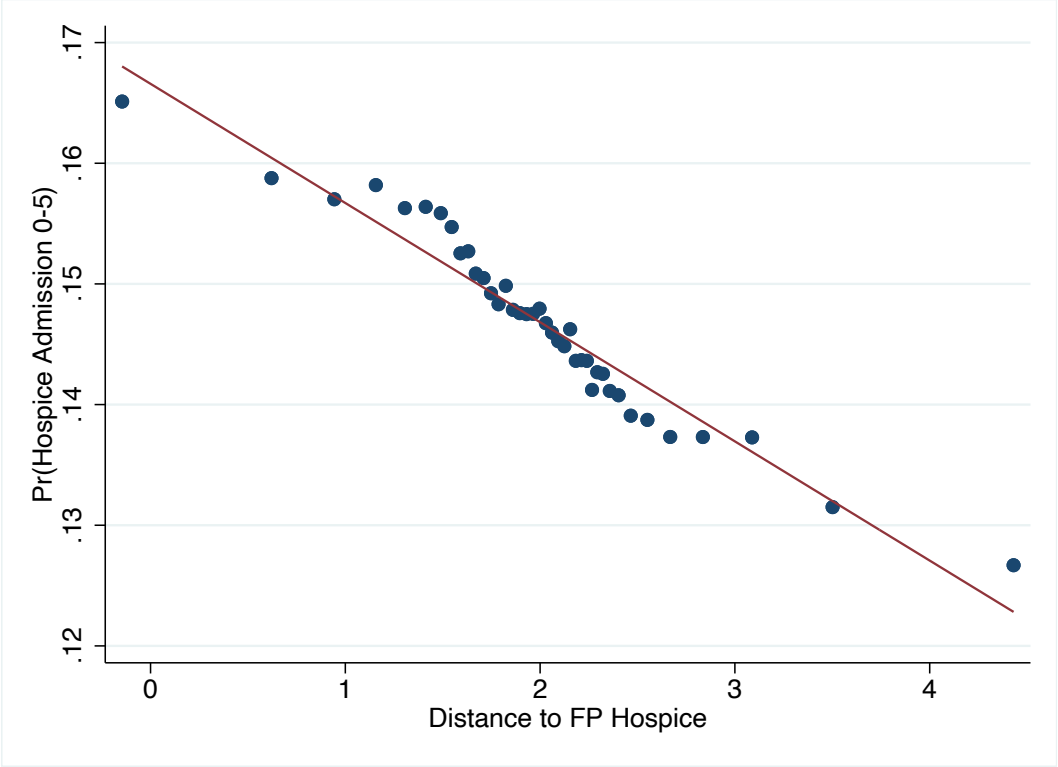
Notes: This figure shows the effect of for-profit hospice use on spending and days supply of drugs by Anatomical Therapeutic Chemical (ATC) Class. Panel A shows spending within each ATC Level 1 code, while Panel B shows days. Data are taken from a 20% sample of Part D claims, and mapping into ATCs is performed using data from the National Institutes of Health RxNav. Each point estimate and confidence interval are drawn from an instrumental variables regression as in our main specification. Means of each category are presented on the right. Spending on most types of drugs fall, but nervous system drugs (including pain medication) rise in both days supply and spending.

Figure A5: Changes in Distance to For-Profit and Non-Profit Hospices



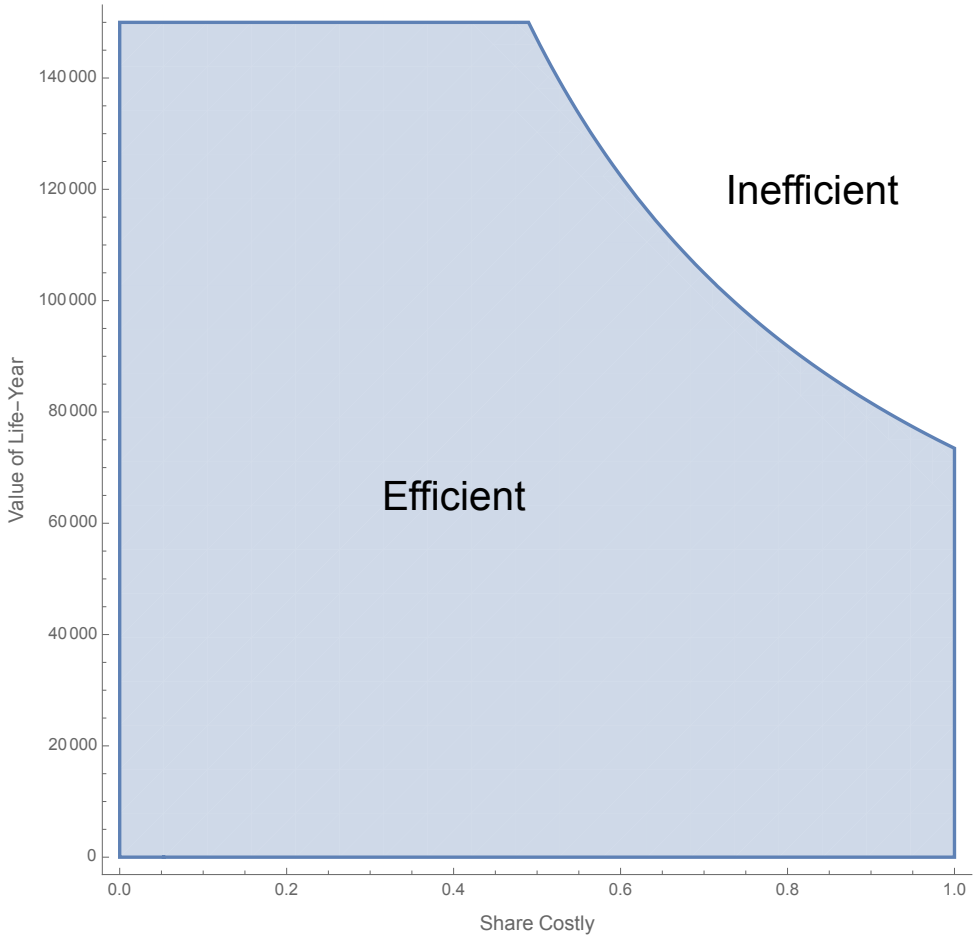
Notes: This figure shows a histogram of zip-code-year changes in distance to for-profit and non-profit hospice, excluding 0s. Both for-profit and non-profit hospice distances show substantial year-to-year variation.

Figure A6: Distance and Probability of For-Profit Hospice



Notes: This figure plots a binscatter of distance to for-profit hospice (scaled in 10-mile units) against probability of for-profit hospice enrollment, adjusting for patient-level demographic and chronic condition fixed effects, zip and cohort fixed effects, and controls for non-profit distance.

