Online Appendix

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

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Appendix A: Related Literature

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

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

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

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

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

The rapid entry of for-profit hospices and, more recently, acquisitions of hospices by other providers (e.g., home health agencies and nursing homes) (Gozalo, Mlotzke, Mor, Miller, & Teno, 2015; Stevenson, Sinclair, Zhang, Meneades, & Huskamp, 2020; Fowler, Grabowski, Gambrel, Huskamp, & Stevenson, 2017) and private equity firms (Braun, Stevenson, & Unruh, 2021) has spurred interest in the impact of hospice ownership on firm behavior. For-profit hospices admit more patients with a primary diagnosis of dementia, have longer average lengths of stay (Dalton & Bradford, 2019; Lindrooth & Weisbrod, 2007; Wachterman, Marcantonio, & Davis, 2011), and receive more referrals from nursing homes (Gandhi S. O., 2012). Differences in behavior are generally attributed to differences in the weight for-profit and non-profit hospices assign to patient welfare but may also arise from non-profit hospices' dependence on charitable donations. If revenue from donations depends on the number of patients served rather than the duration of service, non-profit hospices will face a stronger incentive to admit short-stay patients (Dalton & Bradford, 2019). Hospices can influence enrollment by cultivating referral relationships with other providers (e.g., case managers at hospitals) and by setting admission standards (for example, will the hospice accept patients receiving transfusions). For-profit hospices are more likely to impose restrictions on the patients they will accept (Aldridge Carlson, Barry, Cherlin, McCorkle, & Bradley, 2012).

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

Appendix B: Firm Dynamics

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

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

years, and the average age among non-profit firms is 8.87 years, reflecting greater entry by non-profits.

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

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

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

Appendix C: Distance metric and instrumental variables design details

C.1: Computation of the Distance Metric

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

C.2 Treatment Effect Margin Calculations

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix D: Continuous Event Study Details

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

However, changes in distance take on continuous values, which inhibits traditional event studies, which would focus on discrete events such as large changes in distance. Instead, we use a continuous event study, which allows us to estimate the average effect of every 10-mile change in for-profit distance. This mechanism was first proposed in Schmidheiny and

Siegloch (2023), which uses a distributed lags model to estimate "continuous difference-in-difference" effects. Specifically, following this work, we estimate coefficients for a set of lags and leads of the continuous treatment – that is, all changes in distance to a for-profit hospice – on the outcome, and then accumulate these estimates to compute the effect of a one-unit change in treatment at time periods before and after that change. Schmidheiny and Siegloch (2023) prove that this procedure is equivalent to a standard TWFE model (with binned endpoints) when treatment is binary and that the lag and lead coefficients can be interpreted analogously to a standard TWFE event study.

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

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

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

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

Appendix E: Additional Cap Details

E.1 Computing the Cap

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

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

E.2 Patient-Month Estimates

To construct the patient-month sample that estimates Equation (4), we use the following criteria. We start with cap years 2001 through 2019, where cap year 2001 began in October 2000 and cap year 2019 began in October 2018. The sample ends in December 2018 to ensure we can observe 12 months after a given month for spending and care outcomes. We restrict the sample to hospices not in their first cap year, because partial years distort the cap calculation. We consider a patient's first visit to hospice; patients who are live discharged and ever re-enter hospice are excluded (though subsequent hospice episodes are included in the aggregate cap payment). We also exclude patients whose death date is before the first of that month.

E.3 Probability of Exceeding the Cap

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

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

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

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

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

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

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

A major factor driving the reduction in care is that many patients who are live discharged return to hospice. Among our sample patients live-discharged with a high cap value, 70% will ever return to hospice. The median time to hospice after live discharge is 28 days, and

38% of those who return to hospice will be treated by the same provider. These statistics are consistent with gaming behavior – wherein hospices cycle patients in and out of hospice to avoid the cap. Moreover, it may speak to a taste for hospice, where patients who have begun palliative care prefer to continue it, which also indicates that live discharge is costly to the patients.

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

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

Appendix G: Matching FOIA Data into Medicare Claims

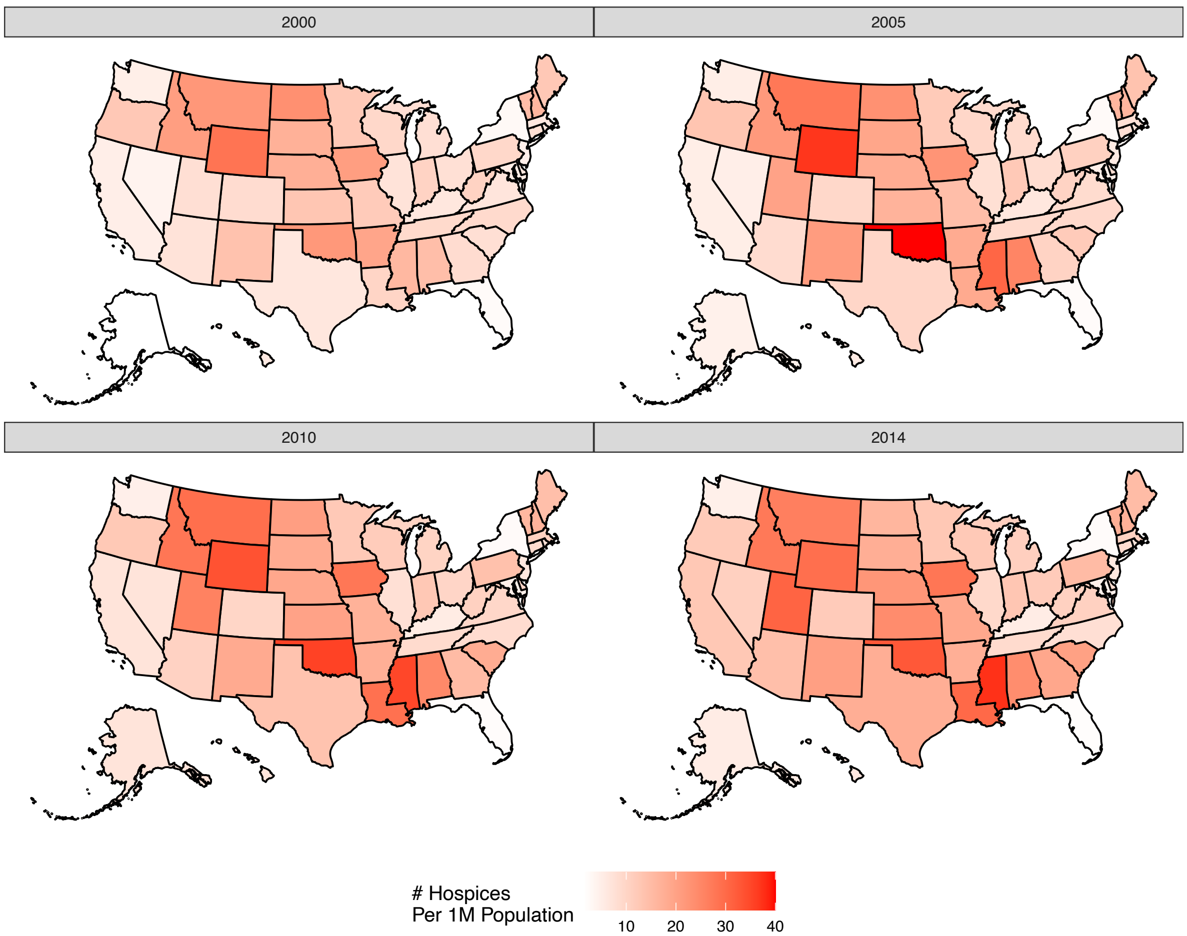
This appendix describes the steps we took to identify hospices that were defendants in False Claims Act lawsuits in the Medicare data.

