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

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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 cost-saving admissions.

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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). Policymakers have responded by authorizing payment for alternatives to traditional physician and inpatient care, such as hospice care. First introduced in 1983, the hospice benefit 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. The hope was that hospice care would improve the experience of dying while reducing Medicare spending (Davis, 1988). Since its inception, hospice use has grown enormously, accounting for more than $20 billion in federal spending by 2019, amounting to $13,000 per enrollee or $500 per Medicare beneficiary in the U.S.

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, eligibility standards are open to interpretation: hospices are required to certify that their patients have a life expectancy of less than 6 months to be eligible, but predicting life expectancy is challenging. The greatest end-of-life costs are incurred by patients who die unexpectedly; Einav *et al.* (2018) show that just 5% of end-of-life spending comes from individuals with a greater than 50% predicted mortality.

Hospice care, like most Medicare services, is provided by private providers who are reimbursed by Medicare. These private firms face a financial incentive to disregard Medicare's hospice eligibility rules and admit patients who are not within 6 months of death. Hospices' costs of providing care are highest in the period immediately following admission and the period immediately preceding death and lower in the intervening period (Huskamp, Newhouse, Norcini, & Keating, 2008; MedPAC, 2006). Yet, hospices are paid a fixed daily rate; consequently, patients with longer lengths of stay are more profitable than short-stay patients. Moreover, physicians employed by hospices themselves are often the judges of whether patients meet the uncertain eligibility standard.

The rapid growth of the for-profit sector in hospice care has potentially exacerbated the mismatch between hospice's financial incentives and Medicare's eligibility guidelines. From

2000 to 2019, the number of for-profit hospice firms quintupled while the number of non-profit firms was roughly unchanged. Concurrent with this growth has been an enormous expansion of Medicare spending on the hospice program, which increased from roughly $2.5 billion in 1999 to over $20 billion in 2019 (MedPAC, 2004) (MedPAC, 2021). Recent press coverage has highlighted pernicious behavior by for-profit hospices, such as actively seeking to enroll non-terminally ill beneficiaries (Kofman, 2022). 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. Yet, 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.[1]

Accusations of unnecessary admissions have often focused on patients with Alzheimer's Disease and Related Dementias (ADRD), who tend to have long hospice lengths-of-stay and a particularly uncertain prognosis. For example, the hospice firm Evercare paid $18 million to settle allegations that it admitted ineligible patients. Whistleblowers alleged that the firm sought out patients with Alzheimer's disease and dementia because "once certified as 'terminally ill', [d]efendants would be able to keep these types of patients on census for lengthy periods of time."[2] The entry of for-profit hospices over the past several decades has coincided with a large increase in the number of patients admitted with a diagnosis of ADRD. In 1999, about 4.4% of ADRD patient-years included a hospice stay. By 2019, that number had risen to nearly 14.7%. ADRD patients now make up 38% of hospice episodes and account for roughly half of all hospice episodes that last more than six months.

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[1] See: United States vs Aseracare, Inc. The Eleventh Circuit Court affirmed a judgement by the Northern District of Alabama that: "contradiction based on clinical judgment or opinion alone cannot constitute falsity under the FCA as a matter of law." Moreover, they wrote "a clinical judgment of terminal illness warranting hospice benefits under Medicare cannot be deemed false, for purposes of the False Claims Act, when there is only a reasonable disagreement between medical experts as to the accuracy of that conclusion, with no other evidence to prove the falsity of the assessment." For legal analysis, see (Hogan Lovells FCA Alert, 2019).

[2] See: United States ex rel. Fowler v. Evercare Hospice, Inc., case 11-cv-000642, District of Colorado. Quote is from the whistleblower, as relayed by Judge Phillip A. Brimmer in a motion dated September 21, 2015. Available online at: https://www.casemine.com/judgement/us/5914ad9cadd7b04934743575

In this paper, we study the effects of for-profit hospice usage on Medicare spending in the ADRD population and evaluate the impact of policies designed to curtail overuse of the hospice benefit. Besides their inherent interest as the population for which hospice care is most controversial, a focus on ADRD patients offers an empirical advantage as well: they form a cohort that has both a non-negligible risk of hospice entry and particularly questionable hospice eligibility. Moreover, by focusing on a group with a particular date of diagnosis, we are able to select a clear exposure period, years 0-5 after diagnosis. This cohort design mitigates econometric issues that could arise from differential lengths of time in the data for treated and untreated patients.

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 variation in a standard distance-based instrument with locality fixed effects to identify the effects of for-profit hospice care using changes in for-profit hospice access among people living in the same zip code but diagnosed at different times.

We find striking evidence that, despite concerns about fraudulent behavior, for-profit hospice for the marginal ADRD patient saves money, mostly due to large reductions in the use of skilled nursing facilities 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 5 years post diagnosis. Our results suggest that, on the margin, expanding hospice eligibility would reduce Medicare costs, even if it meant bringing in patients who might live longer than 6 months. These results may underestimate the cost savings of hospice care, as we only estimate savings to the Medicare program and do not include savings to the Medicaid and Social Security programs. We also find that the marginal for-hospice patient with ADRD is about 9 percent more likely to die in five years if she enrolls in for-profit hospice. The welfare implications of mortality increases are unclear, however, given that hospice patients agree to forgo life-saving care.

The entry of for-profit hospice causes changes to care among 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.

The government recognizes concerns about overuse of hospice care and has implemented a number of tools to address it. Two of most significant are an aggregate revenue cap and antifraud litigation. The finding that for-profit hospice exposure saves money for ADRD patients suggests that a careful evaluation of such policies is warranted. We therefore provide new evidence on the impact of these policies on patient costs and outcomes.

The aggregate cap on hospice revenues is used to limit long stays. The cap equals a fixed dollar amount multiplied by the number of patients admitted in a given fiscal year, computed for each hospice. Hospices must refund any revenues in excess of this amount, thereby counteracting hospices' incentives to admit long-stay patients. Hospices face a cliff in their revenue if patients stay too long, but the cap binds *in aggregate* for the firm, not at the patient level. 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. The cap also lowers patient-level spending, but only by roughly $2,300 over 12 months.

Second, the government seeks penalties from hospices suspected of over-admitting patients under the False Claims Act, a federal anti-fraud statute. 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 litigated 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 the patients for whom hospice is unlikely to be cost-saving. Because marginal patients save money by going to hospice, federal litigation actually discourages hospices from admitting cost-saving patients. Hospice use is an unusual case where federal anti-fraud initiatives increase costs because the marginal admittee saves money.

Despite the widespread use of the hospice benefit and the open question of its effectiveness, there is relatively little work on the topic. Prior studies of the effects of hospice care restrict attention to samples of decedents, thereby excluding the marginal or (potentially) fraudulently admitted patient (Kelley, Deb, Du, Aldrige Carlson, & Morrison, 2013). Some decedent studies compare hospice patients to non-hospice-goers, failing to address selection on unobservables (Aldridge, Moreno, & McKendrick, 2022). Patients admitted to hospice may be more or less healthy than those who are not, particularly in light of allegations of fraudulent or inappropriate admissions decisions by for profit firms. Section 2.2 reviews the literature specific to hospice care.

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 and measuring a rise in fraudulent overprovision of care by profit-maximizing firms. Leder-Luis (2019) reports that hospice is one of the large categories 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. In the context of for-profit care, 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 discusses the tradeoff between increased productive efficiency versus reductions in the quality of care.

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 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. Section 7 discusses our overall results, and Section 8 concludes.

2. Background: The Medicare Hospice Program

2.1 Hospice Program Overview

Terminally ill 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, they cannot receive 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. Hospice is generally provided at patients' place of residence, either their home or a long-term care facility.

There are multiple levels of hospice care, each of which is reimbursed at a different rate. In practice, 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, and since 2015, days beyond day 61 are paid at about $150. Payment is not adjusted for patient diagnosis. Hospices also have the ability to 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 the patient needs the greatest care (Huskamp, Newhouse, Norcini, & Keating, 2008). Hospices 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 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 admitting patients who were not terminal or 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, who were 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 on the value of the application of the False Claims Act to hospices' admission decisions.

2.2 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, as well as to identify 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 early 1980s National Hospice Study sought to evaluate 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 K. L., Cenzer, Ankuda, Hunt, & Aldridge, 2022; Kelley, Deb, Du, Aldrige Carlson, & Morrison, 2013; Leibowitz, Tan, & Gildner, 2020; Taylor Jr, Ostermann, Van Houtven, Tulsky, & Steinhauser, 2007). 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 & Neuman, 2015).

These studies suffer from two key empirical limitations. First, 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, they 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 & Neuman (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. They find 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., the types of patients for whom use of hospice is affected by antifraud enforcement and related policies because of their uncertain eligibility.

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. 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).

Seeking to reduce incentives to admit long-stay patients, in 2014 Congress enacted the Improving Medicare Post-Acute Care Transformation (IMPACT) Act which, among other provisions, subjected hospices with a high proportion of stays over 180 days to audits. In 2016, CMS increased the routine home care per diem payment for the first 60 days and last 7 days (for decedents) of an episode and lowered the payment for the intervening period. A time-series study (Gianattasio, Ali, Lupu, Prather, & Power, 2022) found that, after 2014, the proportion of patients admitted with an ADRD diagnosis initially declined but then increased, suggesting that hospices may have initially overestimated the stringency or intensity of audits. The shift away from uniform per diem payments had only a small effect on admission patterns.

As a result of the cap on their payments, discussed further 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.

3. Data and Descriptive Statistics

3.1 Data

We use 100% samples of Medicare Fee-for-Service claims data from 1999 through 2019,[3] including hospice claims, beneficiary enrollment files, chronic conditions indicators, hospitalization claims, and cost and use files. These data provide a wealth of information for a virtual census of those aged 65 and older, as well as younger disabled individuals who qualify. The hospice claims data allow us to identify patient-level hospice usage, 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 Alzheimer's Disease and Related Dementias (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 better understand the nature of hospice litigation, we use data from the Department of Justice on fraud cases. We conducted a Freedom of Information Act (FOIA) request to identify all hospices subject to False Claims Act litigation. The Department of Justice 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 (PACER) system. We further 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

[3] As is standard in the health economics literature, we cannot observe patients who enroll in Medicare Advantage (Part C).

supplement our understanding through numerous interviews with Department of Justice attorneys who litigated hospice fraud cases.

3.2 Descriptive Statistics on Hospice Use

We begin by documenting trends in the hospice industry that highlight concerns about overuse. Panel A 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. Panel B 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.