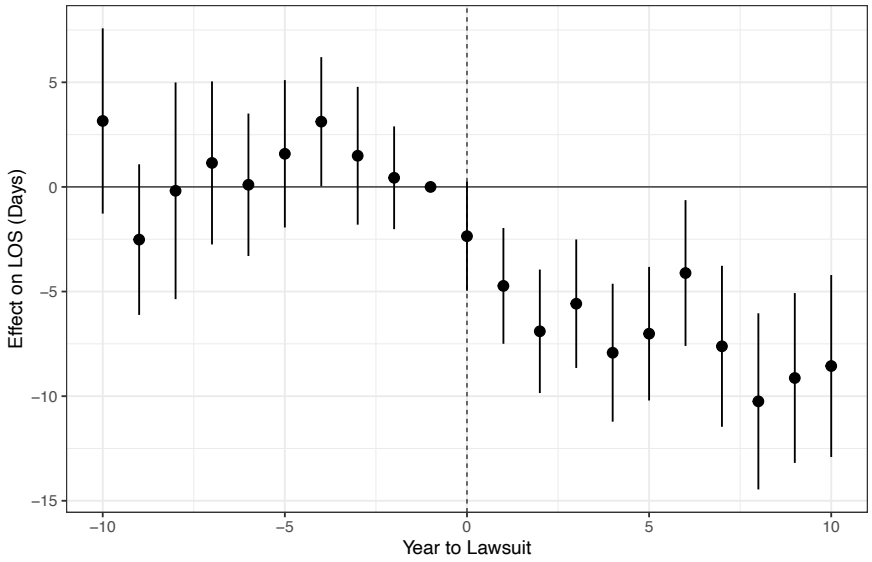
Figure A7: Welfare Bounds Calculations



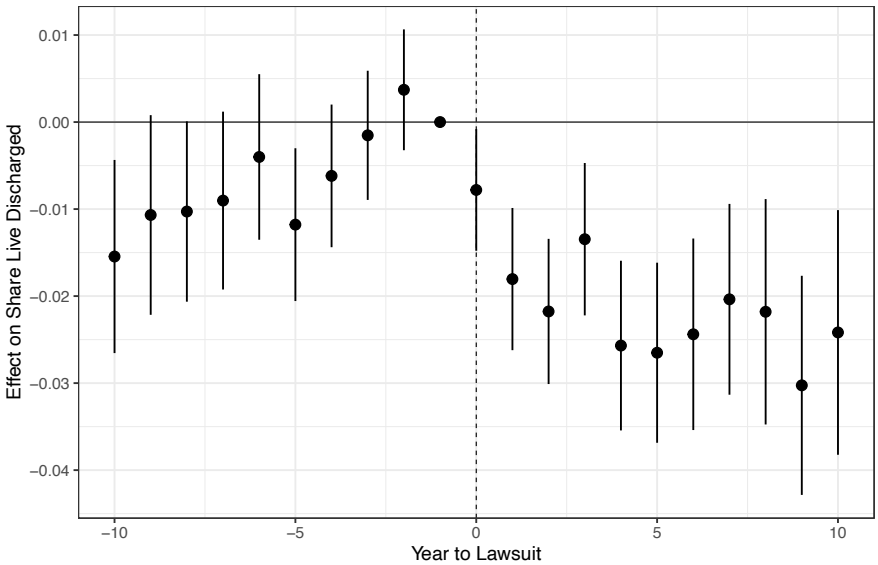
Notes: This figure describes the tradeoff between cost-savings and mortality described in Equation (3). Hospice saves money for ADRD patients, but increases mortality; however, most patients voluntarily accept the reduction in curative care to improve quality of life. This figure shows the share of patients that would need to have been uninformed about the consequences of hospice – and therefore whose mortality should be counted as a cost – for the program to be inefficient. It is plotted against the value of a life-year. For most reasonable quality-adjusted estimates for the value of an ADRD patient's last months, this tradeoff is efficient.

Figure A8: Event Studies of Effects of Lawsuits on Hospice Patient Composition

A8.A: Effect of Lawsuit on Average Length of Stay



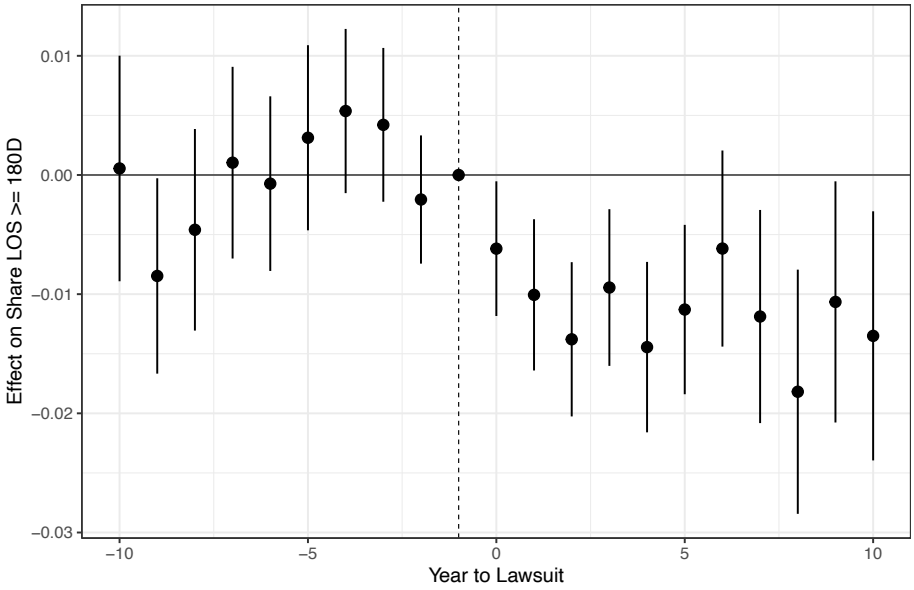
A.8.B: Effect of Lawsuit on Share Live Discharged



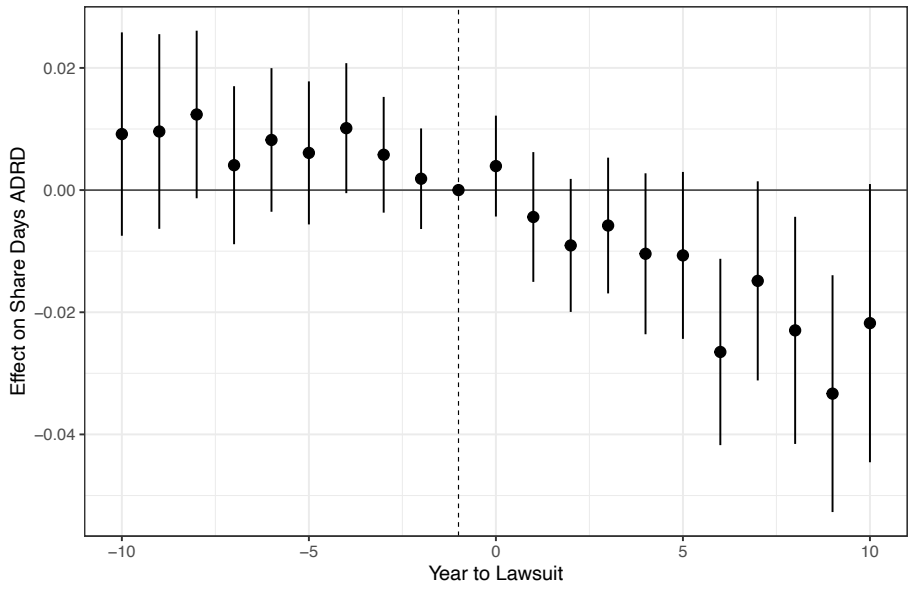
Notes: These figures show more outcomes of the event study described in equation (5) and presented in Figure 3. Specifically, the figures show the dynamic effects of a lawsuit in year 0 on the average length of stay for admissions (Panel A) and on the share live discharged (Panel B), measured relative to the year of patient admission Error bars correspond to 95% confidence intervals. Each event study is normalized such that the coefficient corresponding to year -1 is 0.

Figure A9: Event Studies of Effects of Lawsuits on Hospice Patient Composition with Alternative Specification