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

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

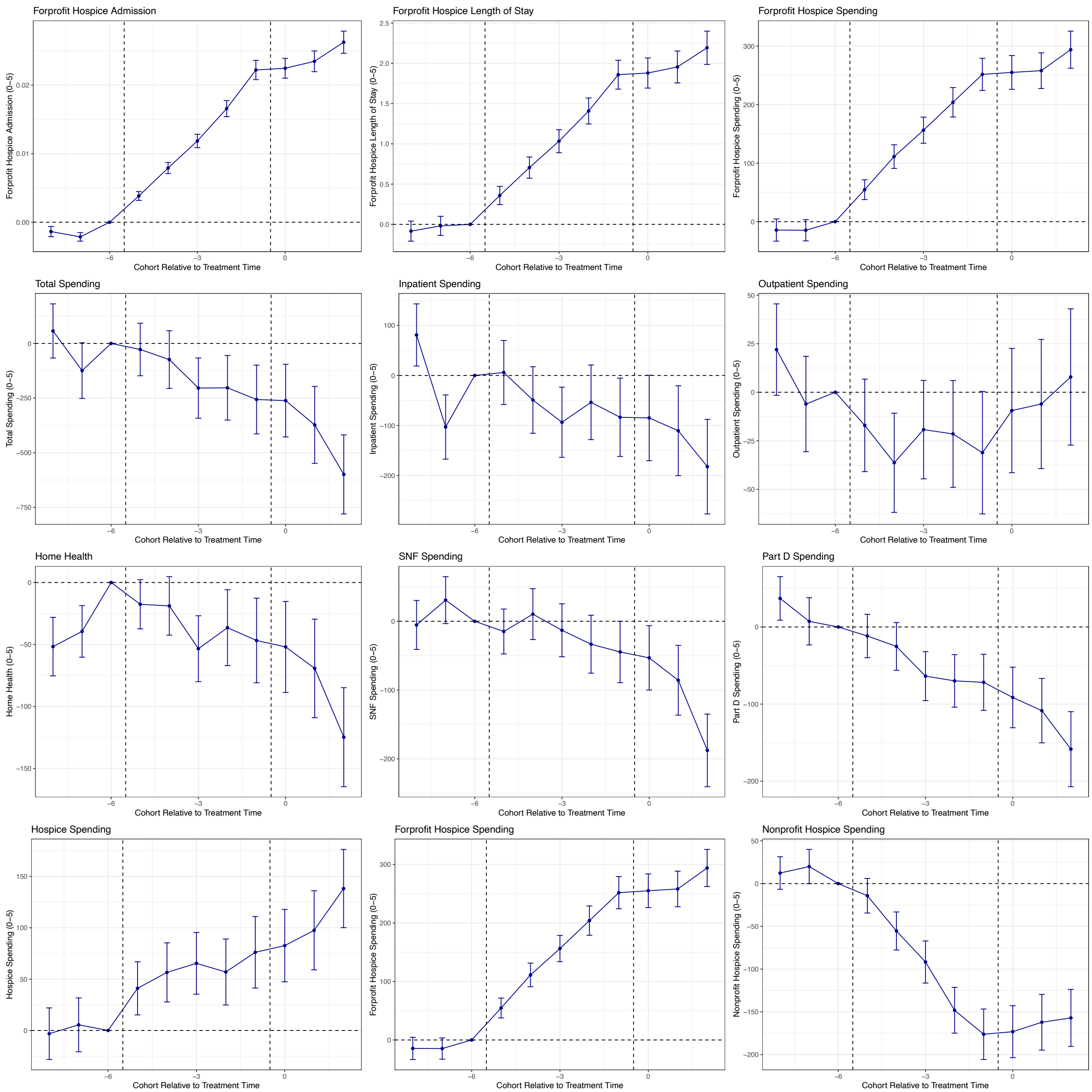
Appendix Tables and Figures

Figure A1: Geographic Trends in Hospices



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

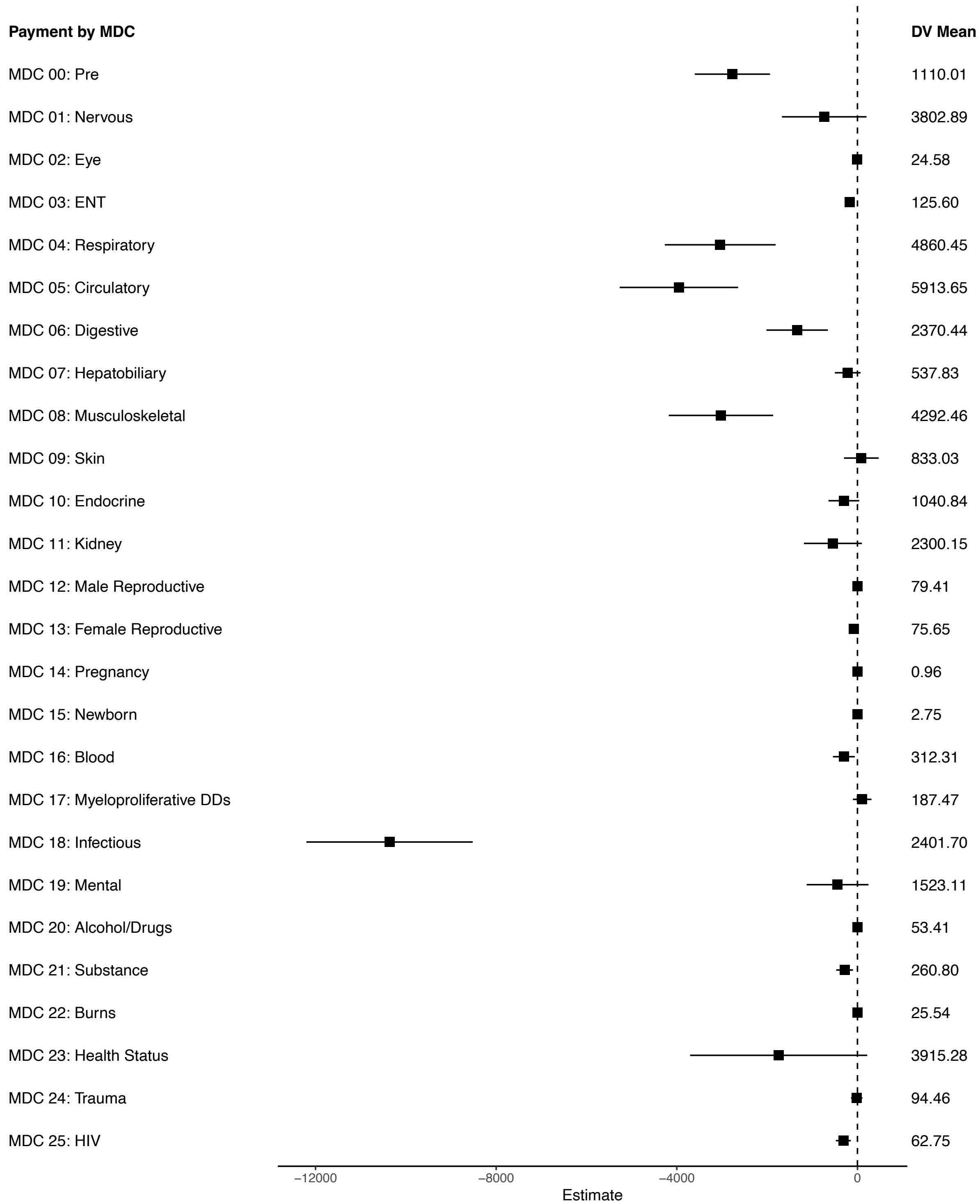
Figure A2: Continuous Event Study Design