As for-profit hospices have proliferated, the share of hospice patients that die within 6 months of admission has fallen. The share of hospice episodes for which the patients died within six months declined from 86.4% in 2000 to 79.2% in 2018, driven by trends in for-profit care; in fact, only 73.4% of 2018 for-profit hospice patients died within 6 months. While it is to be expected that some patients do not die within 6 months because death is hard to predict, it is unclear why life expectancy should be getting harder to predict over time. This is consistent with allegations that for-profit hospices are not rigorously restricting admission to patients expected to live less than six months.

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

4.1 Empirical Design

The goal of our empirical analysis is to understand the effect of for-profit hospice usage on patient spending and health outcomes. Because the patients that attend hospice may be selected along unobservable characteristics, we cannot compare those who attend to those who do not. Previous studies of hospice have started with the cohort of patients who died, and then matched hospice and non-hospice patients based on observable characteristics to estimate the effect of hospice usage (Aldridge, Moreno, & McKendrick, 2022). However, because death is only one potential outcome of hospice – particularly when the patient may be marginally eligible and not acutely terminally ill – a sample of decedents is heavily selected on outcomes.

Our strategy for estimating the effects of for-profit hospice relies on variation in patients' exposure to for-profit hospices based on where they live and the timing of their diagnosis among the sample of patients ever diagnosed with Alzheimer's Disease and Related Dementias (ADRD). We used the chronic conditions warehouse 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 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.[4]

Hospice use may change the length of time a patient spends in our sample (for example, if hospice use impacts death), impeding a cross-sectional analysis strategy. Therefore, we construct a cohort-based study where, for each patient, we consider the patient's health and spending outcomes in a fixed window of time following ADRD diagnosis (providing another advantage for our ADRD focus). The choice of a time window has trade-offs: using a longer window allows us to examine longer-term outcomes, but longer windows also force us to restrict our sample to patients for whom we have more years of data. Because there is no clear correct answer for the window to use, 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 leads to a sample of patients 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

[4] 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.

patients are female and 86% are white. The patient population is relatively sickly: 59% have hypertension and 27% have diabetes at baseline. Sixty-seven 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, 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.

Importantly, 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. That is, 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 general trends in both hospice entry and patient outcomes, and distance to a non-profit hospice. Appendix A presents more details about the distance calculations. To address potential concerns about the endogeneity of for-profit hospice entry with respect to trends in patient characteristics within markets, we 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:

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

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 nonprofit hospice; and X_{icz} is a matrix 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 control for distance to a non-profit hospice, to allow for consistency of our main results with our decomposition of the overall effect into its different margins below, following the design of (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:

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

where Y_i is spending on different categories of care or indicators for death.

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, only affects outcomes like spending and mortality through enrollment in for-profit hospice. In Section 4.3 below, we further explore substitution between nonprofit and for-profit hospice as a function of entry by for-profit hospices. Section 4.4 presents robustness estimates to alternative specifications as well as tests of our assumptions.

4.2 Results

Table 2 presents the first-stage estimates of the coefficient β from Equation (1). Distance is scaled so that 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 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 ever-ADRD population of 10.8 million individuals and are very precise, with $p < 0.01$ for each estimate and an F-statistic of 707 for the extensive margin model.

Figure 2 presents results from an analysis that treats the first stage as an event study (see Appendix B for details). Here, we consider zip codes that are treated discretely, which go from having no for-profit hospice within 50 miles to having a for-profit hospice within 10 miles. We plot the coefficients of first-stage extensive margin for-profit hospice usage among ADRD patients by year relative to hospice entry. There is no evidence of pre-trends, and the entry of a for-profit hospice is associated with about a 2 percentage point increase in for-profit hospice usage in subsequent years. This is similar, if somewhat smaller, than our main first stage estimate in Table 2 of a 1 percentage point increase in hospice use per 10 miles closer distance to for-profit hospice. Importantly, the first stage estimates we use in our two stage least squares design exploit the full range of changes in distance to a for-profit hospice at a zip code level, while this figure restricts attention to large discrete changes. We discuss robustness of this result to alternative specifications in Section 4.4 below.

Table 3 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 suggest that use of for-profit hospice increases spending, but these are biased positively by the sicker population that enrolls in hospice.

The two-stage-least-squares estimates in Table 3 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. Next, we decompose these cost savings by spending on different categories of care.

For-profit hospice exposure increases spending on for-profit hospices by about $10,200. At the same time, there is a shift away from spending on non-profit hospices of about $2,800. The net effect is a $7,400 increase in total hospice spending. That is, 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 4.3 below, where we examine multiple treatment margins including substitution away from non-profit hospice.

Although hospice use increases hospice spending, it substantially decreases spending on two other expensive forms of care: skilled nursing and home health care. Among compliers, for-profit hospice enrollment causes a reduction in skilled nursing care spending of about $12,600 from a baseline mean of $12,700; similarly, enrollment reduces home health expenditures by about $7,000 from a population mean of about $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 care causes a substitution away from inpatient treatment and toward outpatient treatment. We estimate that enrollment reduces 5-year spending on inpatient care by $8,700 from a base 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 conductions 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 skilled nursing and home health care, we conduct a supplementary analysis to examine the discharge destination of ADRD patients following hospitalization. Both skilled nursing care and home care are used to provide post-acute care 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 skilled nursing or home health or discharged home without care, versus discharged into hospice care or died in the hospital. Appendix Table A2 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 and are 0.4 percentage points less likely to be transferred to another medical facility from a baseline mean of 50%. 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 earlier finding that for-profit hospice reduces the use of skilled nursing 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. The result also shows that even hospice patients use inpatient care to some degree at the end of life.

Table 4 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 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 0.01% level, and the first-stage F-statistic is 707.

4.3 Decomposing Treatment Margins

For-profit hospice entry has two distinct margins along which it affects patients: patients can be "diverted" into for-profit hospice instead of eventually enrolling in non-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.

Estimation of the parameters of interest can be accomplished using an instrumental variables design that exploits a second instrument, distance to a non-profit hospice. Although the number of non-profit hospices has not changed much over our study period, there has been sufficient entry and exit to identify our model: 57% of zip codes experience a change in non-profit distance over our sample period. Mountjoy (2022) provides a tractable framework for estimating these parameters. In particular, 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 only increase the probability of going to any hospice by 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 prescribed 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 states in our circumstance that the marginal patient deterred from non-profit hospice by a marginally higher non-profit distance, or induced to for-profit hospice by a marginally lower distance, are alike in the limit. Appendix A.2 gives the estimating equations used for this exercise.

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 use no hospice, and 42% of patients are diverted from non-profit hospices. We find reductions in spending for both groups. Patients induced to hospice who would otherwise not attend hospice save about $44,000, while patients induced from nonprofit hospice save about $8,000. For patients induced from a no-hospice alternative, we can reject 0 savings at a *p = 0.05* level using bootstrap estimates. For patients diverted from non-profit hospice, the point estimate of savings is negative, but we cannot reject 0 savings using the bootstrapped confidence interval. This is reasonable, as for-profit and non-profit hospice provide largely similar services.

Much like the savings effects, we find that 5-year mortality effects are concentrated among patients induced into hospice from a no-hospice alternative, with a 15% increase in 5-year mortality. Patients induced from non-profit hospice have estimates on 5-year mortality near 0. The lack of 5-year mortality effects along this margin indicates that for-profit hospice does not increase overall 5-year death rates as compared to non-profit hospice. This is sensible, as patients who would otherwise attend non-profit hospice would also forgo curative care.

Table 5 explores two further potential avenues for changes in care due to for-profit hospice: changes in 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 nonprofit hospice. In fact, we find that the overall treatment effect of for-profit hospice is a 5 month reduction in survival over 5 years, which is a combination of a 7 month reduction in months alive for patients induced from no hospice and a 2 month reduction among patients diverted from non-profit hospice, although we cannot rule out a 0 effect for the latter population.

Our results show an interesting new application of the multiple treatment effects margin literature. Although the direct of spending effects is similar, for-profit hospice has a much larger effect on the spending of patients who would otherwise receive no hospice care compared to patients who would otherwise receive treatment in non-profit hospices. In Section 4.5 below, we discuss how these estimates can be used for discussions about welfare concerns.

4.4 Robustness

In this section, we demonstrate the robustness of our main effect estimates to different specifications. Appendix Figure A2 repeats the first stage event study analysis of Figure 2, taking into account recent critiques of two-way fixed effects estimators. We implement Sun and Abraham's (2021) two-way-fixed effect corrected estimator. Our results are robust to this alternative estimator and show the same increases in for-profit hospice usage at the time of hospice entry.

We selected the window [t, t+5] 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 A3 presents parallel estimates using the window [t,t+2] 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 A4 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 A5 shows the covariate balance across patients above and below the median distance. 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. They also spend more money on healthcare on average (while our IV estimates suggest that hospice reduces spending on the margin).

Our method also extends to patients beyond the ADRD pool, which provide both an opportunity to evaluate the effects of for-profit hospice among other patients, as well as to ensure our method gives reasonable results in other contexts. Appendix Table A6 repeats the distance-based analysis on the sample of patients with cancer diagnoses (as indicated by any cancer flag in the Chronic Conditions File). Cancer is highly predictive of hospice: as shown in Table A1, the next three chronic conditions that are the strongest predictors of hospice use, after ADRD, are lung cancer (a close second to ADRD), endometrial cancer, and colorectal cancer. We repeat the same cohort-based design and follow patients for 5 years. The exposure of cancer patients to for-profit hospice increases for-profit hospice usage in the first stage, reduces five-year spending, and increases mortality. Five-year spending decreases by $24,800 among compliers, while five-year mortality rises by 9 percentage points. A big portion of these savings are due to a reduction in spending on pharmaceuticals. These results indicate that the cost of for-profit hospice extend beyond the ADRD population, although the eligibility of cancer patients is less questionable and therefore not our main focus.

4.5 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. Our results suggest that enrollment in for-profit hospice on the margin significantly reduces Medicare costs.

At the same time, we find that hospice expansion is associated with increased mortality, particularly among patients whose outside option is no hospice. Among those patients we find a 15 percentage point increase in 5-year mortality and a 7 month reduction in survival.

The fact that for-profit hospice saves federal money while reducing longevity poses ethical questions, the full extent of which are beyond the scope of this paper. For patients induced into for-profit hospice from non-profit hospice, we estimate roughly 0 mortality effects. However, among patients induced from no hospice, electing hospice means increasing their probability of death substantially.