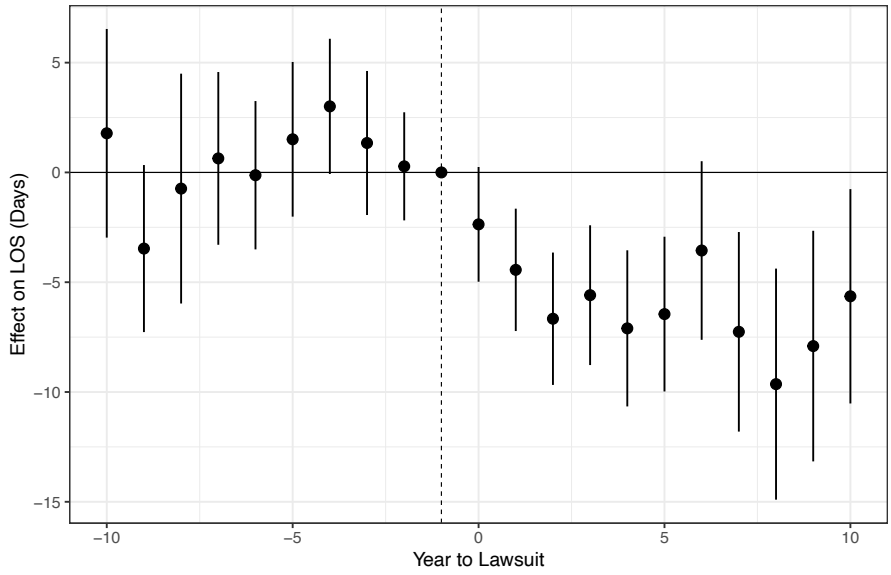
A9.A: Stays Above 180 Days



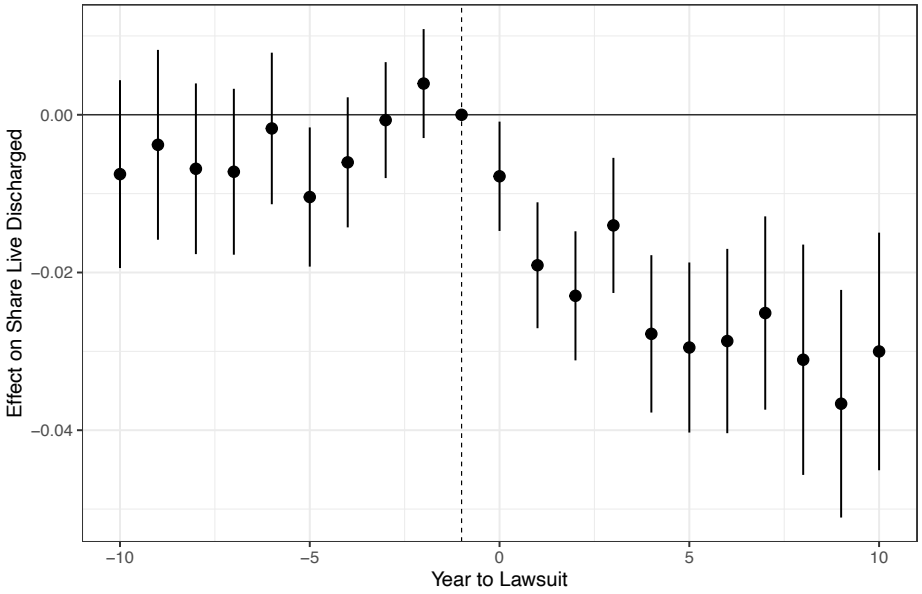
A9.B: Share of ADRD Patient-Days



A9.C: Average Length of Stay

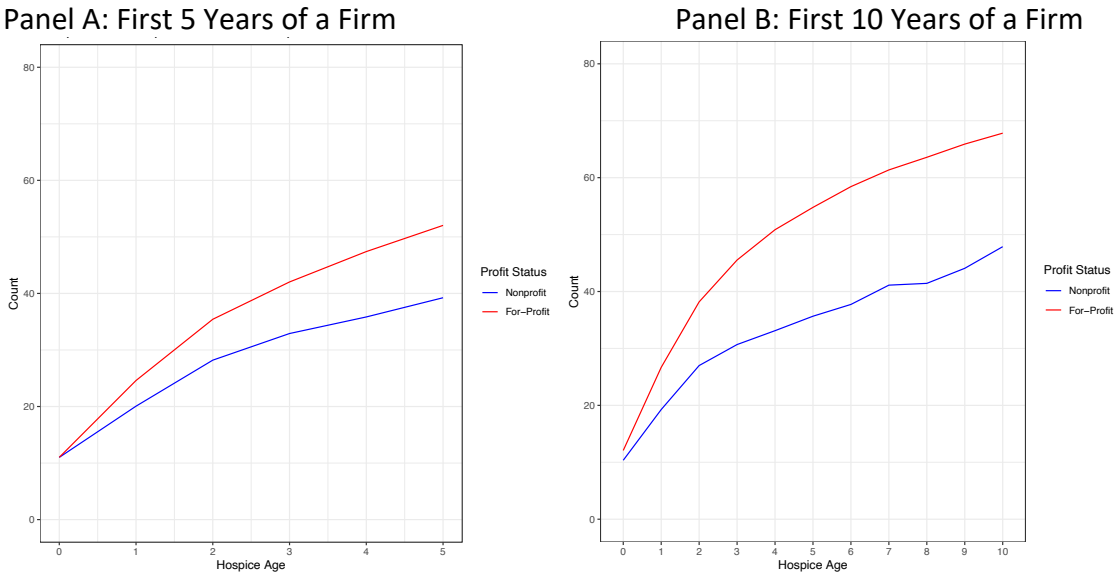


A9.D: Share Live Discharged



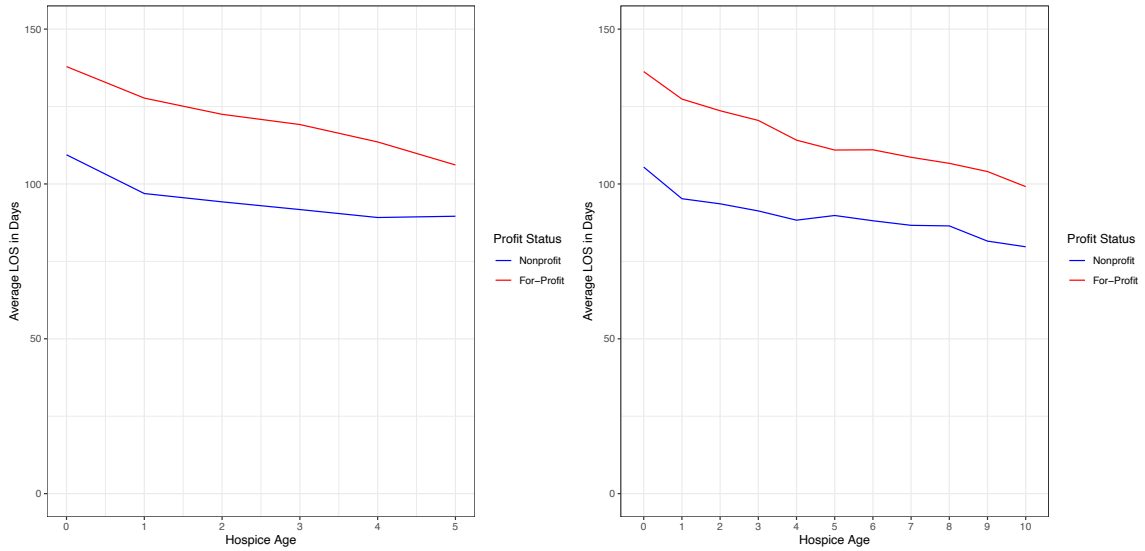
Notes: These figures show alternative specifications of the event study described in equation (5) and presented in Figures 3 and A8, using the estimator proposed in Sun and Abraham (2021). Panel A shows the effect on hospice stays over 180 days; panel B shows the effect on the share of days from patients with an ADRD diagnosis; panel C shows the effect on average length of stay; and Panel D shows the effect on the share of patients live discharged.

