Financial Incentives in End-of-Life Care: Evidence from Hospice Providers

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Abstract

End-of-life expenditures account for 25% of all Medicare spending. Over the past few decades, hospice care, which provides palliative rather than curative care at the end of life, has increased in prominence, being used by 47% of Medicare decedents in 2021. The simultaneous increase in hospice expenditures during this period has resulted in several policy attempts to rein in spending. In this paper, I study hospice provider responses to a 2016 reform which decreased the profitability of long stays relative to short stays. Using variation in exposure to the policy and a difference-in-differences strategy, I find that the policy resulted in a 9% reduction in the share of long stays for more exposed hospices. The margins of response are heterogeneous across hospice type, with nonprofit hospices exhibiting larger responses through the admissions margin and for-profit hospices exhibiting larger responses through the discharge margin. At the patient level, in a sample of Medicare beneficiaries diagnosed with Alzheimer's/dementia, I document a 7% reduction in hospice admission for those made less profitable by the policy, suggesting meaningful impacts on access to hospice care.

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I Introduction

Between 2000-2010, the share of Medicare decedents using hospice services in their final year of life increased from 23% to 43% (Griffin, Cubanski, Neuman, Jankiewicz, Rousseau, et al., 2016). Hospice care, which provides symptom and quality of life management rather than curative treatment for patients with a 6-month prognosis, has been promoted as a cost-saving alternative to intensive end-of-life treatments (Kelley, Deb, Du, Aldridge Carlson, and Morrison, 2013; Obermeyer, Makar, Abujaber, Dominici, Block, and Cutler, 2014; Taylor Jr, Ostermann, Van Houtven, Tulsky, and Steinhauser, 2007). However, between 2000-2010, average spending per hospice beneficiary surged, rising from $6,000 to $13,000. This increase in spending was largely driven by increases in average lengths of stay, stemming from shifts in the composition of hospice patients.[1] At its inception, hospice was largely limited to patients with a terminal cancer diagnosis (Buck, 2011). Between 2000-2010, the share of patients in hospice with a primary diagnosis of "neoplasm" (i.e., cancer) decreased from 50% to 30%, while the share of patients with a primary diagnosis of "mental disorder" increased from 5% to 10% (Aldridge, Canavan, Cherlin, and Bradley, 2015). Disorders that are mental or cognitive in nature, such as Alzheimer's, dementia, and Parkinson's, are more difficult to prognosticate and tend to involve the longest lengths of stay (nhp, 2022; Downar, Goldman, Pinto, Englesakis, and Adhikari, 2017). These long lengths of stay have implications for profit margins - as hospices were traditionaly reimbursed at a non-risk adjusted per-diem rate, longer stays tended to be more profitable than shorter ones. This shift in patient composition, along with the increase in average lengths of stay, has raised concerns that hospice care has become poorly targeted. In other words, there is concern that hospice providers are admitting patients who may not be truly appropriate for hospice care.

In this paper, I study hospice responses to the first major reform to reimbursement rates that was meant to address this potential mistargeting of care. Specifically, the reform shifted hospice payments from a flat per-diem rate to a 2-tiered rate based on length of

[1] In 2000, the average length of stay in hospice was 48 days. By 2010, this was 70 days.

stay, where days 1-60 were paid a higher rate and days 61 on were paid a lower rate. This made long stays relatively less profitable than short stays, in stark contrast to the pre-policy status quo. I begin by quantifying hospice responses to the policy. To do this, I conduct a hospice-level analysis that exploits variation in a hospice's exposure to the policy stemming from its pre-policy patient mix. Specifically, using a sample of hospice patients observed prior to the policy, I apply pre-policy and post-policy payment rates to each patient, and then take difference between the two. I then average these differences at the hospice level, which represents the average difference in reimbursements a hospice would have experienced had it kept it's patient mixed fixed into the post-policy periods. In other words, this is the windfall a hospice would have experienced had it kept its patient mix unaltered. I use this as a measure of a hospice's exposure to the policy in a continuous difference-in-differences empirical strategy. I find that a 1 standard deviation (SD) increase in a hospice's exposure to the policy (equivalent to $510 per patient) results in a 3% decrease in the share of stays greater than 60 days and a 9% decrease in the share of stays greater than 180 days. Reductions in length of stay can be achieved through patient selection (i.e., admitting patients with lower expected lengths of stay) or live discharge (i.e., discharging patients who have long lengths of stay). I examine each mechanism separately. I find that on average, a 1SD increase in hospice exposure results in a 2% reduction in predicted length of stay among admitted patients and a 4% increase in live discharge rates. Heterogeneity analysis suggests that hospices do not necessarily adjust along both margins. Rather, the largest changes in patient composition are driven by nonprofit hospices, while the effects on live discharge are driven by for-profit hospices. This is consistent with the idea that nonprofit hospices are not only older and thus better able to predict length of stay on admission, but also have a larger pre-policy referring base of short-staying patient types, which could allow them to flexibly shift admission patterns. This is also consistent with existing models of nonprofit behavior, which imply that nonprofits place higher weight on quality and would be less likely to pursue live discharges, which are known to be burdensome for both the patient and their

family (Luth, Brennan, Hurley, Phongtankuel, Prigerson, Ryvicker, Shao, and Zhang, 2024; Wladkowski, 2017).

In the hospice level analysis, changes in patient mix could be completely driven by reshuffling patients across hospices without representing a true decrease in access for long-staying patient types. To test if this policy resulted in absolute reductions in access to care, I also conduct a patient-level analysis on a sample of Alzheimer's/dementia (ADRD) patients, a group that is of particular concern for policymakers aiming to improve the targeting of hospice care (Gruber, Howard, Leder-Luis, and Caputi, 2023). For each patient in my sample, I use baseline health and demographic information to predict their length of stay in hospice. I then apply the pre-policy and post-policy reimbursement rates to this predicted length of stay and take the difference. This measure, which captures the change in predicted profitability as a result of the policy, represents the patient-level exposure to the policy. I combine this source of variation with a difference-in-differences strategy at the patient level to test for changes in the probability of admission. I find that a 1SD increase in patient exposure (roughly $100) results in a 7% decrease in the probability of admission, suggesting that this policy decreased accesses to hospice care for certain patients. Given that utilization of hospice care has been shown to differ by gender and race/ethnicity (Cohen, 2008; Wong and Phillips, 2023), I test whether the effects on hospice access that I estimate also differ by gender, race, or socioeconomic status. I find no differences by demographic groups, suggesting that across patient subpopulations, hospices consistently responded to changes in predicted profitability that were driven by predictable variation in health status.

This paper contributes to the literature on provider responses to incentives by focusing on a much understudied and increasingly prominent provider in the healthcare market - hospices. A large literature in economics has estimated supply elasticities across a variety of patient and provider settings, including the outpatient setting (Cabral, Carey, and Miller, 2021; Clemens and Gottlieb, 2014; Devlin, 2022), hospitals (Einav, Finkelstein, and Mahoney, 2018; Gross, Sacarny, Shi, and Silver, 2022; Gupta, Howell, Yannelis, and Gupta,

2021), and skilled nursing facilities (Gupta, Howell, Yannelis, and Gupta, 2021). These papers have generally found that healthcare providers are highly responsive to financial incentives. However, literature on hospice responses to incentives is sparse. There are two recent papers in economics that study hospice providers: Coe and Rosenkranz (2023) study the effect of an aggregate revenue cap on patient churn and discharge rates. Gruber, Howard, Leder-Luis, and Caputi (2023) estimate the causal effect of for-profit hospices on healthcare expenditures. However, neither of these papers estimate an elasticity of hospice behavior with respect to reimbursement rates. Closer in spirit to this paper, (Gianattasio, Moghtaderi, Lupu, Prather, and Power, 2022) and (Gianattasio, Power, Lupu, Prather, and Moghtaderi, 2023) study hospice responses to a combination of policy changes, including the 2-tier reform. (Gianattasio, Moghtaderi, Lupu, Prather, and Power, 2022) studies changes in ADRD enrollment rates, while (Gianattasio, Power, Lupu, Prather, and Moghtaderi, 2023) studies length of stay and live discharge. Both studies use a trend-break analysis that compares slopes pre vs. post policy and are thus limited in their ability to make causal statements. Thus, to my knowledge, this is the first paper to document the causal effect of changes in reimbursement rates on hospice behavior.

Contrasting physicians and hospitals with hospice providers is of interest, as hospice providers face unique institutional barriers to changing their behavior relative to other healthcare providers. For one, at the time of admission, a hospice must attempt to predict a patient's prognosis to estimate length of stay, a task that is prone to error even with the most sophisticated models (Einav, Finkelstein, Mullainathan, and Obermeyer, 2018). Secondly, unlike a hospital, a hospice is unable to discharge patients with full flexibility, given fixed re-certification schedules and CMS regulatory scrutiny. These barriers make it ex-ante unclear whether one would expect a hospice provider to respond to financial incentives in the same manner as other healthcare providers. Understanding the magnitude of hospice responses to incentives is thus crucial in designing optimal hospice payment policies.

Secondly, this paper also contributes to the literature on the high end-of-life costs in the United States, of central concern for policymakers. Existing work has found that increasing take-up of advanced care planning (Chen and Li, 2024) and palliative care (Brumley, Enguidanos, Jamison, Seitz, Morgenstern, Saito, McIlwane, Hillary, and Gonzalez, 2007) are promising approaches to curbing end-of-life costs. Hospice care, which provides palliative care and is often a byproduct of advanced care planning, has been cited as a solution to high end-of-life costs and has been shown to be cost-reducing relative to alternative aggressive end of life treatments (Gruber, Howard, Leder-Luis, and Caputi, 2023). However, rising per-patient hospice costs along with increased hospice utilization has spurred an interest in reducing costs *within* hospice by improving the targeting of hospice care. This paper finds that a reimbursement structure which more closely aligns revenues with costs can be an effective tool to improve the targeting of hospice care.

The paper proceeds as follows. Section 2 discusses the institutional background on hospice care in the U.S., Section 3 discusses the data and samples, Section 4 presents a motivating framework, Section 5 presents an empirical framework, Section 6 presents the results, and Section 7 concludes.

II Institutional Background

Hospice Care in the U.S.

Hospice provides palliative care for patients at the end of their life and is largely provided in the community setting.[2] The goal of hospice is to provide an alternative to aggressive end-of-life treatments that focuses on palliation and quality of life.[3] Hospice care can be provided in a variety of settings, but the majority is provided in a patient's home. Services provided

[2]Palliative care focuses on improving quality of life though symptom alleviation rather than treating the underlying illness.

[3]These alternative end-of-life treatments include those provided at acute inpatient hospitals and skilled nursing facilities.

include visits from hospice staff (e.g., skilled nurses and home health aides), medication for symptom management, grief counseling, and short term inpatient respite care. There are four levels of hospice care: routine home care, continuous home care, inpatient respite care, and general inpatient care. Routine home care is the most commonly provided type of care, representing 98-99% of hospice care days (nhp, 2022).

The Medicare hospice benefit, established in 1982, covers hospice services for patients with a 6-month prognosis. In order to qualify for hospice care under the Medicare benefit, a patient is first referred to hospice care. Patients can refer themselves or be referred by a provider, such as a primary care physician or their nursing home provider. In order for the patient to qualify for admission to hospice, both the patient's physician and the hospice medical director must conduct an evaluation and certify that the patient has a 6-month (or less) prognosis. The Center for Medicare and Medicaid Services (CMS) provides eligibility criteria through Local Coverage Determinations (LCDs), which list the criteria that CMS instructs its administrative contractors to use when reviewing hospice claims. They also serve as guidelines for hospice physicians to use when certifying a patient. Failure of a hospice physician to provide sufficient documentation supporting a patient's terminal status can result in denial of the hospice claim. Examples of criteria that physicians are encouraged to consider include: (1) whether the patient meets non-disease specific guidelines for decline in clinical status, (2) whether the patient meets disease-specific guidelines for decline in clinical status and certain baseline guidelines, and (3) the presence of comorbidities. The level of documentation a hospice physician is expected to provide for a patient differs by primary diagnosis. For example, a patient with a primary diagnosis of lung cancer may require less documentation to prove terminal status compared to a patient with a primary diagnosis of Parkinson's (CMS, 2015).