These moral concerns are somewhat offset by the fact that hospice is optional. When patients enter hospice, they or their caregivers must sign a form indicating they understand that they will receive palliative care and not curative care. If effect, they are agreeing to accept a higher risk of death by forgoing curative care in return for gaining access to hospice care, which can improve quality of life. It is not obvious that increased mortality due to hospice enrollment among patients whose alternative is no hospice care reduces patient welfare.

On the other hand, 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.

While there is no comprehensive data on the share of hospice enrollees who do not understand the implications of enrollment, we can consider a very simple bounds analysis. Over the window between diagnosis and 5 years later, the average marginal for-profit hospice enrollee who would otherwise attend no hospice saves $44,082 and is 15% more likely to die. On average, compliers lose roughly 7.2 months (0.6 years) in this window, as shown by Table 5. If we are willing to consider death as a welfare cost only for those patients who enrolled unknowingly, 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 A3 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 A3, 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 that hospice increases the risk of death – despite signing paperwork agreeing to forgo curative care – for this regime to be inefficient. Moreover, if the value of the lost 0.6 life-years was worth less than $44,082 – a reasonable estimate given the low quality of life for end-of-life ADRD patients – this tradeoff is efficient even if we consider death a cost for all patients regardless of if they made an informed decision.

This discussion is somewhat more complicated for patients induced into for-profit hospice from non-profit hospice. These patients lose an estimated 2 months of life but save Medicare about $8,000, although the confidence intervals do not rule out either 0 savings or 0 mortality effects. Taking the point estimates, these patients face roughly the same dollar-longevity tradeoff among patients induced into for-profit hospice from no hospice. However, patients may not understand that the profit status of their hospice affects longevity, so the welfare impacts are much less clear.

There are reasons to believe the welfare gains from ADRD enrollment in hospice are even higher than those reported here. First, many patients (and their family members) report high satisfaction with hospice, and therefore it could improve quality of life even if total life expectancy falls. Indeed, this is one of the primary motivations for hospice. Second, the cost savings as measured in this paper are the cost savings from the Medicare program only. Most of the ADRD patients in our sample collect Social Security, and many live in Medicaid-funded long-term care facilities. The estimates of cost savings presented here do not include savings by these other social programs.

Our analysis of the implications of higher death rates is rudimentary and is not the primary focus of our analysis, which is instead focused on costs. We offer these calculations and arguments to illustrate that a strong case must be made that decisions about hospice enrollment are suboptimal for the cost savings of the program not to exceed potential costs to the uninformed.

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.

5. The Hospice Cap

One longstanding policy designed to limit the overuse of hospice is a cap on hospices' revenues based on the number of patients they serve. 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: if a hospice received payments from Medicare that exceeded this amount, it would have to refund the entire difference to Medicare. Payments to hospices are measured over the cap year, which runs from November 1 to October 31 the following year. Appendix C presents more 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 data.

For each hospice-year, we calculate the ratio of received revenues to the hospice's cap (the per patient cap multiplied by the number of patients admitted). Figure 3 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%). The proportion of hospices that exceed that cap at least once during the twenty year period we study is 50% of for-profit hospices, (2,182 out of 4,359), and 14.6% of non-profit hospices, (374 out of 2,568).

Figure 3 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. Hospices' referral relationships with hospitals, nursing homes, oncologists, and other providers take time to develop. Faced with cap pressure, hospices cannot suddenly request an inflow of short-stay patients to balance out the stays of patients who survive longer than expected. Hospices can and do discharge patients alive, but hospices that discharge too many patients may harm their reputations and jeopardize future referrals. Hospice consultants encourage hospices to monitor their proximity to the cap, but patient longevity, and hence firms' proximity to the cap, are highly uncertain.

Appendix Table A7 shows the inability of firms to predict patient stay length. We regress patient stay length in hospice, or an indicator variable for dying beyond 180 days after admissions, on a patient's chronic condition indicators and demographics, with year of admission fixed effects. The R^2 estimate of these regressions is between 0.02 and 0.03, indicating the error inherent predicting 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 want to evaluate the spending and health effects of the cap, a tool designed to limit long hospice stays. We begin with a sample of all patient-months in hospice from 2000 through 2019, with 53 million patient-months, and consider patient spending, care, and health outcomes in the 12-month period following each patient-month in hospice as a function of the 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 have effects on any hospice patient. Appendix C provides details on the sample construction.

A primary threat to identification is that hospices which admit long-staying patients, leading to higher cap proximity, 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 C 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 *not* by a hospice's long-term admission patterns but rather from within-year variation in patient longevity and length of stay.

Table 6 presents estimates of β from equation (4), with spending outcomes over a 12-month period following each patient-month. When a firm faces the cap, patient spending is reduced by $2,400 over the subsequent 12 months. This effect is nearly entirely driven by a reduction in hospice spending, although 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 7 presents estimates from equation 4 for a number of different outcomes reflecting hospice care choices and patient health that may respond to cap pressure. When facing cap pressure, patients are substantially more likely to be discharged alive: an increase of 1 percentage points from a baseline mean of 4.6%. 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).

Finally, and most worrisome, Table 7 shows that patient mortality increases by 2 percentage points in response to cap pressure 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 patient 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 clearly costly in welfare terms, as patients do not ex-ante sign up for effectively random changes in their treatment or discharge.

In summary, the hospice aggregate cap distorts patient care, with the goal of deterring the use of hospice for long-staying patients. However, our results have shown that hospice is cost-saving, even for the marginally eligible and often long-staying ADRD population. In light of those findings, the fact that the cap is so disruptive to patient care, causing live discharges among a sick population and increasing the probability of death, indicates that the cap may be an inefficient way to regulate hospices. These are particularly important results given recent calls by a Congressional advisory panel, MedPAC, to *lower* the hospice cap, which would increase the cap pressure on hospices (MedPAC, 2021).

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 billing standards. 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 firms face legal action in federal civil court, which can end with large settlements or penalties equal to treble the amount of fraudulent billings plus a fine of roughly $11,000 per claim. False Claims Act civil lawsuits are generally settled or dismissed; few go to trial. For a deeper treatment of the economics of the False Claims Act, see Leder-Luis (2019).

The over-admission of ADRD patients has been a major source of litigation against hospice companies. For example, in a False Claims Act lawsuit against Evercare, a multi-state hospice chain, the civil complaint states:

> *“Defendants targeted for admission ineligible elderly patients with conditions like debility, dementia, Alzheimer’s and cardiac or pulmonary irregularities 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 False Claims Act cases.

Appendix Table A8 provides descriptive statistics about these cases, using data from a Freedom of Information Act request we filed with the Department of Justice. 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. These 163 cases are often against large chains, encompassing multiple individual hospice locations. Appendix D describes the matching process between the Freedom of Information Act Request and the Medicare data to identify prosecuted firms.

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, and the impact of civil litigation, 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. Firms that are sued may admit fewer long-staying patients and ADRD patients due to the direct intervention of the federal government in enforcing the hospice eligibility rules with civil penalties. Lawsuits could unintentionally increase Medicare costs if they inhibit the use of hospice care by patients for whom hospice care would be cost saving.

It is important to note the 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 A7 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 ADRD diagnosis in the year before coming to hospice, hospices' mean length of stay, and live discharge rates. For each hospice year, we consider whether the hospice was sued, and when, using data from the FOIA request we filed with the Department of Justice. 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. Specifically, we estimate:

$$Y_{ht} = \alpha + \beta D_{ht} + \gamma_h + \eta_t + \varepsilon_{ht} \qquad (5)$$

Where Y_{ht} is an outcome for hospice h at year-month 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. The coefficient of interest is β, which captures the effect of being sued on the hospice-level outcome.

Table 8 presents the results of the difference-in-difference specification (5) on the firm-level patient population for each outcome. 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 point from a baseline mean of 41% in the years following their lawsuit. Interestingly, the proportion of patients who are discharged alive declines by 1.8 percentage points from a mean of 22%. After being sued, hospices may admit fewer non-terminally ill patients 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 ADRD patients save money on average, it appears that lawsuits limiting their exposure to hospice care are cost-increasing. However, this conclusion assumes that the lawsuits are not well targeted – that is, that they do not selectively forgo admitting particularly inappropriate patients.

To examine this hypothesis, we conduct a heterogeneity analysis. We break ADRD hospice patients by their spending in the year before hospice admission and repeat the difference-in-difference design of Equation (5). Appendix Table A9 presents the results. Lawsuits reduce hospice use pretty 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.

For completeness, we also evaluate the effects of lawsuits on patient mix and length of stay using event study specifications. We estimate:

$$Y_{ht} = \alpha + \sum_{\tau \in [-5,5], \tau \neq -1} \beta_\tau D_{h\tau} + \gamma_h + \eta_{tm} + \varepsilon_{ht} \qquad (6)$$

We include dynamic estimates of the effects in the 5 years before and after the hospice is sued, and we include firm and year-month fixed effects. We present the estimates of β_τ, where the outcome is the share of long-staying patients and ADRD patients, as event study figures in Figure 4. The results match the results presented in Table 8 and show that the proportions of long-stay patients and ADRD patients decline following lawsuits. They do not show strong pre-trends. Appendix Figure A4 presents event study figures for additional outcomes including the average length of stay and share of patients live discharged, which also decline and do not exhibit pre-trends. Appendix Figure A5 repeats this specification to account for modern critiques of two-way fixed effects designs, following (Sun & Abraham, 2021). Our results are robust to this alternative approach.

6.3 Discussion

Our results show that, in general, 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 substitute away from ADRD patients, who are most likely to experience longer stays. They appear to reduce admissions of ADRD patients across the spending distribution, rather than only restricting enrollment of ADRD patients with the best prognoses. This result should be interpreted cautiously, however, because pre-hospice spending may be only a weak signal of life expectancy.

It is an open question *why* litigation against hospice firms changes their behavior. Rational firms would not over-admit patients in the first place if the threat of litigation and expected penalty were high enough. However, our findings are in line with previous studies that show large effects from realized lawsuits (Howard & McCarthy, 2021; Leder-Luis, 2019). In the case of hospice fraud, one potential mechanism is the use of corporate integrity agreements, a form of increased monitoring which firms often agree to while signing False Claims Act settlements. Firms may also believe that the profits from fraudulent admissions are high enough to outweigh the expected cost of settlements, and it is only when facing increased scrutiny that they must comply with eligibility standards.

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 on fraud enforcement, which largely shows high levels of cost savings (Howard & McCarthy, 2021) (Leder-Luis, 2019).