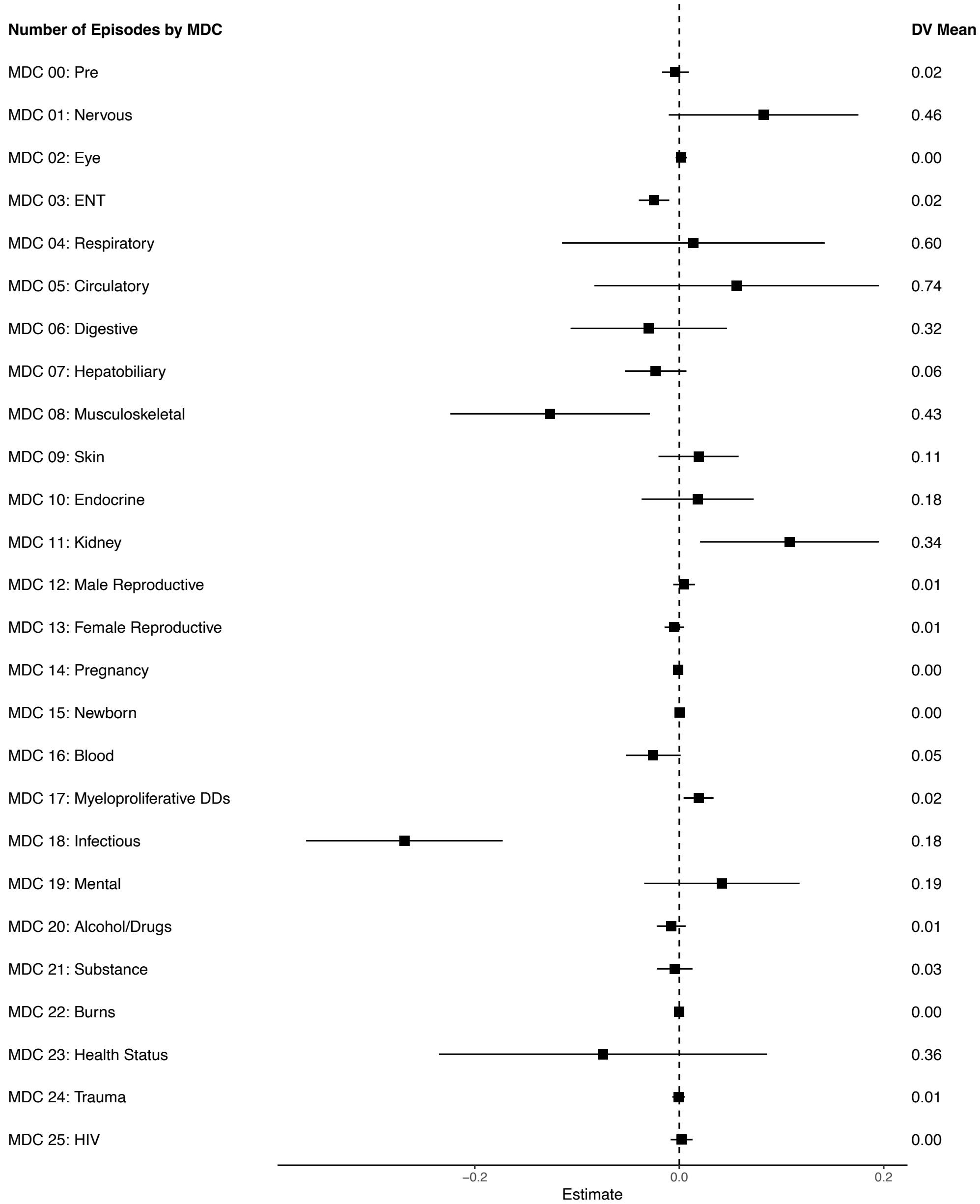
Notes: The figure shows the coefficient estimates and 95% confidence intervals for a continuous event study specification, following Scmidheiny and Siegloch (2023). Treatment is where a zip code experiences a change in distance to a for-profit hospice, with a one unit change corresponding to a 10 mile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