Once the patient is enrolled in hospice, Medicare covers two 90-day periods, followed by an unlimited number of 60 days periods. At the end of each period, the hospice medical director must meet face-to-face with the patient and re-certify that the patient continues

to satisfy the 6-month prognosis criterion. If the director determines that the patient's condition has improved and is no longer terminal, the patient can be discharged.[4] However, in hospice care, unlike in other institutional settings, discharges can only be executed under specific criteria: (1) the patient dies (2) the patient revokes hospice care and returns to curative treatment (3) the patient moves location or (4) the patient is deemed no longer terminal (i.e., a live discharge). Live discharges have been shown to be burdensome for both the patient and family (Luth, Brennan, Hurley, Phongtankuel, Prigerson, Ryvicker, Shao, and Zhang, 2024; Wladkowski, 2017) and is a component of the 2023 Hospice Quality Index (Allison Muma, 2022).

Policy Change

Since the introduction of the Medicare hospice benefit, hospices were paid for routine home care (RHC), representing 98-99% of covered days, at a flat per-diem rate.[5] This rate was not adjusted for diagnosis or length of stay. However, several studies have shown that though reimbursements are flat across a patient's length of stay, costs of care provision are not. Rather, costs follow a U-shaped curve, with costs being highest during the first few days of admission and during the last few days before death (MedPAC, 2006; Sheingold, Bogasky, and Stearns, 2015). Thus, patients with longer lengths of stay, for whom the flat portion of the U-curve is longer, are profitable for the hospice.

To better align costs and revenue, in 2016, CMS introduced a two-tiered payment structure in which RHC days 1-60 were paid a higher rate of $187.54 and days 61 on were paid a lower rate of $145.14. I graphically depict the implications of this policy in panels A and B of Figure 1. Panel A shows the per-diem rates by length of stay, separately, for the years 2015 and 2016. Panel B shows the difference in post-policy and pre-policy revenue as a function of length of stay. Note that due to the non-linearity in the payment structure, the

[4]Note that this can occur if the patient's condition improves on its own or if the condition does not decline as rapidly as initially expected.

[5]In fiscal year 2015, this was $159.34.

change in revenue is positive and increasing up to day 61, positive and decreasing between days 61 and day 179, and negative and decreasing beginning on day 180. This reflects the policy's goal of improving targeting to patients with a 6 month (180 day) prognosis. The policy was proposed in May 2015, announced in August 2015, and implemented in January 2016. Patients were grandfathered in, meaning that patients already on hospice in January 2016 were paid based on their previous length of stay, rather than having their clock reset. For patients who had multiple hospice stays, the number of days followed the patient, as long as the break between hospice stays was less than 60 days. For example, a patient who was discharged from a hospice after 60 days, returned home for 10 days, and then was re-admitted to the same or different hospice would be reimbursed at the lower rate throughout their second hospice stay. This reform represented the most consequential change to hospice payment policy since the introduction of the hospice benefit.

III Conceptual Framework

The change in revenue that a hospice experienced as a result of the policy can be decomposed into two parts: (a) the effect coming from the change in patient mix, keeping payment rates constant and (b): the effect of the change in payment rates, keeping patient mix constant. To illustrate this for, let t index time relative to the reform ($t = 0$ for periods before the reform and $t = 1$ for periods after the reform), and let j index a firm. I let $m_{j,t}$ represent firm j's patient length-of-stay mix at time t. Specificaly $m_{j,t,\leq 60}$ is the number of patient-days that are less than 60 days and $m_{j,t,>60}$ is the number of patient-days that are greater than 60 days. I let p_t denote the pricing regime at time t, with $p_{t,\leq 60}$ being the price per patient-day for days less than 60 days and $p_{t,>60}$ being the price per patient-day for days greater than 60 days.

Revenues are captured by:

$$R_{j,t}(p_t, m_{j,t}) = m_{j,t,\leq 60} \times p_{t,\leq 60} + m_{j,t,>60} \times p_{t,>60}$$

Before the policy change:

$$R_{j,0}(p_0, m_{j,0}) = m_{j,0,\leq 60} \times p_{0,\leq 60} + m_{j,0,>60} \times p_{0,>60}$$

where $p_{0,\leq 60} = p_{0,>60}$

After the policy change:

$$R_{j,1}(p_1, m_{j,1}) = m_{j,1,\leq 60} \times p_{1,\leq 60} + m_{j,1,>60} \times p_{1,>60}$$

where $p_{1,\leq 60} > p_{1,>60}$

Change in Revenue:

$$R_{j,1}(p_1, m_{j,1}) - R_{j,0}(p_0, m_{j,0})$$

A counterfactual - new prices, old mix:

$$R_{j,c}(p_1, m_{j,0}) = m_{j,0,\leq 60} \times p_{1,\leq 60} + m_{j,0,>60} \times p_{1,>60}$$

Decomposed change (subtract and add $R_{j,c}(p_1, m_{j,0})$):

$$\overbrace{[R_{j,1}(p_1, m_{j,1}) - R_{j,c}(p_1, m_{j,0})]}^{\text{behavioral effect}} + \overbrace{[R_{j,c}(p_1, m_{j,0}) - R_{j,0}(p_0, m_{j,0})]}^{\text{mechanical effect}}$$

The second term, denoted the mechanical effect, measures the change in revenues coming from the change in pricing only, holding patient mix constant at pre-reform levels. The first term, denoted the behavioral effect, measures the change in revenues coming from the change in patient mix only, holding the pricing formula fixed at the post-reform schedule. Understanding the magnitude of the behavioral effect is a key input for policymakers designing hospice reimbursement policies, and is the focus of the remainder of this paper.

IV Data

I use 100% Medicare claims from the Hospice File to construct a sample of hospice beneficiaries between 2010-2019. From the hospice claims, I observe date of admission and discharge for each patient. I also observe the type of discharge (e.g, discharged alive or discharged dead). Finally, I observe services rendered at the daily level (e.g., skilled nursing visits and home health visits) and Medicare reimbursements at the monthly level. I supplement the claims data with provider of service (POS) files from 2012-2019. This provides information on the ownership type of the hospice (for profit vs. nonprofit) and the year of hospice entry.

For the purposes of constructing predictions of patient length of stay, I use diagnosis, utilization, and enrollment data from the Medicare claims files. To obtain diagnosis information that is independent of hospice reporting behavior, I use the 100% Medicare Chronic Condition Warehouse (CCW) files, which provides both a flag that indicates whether the beneficiary met the criteria for each of 62 chronic conditions in a given year and the exact date that the beneficiary originally met the criteria.[6] Finally, using the 100% Master Beneficiary Summary File and the 100% Medicare Cost and Use files, I obtain patient demographics (e.g, race, gender, zip code) and yearly healthcare utilization across settings.

How do these variables compare to the guidelines that CMS instructs hospice physicians to use when making their initial certifications? Though claims data does not provide information on the detailed clinical indications that are listed in CMS hospice eligibility guidelines (e.g., evidence of rapid weight loss, lab measures, and measures of functional status), it does allow me to observe inpatient and emergency department utilization, a full set of co-morbidities, and proxies for ability to perform activities of daily living (ADLs), all of which are also used in the certification process.[7]

[6]The criteria for the flags vary by condition. See https://www2.ccwdata.org/web/guest/condition-categories-chronic for a full list of the chronic conditions and their definitions.

[7]Faurot, Jonsson Funk, Pate, Brookhart, Patrick, Hanson, Castillo, and Stürmer (2015) show that use of durable medical equipment is a strong predictor of performance on tests that measure ADL.

IV.I Hospice Sample

For the hospice-level analysis sample, I define a "stay" as a unique combination of provider CMS Certification Number (CCN), patient ID, and admission date for the years 2014-2019. To deal with confusion during early implementation regarding how length of stay for patients who were discharged and then re-admitted would be determined, I limit the sample to the first hospice stay for each patient. I then drop stays where the admission date is later than the discharge date. Finally, I drop all beneficiaries covered under Medicare Part C, as these patients do not have reliable diagnosis or healthcare utilization records.[8] This leaves me with 4,056 unique hospice providers. Table 1 presents summary statistics of the full sample. The majority of hospices (64%) are for-profit. Average length of stay is 113 days, while 19% of stays are longer than 180 days.

IV.II Patient Sample

For the patient-level analysis, I construct a monthly panel of all Medicare beneficiaries with an active ADRD diagnosis in 2015. I choose ADRD because it represents the longest-staying primary diagnosis in hospice and is a policy-relevant group within hospice care. Using baseline data from hospice claims for 2010-2013, I identify the primary diagnosis (as listed on hospice claims) associated with the longest lengths of stay - ICD 331.0-Alzheimer's disease, unspecified.[9] The primary diagnosis of ICD 331.0 represents 5% of all hospice patients between 2010-2013, but represents 11% of hospice patients with length-of-stay greater than

[8]Though this represents a non-trivial drop in the sample size, it should not affect the external validity of the results. This is because when Medicare Part C patients enroll in hospice, Medicare fee-for-service pays for all costs associated with their terminal illness. Thus, from the perspective of the hospice provider, the incentives are the same in both samples.

[9]Note that prior to 2014, hospices were allowed to list ICD codes associated with "debility" or "failure to thrive" as a primary diagnosis. These are unspecific diagnoses that do not map to chronic conditions. Beginning in October 2014, hospices were no longer allowed to list these as primary diagnoses. For patients with these diagnoses listed as a primary diagnosis, I use their secondary diagnosis, if any is recorded.

60 days.[10] I then map this ICD code to its counterpart in the chronic condition files - "Alzheimer's and related senile dementia".

I place certain restrictions on the patient sample. Firstly, I keep only those Medicare beneficiaries with an active mid-year chronic condition flag for Alzheimer's and related senile dementia in 2015. As in the hospice analysis, I drop all patients covered under Medicare Part C. Additionally, I impose the restriction that the patient must be observed in the data in 2014, which is the year from which I pull data on demographics, other end-of-year condition flags, and overall healthcare utilization. I then follow this sample of beneficiaries from January 2015 to December 2019. I refer to this sample as the "ADRD sample" for the remainder of this paper. Table 2 presents summary statistics of the ADRD sample compared to the average Medicare beneficiary observed in 2015. On average, ADRD patients are older, more likely to be dually-eligible for Medicaid, and of poorer health status.

V Empirical Framework

V.I Hospice Level Analysis

The 2016 policy applied nationally to all hospice providers. Thus, there are no pre-determined "treated" and "control" groups. My empirical strategy exploits the fact that certain types of hospices were more likely to be affected by the policy, based on their pre-policy patient mix. For example, a hospice with a high share of patients staying longer than 180 days would experience the largest negative shocks to total reimbursement if they maintained the same patient mix, while a hospice with a high share of patients staying exactly 60 days would experience the largest windfalls if they maintained the same patient mix. To formalize this into a hospice level measure of exposure, I take the following approach. For each patient in each hospice observed in 2010-2013, I calculate the patient's total length of stay in a given

[10] These values refer the share of patients with a primary diagnosis of ICD 331.0, which is just one of many possible diagnosis codes related to ADRD.

month.[11] Next, I calculate the actual payment a hospice received using the statutory payment rates for 2015. Then, using the 2016 2-tiered formula, I calculate the payment that the hospice *would have received for that patient*, had the patient been observed in 2016 with the same length of stay. I do this in a method that accurately represents what the hospice would have received for a given patient in a month, taking into account the patient's cumulative length of stay up until the month in question. I call this the "predicted payment" for that patient. The difference between the predicted and actual payment is the patient-specific "exposure". I then average these patient-level exposures at the hospice level and take the negative of that value-such that a larger value of exposure indicates a smaller windfall - to obtain a continuous measure of treatment for each hospice.[12] [13] Finally, I winsorize outliers at the 1st and 99th percentiles.