Our estimates are a conservative measure of the effects of hospice litigation firm behavior toward ADRD patients. We have not assessed 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 be attenuated, *understating* 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 forgoing ADRD or otherwise ineligible patients in the first place. We expect that enforcement actions overall decrease the likelihood a hospice firm is willing to treat ADRD patients, and so these deterrence effects further inhibit hospice use by 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 usage among marginally eligible ADRD patients.

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, in light of the fact that these patients elect to forgo curative care in favor of hospice. However, a full treatment of the relevant ethical questions is beyond the scope of this paper. Future work could include richer information on the impact of hospice on quality of life to uncover the full welfare impacts of hospice enrollment.

If hospice enrollment is welfare-improving, then policies that limit hospice use on the margin may be inefficient. We find that aggregate cap on hospice revenues distorts patient care, increasing live discharges and patient mortality in return for minimal savings. 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. They may cost the government money relative to the alternative or keeping these patients in the hospice program. While for-profit admission of ADRD patients without an acutely terminal diagnosis may be considered fraudulent or improper 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 sector. 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.

The use of for-profit hospice for ADRD patients provides 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.

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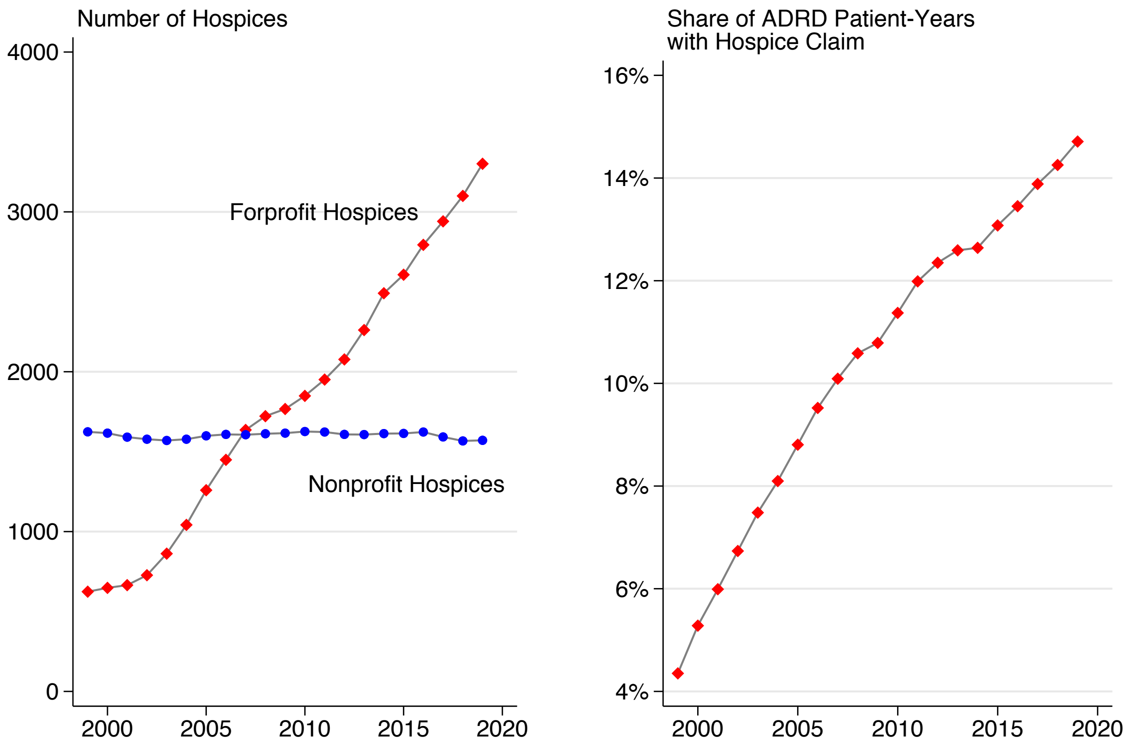
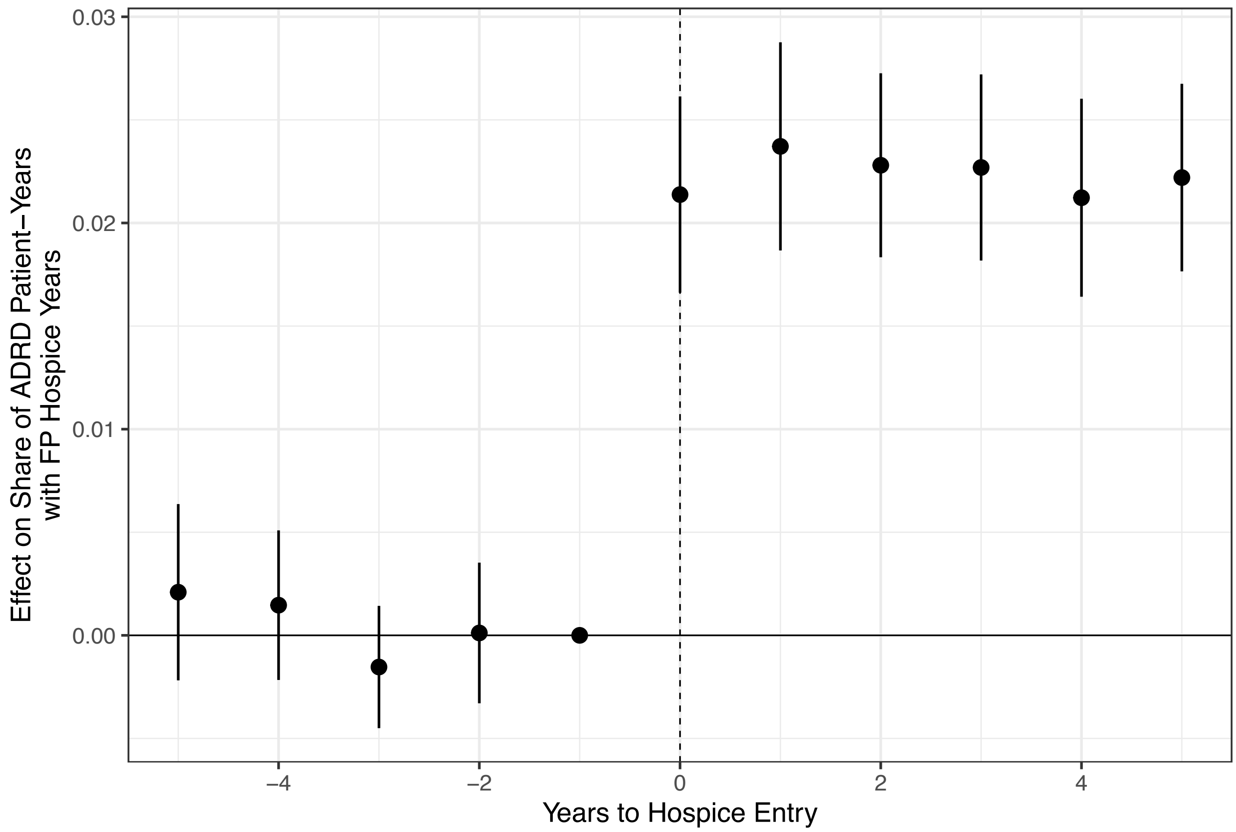
Tables and Figures

Figure 1: Proliferation of Hospice Over Time



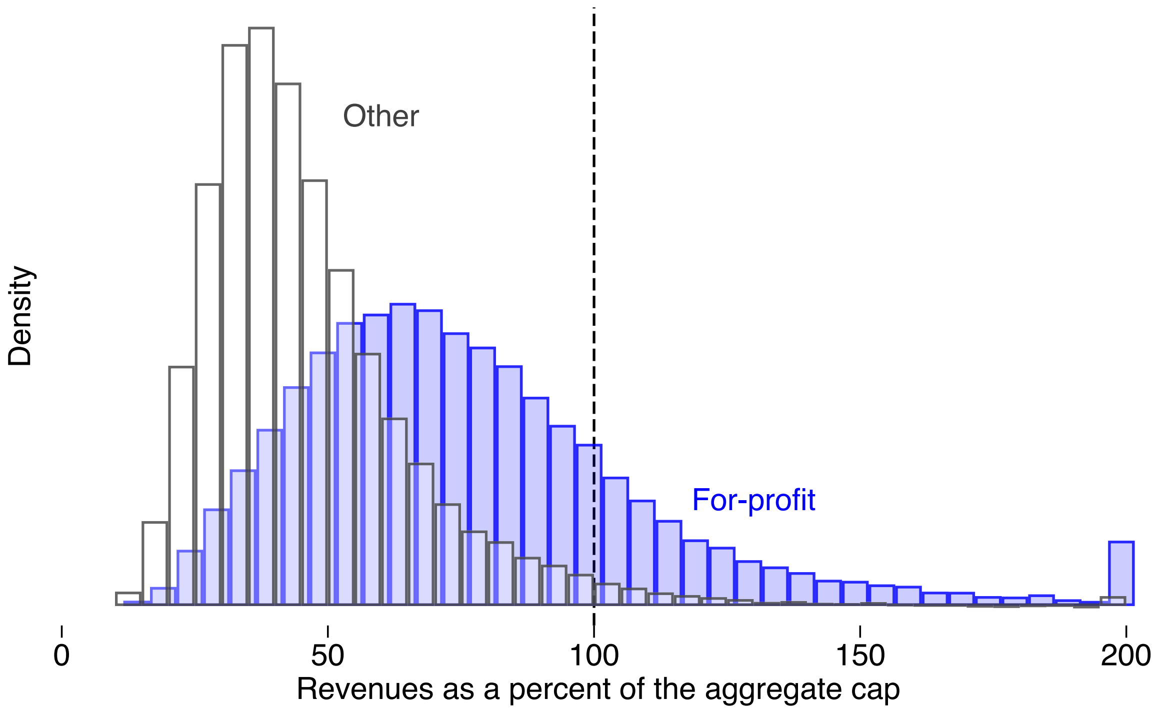
Notes: This figure shows the expansion of hospice over time using Medicare Provider of Service data matched to Medicare claims. The left panel shows the number of hospices that serve Medicare patients, by profit status and year. The right panel shows the share of Alzheimer's and Dementia patient-years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

Figure 2: First Stage Event Study



Notes: The figure shows the coefficient estimates and 95% confidence intervals for an event study specification related to our first stage. Appendix B provides details of the specification. We show the effect on ADRD patient for-profit hospice usage in a zip code when the nearest for-profit hospice moves from greater than 50 miles away to less than 10 miles away. The regression is conducted at the zip-year level with zip and year fixed effects. Appendix Figure A2 repeats this estimate with other estimators robust to critiques of two-way fixed effects models.