Figure A10: Hospice Census by Profit Status and Firm Age



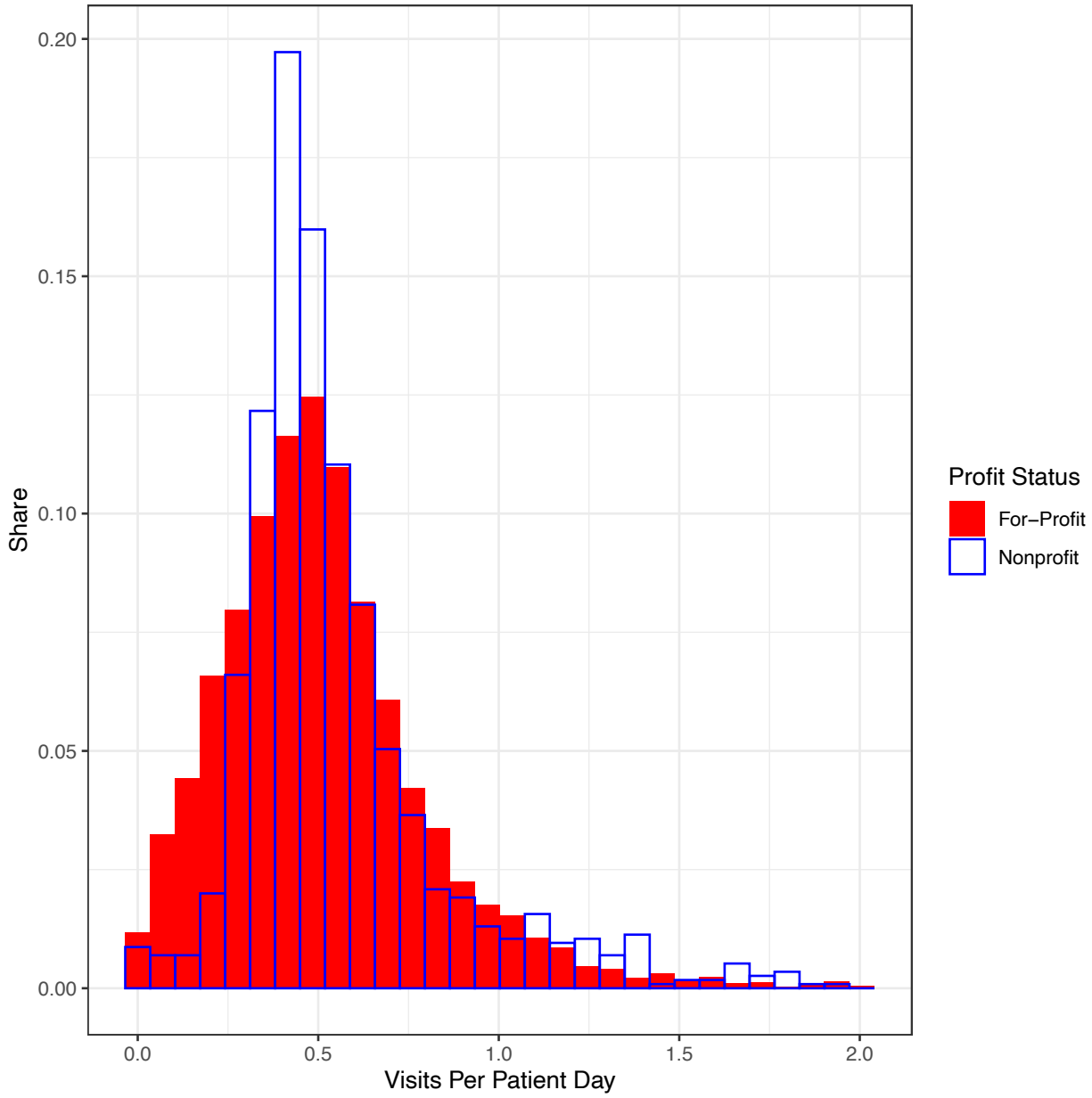
Notes: The figure shows the average monthly hospice census over years 0 through 5 (Panel A, Left) and years 0 through 10 (Panel B, right). We observe each hospice firm in our data by profit status at opening and condition the mean on hospices remaining open (i.e. having nonzero patients). Both types of firms grow over time, and for-profit hospices adopt a larger scale than non-profit hospice firms.

Figure A11: Average Length of Stay by Hospice Age and Profit Status



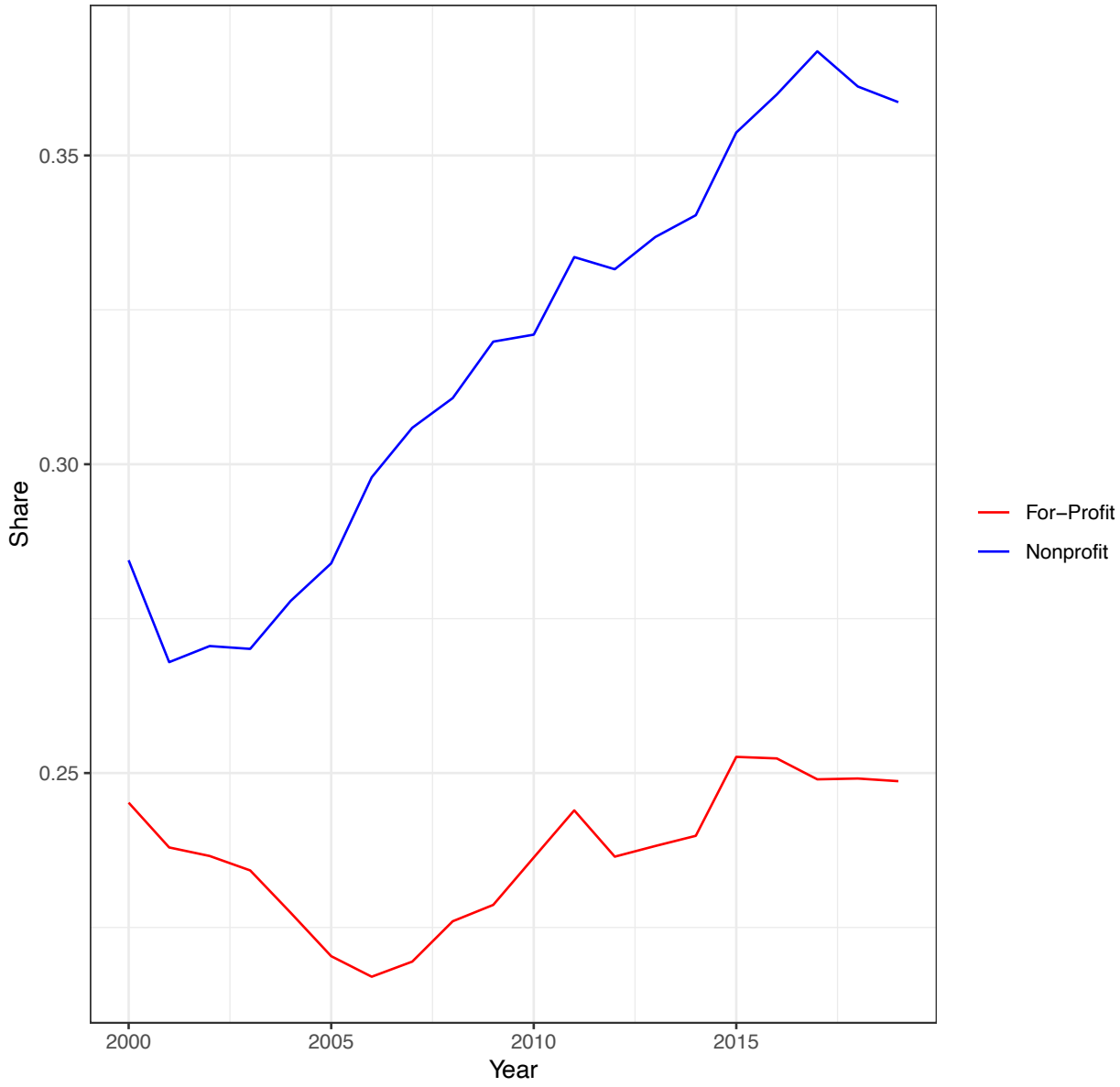
Notes: The figure shows the hospice average length of stay over the first 5 years (Panel A, Left) and 10 years (Panel B, right) we observe each hospice firm in our data, by profit status. Panel A uses data from 2000 to 2014, and Panel B uses data from 2000 to 2009. Both types of firms show similar slight declines in LOS over time, but average LOS is longer in for-profit hospices.

Figure A12: Visits by Firm Profit Status by Patient Day



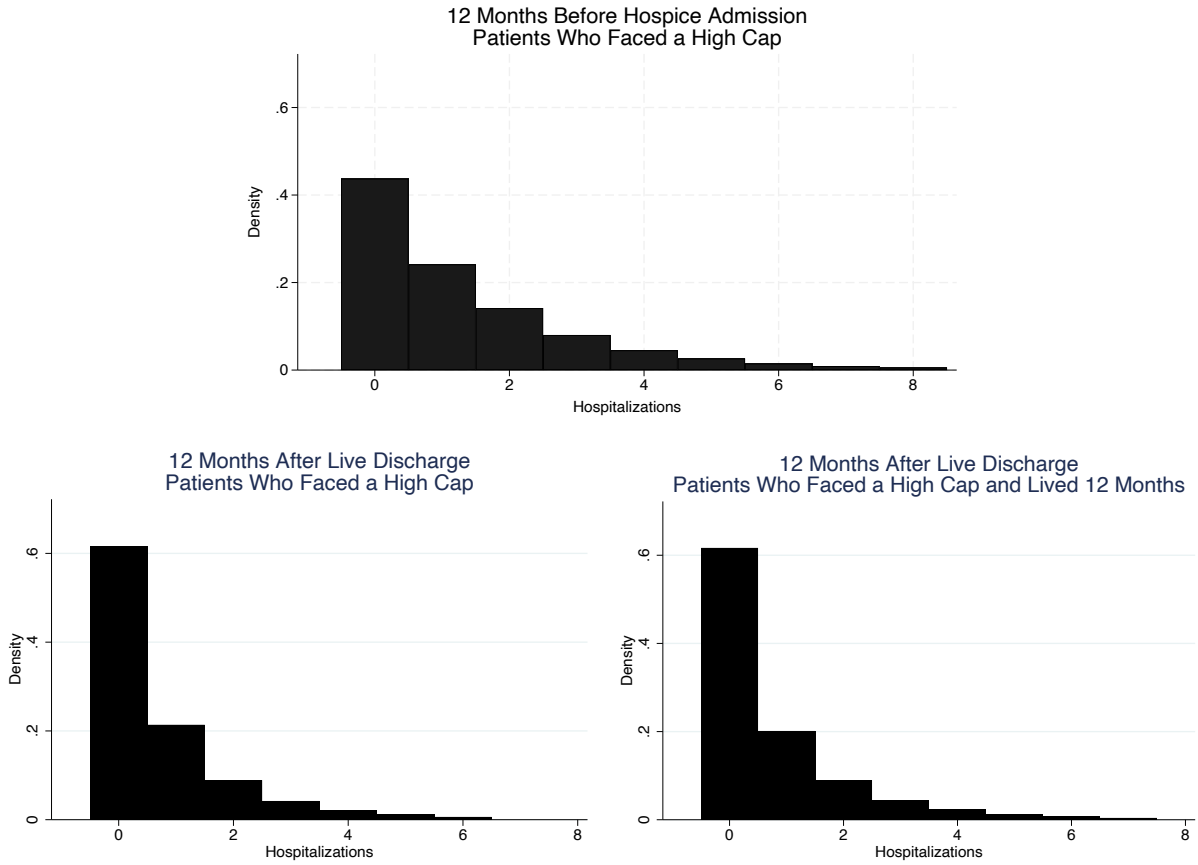
Notes: This figure plots the hospice-year distribution of number of visits, computed from California state data, divided by the mean stay length among for-profit and non-profit hospice patients, computed from the Medicare claims from California hospices from 2002-2019. For-profit hospices show more variability, but the distributional means are similar. Daily visits are truncated at the 99th percentile.