I plot the distribution of "exposure" for all hospices and seperately by for-profit status in panels A and B of Figure 2. The average shock size is small- -$65/patient, suggesting that the average hospice would have received a small positive windfall per patient. However, there is considerable variation. The standard deviation is $510/patient, roughly 5% percent of Medicare spending per hospice patient in 2015. Note that the distribution of shock size is both wider and more skewed right for for-profit hospices relative to nonprofit hospices. In Figure 3, I present correlations between baseline hospice covariates and exposure, where all covariates other than nonprofit status are standardized. In panel A, I present coefficients from separate regressions which suggest that more exposed hospices are younger and have a higher share of long stays, live discharges and transfers, and black, female, and dual eligible patients. They are also less likely to be nonprofit. In panel B, I present coefficients from a pooled regression of all baseline covariates. Once accounting for the share of long

[11]The choice of years in which I calculate exposure is driven by mean reversion concerns. Treatment effects estimated using exposure immediately prior to the policy could be driven at least partially by mean reversion. To address this, I calculate exposure using claims from 2010-2013 and begin the analysis sample in 2014.

[12]Note that this method applies post-policy payment rates to the pre-policy patient mix and thus is exactly the mechanical effect from equation III.

[13]Because hospices submit claims (and thus are paid) at a monthly frequency, I use a monthly panel to calculate monthly "exposure" and average these shocks across the years 2010-2013

stays, which remains highly predictive, many covariates are no longer predictive of hospice exposure. Interestingly, nonprofit status is now *positively* correlated with exposure status. This is likely driven by the distribution of length of stay in non-profit hospices. Conditional on the share of very long-stays (> 180 days), nonprofits have a larger share of very short stays (<7 days) while for-profits have a larger share of stays between 60 and 180 days. Given the non-linearity of the reimbursement structure (Panel B of Figure 1), this would result in nonprofits having larger exposure to the policy, conditional on the share of long stays.

Using this exposure measure as my treatment variable, I then run a continuous event-study difference-in-differences analysis using the following specification :

$$y_{ht} = \alpha_h + \alpha_t + \sum_{r \neq -1, r=-5}^{r=18} \beta_r \text{ x } I_r \text{ x exposure}_h + \epsilon_{h,t} \tag{1}$$

where y_{ht} is outcome y for hospice h in time t. α_h and α_t are hospice and quarter fixed effects, respectively. I_r represents quarters relative to the quarter of initial policy proposal (2015Q2) and $exposure_h$ is the continuous measure of exposure, measured in standard deviations. Standard errors are clustered at the hospice level. The identifying assumption is that in the absence of the policy, more and less exposed hospices would follow parallel trends in outcomes. Under this assumption, β_r, for $r > 0$, represents the causal impact of a 1SD increase in exposure on the outcome of interest, r quarters after policy announcement.

To estimate average effects of a 1SD increase in per-patient exposure, I run a pre-post version of equation 1 using the following specification, while still allowing for dynamic effects:

$$y_{ht} = \alpha_h + \alpha_t + \beta_1 \text{post}_{0,8} \times \text{exposure}_h + \beta_2 \text{post}_{9,18} \times \text{exposure}_h + \epsilon_{h,t} \tag{2}$$

where $post_{0,8}$ is a dummy which identifies relative quarters 0-8 and $post_{9,18}$ identifies relative quarters 9-18.

V.I.1 Defining Patient Type

To construct a measure of patient composition, I use hospice claims from 2010-2013 (prior to the analysis period) to predict length of stay using chronic condition information, healthcare utilization, and demographics, all measured in the year prior to admission. I include hospice fixed effects to allow for the possibility that each hospice has a different production function, and that a hospice uses its own data to predict length of stay for a given patient.

$$y_{ih} = \alpha_h + \beta \text{diagnoses}_{ih} + \gamma \text{utilization}_{ih} + \mu \text{demographics}_{ih} + \epsilon_{i,h} \tag{3}$$

where y_{ih} is the total length of stay for patient i in hospice h, α_h are hospice fixed effects, and *diagnoses* is a vector of chronic condition flags for each of the CCW 62 chronic conditions. *Utilization* is a vector of healthcare utilization in the prior year.[14] Finally, *demographics* includes a dummy for female, a dummy indicating whether the patient was dually eligible for Medicare and Medicaid, the original reason for entitlement, a dummy for end-stage renal disease, a nonwhite dummy, age dummies (measured at admission), and zip code fixed effects. I then apply these predictions to the analysis sample, winsorizing the predictions at the 1st and 99th percentiles. Highlighting the complexity of predicting mortality, the R-squared on these predictions is low, at 30%. Though the predictive power may be increased with the addition of more granular data and a more complex specification, the goal of this exercise is to approximate the predictions a hospice is able to make with the information they observe for any given patient.

V.II Patient-Level Analysis

To define treatment for the patient-level analysis, I run the same prediction model for length of stay as detailed in section V.I.1, with certain adjustments. Firstly, I do not include hospice fixed effects. Note that in the hospice level analysis, all patients in the sample are

[14] This includes utilization (# of visits), total Medicare spending, and patient spending across different healthcare settings.

already enrolled in hospice, allowing me to include hospice fixed effects in the length of stay prediction model. However, in the patient analysis, the sample includes all patients with an ADRD diagnosis, regardless of hospice use. Thus, hospice fixed effects are not feasible in this sample. Secondly, because I will be applying the hospice reimbursement schedule to the predicted length of stay, my predictions must be non-negative. To this end, I apply a poisson specification to account for the count nature of the outcome variable. In Figure 5, I present correlates of the predicted length of stay measure, where the coefficients in panel A come from individual regressions and the coefficients in panel B come from a pooled regression. Note that even after controlling for healthcare utilization, diagnoses remain strongly correlated with predicted length of stay. I then apply these predictions to the analysis sample, such that I observe a predicted length of stay for each patient in my sample. To convert this to dollar values, I apply the 2015 statutory rates to the predicted length of stay to calculate predicted reimbursement under the previous regime, and then apply the 2016 rates to calculate predicted reimbursement under the 2-tier regime. I then calculate the $ change in reimbursement ("exposure") for each patient. take the negative of this so that a larger exposure indicates a *lower* change in profitability as a result of the policy. Figure 6 plots the distribution of exposure for the full sample. Note that, though all values are negative (which would suggest *increased* profitability due to the policy), these values are based on predictions with low predictive power. The identification strategy hinges on *relative* values of exposure (i.e., comparing patients with an exposure of -$100 to patients with an exposure of -$2000) rather than the absolute levels.

I then run a continuous event-study difference-in-differences model using the following specification :

$$y_{it} = \alpha_i + \alpha_t + \sum_{r \neq -1, r=-4}^{r=18} \beta_r \text{ x } I_r \text{ x exposure}_i + \epsilon_{i,t} \tag{4}$$

where y_{it} is outcome y for patient i in time t. α_i and α_t are individual and month fixed effects, respectively. I_r represents months relative to May 2015, the month of initial

policy proposal. $Exposure_i$ measures the predicted $ change in reimbursement obtained from predicted length of stay, measured in standard deviations. Standard errors are clustered at the individual level.

I also estimate average effects using the following specification:

$$y_{it} = \alpha_i + \alpha_t + \beta_1 \text{post}_{0,5} \times \text{exposure}_i + \beta_2 \text{post}_{6,11} \times \text{exposure}_i + \beta_3 \text{post}_{12,18} \times \text{exposure}_i + \epsilon_{h,t} \quad (5)$$

where $post_{0,5}$ is a dummy which identifies relative months 0-5, $post_{6,11}$ identifies relative months 6-11, and $post_{12,18}$ identifies relative months 12-18.

VI Results

VI.I Hospice Analysis

In the following section, I present results for the hospice level analysis which compares outcomes for more vs. less exposed hospices, pre vs. post policy.

Share of Long Stays

I begin by testing whether hospices respond to the policy by changing the share of stays that are longer than 60 days. In Figure 4, I present event study results from equation 1 for the full sample. The estimates suggest that more and less exposed hospices were largely on parallel trends in the quarters prior to the policy announcement. To interpret the effect sizes, I turn to column 1 of Table 2. The longest run estimate of β_2 suggests that a 1SD increase in exposure is associated with a 3% decrease in the share of stays longer than 60 days. In column 2 of table 2, I present results for the share of stays that are longer than 180 days. Note that the change in reimbursement for a given patient is positive for length of stay between 1-179 and only becomes negative beginning on day 180. This is in line with the goal of the policy to improve targeting to patients with a 6-month prognosis. Indeed,

it appears that hospices are more responsive to this higher threshold - a 1SD increase in hospice exposure is associated with a 9% decrease in the share of stays longer than 180 days.

What are the mechanisms through which a hospice could reduce the share of long stays? One margin is patient selection, in which hospices admit fewer patients with long expected lengths of stay. Alternatively, hospices can reduce long stays by discharging patients alive. I explore each of these mechanisms in turn below. Given the low incidence nature of the following outcomes, I present effect sizes in table forms, but include the corresponding event study figures in the Appendix.

Margins of Response

To test whether hospices achieve the reduction in the share of long stays through patient selection mechanisms, I examine average predicted length of stay among admitted patients. Predicted values come from the specification outlined in section V.I.1. This approach allows me to isolate the role of patient selection from other changes in patient composition which could also be achieved through discharge. The estimates in column 1 of Table 3 suggest that a 1SD increase in exposure results in a 2% reduction in predicted length of stay, with effect sizes increasing over time. The results suggest that though the policy did achieve some length of stay reduction through patient composition, the magnitude of effects are small.

In column 2 of Table 3, I move to testing responses along the live discharge margin. Note that in contrast to the pattern found in the patient selection analysis, the effect on live discharge rates attenuates over time. This is consistent with a model in which hospices use the live discharge margin to immediately address a large pre-existing stock of long-staying patients, while the selection of shorter-staying patients is a slower moving response. Taking the shorter-run estimate, I find a 1SD increase in exposure results in a 4% increase in the live discharge rate. This suggests that hospices were responding more strongly through the discharge margin rather than the selection margin, which may reflect the inherent difficulty in predicting patient length of stay at admission.

However, the analysis of the live discharge rate can be difficult to interpret when patient composition is also changing. If the share of long-staying patient types was also decreasing through selection, then hospices may be *less* likely to utilize live discharges. To address this, I next limit the sample to patients who were admitted *prior* to the announcement of the policy. I then run a high frequency monthly analysis where the outcome is the live discharge rate. This allows me to shut down the patient selection channel and isolate the (short-run) effects on discharge rates. In Table 6, I find that similar to the discharge analysis in the full sample, the effects on live discharge dissipate over time in the sample of previously admitted patients. The effect sizes are larger, with a 1SD increase in exposure resulting in a 7% decrease in the live discharge rate. This suggests that the smaller effect size found in the full sample is a result of simultaneous changes in patient composition.