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

A3.A: Spending by MDC



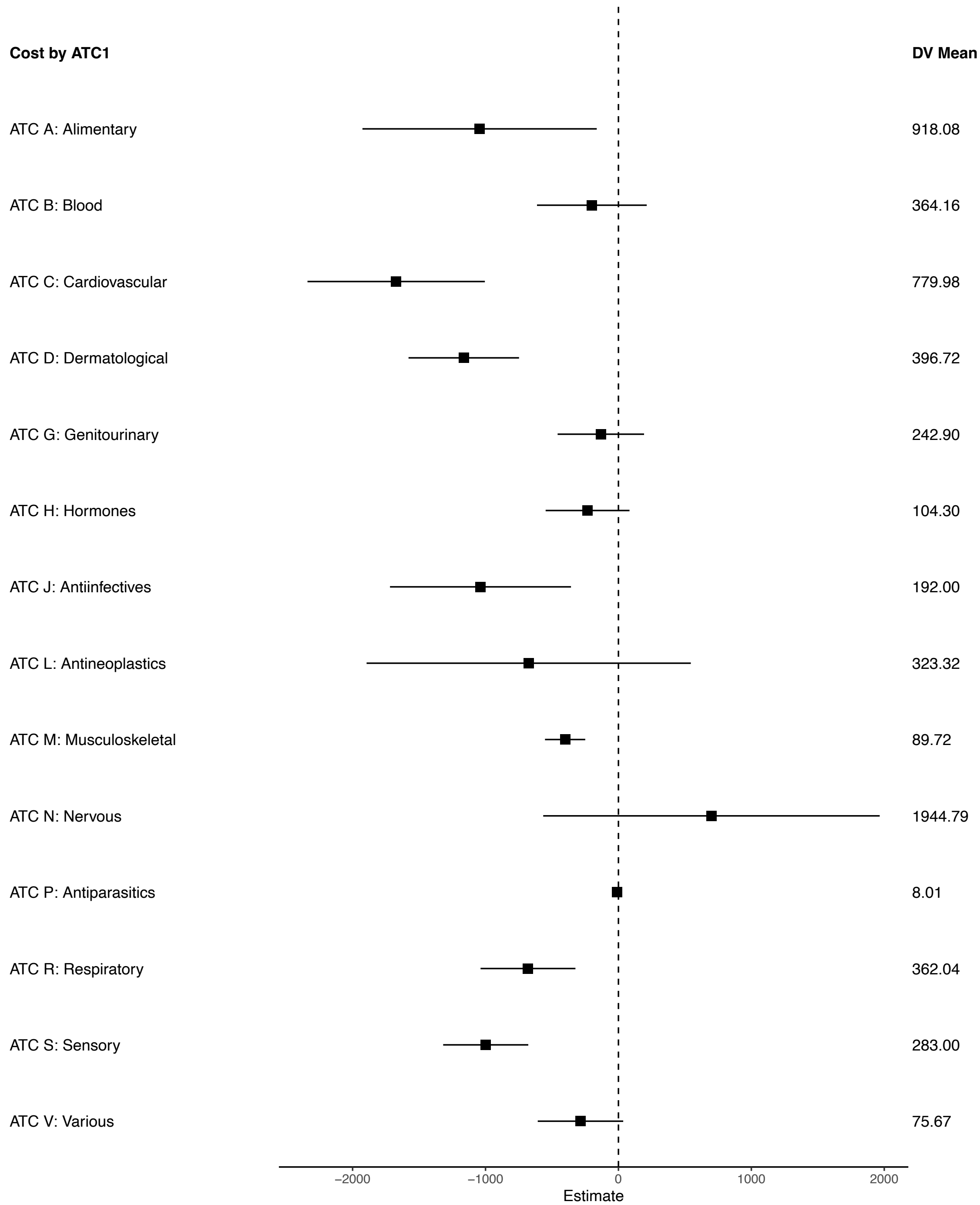
A3.B: Visit Count by MDC



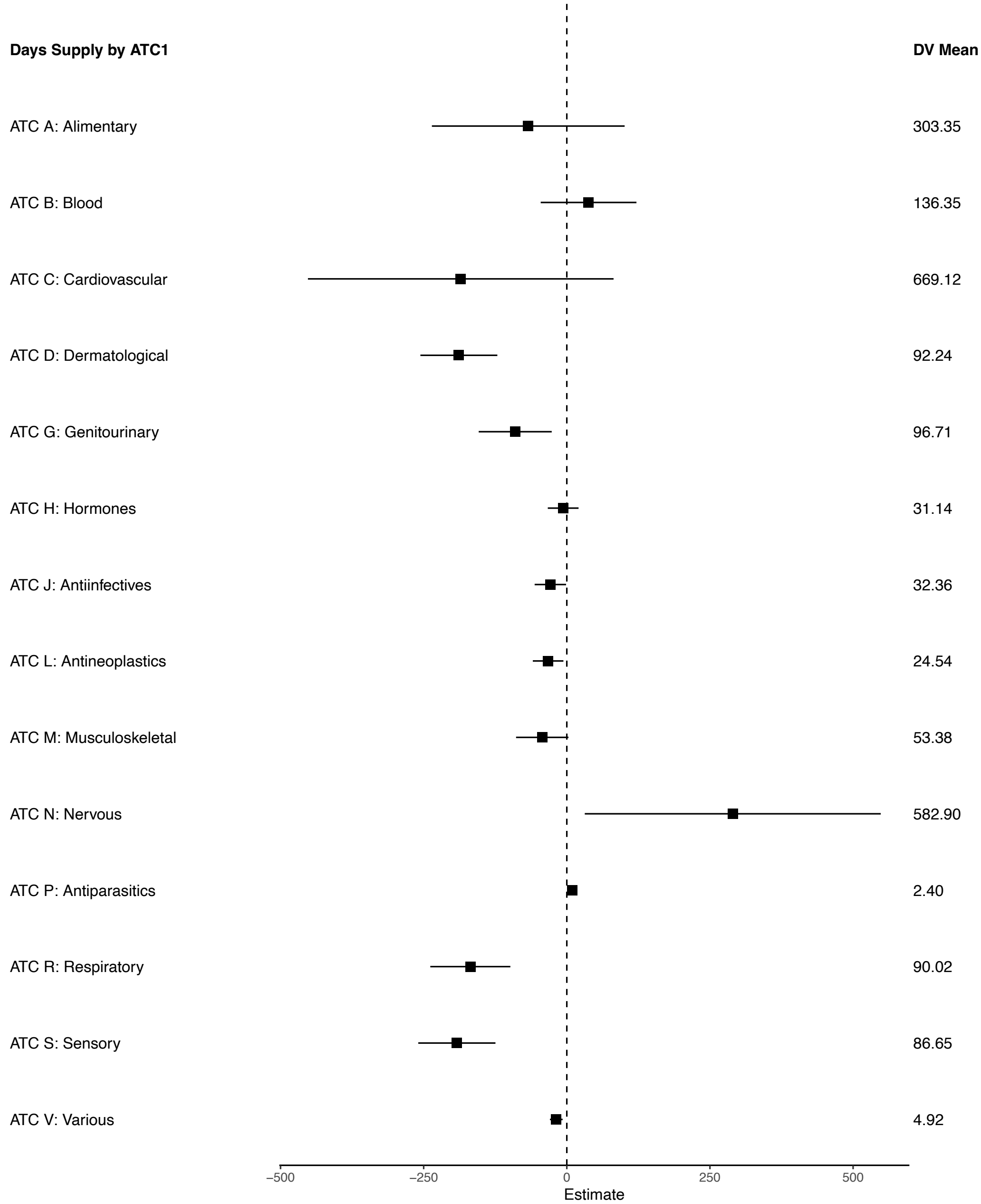
Notes: This figure shows the effect of for-profit hospice use on spending and visit counts by Major Diagnostic Category (MDC). Panel A shows spending within each MDC, while Panel B shows visit counts within each MDC. Data are taken from a 100% sample of MedPAR, which contains hospitalizations and Skilled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

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

A4.A: Spending by ATC1 Group

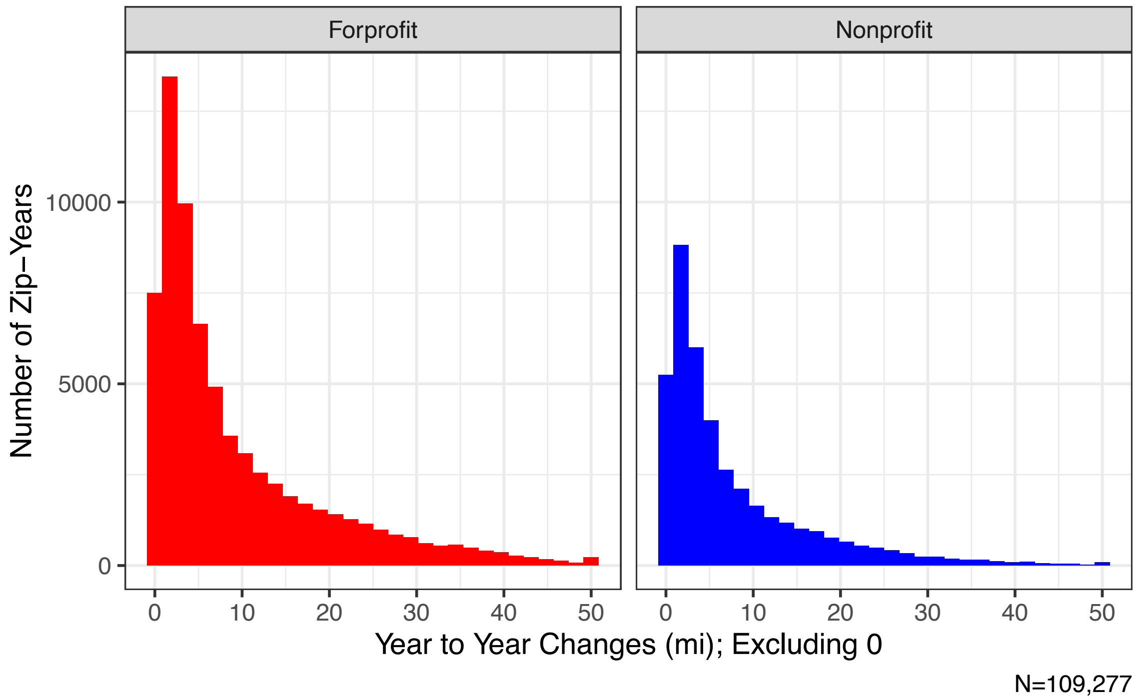


A4.B: Days Supply of Drugs by ATC1 Code



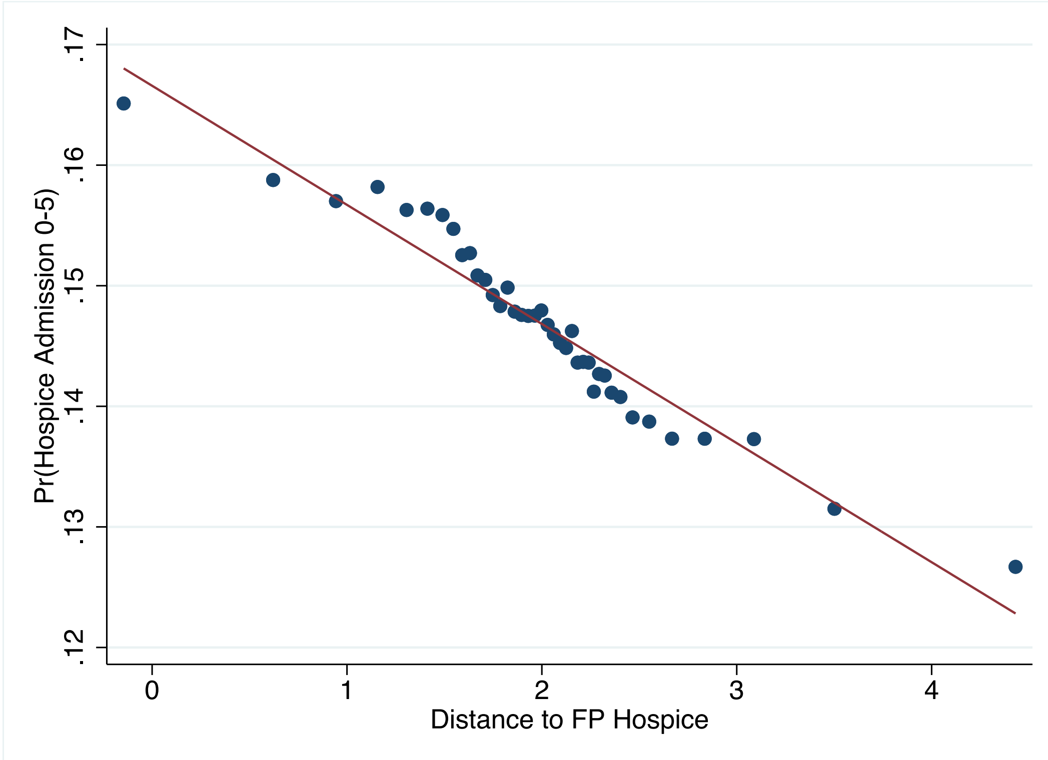
Notes: This figure shows the effect of for-profit hospice use on spending and days supply of drugs by Anatomical Therapeutic Chemical (ATC) Class. Panel A shows spending within each ATC Level 1 code, while Panel B shows days. Data are taken from a 20% sample of Part D claims, and mapping into ATCs is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