Figure A13: Share of Hospice Episodes Preceded by Hospital Visit, by Profit Status



Notes: This figure plots the share of ADRD patients in our sample whose hospice visit began with a hospitalization, by month of entry and profit status of the hospice. Non-profit hospices accept more patients from hospitals.

Figure A14 Inpatient Care Before/After Hospice ending in Live Discharge



Notes: This figure shows the distribution of patient hospitalization in the 12 months preceding hospice (first panel), versus the 12 months after a live discharge from hospice. The sample are patients discharged from a hospice during periods where the cap is close to being exceeded (90% probability or above). The last panel conditions on patients living 12 months or more post discharge. Following a live discharge, patients are much less likely to receive care than before hospice. This result should be interpreted with caution, as it may also result from mean-reversion.

Table A1: Predictors of Hospice Use

Dependent Variables:	Admission	Admission Over 180D	Live Discharge	Admission Over 180D or LD
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-4.573*** (0.0037)	-6.697*** (0.0105)	-6.482*** (0.0096)	-6.085*** (0.0078)
Acute Myocardial Infarction	-0.1198*** (0.0205)	-0.2431*** (0.0595)	-0.0849* (0.0493)	-0.1679*** (0.0424)
Atrial Fibrillation	0.2528*** (0.0082)	0.0503** (0.0225)	0.0400* (0.0207)	0.0588*** (0.0169)
ADRD	1.363*** (0.0062)	2.018*** (0.0166)	1.545*** (0.0157)	1.716*** (0.0126)
Cataracts	-0.1888*** (0.0072)	-0.2962*** (0.0203)	-0.2133*** (0.0181)	-0.2429*** (0.0150)
Chronic Kidney Disease	0.2435*** (0.0071)	-0.0048 (0.0193)	0.1108*** (0.0175)	0.0804*** (0.0144)
COPD	0.3519*** (0.0073)	0.2910*** (0.0195)	0.3835*** (0.0176)	0.3571*** (0.0145)
Heart Failure	0.4064*** (0.0072)	0.3510*** (0.0191)	0.4079*** (0.0177)	0.3809*** (0.0145)
Diabetes	-0.0820*** (0.0063)	-0.1707*** (0.0171)	-0.0171 (0.0153)	-0.0878*** (0.0127)
Glaucoma	-0.0582*** (0.0095)	-0.0898*** (0.0261)	-0.1359*** (0.0244)	-0.1211*** (0.0198)
Hip Fracture	0.1711*** (0.0176)	0.2382*** (0.0404)	0.1081*** (0.0414)	0.1592*** (0.0326)
Ischemic Heart Disease	0.1255*** (0.0064)	0.0627*** (0.0169)	0.1047*** (0.0156)	0.0933*** (0.0128)
Depression	0.1168*** (0.0067)	0.2332*** (0.0168)	0.2206*** (0.0159)	0.2195*** (0.0129)
Osteoperosis	0.1648*** (0.0095)	0.2172*** (0.0233)	0.1262*** (0.0228)	0.1762*** (0.0182)
Rheumatoid Arthritis	-0.0445*** (0.0059)	0.0441*** (0.0154)	0.0281** (0.0143)	0.0177 (0.0117)
Stroke / Transient Ischemic Attack	0.1771*** (0.0097)	0.1688*** (0.0243)	0.1797*** (0.0230)	0.1722*** (0.0187)
Breast Cancer	0.3698*** (0.0137)	0.1403*** (0.0389)	0.2405*** (0.0345)	0.2239*** (0.0285)
Colorectal Cancer	0.6668*** (0.0157)	0.3244*** (0.0465)	0.4782*** (0.0396)	0.4649*** (0.0329)
Prostate Cancer	0.4398*** (0.0127)	0.0612 (0.0403)	0.2370*** (0.0338)	0.2045*** (0.0283)
Lung Cancer	1.334*** (0.0143)	0.6879*** (0.0452)	0.8590*** (0.0373)	0.8518*** (0.0314)
Endometrial Cancer	0.6888*** (0.0358)	0.2963*** (0.1091)	0.3834*** (0.0952)	0.3621*** (0.0794)
Anemia	0.4331*** (0.0063)	0.2269*** (0.0170)	0.3098*** (0.0159)	0.2923*** (0.0129)
Asthma	-0.1462*** (0.0118)	-0.1073*** (0.0316)	0.0182 (0.0271)	-0.0333 (0.0228)
Hyperlipidemia	-0.3844*** (0.0060)	-0.4199*** (0.0165)	-0.3911*** (0.0149)	-0.4054*** (0.0123)
Benign Prostatic Hyperplasia	0.0773*** (0.0104)	-0.1098*** (0.0303)	-0.0682** (0.0270)	-0.0593*** (0.0221)
Hypertension	0.0525*** (0.0062)	0.0684*** (0.0164)	0.0792*** (0.0152)	0.0722*** (0.0124)
Acquired Hypothyroidism	0.1363*** (0.0077)	0.2060*** (0.0196)	0.0986*** (0.0189)	0.1593*** (0.0152)
Fit statistics				
Observations	10,622,914	10,622,914	10,622,914	10,622,914
BIC	1,712,029.6	314,815.9	368,023.1	515,485.0
Dependent variable mean	0.01751	0.00230	0.00268	0.00405
Squared Correlation	0.01944	0.00462	0.00326	0.00586
Pseudo R^2	0.08632	0.08884	0.06757	0.08000

Clustered (Patient) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table provides the estimates of a logistic regression to predict hospice use, long hospice stays, or hospice stays ending in live discharge as a function of patient characteristics. Chronic conditions are measured in the year before potential hospice enrollment. This regression is conducted on a 1% sample of patient-years in the Medicare enrollment file from 2000-2019 and clustered at the beneficiary level. ADRD is the strongest predictor of hospice admission, with lung cancer a close second. ADRD is the single greatest predictor of long hospice stays or eventual live discharge.

Table A2: First Stage Estimates

Dependent Variables:	FP Hospice Admission	LOS	Forprofit Hospice	Any Hospice
Model:	(1)	(2)	(3)	(4)
Variables				
Distance to FP Hospice (10mi)	-0.0099***	-0.8545***	-100.4***	-0.0057***
	(0.0004)	(0.0527)	(7.760)	(0.0003)
Distance to NP Hospice (10mi)	0.0096***	0.9734***	106.0***	-0.0003
	(0.0007)	(0.1143)	(14.92)	(0.0005)
Fixed-effects				
Demographics Controls	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	10,856,158	10,856,158	10,856,158	10,856,158
R^2	0.10412	0.03381	0.03498	0.09404
Within R^2	0.00078	0.00012	7.4×10^{-5}	9.39×10^{-5}
Dependent variable mean	0.14677	14.779	2,331.4	0.33009

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports OLS estimates of equation (1). The dependent variables are measures of hospice use, all measured within years 0-5 after ADRD diagnosis: (1) an indicator for whether the patient enrolled in for-profit hospice, (2) number of days in for-profit hospice, and (3) Medicare spending on for-profit hospice. The independent variable is distance to for-profit hospice (scaled to 10 miles). Each regression includes controls for zip code, diagnosis year cohort, patient characteristics (age, sex, race, chronic conditions) in the year before diagnosis, and distance to non-profit hospice. The negative sign indicates that, the further that a for-hospice is from a patient, the less likely they are to use hospice.