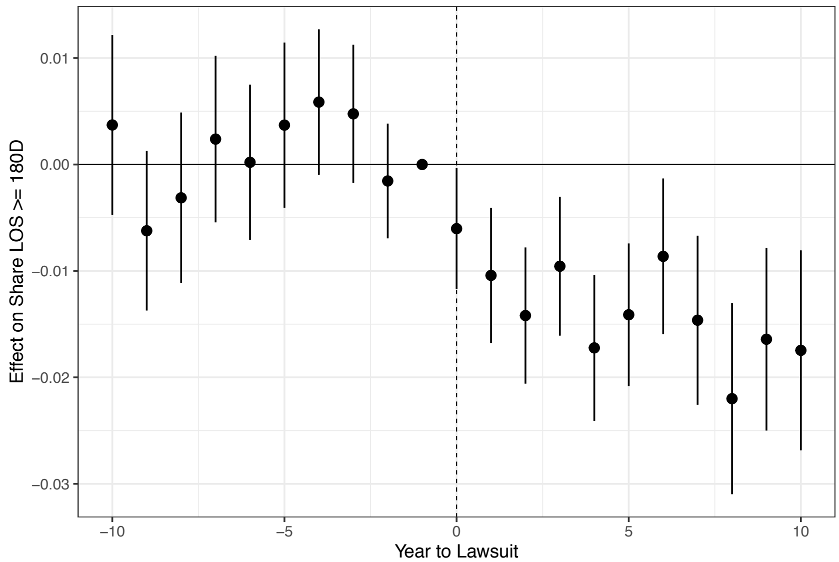
Figure 3: Histogram of hospice Revenue Relative to the Cap by Ownership Type



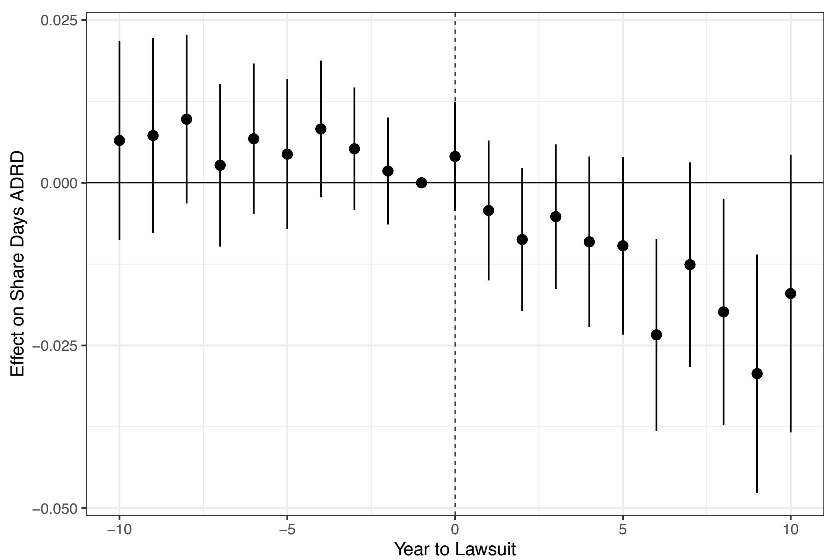
Notes: The graph shows histograms of hospices' annual cap-year revenues as a percent of the aggregate cap, by for-profit status. The aggregate cap was calculated by multiplying the number of admissions during the cap year by the per patient cap in a given year. Data were winsorized at 200%. Appendix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

Figure 4: Event-Study Estimates of Impact of Lawsuits

4A. Effect of Lawsuit on Patients Staying Over 6 Months



4B. Effect of Lawsuit on Share ADRD Days



Notes: These figures show outcomes of the event study described in equation (6). 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	85,053.94
Year of DX		2007	4.38
Age at DX		81.03	9.75
5Y Mortality		0.67	0.47
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 / Transiet 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 = 10,856,154

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: First Stage Estimates

Dependent Variables:	FP Hospice Admission	LOS	Forprofit Hospice Spending
Model:	(1)	(2)	(3)
Variables			
Distance to FP Hospice (10mi)	-0.0099***	-0.8545***	-100.4***
	(0.0004)	(0.0527)	(7.760)
Fixed-effects			
Demographics Controls	Yes	Yes	Yes
Chronic Conditions Controls	Yes	Yes	Yes
Zip	Yes	Yes	Yes
Diagnosis Year	Yes	Yes	Yes
Fit statistics			
Observations	10,856,158	10,856,158	10,856,158
R^2	0.10412	0.03381	0.03498
Within R^2	0.00078	0.00012	7.4×10^{-5}
Dependent variable mean	0.14677	14.779	2,331.4

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: (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, and all within years 0-5 of ADRD diagnosis. 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 3: 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 4: IV Results for Mortality Outcomes

Dependent Variables:	30D Mortality	90D Mortality	1Y Mortality	2Y Mortality	5Y Mortality
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	0.0127	0.0402***	0.0680***	0.0723***	0.0864***
	(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	0.17827
Within R^2	-0.00170	-0.00475	-0.00482	-0.00168	0.01708
Dependent variable mean	0.06868	0.12715	0.26315	0.39000	0.66577
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 5: Decomposition of For-Profit Hospice Treatment Effects

Outcome	MTE_{FP}	$MTE_{FP \leftarrow NP}$	$MTE_{FP \leftarrow 0}$	ω
Total Pmt (USD)	-29027.6	-7932.5	-44082.2	0.58
	[-36855.4, -21769.4]	[-19801.3, 6982.6]	[-58391.1, -30875.2]	[0.54, 0.66]
Hospice Length of Stay (Days)	61.5	51.5	68.7	0.58
	[50.1, 72.4]	[19.2, 81.8]	[50.5, 90.7]	[0.54, 0.66]
Life in Y1-5 (Months)	-5.0	-1.9	-7.2	0.58
	[-7.2, -2.6]	[-6.4, 6.2]	[-12.6, -1.7]	[0.54, 0.66]
5Y Mortality (pp)	8.6	-0.7	15.3	0.58
	[4.1, 13.5]	[-7.9, 3.2]	[6.4, 22.7]	[0.54, 0.66]

Notes: This table decomposes the spending effects of for-profit hospice from Table 3 and the mortality effects from Table 4 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. 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. Bootstrapped 95% confidence intervals are presented in brackets.

Table 6: Impact of Cap Proximity 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)	-2,417.6***	-117.5***	-55.63*	-0.2509	-2,273.8***	44.61***	-14.99**
	(113.5)	(31.99)	(28.54)	(10.20)	(98.09)	(6.130)	(7.552)
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	0.14626	0.02373	0.02824	0.02058	0.18460	0.03890	0.01643
Within R^2	6.13×10^{-5}	8.19×10^{-7}	3.22×10^{-7}	4.32×10^{-11}	9.86×10^{-5}	5.6×10^{-6}	2.2×10^{-7}
Dependent variable mean	20,134.1	1,418.3	1,216.1	383.35	16,669.3	199.30	247.64

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

Notes: This tables 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.

Table 7: Impact of Cap Proximity on Patient Care

Dependent Variables:	Live Discharge	Died w/in 1Y	Hospice Inpatient Spending
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	0.01916	0.12191	0.03120
Within R^2	1.47×10^{-5}	1.95×10^{-5}	1.25×10^{-6}
Dependent variable mean	0.04564	0.74786	40.775

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

Notes: This tables presents estimates from Equation (4), which measures the effect of a firm's probability of exceeding the hospice revenue cap on patient care 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.

Table 8: Impact of Lawsuits on 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***	-0.0177***
	(0.0038)	(1.110)	(0.0021)	(0.0034)
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	0.70094
Within R^2	0.00025	0.00150	0.00127	0.00126
Dependent variable mean	0.40730	83.727	0.13476	0.22339

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

Notes: This table presents results from regressions each estimated using equation (5), a difference-in-difference specification that estimates firm-level responses to being sued. The regression is estimated at the hospice-year level. The dependent variables are 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 4 and Appendix Figure A4 present event study figures of the same outcomes.

Appendix for Online Publication

Appendix A: Distance metric and instrumental variables design details

A.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.

A.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 (NP) hospice. 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.

Appendix B: First Stage Event Study Details

We present an event study to illustrate that distance to a for-profit hospice affects ADRD patients' likelihood of going to hospice. While our main specification uses the full richness of changes in distance, this event study estimates the effect of a large discrete jump in distance to a for-profit hospice. We define treatment as the year when a zip code has at least one for-profit hospice within 10 miles and no for-profit hospices within 50 miles in the previous year, i.e., when a zip code shifts from not having any nearby for-profit hospices to having one within 10 miles.

We use the following estimating equation:

$$Y_{zt} = \sum_{k=-5,k\neq-1}^{5} \beta_k D_k + \gamma_z + \gamma_{tm} + \varepsilon_{zt}$$

Where Y_{zt} is the outcome for zip code z in year t, D_k are a series of lags and leads around treatment, γ_z and γ_{tm} are zip code and year-month fixed effects, and ε_{zt} is a stochastic error term. Lags and leads are capped such that D_{-5} is 1 for all years 5 or more years before the treatment and D_{-5} is 1 for all years 5 or more years after the treatment. The coefficients of interest are β_k and are presented in an event study figure, Figure 2.

Appendix C: Additional Cap Details

C.1 Computing the Cap

Hospices are permitted to use varying methods for counting 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 period 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.

C.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. We also exclude patients whose death date is before the first of that month.