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



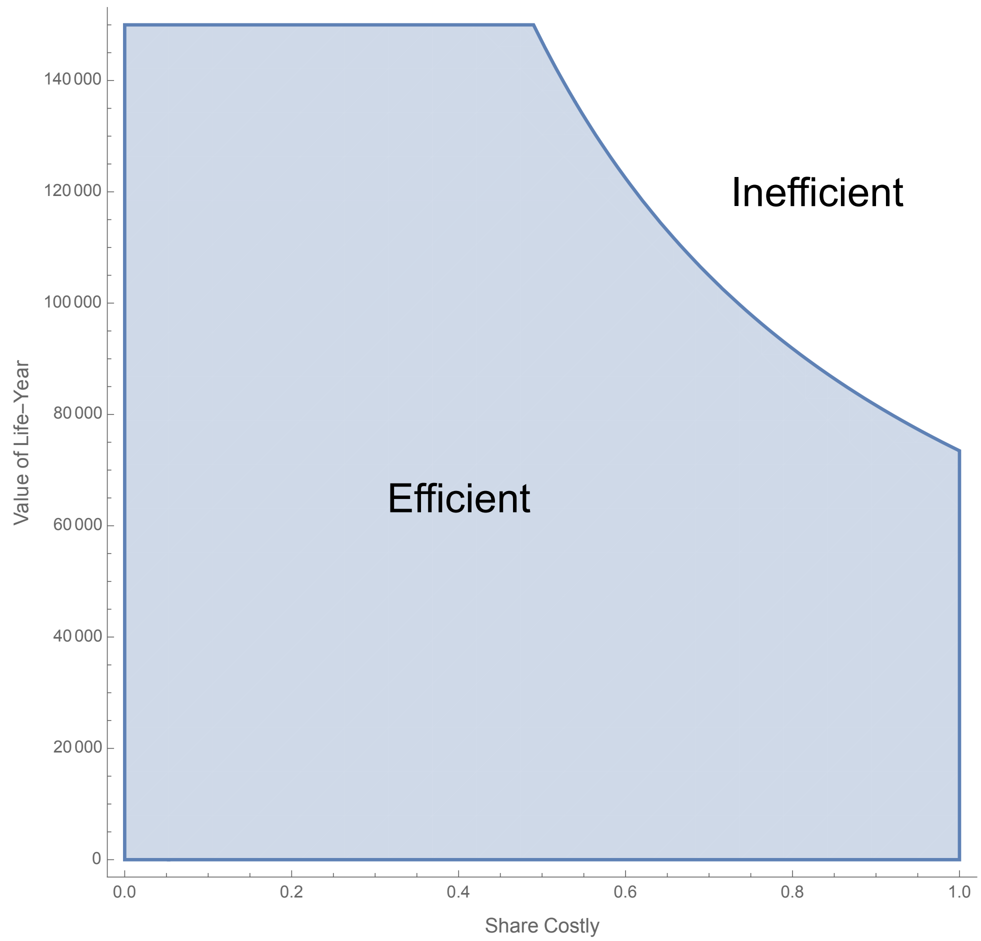
Notes: This figure shows a histogram of zip-code-year changes in distance to for-profit and non-profit hospice, excluding 0s. Both for-profit and non-profit hospice distances show substantial year-to-year variation.

Figure A6: Distance and Probability of For-Profit Hospice



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

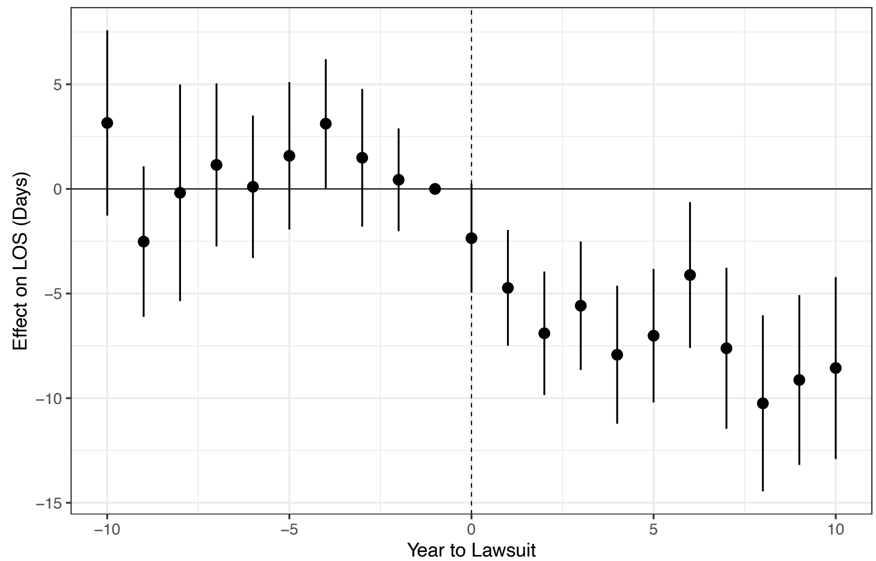
Figure A7: Welfare Bounds Calculations



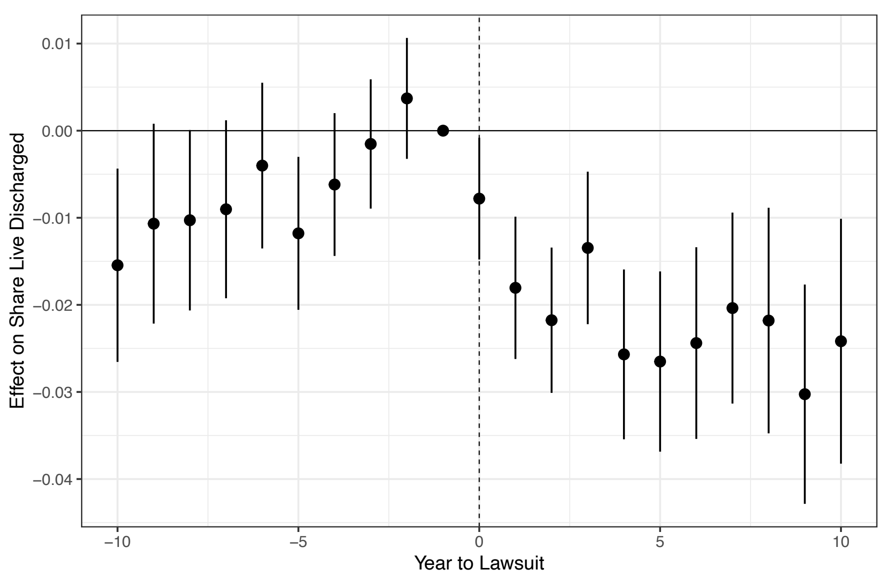
Notes: This figure describes the tradeoff between cost-savings and mortality described in Equation (3). Hospice saves money for ADRD patients, but increases mortality; however, most patients voluntarily accept the reduction in curative care to improve quality of life. This figure shows the share of patients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

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

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



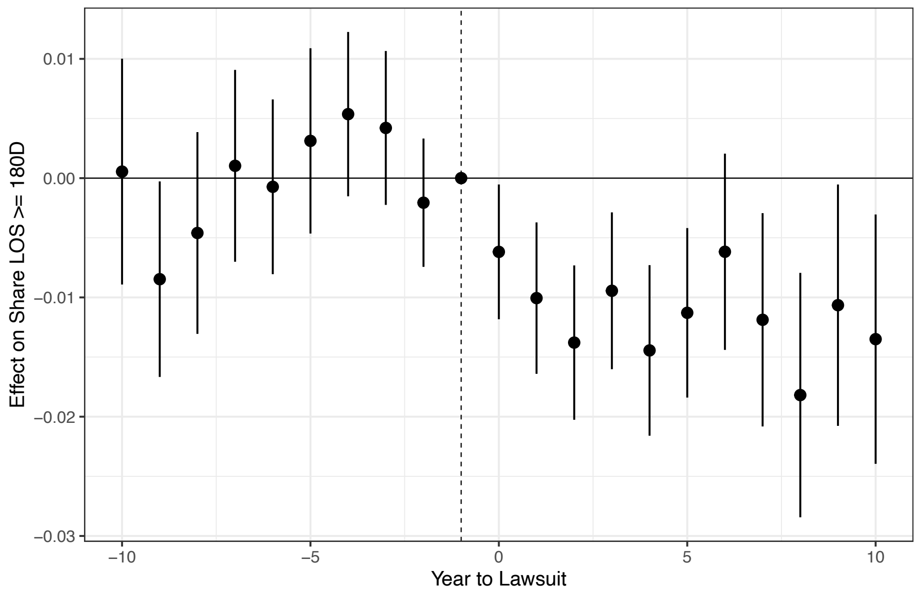
A.8.B: Effect of Lawsuit on Share Live Discharged