Table A3: Distance IV Complier Characteristics

Covariate	Value	Share Among All ADRD	Share Among ADRD FP Compliers	Share Among ADRD FP Goers
Nonprofit Distance	[0,10)	0.609	0.439	0.572
	[10,20)	0.195	0.191	0.203
	[20,30)	0.092	0.106	0.105
	[30,40)	0.038	0.031	0.048
	[40,50]	0.066	0.052	0.073
Nonprofit Distance Over 50mi		0.049	0.025	0.052
Age Group	0-39	0.004	0.001	0.001
	40-64	0.047	0.028	0.028
	65-69	0.074	0.050	0.054
	70-74	0.117	0.089	0.093
	75-79	0.182	0.151	0.164
	80-84	0.230	0.221	0.239
	85+	0.347	0.457	0.421
Sex	Female	0.617	0.619	0.635
End-Stage Renal Disease		0.015	0.017	0.012
Race	Unknown	0.003	0.004	0.002
	White	0.859	0.862	0.874
	Black	0.093	0.085	0.087
	Other	0.009	0.004	0.006
	Asian	0.014	0.002	0.008
	Hispanic	0.019	0.021	0.018
	North American Native	0.004	0.004	0.004
Acute Myocardial Infarction		0.012	0.015	0.012
Atrial Fibrillation		0.121	0.138	0.130
Cataract		0.225	0.209	0.207
Chronic Kidney Disease		0.141	0.159	0.162
COPD		0.149	0.190	0.157
Congestive Heart Failure		0.265	0.335	0.277
Diabetes		0.273	0.284	0.271
Glaucoma		0.114	0.112	0.116
Hip Fracture		0.017	0.021	0.020
Ischemic Heart Disease		0.394	0.434	0.404
Depression		0.167	0.181	0.170
Osteoporosis		0.088	0.085	0.099
Rheumatoid Arthritis		0.314	0.320	0.336
Stroke		0.087	0.097	0.092
Breast Cancer		0.028	0.031	0.031
Colorectal Cancer		0.016	0.024	0.018
Prostate Cancer		0.036	0.039	0.038
Lung Cancer		0.009	0.017	0.012
Endometrial Cancer		0.002	0.003	0.003
Anemia		0.306	0.367	0.321
Asthma		0.041	0.040	0.041
Hyperlipidemia		0.337	0.265	0.344
Hyperparathyroidism		0.060	0.061	0.061
Hypertension		0.592	0.592	0.615
Hypothyroidism		0.101	0.111	0.111

N=10,856,154

Notes: This table presents the characteristics of the for-profit distance instrument compliers, as compared to the entire ADRD population and to the ADRD patients who attend for-profit hospice. For categorical variables such as race, age group and sex, the mean in each bin is presented. For binary variables such as each chronic condition, the fraction of patients with that chronic condition at baseline (year before ADRD diagnosis) is presented.

Table A4: Concurrent Hospice and Hospitalization Discharges

Dependent Variables:	Home - Hospice	Medical Facility	Home	Home - HHA	Home - Home	Died
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Concurrent Hospice	0.2311***	-0.0041***	-0.0249***	-0.1122***	-0.1437***	0.0290***
	(0.0003)	(0.0011)	(0.0011)	(0.0008)	(0.0010)	(0.0005)
Fit statistics						
Observations	45,187,499	45,187,499	45,187,499	45,187,499	45,187,499	45,187,499
R^2	0.01469	3.04×10^{-7}	1.12×10^{-5}	0.00045	0.00046	8.04×10^{-5}
Adjusted R^2	0.01469	2.82×10^{-7}	1.12×10^{-5}	0.00045	0.00046	8.03×10^{-5}
Dependent variable mean	0.01655	0.50311	0.44735	0.14785	0.28289	0.04947

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the correlation between being in hospice at the time of hospitalization discharge and different discharge types among ADRD patients. Each regression is estimated at the hospitalization level, using 100% samples of MedPAR hospitalizations involving a patient diagnosed with ADRD in any year before the visit. In each regression, the independent variable is whether the patient was enrolled in hospice at discharge. Outcome variables reflect how MedPAR codes hospital discharges. The dependent variable is the share of hospitalization discharges that were discharged to hospice (Column 1), to a medical facility (Column 2), home with or without the care of a home health agency (Columns 3, 4, 5), or died in hospital (Column 6).

Table A5: Omega Statistic by Demographic and Chronic Condition Group

Covariate	Value	Conditional Omega
Age Group	0-39	0.404
	40-64	0.664
	65-69	0.400
	70-74	0.573
	75-79	0.561
	80-84	0.617
	85+	0.604
Sex	Female	0.606
End-Stage Renal Disease		0.443
	White	0.538
	Black	0.591
	Hispanic	0.650
	North American Native	0.350
Acute Myocardial Infarction		0.328
Atrial Fibrillation		0.448
Cataract		0.561
Chronic Kidney Disease		0.393
COPD		0.475
Congestive Heart Failure		0.524
Diabetes		0.539
Glaucoma		0.549
Hip Fracture		0.371
Ischemic Heart Disease		0.504
Depression		0.570
Osteoporosis		0.638
Rheumatoid Arthritis		0.483
Stroke		0.585
Breast Cancer		0.568
Colorectal Cancer		0.424
Prostate Cancer		0.427
Lung Cancer		0.314
Endometrial Cancer		0.811
Anemia		0.521
Asthma		0.381
Hyperlipidemia		0.349
Hyperparathyroidism		0.549
Hypertension		0.520
Hypothyroidism		0.489

N=10,856,154

Notes: This table presents the ω statistic, *i.e.* the share of patients in for-profit hospice in for-profit care that come from the no-hospice margin, within different demographic and chronic condition groups among ADRD patients. The conditional ω statistic is computed using the ratio of first stages to produce the ω statistic in the standard way, but only using patients who match the group criteria. Appendix C.2 presents details of this computation.

Table A6: Robustness of IV Estimates for Hospice Effect on Spending and Mortality over [t, t+2] Period

Dependent Variables:	Total		Inpatient	Outpatient	Home Health
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	17,271.5***	-22,119.3***	-7,032.3***	2,697.9***	-3,645.4***
	(75.40)	(3,725.4)	(2,112.0)	(657.7)	(842.0)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	13,153,711	13,153,711	13,153,711	13,153,711	13,153,711
R^2	0.22463	0.19712	0.13578	0.27695	0.09586
Within R^2	0.00677	-0.02846	-0.00729	-0.00905	-0.01815
Dependent variable mean	59,410.8	59,410.8	24,263.6	4,959.4	4,011.6
Wald (1st stage), FP Hospice Admission		1,124.7	1,124.7	1,124.7	1,124.7

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	SNF	Part D	Hospice	Forprofit Hospice	Nonprofit Hospice
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	-11,438.9***	-6,130.6***	6,593.4***	9,455.6***	-2,874.1***
	(1,173.6)	(992.4)	(550.1)	(302.4)	(453.3)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	13,153,711	13,153,711	13,153,711	13,153,711	13,153,711
R^2	0.01468	0.07855	0.13065	0.26293	0.01621
Within R^2	-0.06447	-0.01135	0.10218	0.24113	-0.00870
Dependent variable mean	9,498.0	3,545.7	2,333.2	1,165.9	1,161.9
Wald (1st stage), FP Hospice Admission	1,124.7	1,124.7	1,124.7	1,124.7	1,124.7

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables: Model:	30D Mortality (1)	90D Mortality (2)	1Y Mortality (3)	2Y Mortality (4)
Variables				
FP Hospice Admission	-0.0035	0.0370**	0.0672***	0.0857***
	(0.0114)	(0.0146)	(0.0195)	(0.0222)
Fixed-effects				
Demographics Controls	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,153,711	13,153,711	13,153,711	13,153,711
R^2	0.03080	0.05261	0.10321	0.14537
Within R^2	-7.41×10^{-5}	0.00157	0.00859	0.01880
Dependent variable mean	0.07044	0.12872	0.26290	0.38765
Wald (1st stage), FP Hospice Admission	1,124.7	1,124.7	1,124.7	1,124.7

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table repeats instrumental variables estimates from equations (1) and (2) on mortality and spending outcomes, using a shorter window, [t, t+2] after a patient is diagnosed with ADRD. The results are very similar to the main specification presented in Tables 2 and 3.