Visit Intensity

Next, I study changes in the intensity of skilled nursing care (minutes per day) as a proxy for costs of care provision. A hospice that is constrained in its ability to respond through patient selection or discharge may respond to the policy by reducing its costs. As shown in Table 7, I find no evidence that hospices decreased the intensity of care provision - rather, I find small, though imprecisely estimated, *positive* effects on skilled nursing minutes per day. This is consistent with the changes in patient composition previously documented. Given that long-staying patients tend to have lower average daily care needs (59 skilled nursing minutes/day for patients staying more than 180 days vs 19 skilled nursing minutes/day for patients staying less than 180 days in 2013), as the share of these long staying patient types decreases, hospices may mechanically be forced to provide higher levels of skilled nursing care pay day.

Heterogeneity by Profit Status

The hospice level outcomes suggest that on average, hospices decrease the share of long stays, using a combination of patient selection and live discharges, with relatively larger responses through the live discharge margin. What types of hospices may pursue one margin more than the other? Effective patient selection hinges not only on the ability of a hospice to accurately identify patient type, but also on its ability to change referral sources. For example, a hospice with the majority of its patient population residing in nursing homes (NH) or assisted living facilities (ALF), where patients tend to have conditions which would predict longer hospice stays, may have more difficulty in shifting their admission patterns to favor patients with a terminal cancer prognosis.[15] On the other hand, live discharges are more likely to be used by a hospice with a high preexisting stock of high staying patient types, as well as hospices that place less weight on quality, as live discharge from hospice is known to be burdensome for the patient and the caregivers.[16] This distinction motivates a line of heterogeneity analysis by profit status of the hospice, with the hypothesis that nonprofit hospices, which are older, serve a larger share of inpatient hospice patients, and likely place a larger weight on quality (Newhouse, 1970), would exhibit stronger responses through patient selection while for-profit hospices, which are younger, serve a larger share of NH and ALF patients, and place a smaller weight on patient benefit, would exhibit stronger responses through live discharges.[17]

In columns 1 and 2 of Table 4, I find that nonprofit and for-profit hospices achieved similar reductions in the share of long stays. However, as hypothesized, the mechanisms they use to achieve these reductions are starkly different. Specifically, as displayed in columns 1 and 2 of Table 5, I find that nonprofits decrease predicted length of stay on admission more than for

[15] Between 2010-2013, the average predicted length of stay for patients treated in a NH or ALF is 157 days, while the average predicted length of stay for patients treated in an inpatient hospital setting is 8 days.

[16] Note that, though my measure of exposure may be correlated with the preexisting stock of high staying patient types in the quarter prior to the policy, exposure is calculated in 2010-2013 and thus does not completely explain variation in the stock of patients immediately prior to policy proposal.

[17] In my data, the average age of a nonprofit hospice is 21 years, while the average age of a for-profit hospice is 11 years. 27% of a nonprofit's patient pool is treated in a LTC facility, while 19% of a for-profit's patient pool is treated in a LTC).

profit hospices, a difference that is statistically significant at the 5% level. The responses are also larger in percent effects, with a 1SD increase in exposure resulting in a 3% reduction in length of stay for nonprofits and a 1% reduction in length of stay for for-profits. In columns 3 and 4, I show that among for-profits, 1 SD increase in exposure resulted in a 4% increase in the live discharge rate. The coefficient for nonprofits is negative and not statistically significant (though the differences in coefficients is significant at the 5% level).

VI.II Patient Analysis

The hospice level analysis suggests that the 2-tier policy resulted in shorter stays for more vs. less exposed hospices, and that this was at least partially driven by changes in patient selection. However, the hospice level design is unable to speak to whether *access* to hospice care was reduced as a result of the policy. The changes in patient composition could be entirely driven by the reshuffling of patients from more to less exposed hospices. To address the effects of the policy on access to hospice care, I now turn to the patient level analysis, where I test whether access to hospice care changed differentially for ADRD patients made more vs. less profitable by the policy.

Admission Rate

In Figure 7, I present event study results for equation 4 for the sample of ADRD patients. The event study coefficients suggest a gradual decline, beginning within 1 month post policy announcement, in admission rates for more vs. less exposed patients. Taking the longest run estimate in column 1 of Table 9, this suggests that a 1SD increase in exposure was associated with an 7% decrease in admission rates. In column 2 of Table 9, I present estimates from a prediction model that only includes patient demographics and diagnoses, leaving out utilization and expenditures (which includes DME utilization, considered to be a strong predictor of ability to perform ADLs). The prediction accuracy is correspondingly lower for length of stay, and this leads to more attenuated estimates on admission. This suggests

that utilization and expenditure data adds important predictive power, and leaving these variables out of a prediction model can result in attenuated estimates.

Heterogeneity by Patient Characteristics

In this section, I test whether admission rates differed based on patient demographic characteristics. Previous work has documented that black patients and male patients are disproportionately less likely to utilize hospice, raising concerns over disparities in access to hospice (Cohen, 2008; Wong and Phillips, 2023). In Table 10, I restrict the sample by demographic group to test whether hospices are more responsive to differences in profitability in certain demographics groups than others. Given the high precision, all coefficients are statistically distinguishable from each other. However, the pattern of decreased probability of admission with a 1SD increase in exposure holds across subgroups and the differences in coefficients are not economically meaningful. The implication is that hospices respond to health status-induced differences in profitability, regardless of the demographic status of the patient.

VII Discussion and Conclusion

In this paper, I study the impact of a reform of the hospice reimbursement structure, which shifted payments from a flat per-diem to a 2-tier per diem based on length of stay, making longer stays less profitable than shorter stays. Using variation in exposure to the policy based on pre-policy hospice patient mix and a difference-in-differences design, I find that a 1 standard deviation increase in exposure resulted in a 3% decrease in the share of stays greater than 60 days and a 9% decrease in the share of stays greater than 90 days. Though both nonprofit and for-profit hospices achieved similar reductions in length of stay, for-profit hospices exhibited larger responses through live discharges, while nonprofit hospices exhibited larger responses through patient selection. Given the concern among policymakers that live

discharges can be burdensome for a patient and their family, the propensity of hospices to pursue one margin over the other when responding to payment incentives should be taken into account when designing payment policies.

To test whether the policy resulted in reduced access to hospice care, I construct a sample of all Medicare patients diagnosed with Alzheimer's or dementia, which represents the longest staying primary diagnosis in hospice. I use variation in predicted exposure and a differences-in-differences design to test for changes in hospice admission rates pre vs. post policy. I find that a 1SD increase in patient exposure to the policy results in a 7% decrease in the probability of hospice admission. Given that patient exposure is determined based on predicted length of stay, this result suggests that the policy improved the targeting of hospice care to better reflect hospice eligibility guidelines. However, the welfare effects are ambiguous. If, for example, predicted length of stay is a true measure of low levels of patient benefit from hospice, then this improvement in targeting may have been accompanied by improvements in welfare. However, if predicted length of stay is not an accurate measure of patient benefit from hospice, then this may policy may have been welfare reducing. Future work examining the relationship between a hospice's predictions of length of stay and true prognosis is needed to shed light on this question.

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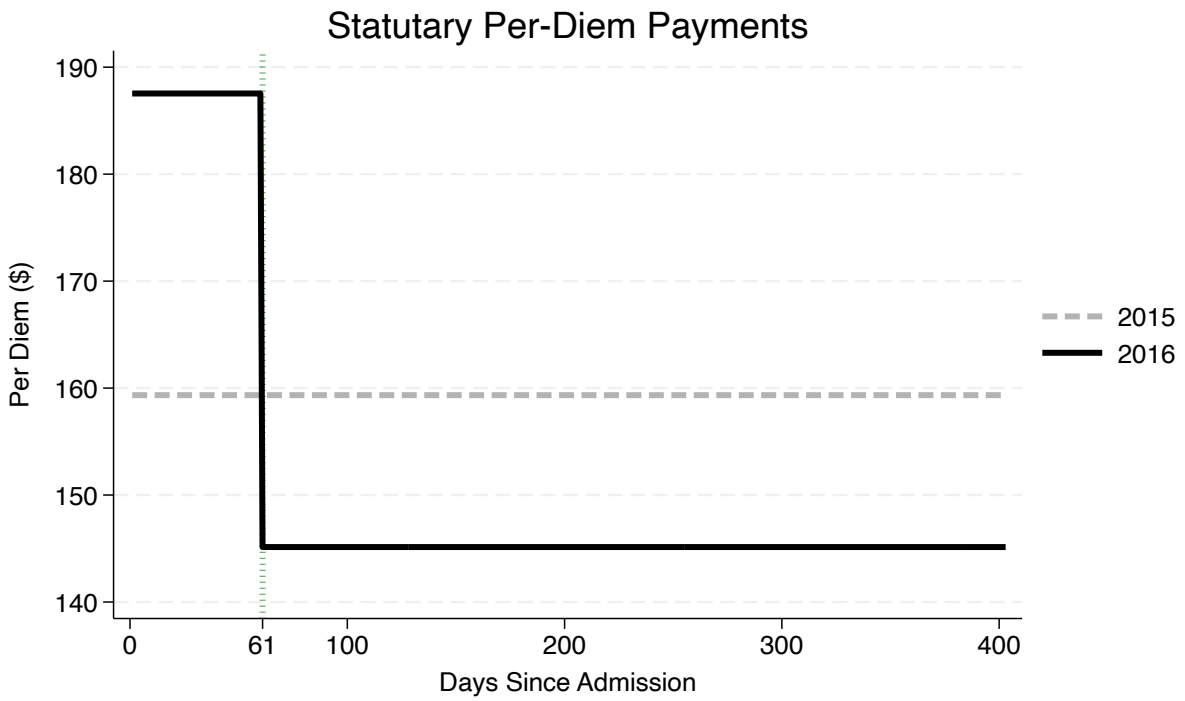
Tables and Figures