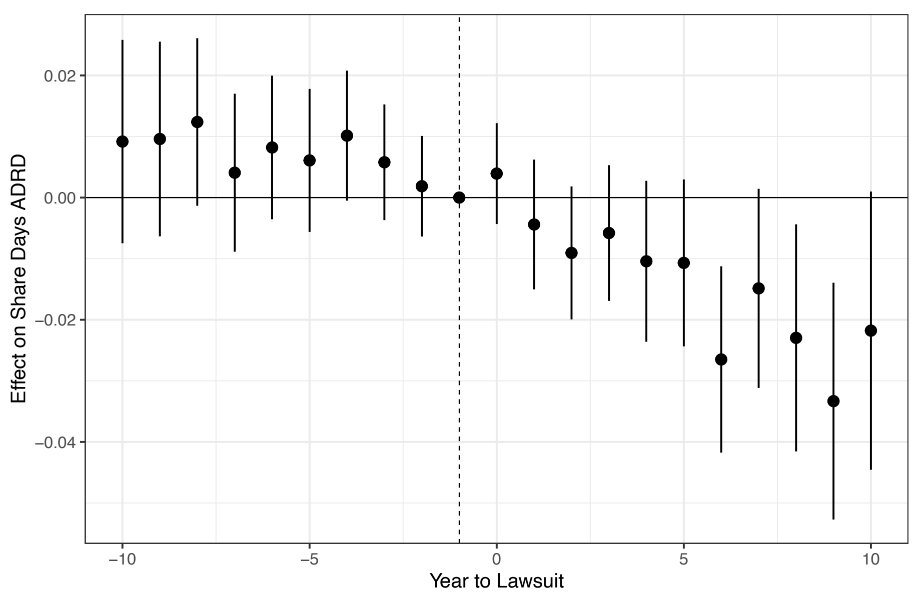
Notes: These figures show more outcomes of the event study described in equation (5) and presented in Figure 3. Specifically, the figures show the dynamic effects of a lawsuit in year 0 on the average length of stay for admissions (Panel A) and on the share live discharged (Panel B), measured relative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