Table A7: Robustness of IV Estimates for Hospice Effect on Spending and Mortality Among Non-Movers

Dependent Variables:	Total		Inpatient	Outpatient	Home Health
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	15,770.5***	-24,739.1***	-7,983.4***	3,193.9***	-6,309.7***
	(97.51)	(4,132.4)	(2,076.5)	(737.3)	(987.4)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	8,835,104	8,835,104	8,835,104	8,835,104	8,835,104
R^2	0.20903	0.18088	0.14288	0.21738	0.06821
Within R^2	0.00537	-0.03003	-0.00622	-0.00847	-0.04289
Dependent variable mean	75,542.0	75,542.0	29,730.1	6,112.1	5,200.6
Wald (1st stage), FP Hospice Admission		753.55	753.55	753.55	753.55

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	SNF	Part D	Hospice	Forprofit Hospice	Nonprofit Hospice
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	-9,756.3***	-5,958.2***	6,466.3***	9,434.0***	-2,980.9***
	(1,164.1)	(1,257.6)	(779.1)	(492.9)	(624.6)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	8,835,104	8,835,104	8,835,104	8,835,104	8,835,104
R^2	0.02521	0.10429	0.10297	0.20794	0.02705
Within R^2	-0.05244	-0.01120	0.07160	0.17827	-0.00244
Dependent variable mean	11,479.3	4,902.1	4,141.7	2,093.6	2,037.3
Wald (1st stage), FP Hospice Admission	753.55	753.55	753.55	753.55	753.55

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables: Model:	30D Mortality (1)	90D Mortality (2)	1Y Mortality (3)	2Y Mortality (4)	5Y Mortality (5)
Variables					
FP Hospice Admission	0.0117	0.0418***	0.0749***	0.0745***	0.0712***
	(0.0118)	(0.0150)	(0.0197)	(0.0217)	(0.0199)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	8,835,104	8,835,104	8,835,104	8,835,104	8,835,104
R^2	0.02987	0.04707	0.09153	0.12790	0.17747
Within R^2	-0.00141	-0.00435	-0.00457	-0.00107	0.01420
Dependent variable mean	0.08438	0.15606	0.31852	0.45652	0.71252
Wald (1st stage), FP Hospice Admission	753.55	753.55	753.55	753.55	753.55

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table repeats instrumental variables estimates from equations (1) and (2) on mortality and spending outcomes, on a sample of patients who do not move in years 0-5 after diagnosis with ADRD. The results are very similar to the main specification presented in Tables 2 and 3.

Table A8: Covariate Balance and Instrumental Validity

		Over 25mi (N=3736574)		Under 25mi (N=7119580)			
		Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Year of DX		2006	4.36	2007	4.33	1.18	0.00
Acute Myocardial Infarction		0.01	0.11	0.01	0.11	-0.00	0.00
Atrial Fibrillation		0.12	0.32	0.12	0.33	0.00	0.00
Cataracts		0.24	0.42	0.22	0.41	-0.02	0.00
Chronic Kidney Disease		0.12	0.33	0.15	0.36	0.03	0.00
COPD		0.15	0.36	0.15	0.36	-0.00	0.00
Heart Failure		0.26	0.44	0.27	0.44	0.01	0.00
Diabetes		0.26	0.44	0.28	0.45	0.03	0.00
Glaucoma		0.11	0.31	0.12	0.32	0.01	0.00
Hip Fracture		0.02	0.13	0.02	0.13	-0.00	0.00
Ischemic Heart Disease		0.38	0.48	0.40	0.49	0.03	0.00
Depression		0.16	0.37	0.17	0.37	0.01	0.00
Osteoperosis		0.08	0.28	0.09	0.29	0.01	0.00
Rheumatoid Arthritis		0.30	0.46	0.32	0.47	0.03	0.00
Stroke / Transient Ischemic Attack		0.09	0.28	0.09	0.28	0.00	0.00
Breast Cancer		0.03	0.16	0.03	0.17	0.00	0.00
Colorectal Cancer		0.02	0.12	0.02	0.13	0.00	0.00
Prostate Cancer		0.04	0.19	0.04	0.19	0.00	0.00
Lung Cancer		0.01	0.09	0.01	0.10	0.00	0.00
Endometrial Cancer		0.00	0.05	0.00	0.05	0.00	0.00
Anemia		0.28	0.45	0.32	0.47	0.04	0.00
Asthma		0.04	0.19	0.04	0.21	0.01	0.00
Hyperlipidemia		0.30	0.46	0.35	0.48	0.05	0.00
Benign Prostatic Hyperplasia		0.06	0.23	0.06	0.24	0.01	0.00
Hypertension		0.56	0.50	0.61	0.49	0.04	0.00
Acquired Hypothyroidism		0.10	0.30	0.10	0.30	-0.00	0.00
		N	Pct.	N	Pct.		
Sex	Female	2,282,354	61.1	4,413,973	62.0		
	Male	1,454,220	38.9	2,705,607	38.0		
Age at DX	¡65	168,203	4.5	335,584	4.7		
	65-74	619,140	16.6	1,197,570	16.8		
	75-84	1,486,382	39.8	2,779,959	39.0		
	85-94	1,278,821	34.2	2,458,220	34.5		
	95+	184,028	4.9	348,247	4.9		
Race	Black	236,713	6.3	772,101	10.8		
	Hispanic	44,639	1.2	158,496	2.2		
	Other	79,308	2.1	237,189	3.3		
	White	3,375,914	90.3	5,951,794	83.6		
ESRD	ESRD	43,182	1.2	119,005	1.7		
	Not ESRD	3,693,392	98.8	7,000,575	98.3		

N = 10856154

Notes: This table tests instrumental validity using covariate values from the analytical sample, i.e., Medicare recipients diagnosed with ADRD between 2000 and 2014 who had not been to hospice before their diagnosis. The first two columns refer to Medicare recipients who, at the year before their diagnosis, were over 25 miles from the nearest for-profit hospice. The third and fourth column refer to Medicare recipients who, at the year before their diagnosis, were under 25 miles from the nearest for-profit hospice. The final two columns present differences in these two samples.

Table A9: IV Validity Tests

Dependent Variable:	Forprofit Distance			
Model:	(1)	(2)	(3)	(4)
Variables				
Share ADRD (Percent)	0.0214***			
	(0.0011)			
Share in Top Spending Quintile (Percent)		-0.0049***		
		(0.0006)		
Share in Bottom Spending Quintile (Percent)			0.0077***	
			(0.0007)	
Number ADRD				-0.0082***
				(0.0005)
Fixed-effects				
Zip Code	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	838,973	799,842	799,842	954,912
R^2	0.84808	0.84250	0.84253	0.85944
Within R^2	0.01861	0.01825	0.01840	0.02171
Dependent variable mean	30.837	30.045	30.045	32.444
NP Distance Control	Yes	Yes	Yes	Yes
Clustered (Zip Code) standard-errors in parentheses				
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*				

Notes: This table presents IV specification tests, regressing distance to a for-profit on ADRD patient shares, and shares by national quintile of spending. These regressions control for zip code and year fixed effects.