Figure 1: 2-Tier Reimbursement Policy



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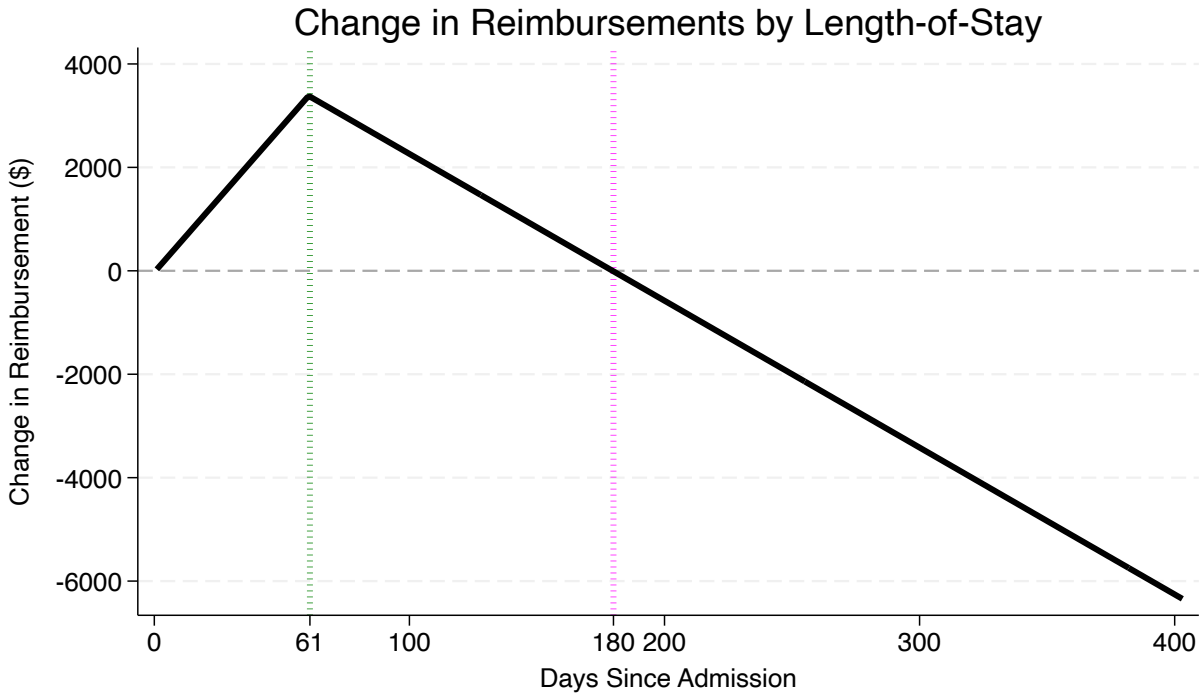
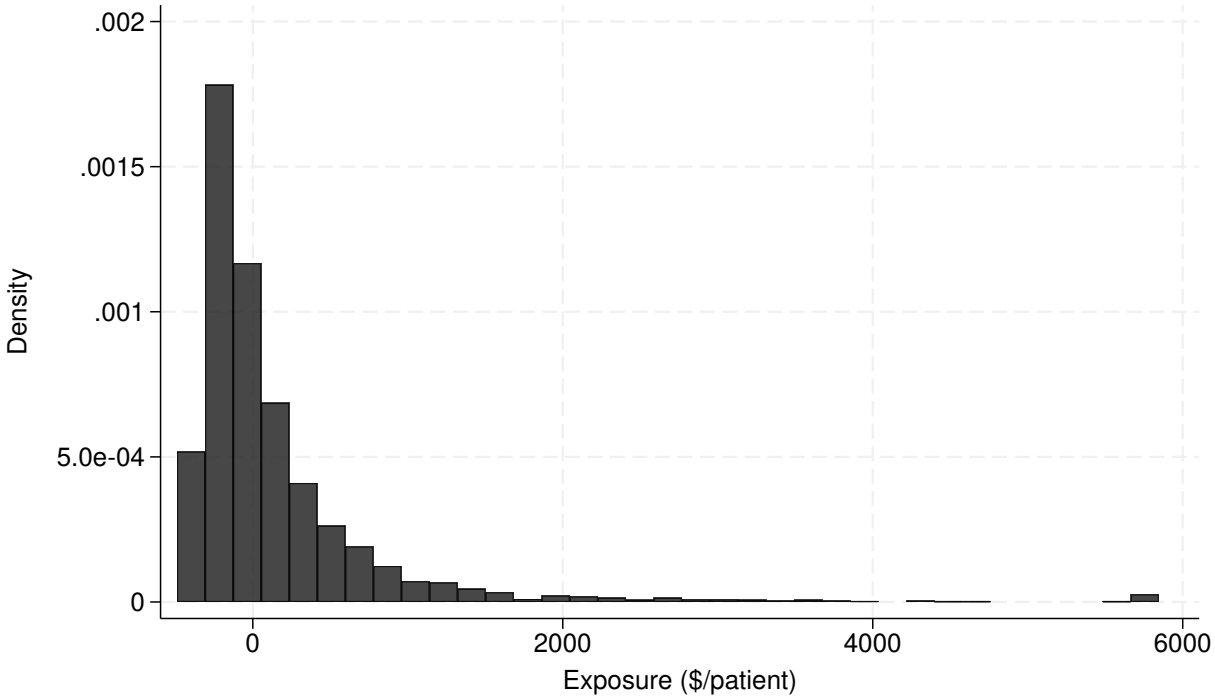


(b)

Notes: Panel A shows the per-diem rate as a function of length of stay, pre vs. post policy. Panel B shows the difference between post-policy and pre-policy revenue at different lengths of stay.

Figure 2: Distribution of Hospice Exposure



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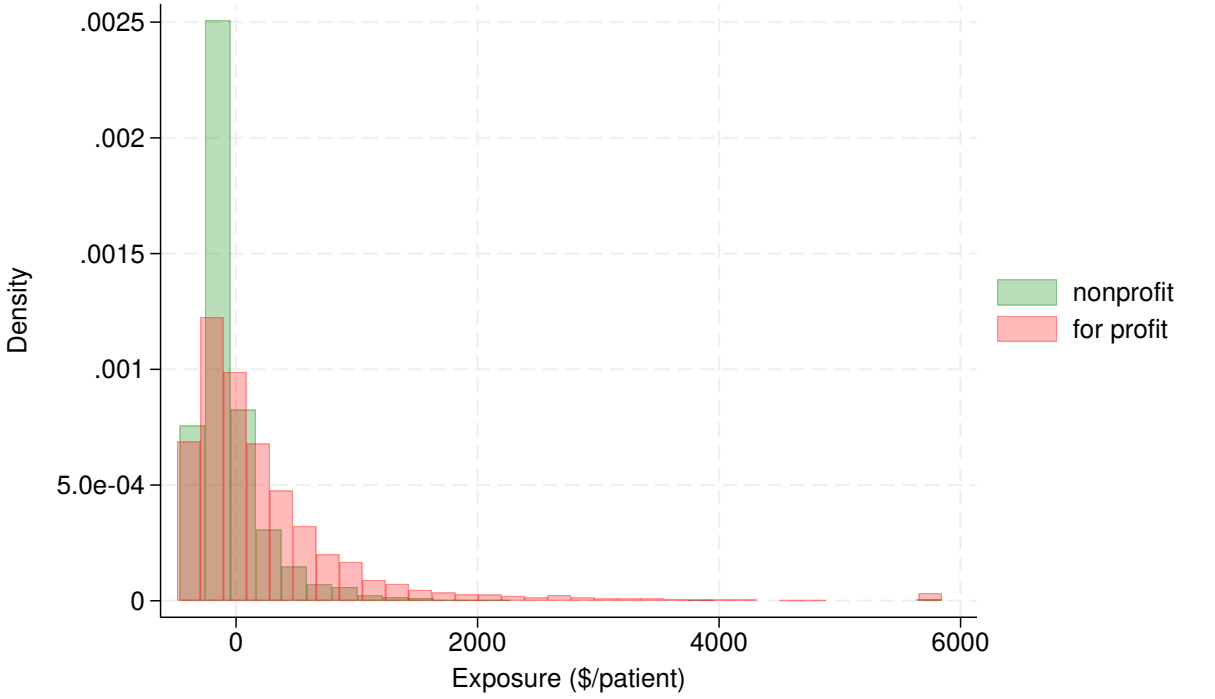

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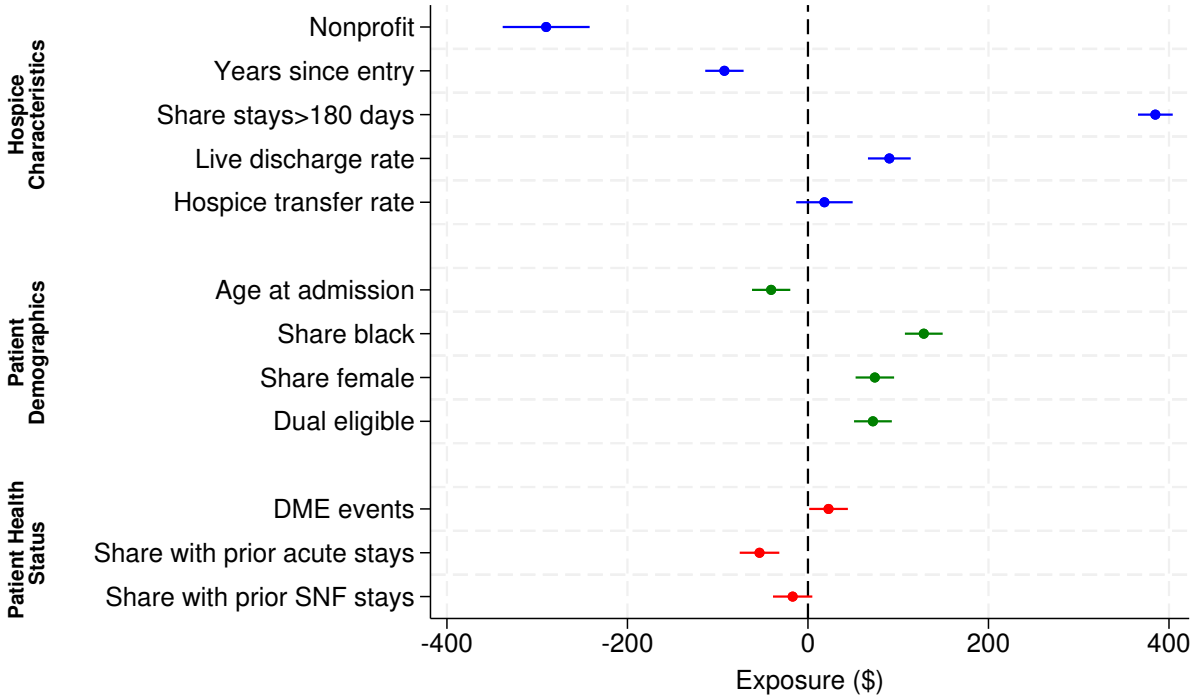
Notes: Figure shows the distribution of hospice exposure, measured in $ per patient. The measure is calculated based on the algorithm presented in section V.I. Larger values indicate higher exposure.