C.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:

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

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 D: Matching FOIA Data into Medicare Claims

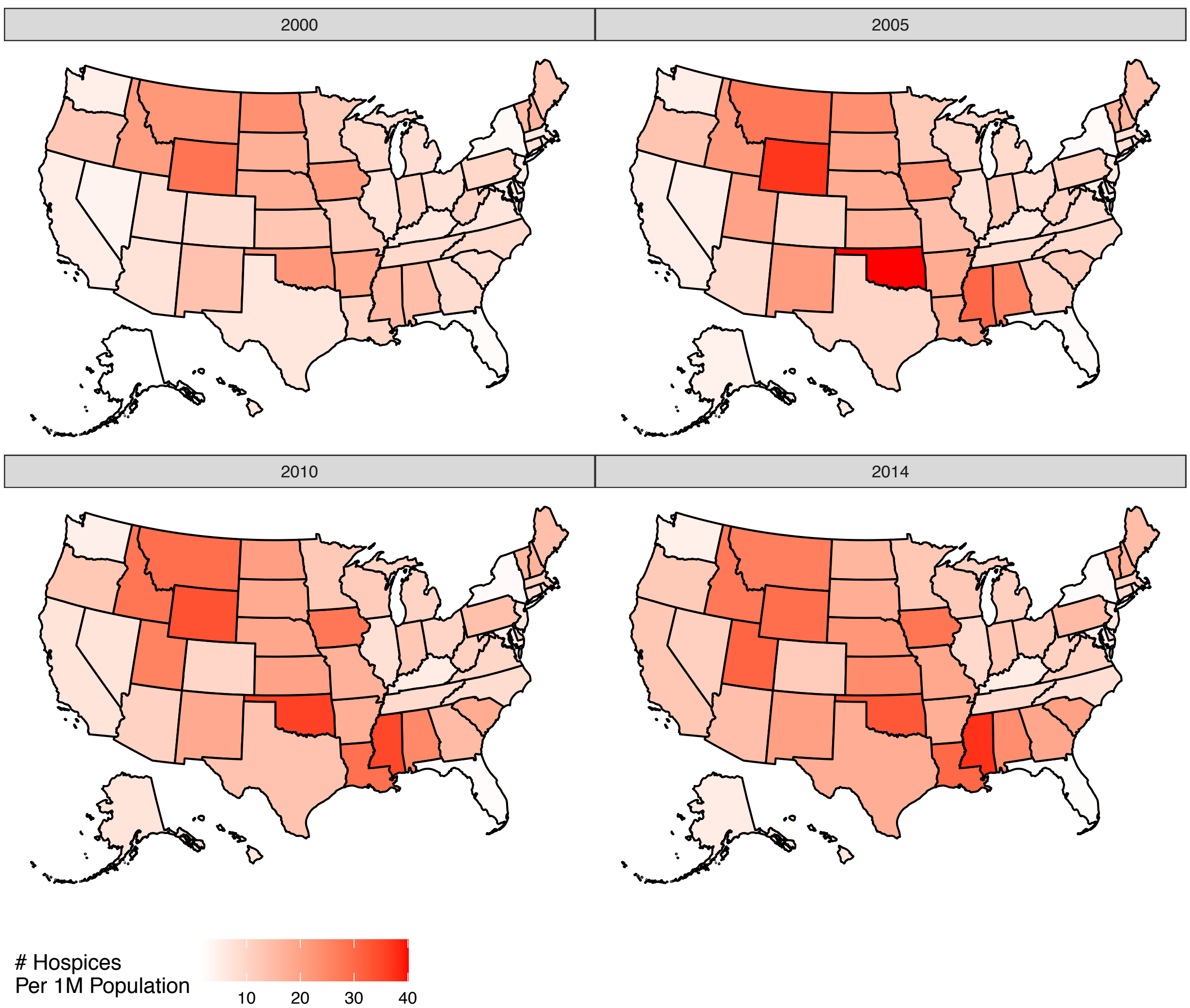
This appendix describes the steps we took to identify hospices that were defendants in False Claims Act lawsuits in the Medicare data.

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.

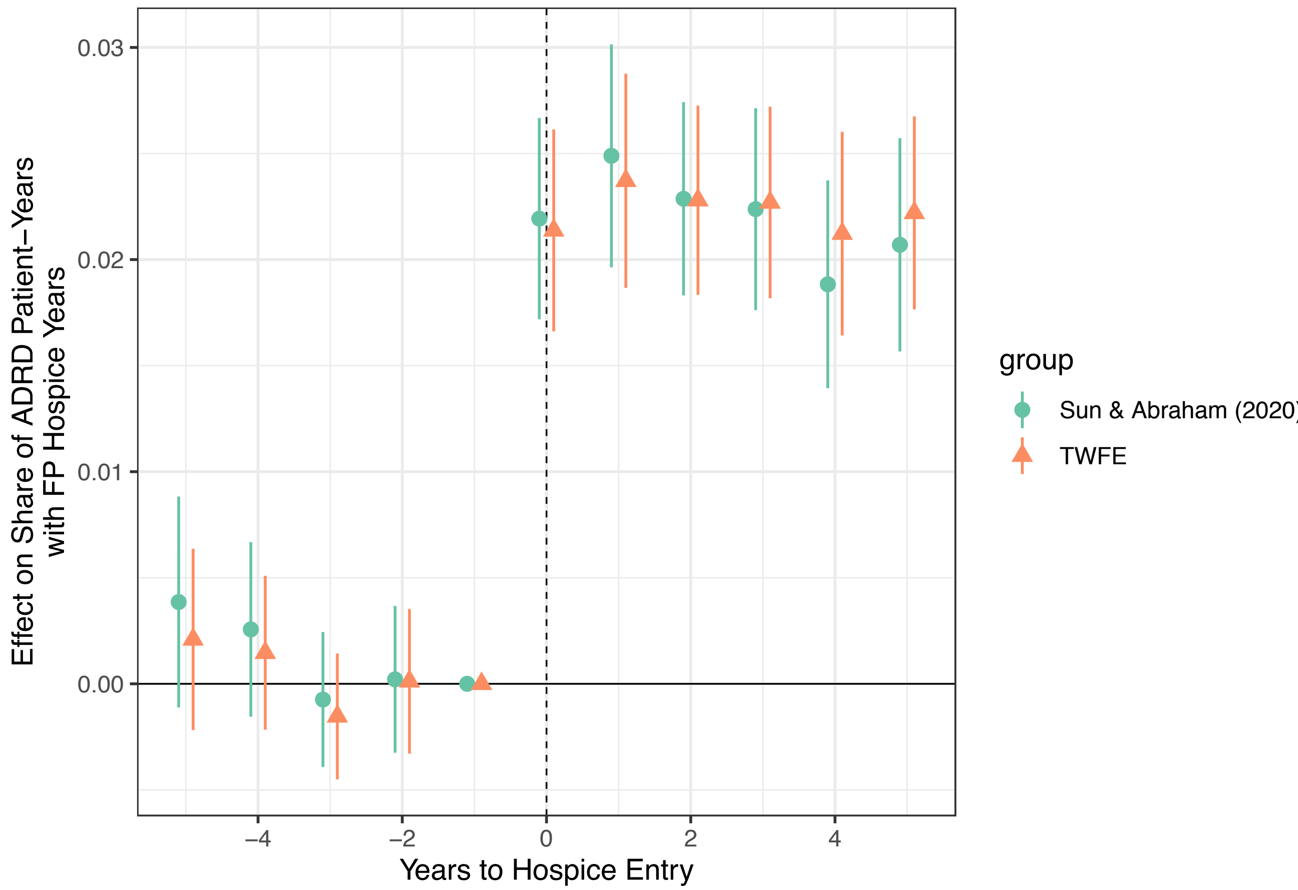
Appendix Tables and Figures

Figure A1. Geographic Trends in Hospices



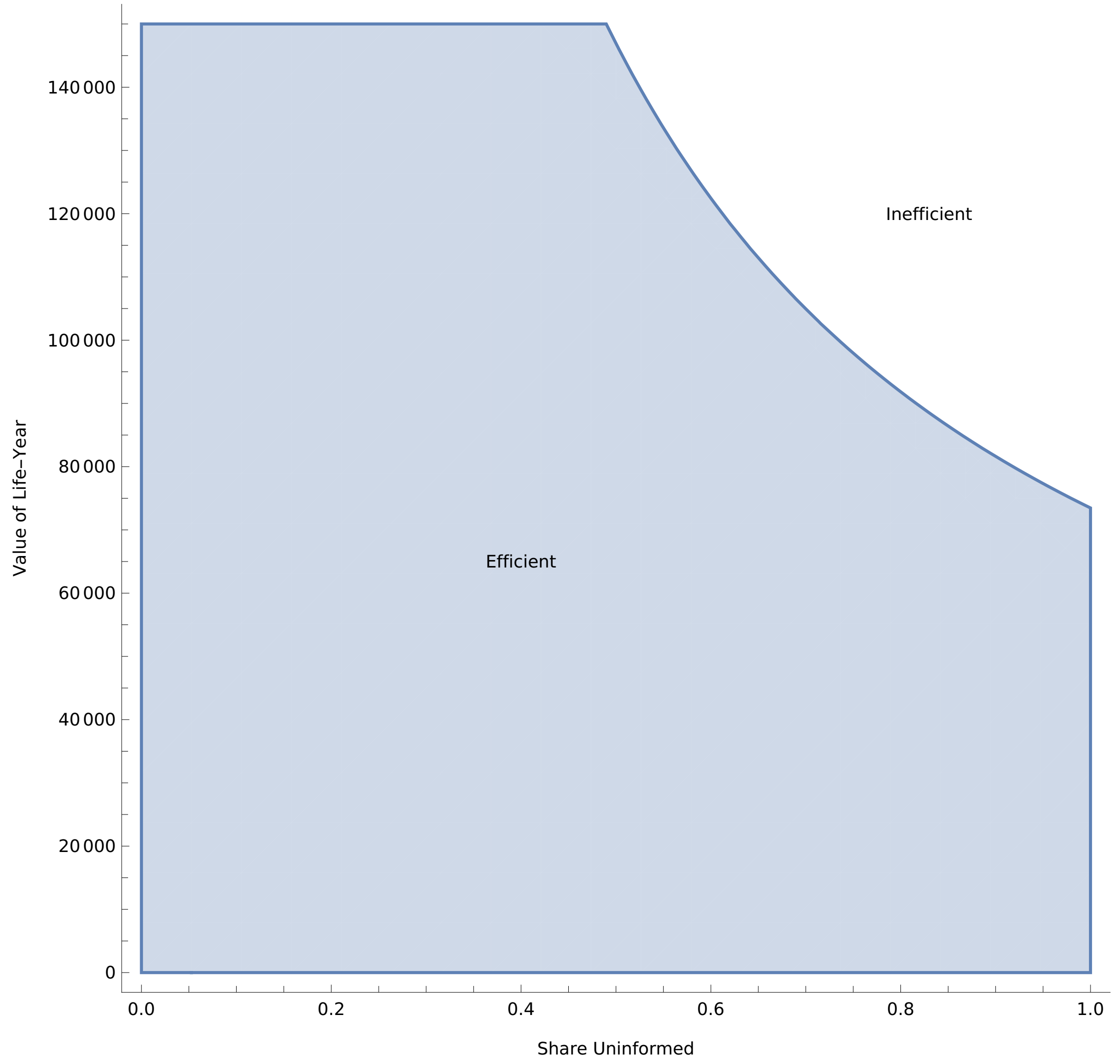
Notes: This figure shows the number of hospices per 1 million residents in each of the 50 states in 2000, 2005, 2010, and 2014. The number of hospices is calculated from the Medicare Claims files, and state population is extracted from the St. Louis Federal Reserve State Population estimates.