Table A10: IV Estimates for Hospice Effect on Spending and Mortality in Cancer Sample

Dependent Variables:	Total		Inpatient	Outpatient	Home Health
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	16,469.9***	-24,829.0***	-5,777.8***	4,312.9**	-2,359.4***
	(140.4)	(4,569.6)	(2,237.8)	(1,840.9)	(537.5)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	6,954,099	6,954,099	6,954,099	6,954,099	6,954,099
R^2	0.14518	0.12435	0.09481	0.13682	0.07836
Within R^2	0.00386	-0.02042	-0.00449	-0.00275	-0.01235
Dependent variable mean	73,811.0	73,811.0	27,686.4	10,269.8	2,816.0
Wald (1st stage), FP Hospice Admission		990.44	990.44	990.44	990.44

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	SNF	Part D	Hospice	Forprofit Hospice	Nonprofit Hospice
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	-6,772.4***	-10,421.5***	3,146.0***	7,415.6***	-4,223.8***
	(756.7)	(1,449.1)	(585.0)	(333.3)	(471.1)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	6,954,099	6,954,099	6,954,099	6,954,099	6,954,099
R^2	0.05250	0.04702	0.07745	0.20661	0.01471
Within R^2	-0.04106	-0.01988	0.04167	0.17911	-0.01680
Dependent variable mean	4,671.3	4,181.4	2,490.8	958.16	1,527.0
Wald (1st stage), FP Hospice Admission	990.44	990.44	990.44	990.44	990.44

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables: Model:	30D Mortality (1)	90D Mortality (2)	1Y Mortality (3)	2Y Mortality (4)	5Y Mortality (5)
Variables					
FP Hospice Admission	-0.0023	0.0534***	0.0472**	0.0654**	0.0863***
	(0.0139)	(0.0185)	(0.0240)	(0.0262)	(0.0271)
Fixed-effects					
Demographics Controls	Yes	Yes	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes	Yes	Yes
Zip	Yes	Yes	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	6,954,099	6,954,099	6,954,099	6,954,099	6,954,099
R^2	0.03995	0.05818	0.09560	0.12666	0.18782
Within R^2	1.15×10^{-5}	0.00064	0.00504	0.00988	0.02234
Dependent variable mean	0.07204	0.13323	0.25893	0.34930	0.50647
Wald (1st stage), FP Hospice Admission	990.44	990.44	990.44	990.44	990.44

Clustered (Zip) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents spending and mortality estimates using the instrumental variables design described in equations (1) and (2) on patients with any form of cancer. Like Tables (2) and (3), we measure spending by category, and mortality over different periods, within 5 years of diagnosis. Hospice use is instrumented with distance to for-profit hospice, including zip-code and diagnosis cohort fixed effects.

Table A11: Predictability of Patient Longevity

Dependent Variables:	Days to Death	Died Over 180D
Model:	(1)	(2)
Fixed-effects		
Demographics Controls	Yes	Yes
Chronic Conditions Controls	Yes	Yes
Year of Hospice Enrollment	Yes	Yes
Fit statistics		
Observations	7,567,838	7,579,866
R^2	0.02189	0.02801
Dependent variable mean	148.81	0.16860

Notes: This table regresses a patient's days to death, or an indicator for living beyond 6 months, using information available to hospices at the time of hospice entry. Chronic conditions and demographics are gathered from patients in the year before hospice admission. The low R^2 value using demographics and chronic conditions highlights the uncertainty hospices face in estimating patient stay length.

Table A12: Descriptive Statistics on Hospice Anti-Fraud Lawsuits

	Value
Court Outcomes	
Dismissed	56%
Pending	7%
Settled	37%
Settlements	
Mean	$5.9 Mil
Median	$2.8 Mil
Total	$351 Mil
Top Judicial Districts (by Case Count)	
Missouri-West	14
Alabama-North	12
Georgia-North	11
Ohio-South	10
Florida-Middle	8
Top Judicial Districts (by Settlements)	
Missouri-West	$81 Mil
Wisconsin-East	$38 Mil
Alabama-North	$30 Mil
Texas-North	$18 Mil
Colorado	$18 Mil
Date Received (Year)	
Min	1998
Median	2013
Max	2021
Time from Date Received to Date Settled (Days)	
Min	28
25th Percentile	647
Median	1152
75th Percentile	1788
Max	3879

Notes: This table presents descriptive statistics from 163 federal False Claims Act anti-fraud lawsuits against hospice companies, using data from a Freedom of Information Act request we filed with the Department of Justice.

Table A13: Impact of Anti-Fraud Lawsuits

A13.A: Effects on Hospice Patient Composition

Dependent Variables:	Share Days ADRD	LOS (Days)	Share LOS $\geq$ 180D	Share Live Discharged
Model:	(1)	(2)	(3)	(4)
Variables				
Firm Sued	-0.0119***	-6.477***	-0.0130***	-0.0148***
	(0.0038)	(1.110)	(0.0021)	(0.0030)
Fixed-effects				
Provider	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	75,068	66,637	66,637	66,637
R^2	0.51056	0.55147	0.52956	0.72040
Within R^2	0.00025	0.00150	0.00127	0.00100
Dependent variable mean	0.40730	83.727	0.13476	0.21491

Clustered (Provider) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A13.B: Effects by Pre-Hospice Spending Quintile

Dependent Variables:	Share Days ADRD	Qntl 1	Qntl 2	Qntl 3	Qntl 4	Qntl 5
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Firm Sued	-0.0119***	-0.0037**	-0.0037**	0.0027	-0.0032*	-0.0041**
	(0.0038)	(0.0018)	(0.0017)	(0.0018)	(0.0017)	(0.0016)
Fixed-effects						
Provider	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	75,068	75,068	75,068	75,068	75,068	75,068
R^2	0.51056	0.24904	0.26489	0.26365	0.27343	0.28230
Within R^2	0.00025	8.65×10^{-5}	8.6×10^{-5}	4.49×10^{-5}	5.63×10^{-5}	9.95×10^{-5}
Dependent variable mean	0.40730	0.08646	0.08345	0.08501	0.08296	0.06942

Clustered (Provider) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents results from regressions each estimated using a difference-in-difference specification that estimates firm-level responses to being sued. The regression is estimated at the hospice-year level. Panel A estimates dependent variables regarding firm composition: the share of days from patients with an ADRD diagnosis (Column 1), average length of stay for admissions (Column 2), the share of stays with a length of stay over 180 days (Column 3), and the share of stays that ended with a live discharge (Column 4). Days by patients with ADRD diagnosis are computed year-by-year for patients spanning the calendar year. Figure 3 and Appendix Figure A8 present event study figures of the same outcomes. Panel B assesses heterogeneous effects across the spending distribution. The dependent variables are the share of patient days among patients with an ADRD diagnosis (Column 1), broken out by quintiles of pre-hospice spending among ADRD hospice patients.

Table A14: Physician Specialty of ADRD Hospice Patient Referrer

	Referring Specialty	Nonprofit	For-Profit
1	Internal Medicine	41.54	43.22
2	Family Practice	39.46	40.56
3	Hospice and Palliative Care	3.75	1.27
4	General Practice	2.29	4.09
5	Hematology/Oncology	1.93	0.74
6	Emergency Medicine	1.17	1.08
7	Hospitalist	1.03	1.54

Notes: This table lists the specialties of physicians who referred ADRD patients to hospice, by the profit status of the hospice the patient attended, from 2015-2019.

Table A15: Specialist Usage Among Live Discharged Patients

	12 months before hospice	12 months after live discharge		12 months after live discharge (12 month survival)	
	Average per-patient visits	Average per-patient visits	Percent Change	Average per-patient visits	Percent Change
Internal Medicine	0.800	0.469	-41.4%	0.651	-18.6%
Family Practice	0.546	0.361	-33.9%	0.457	-16.3%
Emergency Medicine	0.537	0.352	-34.5%	0.428	-20.3%
Cardiology	0.118	0.053	-55.1%	0.062	-47.5%
General Surgery	0.093	0.048	-48.4%	0.073	-21.5%
General Practice	0.074	0.049	-33.8%	0.060	-18.9%
Nurse Practitioner	0.071	0.053	-25.4%	0.110	54.9%
Hematology/Oncology	0.070	0.019	-72.9%	0.023	-67.1%
Neurology	0.055	0.021	-61.8%	0.035	-36.4%
Urology	0.049	0.020	-59.2%	0.031	-36.7%
Gastroenterology	0.048	0.018	-62.5%	0.016	-66.7%
Orthopedic Surgery	0.041	0.023	-43.9%	0.026	-36.6%
Physician Assistant	0.022	0.008	-63.6%	0.009	-59.1%
Ophthalmology	0.019	0.012	-36.8%	0.013	-31.6%
Obstetrics/Gynecology	0.016	0.005	-68.8%	0.005	-68.8%

Notes: This table shows the rate of outpatient specialist visits among patients following live discharges from hospice, comparing the 12 months before hospice admission to the 12 months after. The sample includes patients discharged from a hospice during periods where the cap is close to being exceeded (90% probability or above). Specialties listed are the top 15 among outpatient visits in the sample.