Figure 3: Correlates of Treatment



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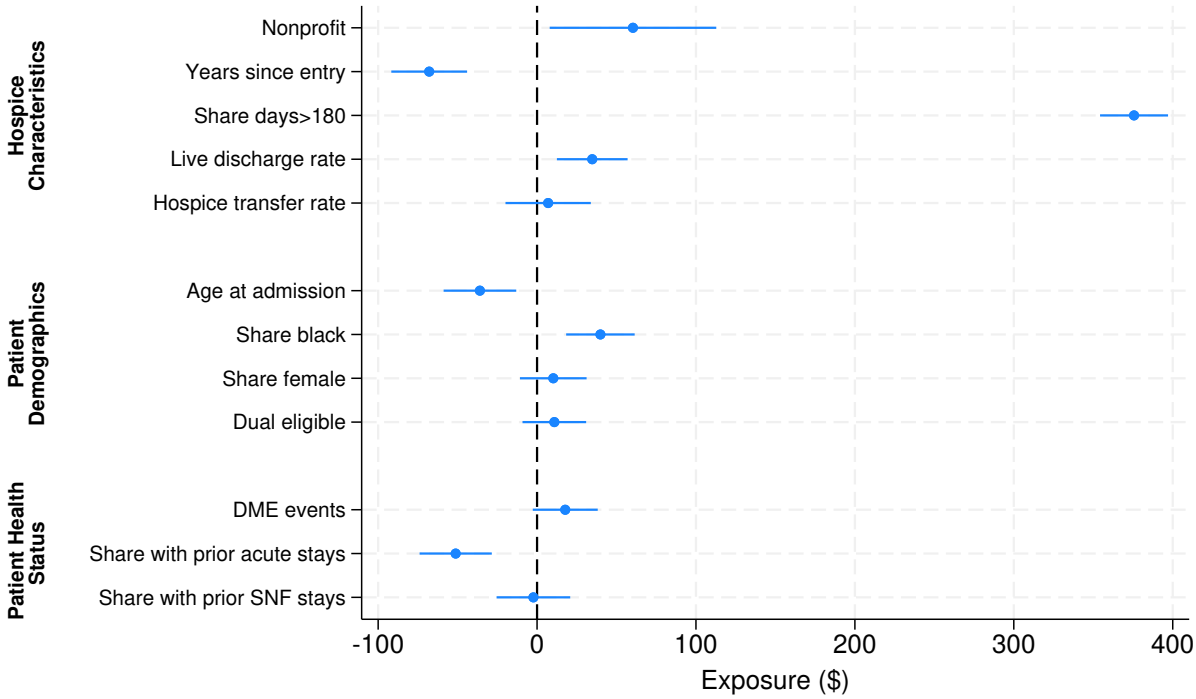
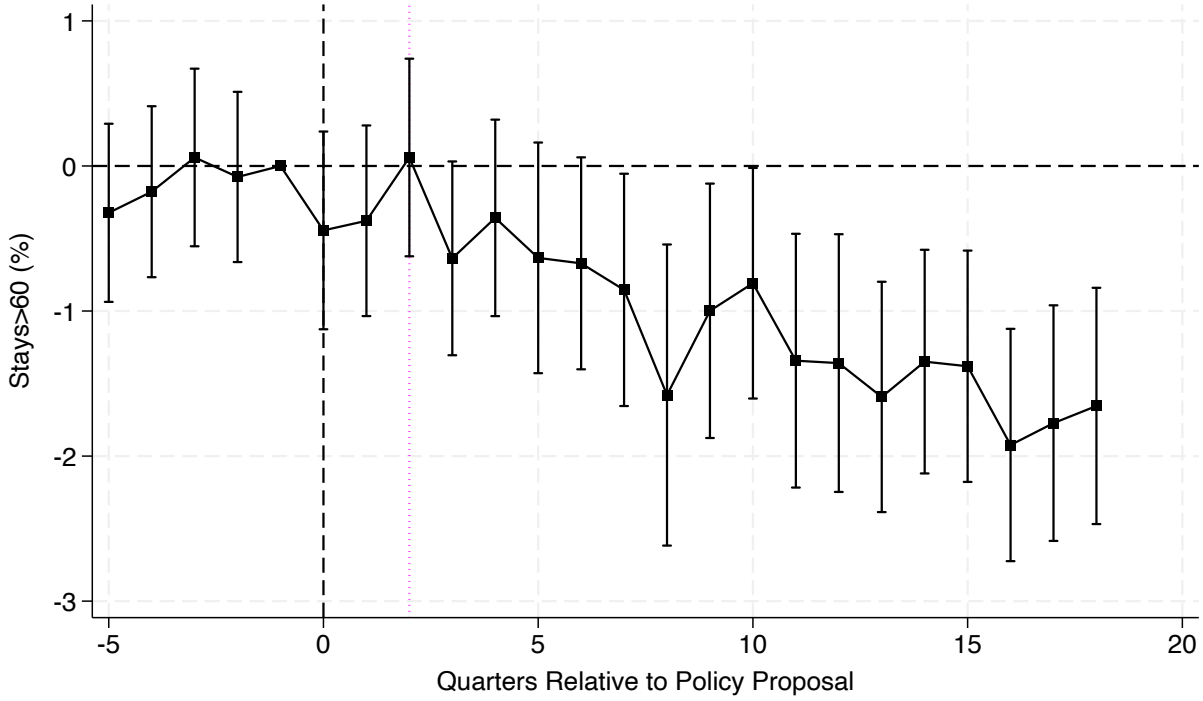


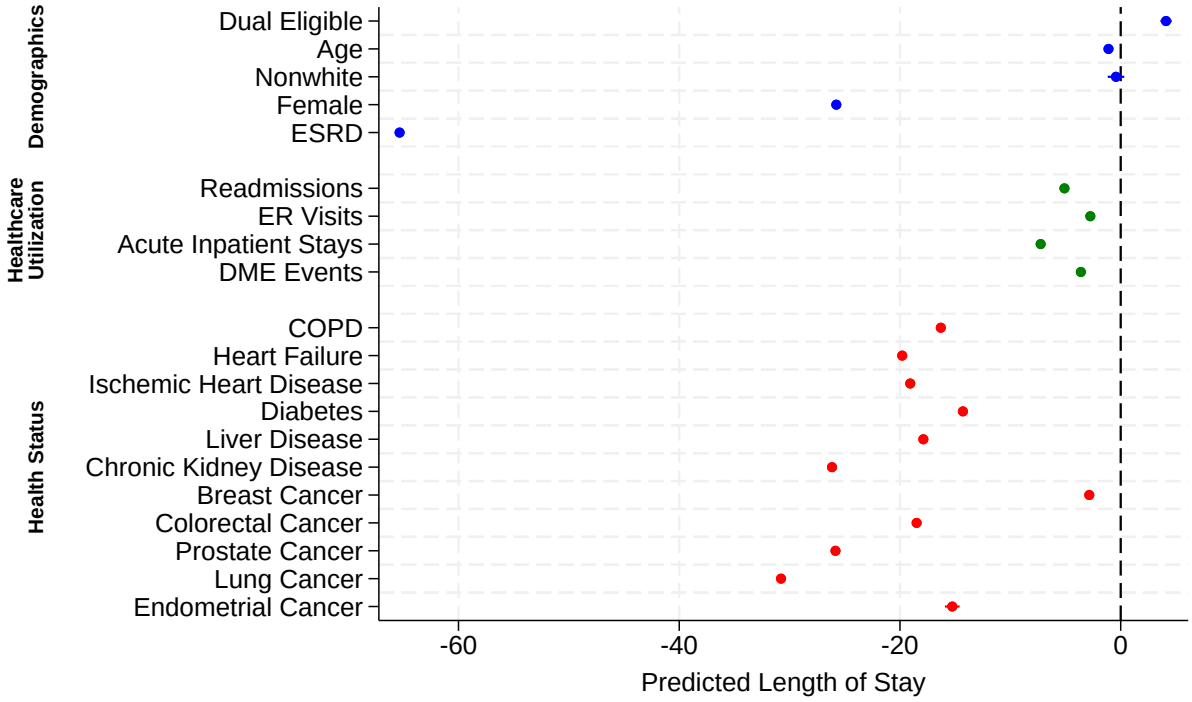
Notes: Figure shows the correlates of exposure, measured as $ per patient. All covariates, other than nonprofit status, are standardized and measured during the baseline period of 2010-2013. Panel A presents coefficients from seperate regressions for each covariate while Panel B presents coefficients from a pooled regression including all covariates.

Figure 4: Effect on the share of stays > 60 days



Notes: Figure presents event study coefficients from the regression specification outlined in equation 1. The outcome variable is the share of stays with length of stay > 60 days. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix.

Figure 5: Correlates of Patient Exposure



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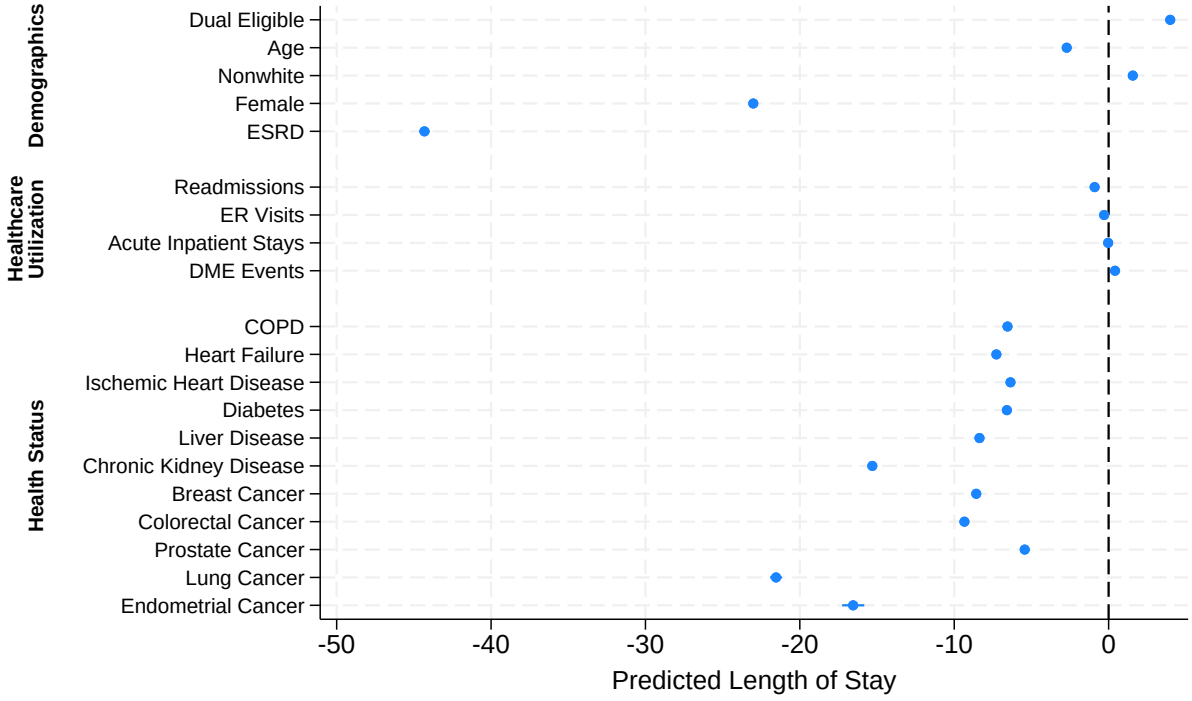
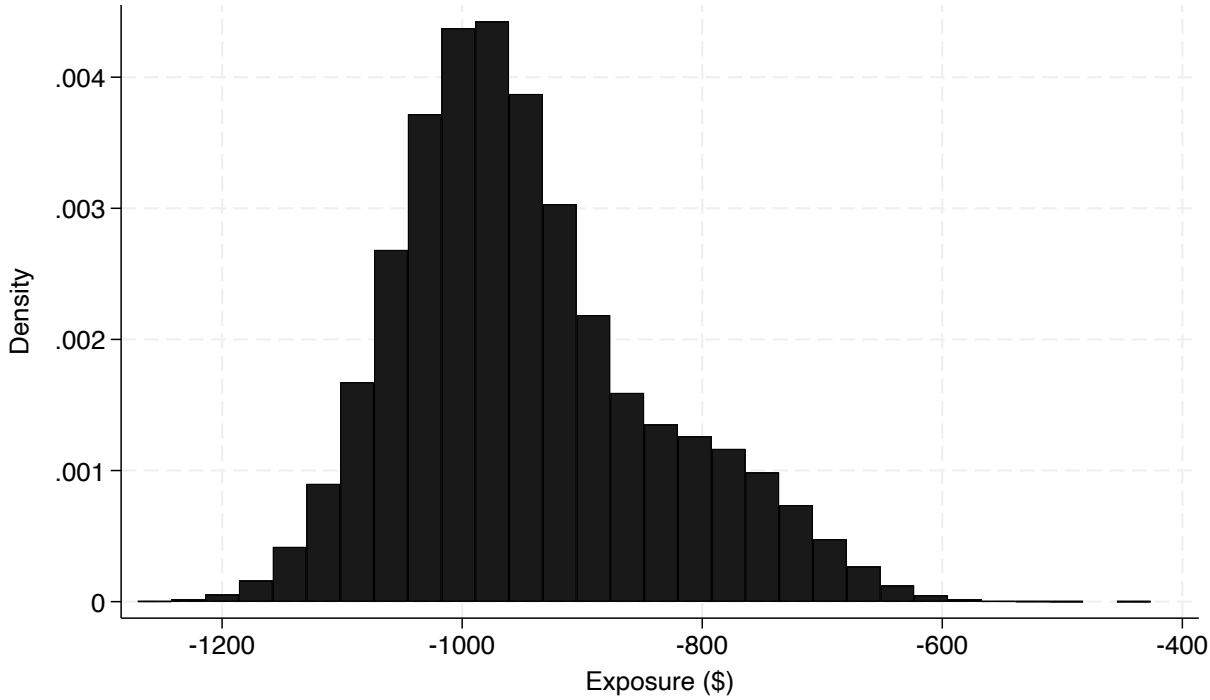