Figure A2: First Stage Difference-in-Difference Alternative Methodology



Notes: The figure repeats the event study of Figure 2, but using the Sun & Abraham (2021) estimator. We plot the coefficient estimates and 95% confidence intervals for the event study specification related to our first stage. Appendix B provides details of the specification. We show the effect on ADRD patient hospice usage in a zip code when the nearest for-profit hospice moves from greater than 50 miles away to less than 10 miles away. The regression is conducted at the zip-year level with zip and year fixed effects.

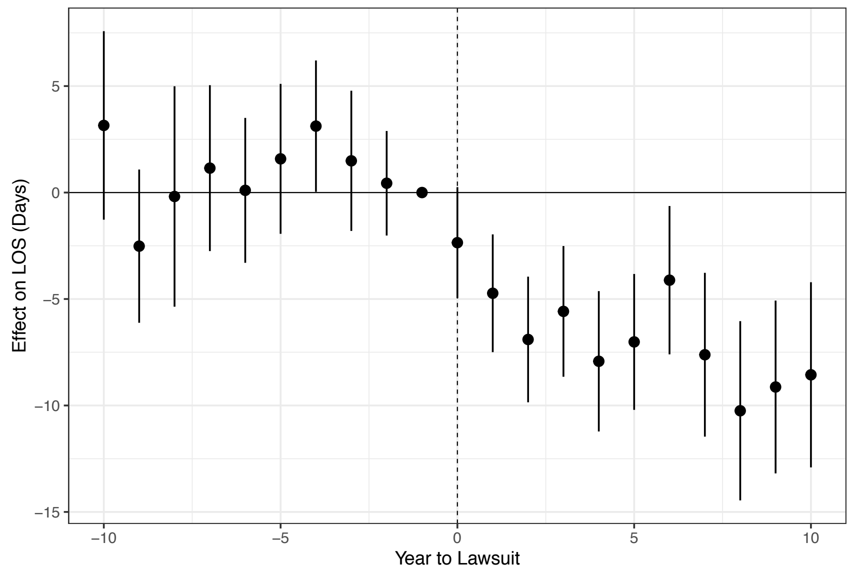
Figure A3: Welfare Bounds Calculations



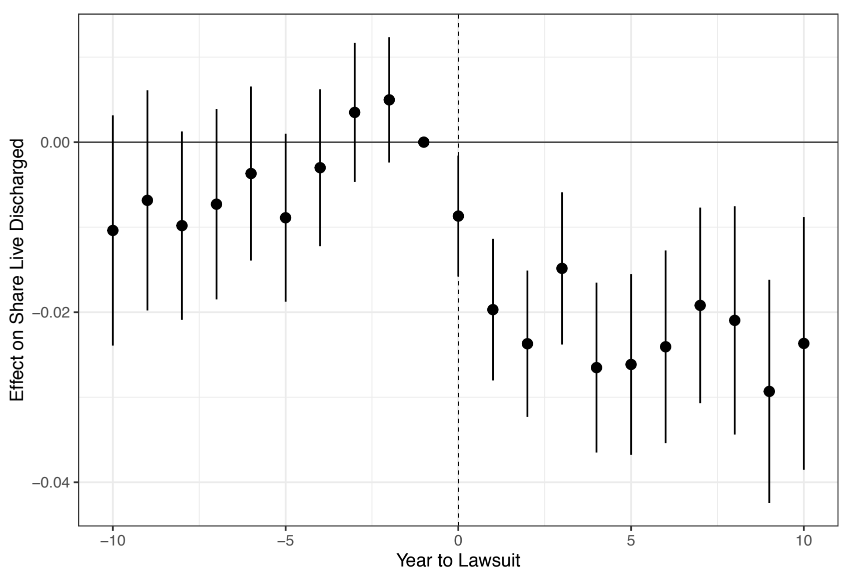
Notes: This figure describes the tradeoff between cost-savings and mortality described in Equation (3). Hospice saves money for ADRD patients, but increases mortality; however, most patients voluntarily accept the reduction in curative care to improve quality of life. This figure shows the share of patients 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 A4: Event Studies of Effects of Lawsuits on Patient Composition

A43.A Effect of Lawsuit on Average Length of Stay



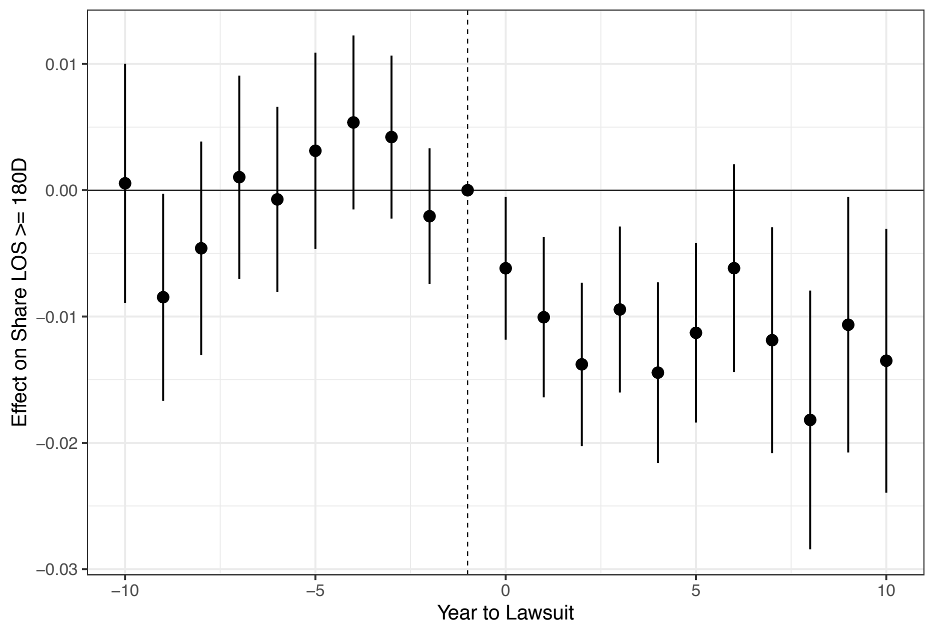
A.4.B: Effect of Lawsuit on Share Live Discharged



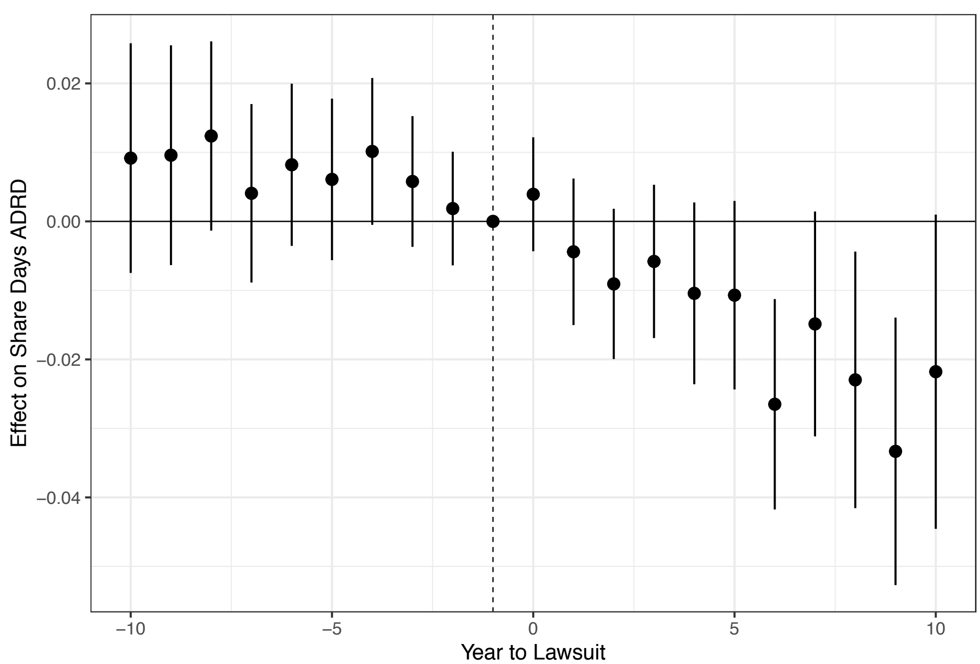
Notes: These figures show more outcomes of the event study described in equation (6) and presented in Figure 4. Specifically, the figures show the dynamic effects of a lawsuit in year 0 on the average length of stay for admissions (Panel A) and on the share live discharged (Panel B). Error bars correspond to 95% confidence intervals. Each event study is normalized such that the coefficient corresponding to year -1 is 0.

Figure A5: Event Studies of Effects of Lawsuits on Patient Composition with Alternative Specification