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

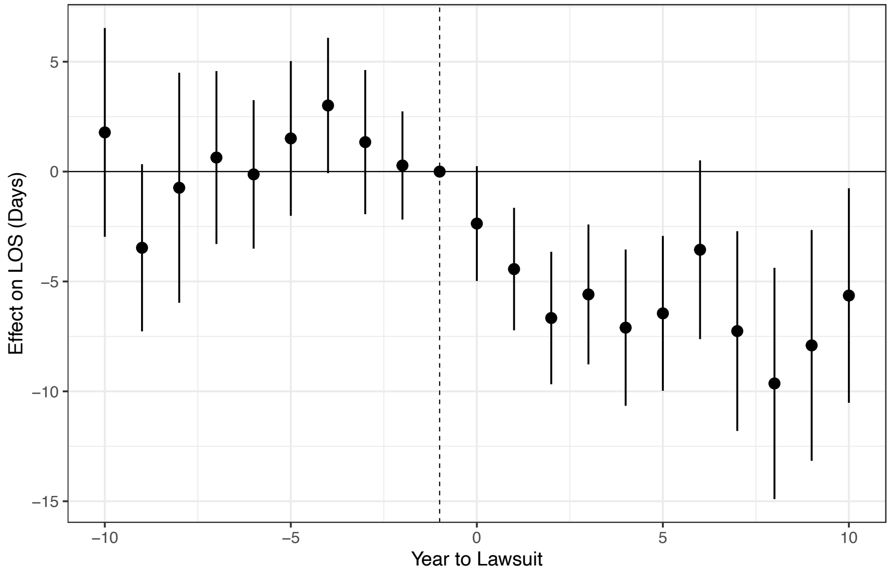
A9.A: Stays Above 180 Days



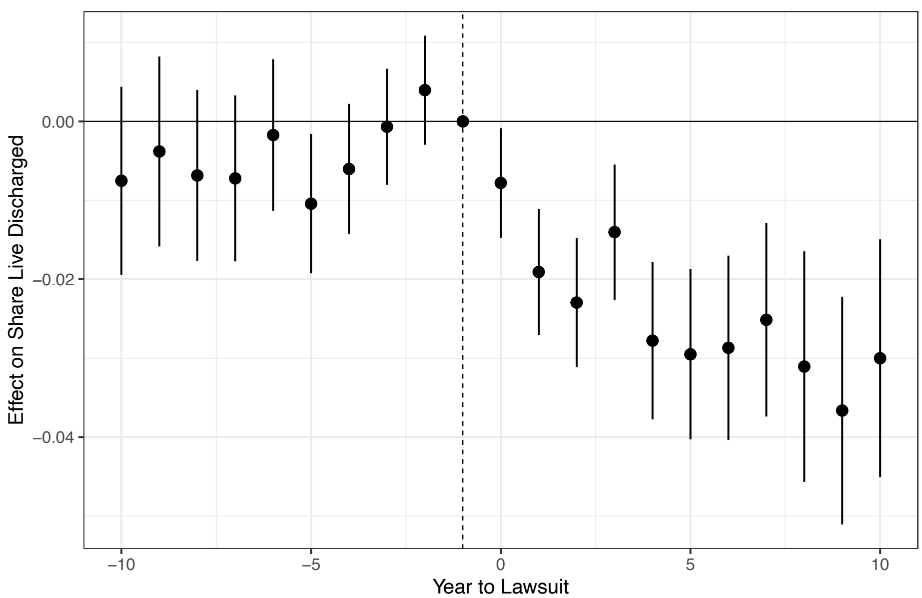
A9.B: Share of ADRD Patient-Days



A9.C: Average Length of Stay

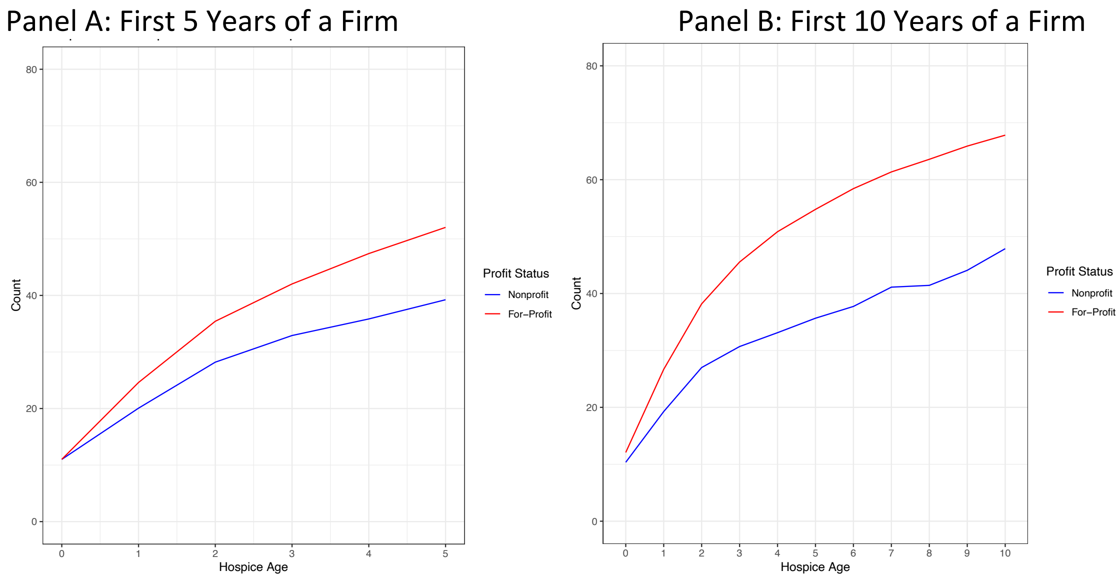


A9.D: Share Live Discharged



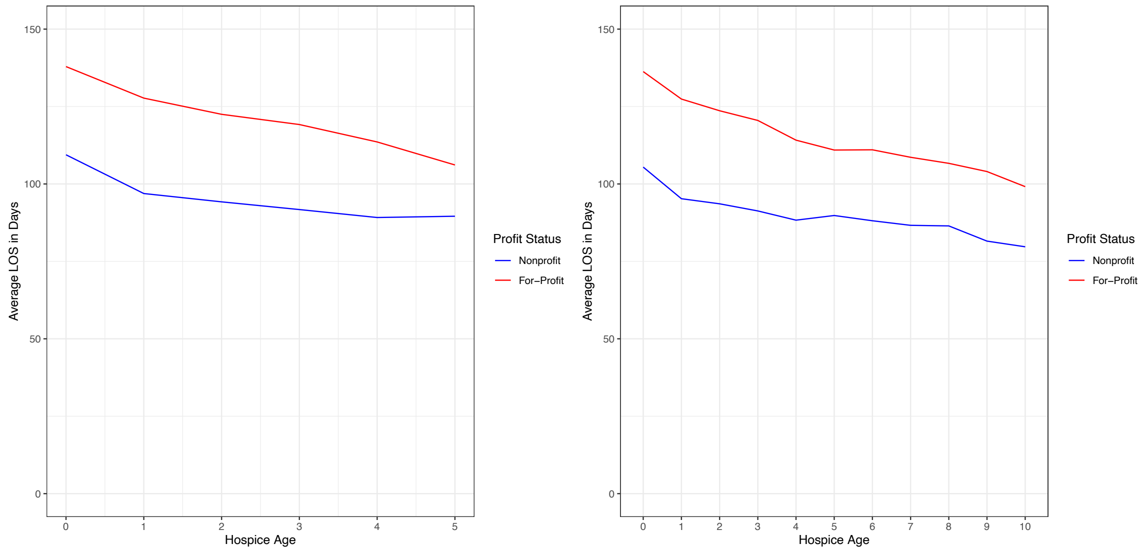
*Note*s: These figures show alternative specifications of the event study described in equation (5) and presented in Figures 3 and A8, using the estimator proposed in Sun and Abraham (2021). Panel A shows the effect on hospice stays over 180 days; panel B shows the effect on the share of days from patients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

Figure A10: Hospice Census by Profit Status and Firm Age



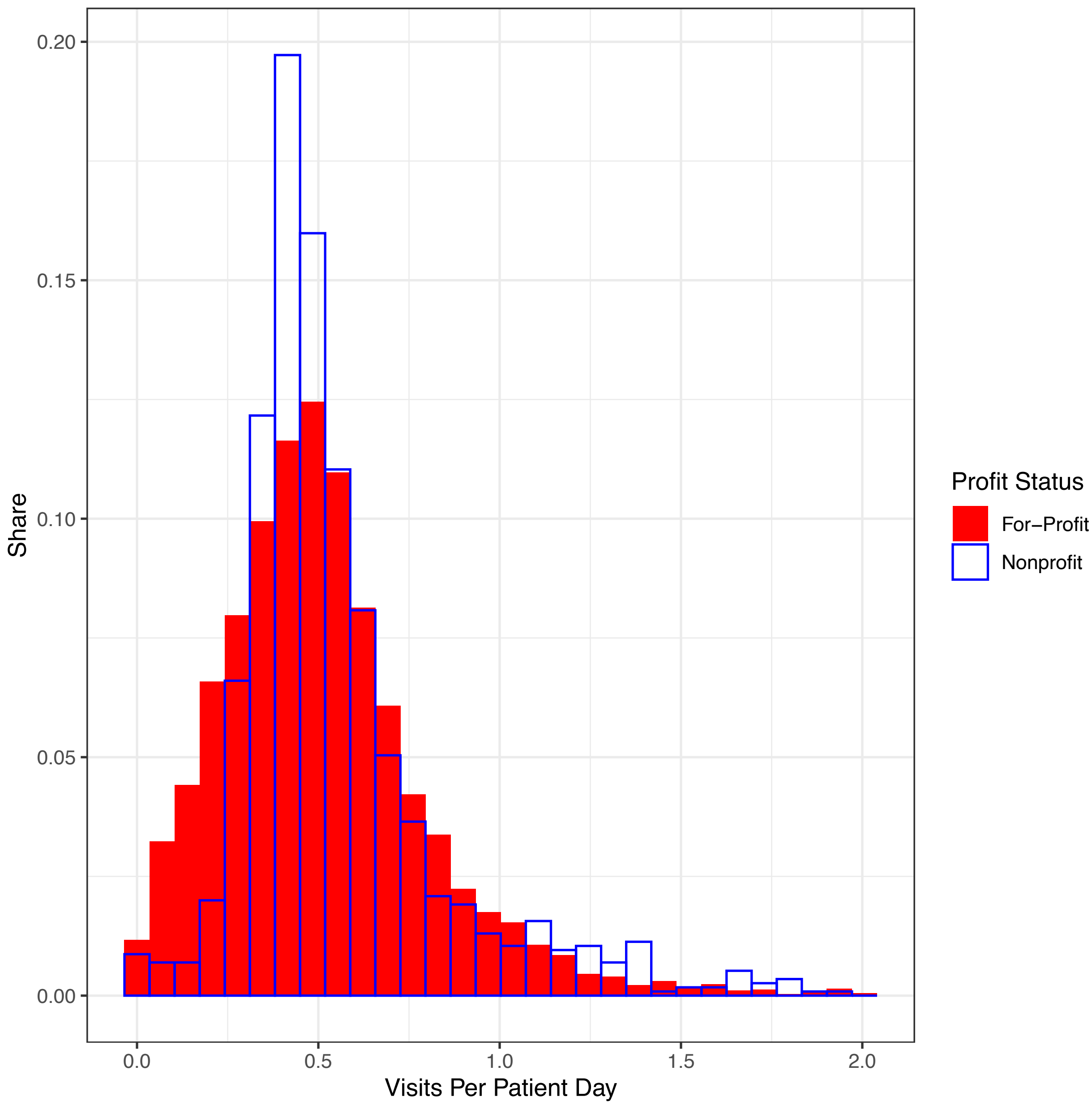
Notes: The figure shows the average monthly hospice census over years 0 through 5 (Panel A, Left) and years 0 through 10 (Panel B, right). We observe each hospice firm in our data by profit status at opening and condition the mean on hospices remaining open (i.e. having nonzero patients). Both types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