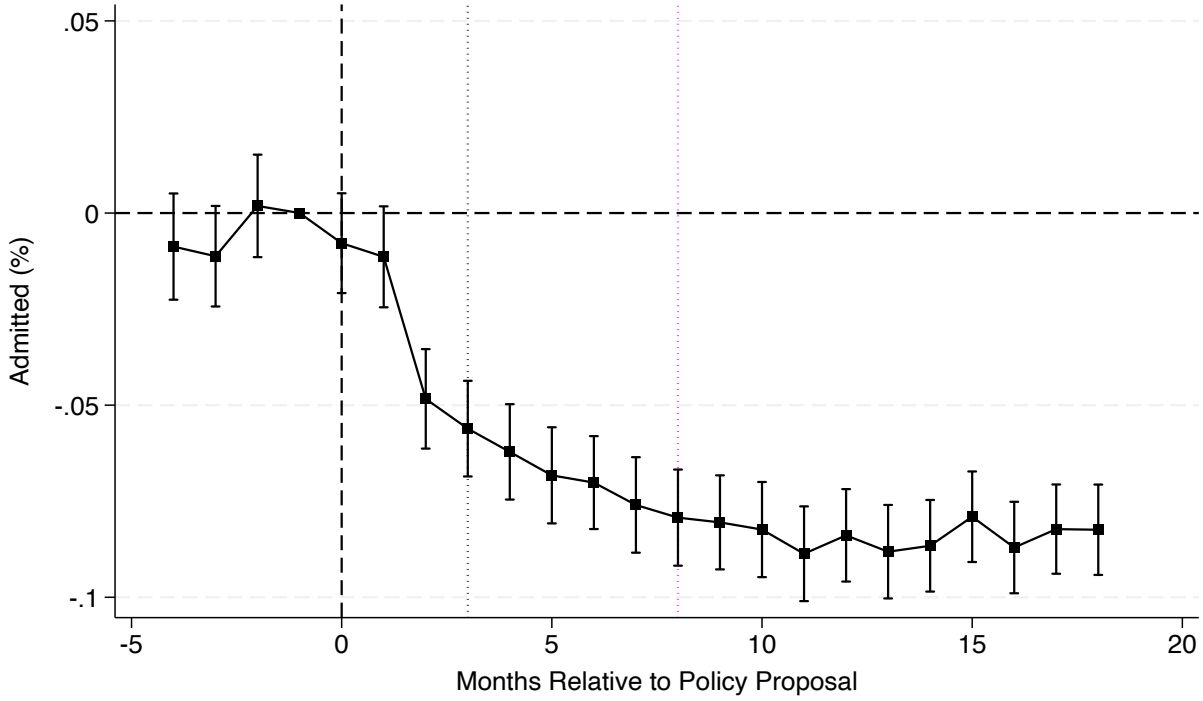
Notes: Figure shows the correlates of patient exposure, measured as $ per patient. All variables are measured during the baseline period of 2010-2013. Continuous variables (healthcare utilization measures and age) are standardized. Panel A presents coefficients from seperate regressions for each covariate while Panel B presents coefficients from a pooled regression including all covariates.

Figure 6: Distribution of Patient Exposure



Notes: Figure shows the distribution of patient exposure, measured in $ per patient. The measure is calculated based on the algorithm presented in section V.II. Larger values indicate higher exposure.

Figure 7: ADRD Sample: Effect on Admissions



Notes: Figure presents event study coefficients from the regression specification outlined in equation 4. The outcome variable is a dummy indicating hospice admission. Treatment is a continuous measure of patient exposure to the policy, estimated using predicted length of stay.

Table 1: Summary Statistics: Hospice Sample

Hospice Characteristics	
Nonprofit	0.35
	(0.48)
Years Since Entry	13.69
	(8.65)
Length of Stay (LOS)	112.77
	(58.78)
Stays $>$ 180 Days	0.19
	(0.12)
Live Discharge rate	0.10
	(0.09)
Patient Characteristics	
Age at admission	81.56
	(2.97)
Dual Eligible	0.91
	(0.20)
Nonwhite	0.14
	(0.17)
Female	0.60
	(0.09)
ADRD	0.46
	(0.15)
Observations	4,056

Notes: Table presents summary statistics for the hospice analysis sample. Nonprofit status and years since entry are measured as of 2014. "Dual Eligible" indicates if the patient had at least 1 month of both Medicaid and Medicare coverage.

Table 2: Hospice Level Outcomes

	Stays > 60 Days (%) (1)	Stays > 180 Days (%) (2)
exposure_h * $\text{post}_{(0,8)}$	-0.448**	-0.998***
	(0.210)	(0.190)
exposure_h * $\text{post}_{(9,18)}$	-1.263***	-1.837***
	(0.262)	(0.233)
N	81367	81367
Mean	41.14	20.22

Notes: Table presents estimates from the regression specification outlined in equation 2. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix. *post1* is a dummy which = 1 for relative quarters 0-8 and *post2* identifies relative quarters 9-18.

Table 3: Hospice Analysis: Mechanisms

	Predicted LOS (1)	Discharged Alive (%) (2)
exposure_h * $\text{post}_{(0,8)}$	-0.852***	0.233**
	(0.189)	(0.111)
exposure_h * $\text{post}_{(9,18)}$	-1.292***	0.143
	(0.230)	(0.127)
N	80206	81367
Mean	80.58	5.83

Notes: Table presents estimates from the regression specification outlined in equation 2. "Predicted LOS" denotes the average predicted length of stay among newly admitted patients. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix. *post1* is a dummy which = 1 for relative quarters 0-8 and *post2* identifies relative quarters 9-18.

Table 4: Hospice Analysis: Heterogeneity in Long Stays by Nonprofit Status

	Stays > 60 Days (%)		Stays > 180 Days (%)	
	Nonprofit	For profit	Nonprofit	For profit
exposure_h * $\text{post}_{(0,8)}$	-0.942**	-0.358	-1.124**	-1.078***
	(0.453)	(0.254)	(0.499)	(0.223)
exposure_h * $\text{post}_{(9,18)}$	-1.934***	-1.153***	-2.056***	-2.023***
	(0.559)	(0.300)	(0.555)	(0.280)
N	26680	46057	26680	46057
Mean	32.08	46.92	13.56	24.39

Notes: Table presents estimates from the regression specification outlined in equation 2. The outcome variable is the share of stays that end in a live discharge. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix. *post1* is a dummy which = 1 for relative quarters 0-8 and *post2* identifies relative quarters 9-18.

Table 5: Hospice Analysis: Heterogeneity in Response by Nonprofit Status

	Predicted LOS		Discharged Alive (%)	
	Nonprofit	For profit	Nonprofit	For profit
exposure_h * $\text{post}_{(0,8)}$	-1.044***	-0.690***	**-0.206**	**0.269****
	(0.327)	(0.230)	**(0.195)**	**(0.132)**
exposure_h * $\text{post}_{(9,18)}$	**-1.911*****	**-0.872*****	-0.113	0.187
	(0.330)	**(0.280)**	(0.208)	(0.157)
N	26473	45194	26680	46057
Mean	66.68	89.47	4.14	6.88

Notes: Table presents estimates from the regression specification outlined in equation 2. "Predicted LOS" denotes the average predicted length of stay among newly admitted patients. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix. *post1* is a dummy which = 1 for relative quarters 0-8 and *post2* identifies relative quarters 9-18. Coefficients in bold indicate that the difference is significant at the 10% level.

Table 6: Hospice Analysis: Discharge Sample

	(1) Discharged Alive
exposure_h * $\text{post}_{(0,8)}$	0.179**
	(0.071)
exposure_h * $\text{post}_{(9,18)}$	0.020
	(0.120)
Observations	102372
Mean	2.5

Notes: Table presents estimates from the regression specification outlined in equation 2. The sample is limited to patients enrolled in hospice prior to the policy proposal. The outcome variable is the percent of stays that end in a live discharge. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix. *post1* is a dummy which = 1 for relative months 0-8 and *post2* identifies relative months 9-18.

Table 7: Hospice Analysis: Intensity of Care

	(1) Skilled Nursing (min/day)
exposure_h * $\text{post}_{(0,8)}$	0.376*
	(0.225)
exposure_h * $\text{post}_{(9,18)}$	0.262
	(0.419)
Observations	81367
Mean	36.85

Notes: Table presents estimates from the regression specification outlined in equation 2. The outcome variable is the average number of skilled nursing minutes per day. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix. *post1* is a dummy which = 1 for relative quarters 0-8 and *post2* identifies relative quarters 9-18.

Table 8: Summary Statistics: ADRD Sample

	ADRD Sample	All Medicare	p-value
Demographics			
Dual Eligible	0.30	0.18	
	(0.46)	(0.38)	(0.00)
Nonwhite	0.17	0.18	
	(0.38)	(0.38)	(0.00)
Female	0.36	0.47	
	(0.48)	(0.50)	(0.00)
Age	81.76	71.53	
	(10.25)	(12.40)	(0.00)
Health Status			
Cancer DX	0.10	0.07	
	(0.30)	(0.26)	(0.00)
ER Visits	0.82	0.40	
	(1.81)	(1.35)	(0.00)
Acute Inpatient Stays	0.57	0.21	
	(1.09)	(0.67)	(0.00)
Readmissions	0.10	0.03	
	(0.50)	(0.29)	(0.00)
DME Events	3.39	2.05	
	(7.68)	(6.06)	(0.00)
Observations	2,957,600	7,257,473	

Notes: Table presents summary statistics for the ADRD patient sample compared to all Medicare beneficiaries in 2015.

Table 9: Patient Level Outcomes

	Admit (%)	
	(1)	(2)
exposure_i * $\text{post}_{(0,5)}$	-0.038***	-0.002**
	(0.003)	(0.001)
exposure_i * $\text{post}_{(6,11)}$	-0.075***	-0.036***
	(0.003)	(0.001)
exposure_i * $\text{post}_{(12,18)}$	-0.080***	-0.038***
	(0.003)	(0.001)
Observations	68024800	68024800
Mean	1.14	1.14
Prediction	Sophisticated	Simple

Notes: Table presents estimates from the regression specification outlined in equation 5. The outcome variable is a 0/1 indicator for admission to hospice. Treatment is a continuous measure of patient exposure to the policy, estimated using predicted length of stay. *post1* is a dummy which = 1 for relative months 0-5, *post2* identifies relative months 6-11, and *post3* identifies relative months 12-18.