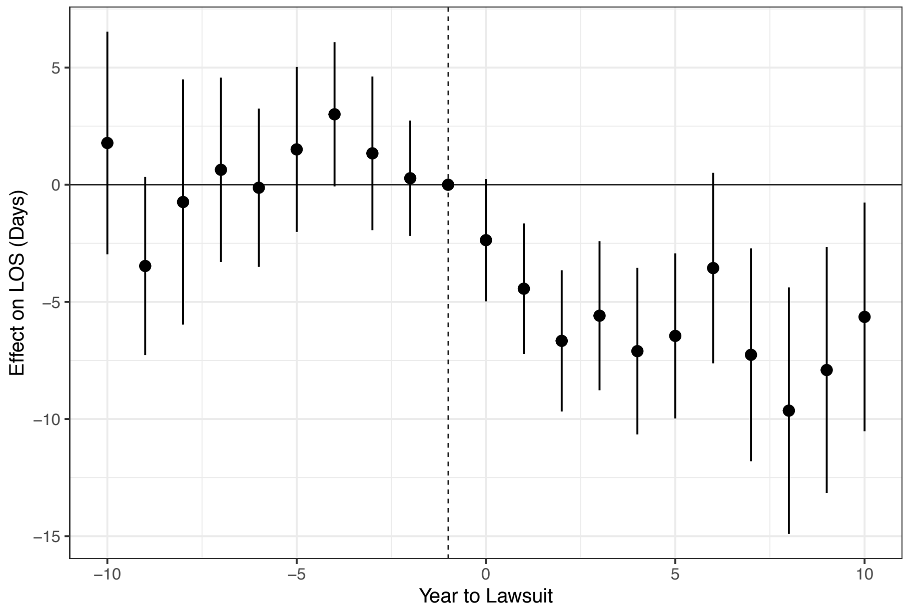
A5.A Stays Above 180 Days



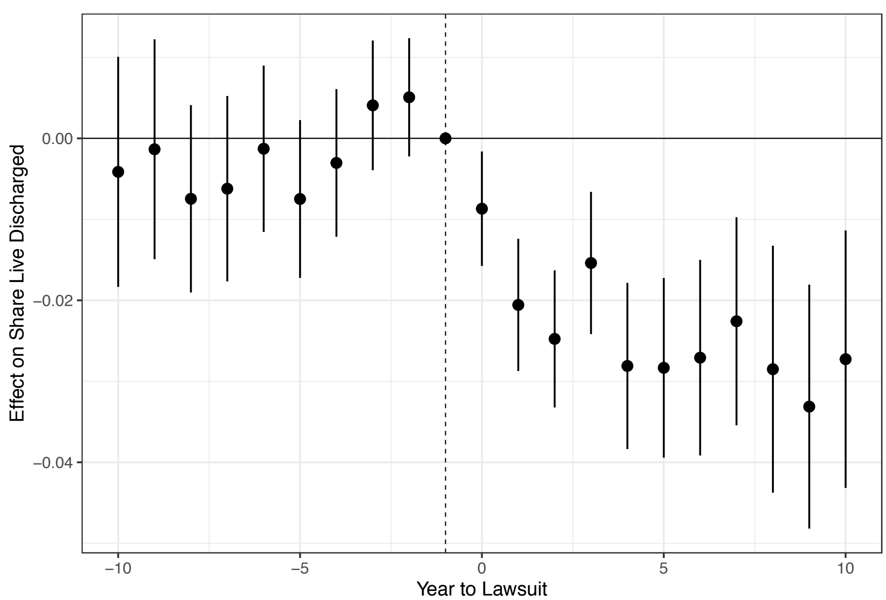
A5.B Share of ADRD Patient-Days



A5.C Average Length of Stay



A5.D Share Live Discharged



Notes: These figures show alternative specifications of the event study described in equation (6) and presented in Figures 4 and A4, 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.

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)	-6.442*** (0.0094)	-6.059*** (0.0077)
Acute Myocardial Infarction	-0.1198*** (0.0205)	-0.2431*** (0.0595)	-0.0911* (0.0485)	-0.1684*** (0.0419)
Atrial Fibrillation	0.2528*** (0.0082)	0.0503** (0.0225)	0.0437** (0.0203)	0.0611*** (0.0168)
ADRD	1.363*** (0.0062)	2.018*** (0.0166)	1.523*** (0.0154)	1.698*** (0.0125)
Cataracts	-0.1888*** (0.0072)	-0.2962*** (0.0203)	-0.1995*** (0.0177)	-0.2328*** (0.0147)
Chronic Kidney Disease	0.2435*** (0.0071)	-0.0048 (0.0193)	0.0994*** (0.0172)	0.0739*** (0.0143)
COPD	0.3519*** (0.0073)	0.2910*** (0.0195)	0.3851*** (0.0173)	0.3591*** (0.0144)
Heart Failure	0.4064*** (0.0072)	0.3510*** (0.0191)	0.4156*** (0.0174)	0.3870*** (0.0143)
Diabetes	-0.0820*** (0.0063)	-0.1707*** (0.0171)	-0.0116 (0.0150)	-0.0825*** (0.0125)
Glaucoma	-0.0582*** (0.0095)	-0.0898*** (0.0261)	-0.1338*** (0.0239)	-0.1198*** (0.0196)
Hip Fracture	0.1711*** (0.0176)	0.2382*** (0.0404)	0.1171*** (0.0405)	0.1620*** (0.0323)
Ischemic Heart Disease	0.1255*** (0.0064)	0.0627*** (0.0169)	0.1087*** (0.0153)	0.0964*** (0.0127)
Depression	0.1168*** (0.0067)	0.2332*** (0.0168)	0.2099*** (0.0156)	0.2125*** (0.0128)
Osteoperosis	0.1648*** (0.0095)	0.2172*** (0.0233)	0.1320*** (0.0224)	0.1789*** (0.0180)
Rheumatoid Arthritis	-0.0445*** (0.0059)	0.0441*** (0.0154)	0.0238* (0.0141)	0.0150 (0.0116)
Stroke / Transiet Ischemic Attack	0.1771*** (0.0097)	0.1688*** (0.0243)	0.1888*** (0.0226)	0.1783*** (0.0185)
Breast Cancer	0.3698*** (0.0137)	0.1403*** (0.0389)	0.2418*** (0.0339)	0.2253*** (0.0282)
Colorectal Cancer	0.6668*** (0.0157)	0.3244*** (0.0465)	0.4933*** (0.0385)	0.4774*** (0.0323)
Prostate Cancer	0.4398*** (0.0127)	0.0612 (0.0403)	0.2474*** (0.0330)	0.2135*** (0.0278)
Lung Cancer	1.334*** (0.0143)	0.6879*** (0.0452)	0.8956*** (0.0361)	0.8738*** (0.0308)
Endometrial Cancer	0.6888*** (0.0358)	0.2963*** (0.1091)	0.4035*** (0.0926)	0.3792*** (0.0779)
Anemia	0.4331*** (0.0063)	0.2269*** (0.0170)	0.3216*** (0.0156)	0.2999*** (0.0128)
Asthma	-0.1462*** (0.0118)	-0.1073*** (0.0316)	0.0087 (0.0267)	-0.0376* (0.0226)
Hyperlipidemia	-0.3844*** (0.0060)	-0.4199*** (0.0165)	-0.4022*** (0.0147)	-0.4117*** (0.0122)
Benign Prostatic Hyperplasia	0.0773*** (0.0104)	-0.1098*** (0.0303)	-0.0678** (0.0265)	-0.0587*** (0.0219)
Hypertension	0.0525*** (0.0062)	0.0684*** (0.0164)	0.0825*** (0.0150)	0.0743*** (0.0123)
Acquired Hypothyroidism	0.1363*** (0.0077)	0.2060*** (0.0196)	0.0916*** (0.0187)	0.1539*** (0.0150)
Fit statistics				
Observations	10,622,914	10,622,914	10,622,914	10,622,914
BIC	1,712,029.6	314,815.9	380,088.4	525,850.6
Dependent variable mean	0.01751	0.00230	0.00278	0.00414
Squared Correlation	0.01944	0.00462	0.00330	0.00587
Pseudo R^2	0.08632	0.08884	0.06725	0.07950

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. 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: 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***	-0.1123***	-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	0.14791	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 A3: Robustness: 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:	30D Mortality	90D Mortality	1Y Mortality	2Y Mortality
Model:	(1)	(2)	(3)	(4)
Variables				
FP Hospice Admission	-0.0035	0.0370**	0.0672***	0.0858***
	(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	0.10322	0.14539
Within R^2	-7.41×10^{-5}	0.00157	0.00859	0.01881
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 3 and 4.

Table A4. Robustness: 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	15,770.7***	-24,738.0***	-7,980.9***	3,193.9***	-6,309.7***
	(97.52)	(4,132.5)	(2,076.6)	(737.4)	(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	8,835,039	8,835,039	8,835,039	8,835,039	8,835,039
R^2	0.20903	0.18088	0.14289	0.21738	0.06821
Within R^2	0.00537	-0.03003	-0.00622	-0.00847	-0.04289
Dependent variable mean	75,542.3	75,542.3	29,730.2	6,112.2	5,200.6
Wald (1st stage), FP Hospice Admission		753.53	753.53	753.53	753.53

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	-9,757.4***	-5,958.4***	6,466.2***	9,434.3***	-2,981.2***
	(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	8,835,039	8,835,039	8,835,039	8,835,039	8,835,039
R^2	0.02520	0.10429	0.10296	0.20795	0.02705
Within R^2	-0.05245	-0.01120	0.07160	0.17827	-0.00244
Dependent variable mean	11,479.4	4,902.1	4,141.7	2,093.6	2,037.3
Wald (1st stage), FP Hospice Admission	753.53	753.53	753.53	753.53	753.53

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

Dependent Variables:	30D Mortality	90D Mortality	1Y Mortality	2Y Mortality	5Y Mortality
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	0.0117	0.0418***	0.0751***	0.0745***	0.0715***
	(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	8,835,039	8,835,039	8,835,039	8,835,039	8,835,039
R^2	0.02986	0.04706	0.09152	0.12790	0.17752
Within R^2	-0.00141	-0.00436	-0.00459	-0.00107	0.01425
Dependent variable mean	0.08438	0.15606	0.31852	0.45652	0.71253
Wald (1st stage), FP Hospice Admission	753.53	753.53	753.53	753.53	753.53

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 after diagnosis with ADRD. The results are very similar to the main specification presented in Tables 3 and 4.

Table A5: Covariate Balance and Instrumental Validity

		Over 25mi (N=3736574)		Under 25mi (N=7119580)			
		Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Total Pmt		69520.28	72096.94	87229.97	90525.61	17709.68	50.42
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 / Transiet 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	2282354	61.1	4413973	62.0		
	Male	1454220	38.9	2705607	38.0		
Age at DX	<65	168203	4.5	335584	4.7		
	65-74	619140	16.6	1197570	16.8		
	75-84	1486382	39.8	2779959	39.0		
	85-94	1278821	34.2	2458220	34.5		
	95+	184028	4.9	348247	4.9		
Race	Black	236713	6.3	772101	10.8		
	Hispanic	44639	1.2	158496	2.2		
	Other	79308	2.1	237189	3.3		
	White	3375914	90.3	5951794	83.6		
ESRD	ESRD	43182	1.2	119005	1.7		
	Not ESRD	3693392	98.8	7000575	98.3		

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 A6. 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 Pmt	Nonprofit Hospice Pmt
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:	30D Mortality	90D Mortality	1Y Mortality	2Y Mortality	5Y Mortality
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
FP Hospice Admission	-0.0023	0.0534***	0.0479**	0.0684***	0.0890***
	(0.0139)	(0.0185)	(0.0240)	(0.0262)	(0.0270)
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	0.09572	0.12751	0.19116
Within R^2	1.15×10^{-5}	0.00064	0.00510	0.01026	0.02310
Dependent variable mean	0.07204	0.13323	0.25901	0.34985	0.50898
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 (3) and (4), 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 A7: 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. The low R^2value using demographics and chronic conditions highlights the uncertainty hospices face in estimating patient stay length.

Table A8. 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 A9: Lawsuit 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 equation (5), a difference-in-difference specification that estimates firm-level responses to being sued. The regression is estimated at the hospice-year level. The dependent variables are the share of admissions with an ADRD diagnosis (Column 1), broken out by quintiles of pre-hospice spending among ADRD hospice patients.