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



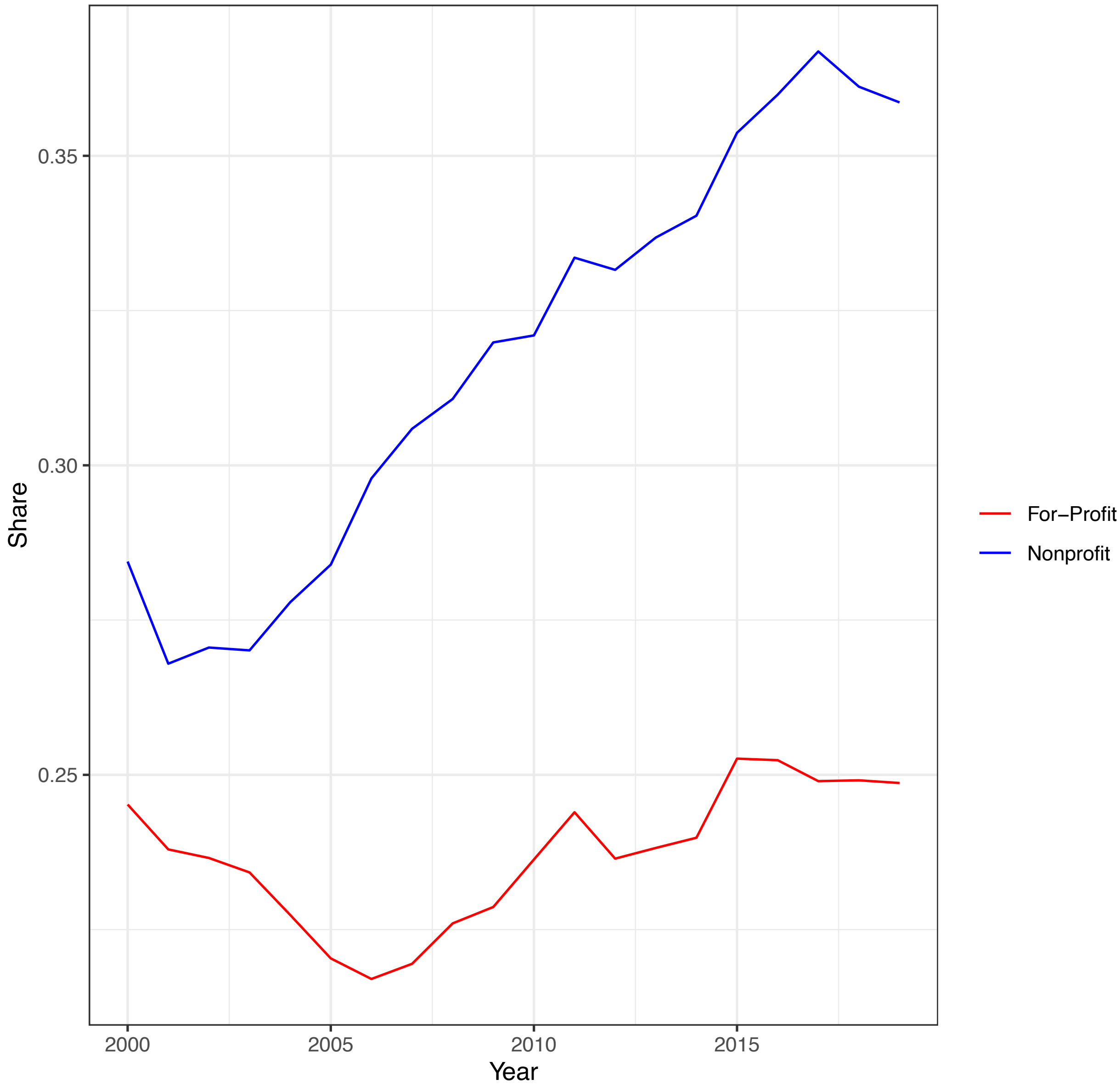
Notes: The figure shows the hospice average length of stay over the first 5 years (Panel A, Left) and 10 years (Panel B, right) we observe each hospice firm in our data, by profit status. Panel A uses data from 2000 to 2014, and Panel B uses data from 2000 to 2009. Both types of firms show similar slight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

Figure A12: Visits by Firm Profit Status by Patient Day



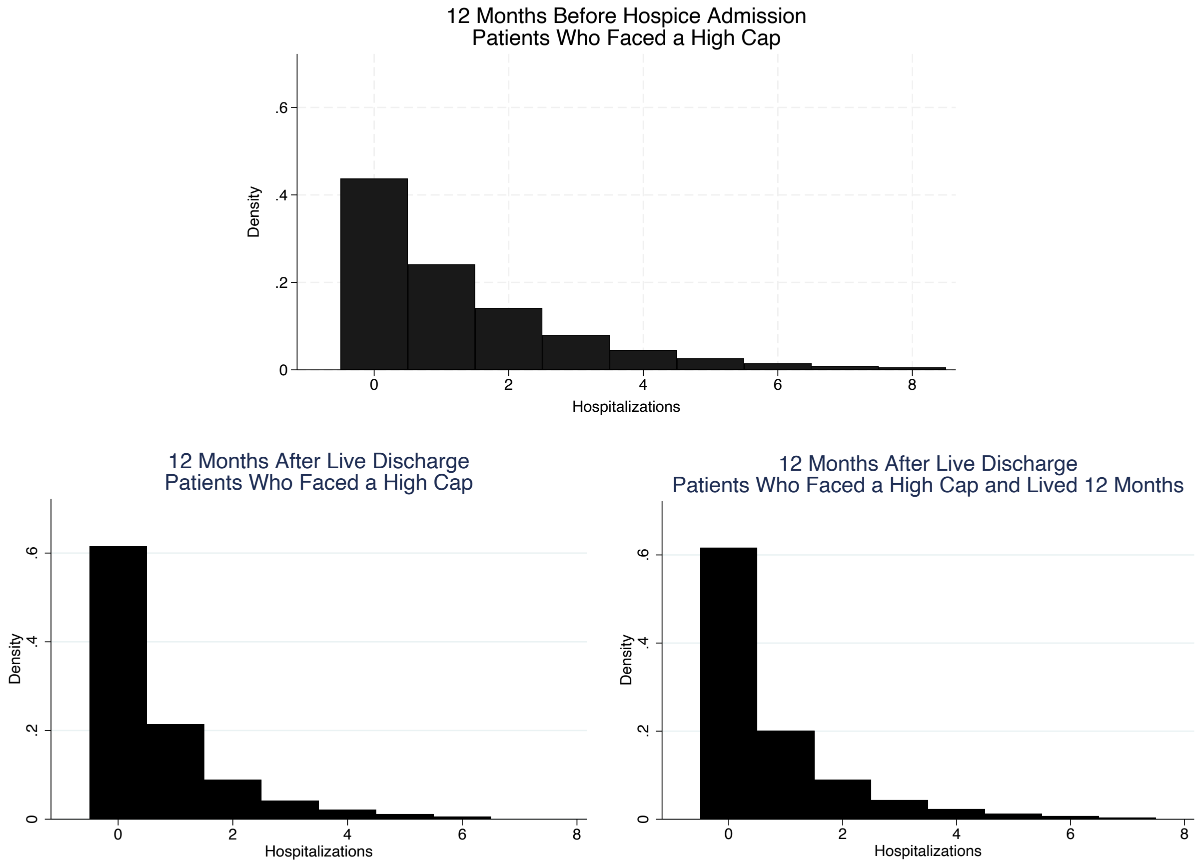
Notes: This figure plots the hospice-year distribution of number of visits, computed from California state data, divided by the mean stay length among for-profit and non-profit hospice patients, computed from the Medicare claims from California hospices from 2002-2019. For-profit hospices show more variability,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

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



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

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



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

Table A1: Predictors of Hospice Use

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

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

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

Table A2: First Stage Estimates

Dependent Variables:	FP Hospice Admission	Any Hospice
Model:	(1)	(2)
Variables		
Distance to FP Hospice (10mi)	-0.0099***	-0.0057***
	(0.0004)	(0.0003)
Distance to NP Hospice (10mi)	0.0096***	-0.0003
	(0.0007)	(0.0005)
Fixed-effects		
Demographics Controls	Yes	Yes
Chronic Conditions Controls	Yes	Yes
Zip	Yes	Yes
Diagnosis Year	Yes	Yes
Fit statistics		
Observations	10,856,158	10,856,158
R^2	0.10412	0.09404
Within R^2	0.00078	9.39×10^{-5}
Dependent variable mean	0.14677	0.33009

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

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

Table A3: Distance IV Complier Characteristics

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

N=10,856,154

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

Table A4: Concurrent Hospice and Hospitalization Discharges

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

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

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

Table A5: Omega Statistic by Demographic and Chronic Condition Group

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

N=10,856,154

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table A8: Covariate Balance and Instrumental Validity

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

N = 10856154

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

Table A9: IV Validity Tests

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

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

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

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

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

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

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

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

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

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

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

Table A11: Predictability of Patient Longevity

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

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

Table A12: Descriptive Statistics on Hospice Anti-Fraud Lawsuits

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

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

Table A13: Impact of Anti-Fraud Lawsuits

A13.A: Effects on Hospice Patient Composition

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

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

A13.B: Effects by Pre-Hospice Spending Quintile

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

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

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

Table A14: Physician Specialty of ADRD Hospice Patient Referrer

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

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

Table A15: Specialist Usage Among Live Discharged Patients

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

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