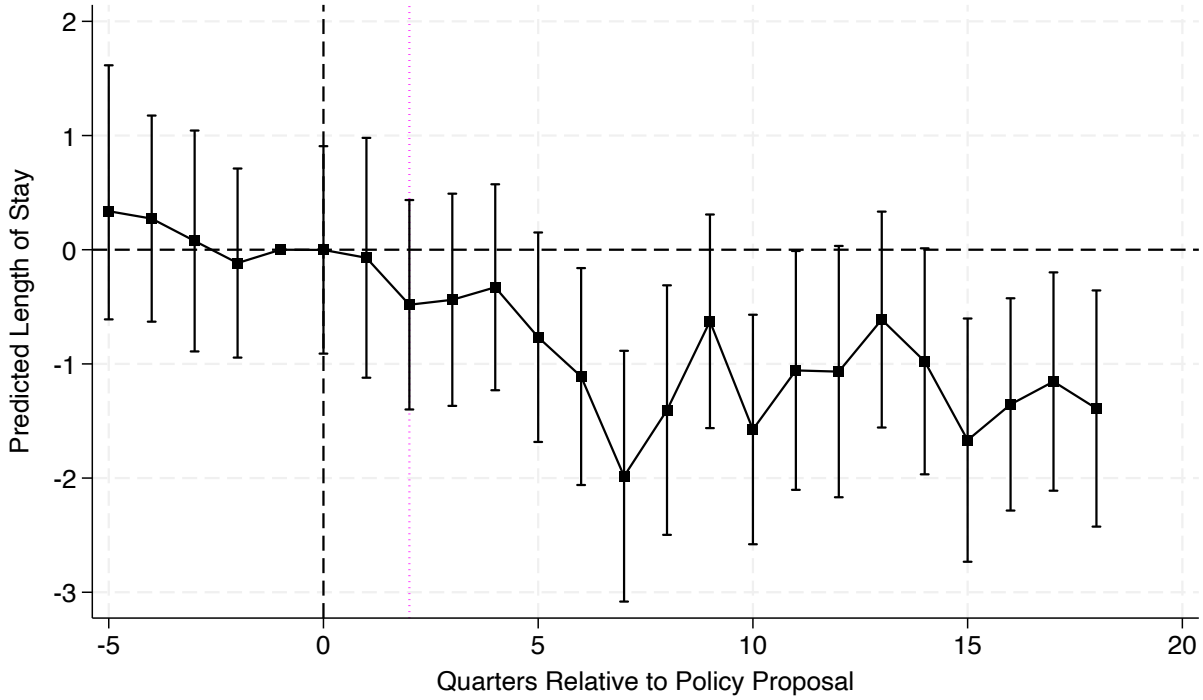
Table 10: Patient Analysis: Heterogeneity by Demographics

	Race		Gender		SES	
	white	nonwhite	male	female	not dual	dual
exposure_i * $\text{post}_{(0,5)}$	-0.038***	-0.036***	-0.037***	-0.040***	-0.042***	-0.026***
	(0.003)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
exposure_i * $\text{post}_{(6,11)}$	-0.076***	-0.066***	-0.074***	-0.074***	-0.083***	-0.054***
	(0.003)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
exposure_i * $\text{post}_{(12,18)}$	-0.081***	-0.067***	-0.077***	-0.081***	-0.090***	-0.054***
	(0.003)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
N	56256689	11768111	43242852	24781948	47290944	20733856
Mean	1.22	.78	1.13	1.15	1.22	.97

Notes: Table presents estimates from the regression specification outlined in equation 5. The outcome variable is a 0/1 indicator for admission to hospice. Treatment is a continuous measure of patient exposure to the policy, estimated using predicted length of stay.*post1* is a dummy which = 1 for relative months 0-5, *post2* identifies relative months 6-11, and *post3* identifies relative months 12-18. In odd number columns, the outcome = 1 if the patient is admitted *and* the hospice is older than 5 years. In odd number columns, the outcome = 1 if the patient is admitted *and* the hospice is 5 years or younger.

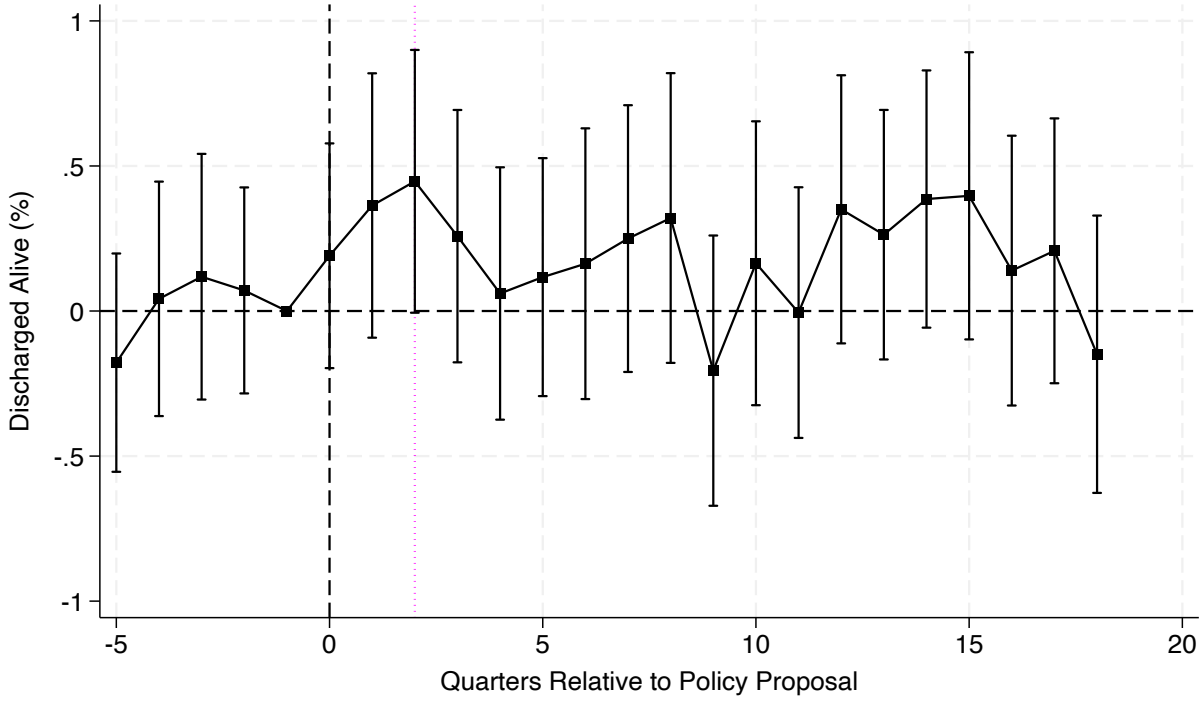
Appendix

Figure 8: Effect on predicted length of stay



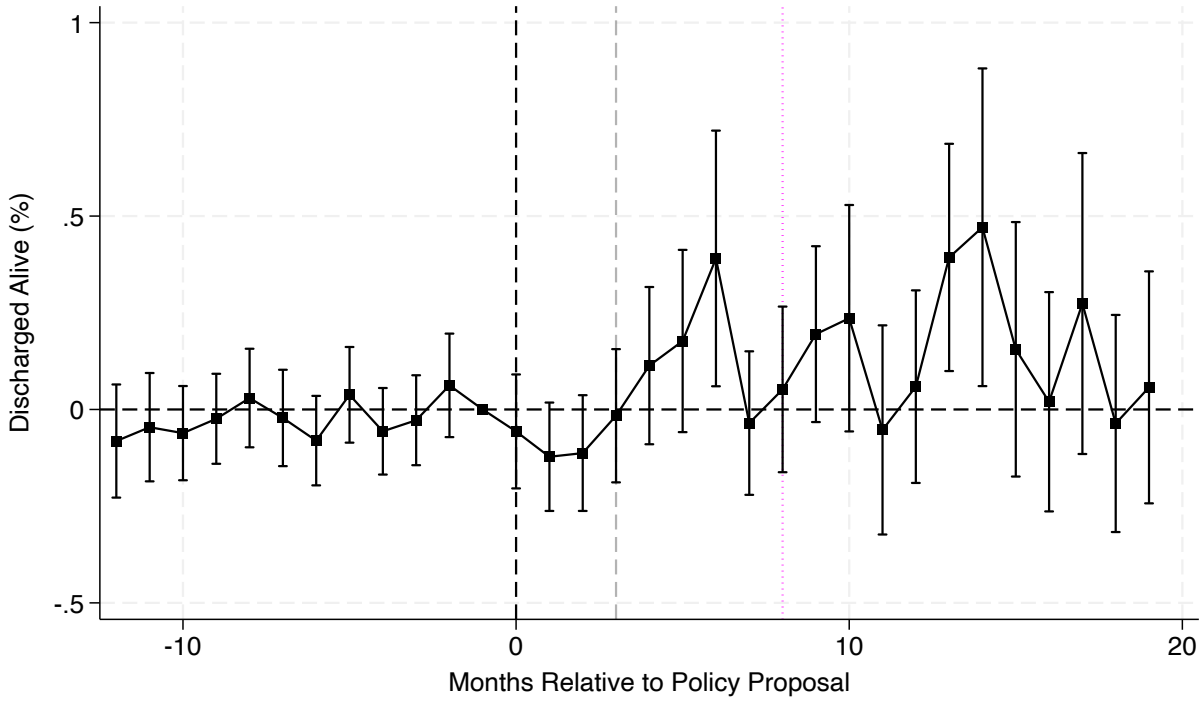
Notes: Figure presents event study coefficients from the regression specification outlined in equation 1. The outcome variable is predicted length of stay, predicted using baseline data from 2010-2013 and the specification in equation 3. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix.

Figure 9: Effect on live discharge rate



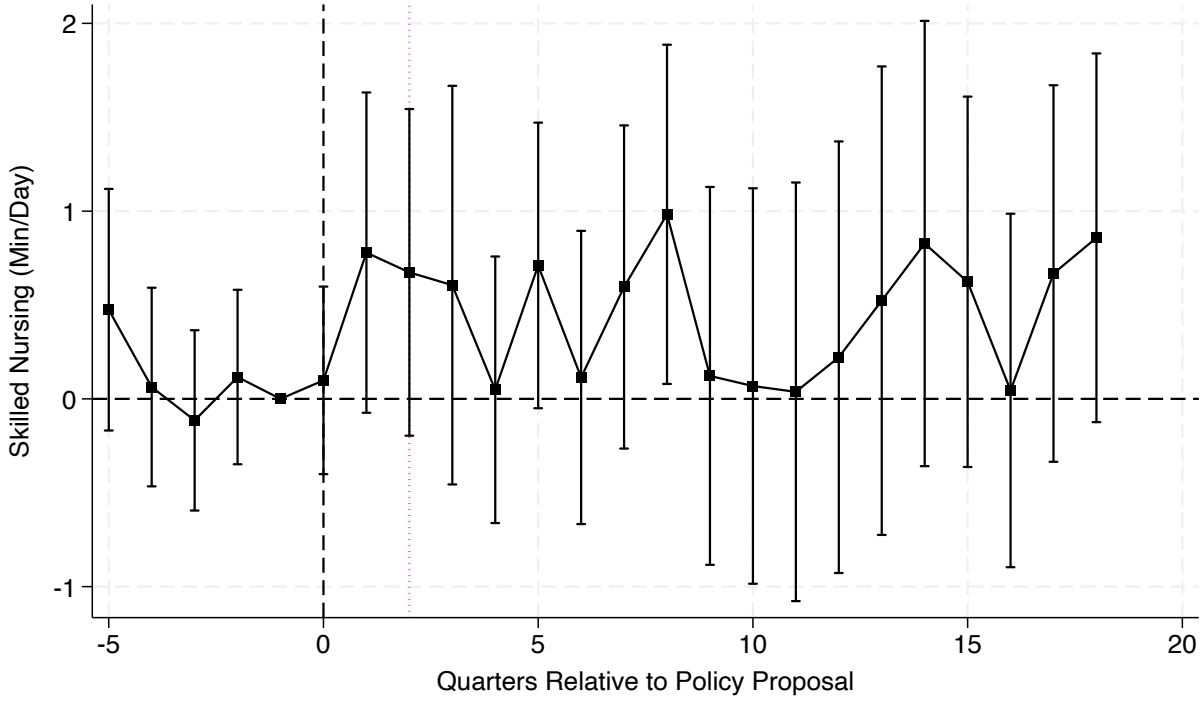
Notes: Figure presents event study coefficients from the regression specification outlined in equation 1. The outcome variable is the share of patients that are discharged alive. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix.

Figure 10: Effect on live discharge rate: high frequency sample



Notes: Figure presents event study coefficients from the regression specification outlined in equation 1. The sample is limited to patients admitted to hospice prior to May 2015, the month of the policy proposal. The outcome variable is the percent of patients that are discharged alive. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix.

Figure 11: Effect on skilled nursing minutes per day



Notes: Figure presents event study coefficients from the regression specification outlined in equation 1. The outcome variable is the average skilled nursing minutes per patient day. Treatment is a continuous measure of hospice exposure to the policy, estimated using baseline patient mix.