Production Costs, For-profits, and Industry Dynamics: An Empirical Study of Hospice Care

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(Link to latest version)

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Abstract

How do entry-exit dynamics affect the distribution of production costs in healthcare provider markets? In the California hospice industry, per-visit costs are lower in markets with greater competition, due to the following. For-profits have lower costs than non-profits, and substantial for-profit entry has driven down the distribution of costs. New entrants have lower per-visit costs than incumbents and prior entrants, and hospices with higher per-visit costs are more likely to exit. However, incumbents facing higher competition do not reduce per-visit costs, and greater competition does not force higher-cost incumbents to exit. I do not find evidence that lower cost reduces quality.

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1 Introduction

What is the effect of entry-exit dynamics on the distribution of production costs in healthcare provider markets? Such industry dynamics may lead to high-cost firms exiting, low-cost firms entering, and incumbent firms being forced to reduce costs to stay competitive. However, there is little empirical evidence on this question for healthcare provider industries. This issue is further complicated by for-profit firms competing with non-profits in the same market. Answering this question will shed light on how competition may (or may not) improve economic efficiency and help reduce rising healthcare costs in the United States.

I study how production costs of hospices in California evolve with entry-exit dynamics. Hospices primarily serve patients by visiting them at their residences, so my main measure of hospice production costs is per-visit cost. Per-visit costs are lower in counties with more hospices, and I find this pattern to be driven by the following. For-profits have lower costs than non-profits, new entrants have lower per-visit costs than incumbents as well as prior entrants, and hospices with higher per-visit costs are more likely to exit. Incumbents facing higher competition do not lower their per-visit costs, and greater competition does not force higher-cost incumbents to exit. These results hold even after controlling for patient characteristics that may influence visit costs. I also do not find any evidence that lowering costs leads to lower quality.

This informs policy discussions on entry barriers and for-profit competition in healthcare markets. Provider markets in US and elsewhere face a wide range of entry restrictions, such as licensing restrictions, scope-of-practice laws, and Certificate-of-Need (CON) laws. Furthermore, entry by for-profits is viewed with suspicion in political circles and the media, and prior research has found that for-profits provide lower quality care in some settings.

More specifically to California, the hospice industry has been a controversial topic recently. The last few years have seen multiple reports from the California legislature, state auditor, and California Department of Justice about fraud committed by hospices in Los Angeles. This has culminated in a moratorium on new hospice entry in California through CON laws, first imposed in 2021 and recently extended through to 2027 and possibly beyond.[1]

This paper sheds light on provider entry without entry restrictions in general, and the California hospice industry in particular. The absence of entry barriers in the California hospice industry has meant that production costs have declined in areas facing greater competition. This cost cutting allows Medicare to pay low reimbursement rate to hospices without risking driving them out of the

[1] See Section I for discussion and links to reports from the California state auditor and Department of Justice, as well as news outlets. The main type of fraud seems to be people setting up fake hospices to bill Medicare without providing services. The concern for fraud appears to be localized in Los Angeles according to the state auditor's investigation. While there have been accusations of widespread fraud in LA, the actual extent of it is unclear, as there have been relatively few prosecutions. However the investigations are ongoing at the time of this writing.

market, and thus lowers healthcare expenditure. Patient access to care has improved significantly due to for-profit entry, with for-profits now serving more patients than non-profits. Both this paper and an earlier paper by the author (Alam (2025)) find that areas facing greater hospice competition also see more frequent visits to patients, suggesting quality improvements. Thus, a key policy insight is that entry barriers – such as the recently implemented CON laws for hospices in Calfornia – can i) impede cost reductions and quality improvements from competition, as well as ii) worsen patient access to care, since for-profits have improved access for patients over the dataset's period.

Hospice staff provide palliative care to terminally ill patients by visiting them at their residence. Most hospice patients are covered by Medicare and Medi-Cal, so hospices do not compete on prices. I use a panel dataset of hospices in California for 2002-2018 containing information about visits, costs, patient volume, and other firm-level statistics. I exclude Los Angeles from my main analysis due to recent allegations of fraud, but present results including LA in the Appendix.

First, I present descriptive results about the California hospice industry. I find that the number of hospices in California has grown tremendously between 2002-2018, and that this growth is mostly driven by entry of for-profit hospices. For-profits have improved patient access by serving many more patients than non-profits, while non-profits (aided by donations) have improved patient access by operating in smaller markets eschewed by for-profits. Hospices in more competitive markets visit their patients more frequently, suggesting increased quality of care. Per-visit costs are highly persistent, which when coupled with the importance of visit costs in overall hospice costs, suggests that it may play an important role in market dynamics.

Using linear and quantile regressions with instrumental variables, I show that per-visit costs are lower in counties with more hospices. I regress per-visit costs on number of hospices to show that a negative relationship exists (using instrumental variables and controlling for cost trends to show robustness to confounding factors). I also use a grouped-quantile IV regression (Backus (2020), Larsen et al. (2023)) to show that the distribution of per-visit costs shifts left with greater competition.

I examine the factors that drive the negative relationship between per-visit costs and competition using a variety of regression methods.[2] First, I show that for-profits have lower costs than non-profits, and the substantial entry of for-profits helps drive down the distribution of costs in the market. Second, I show that entrants have lower costs than incumbents, and successive entrants have lower costs than prior entrants. Third, I show that higher-cost incumbents are more likely to exit the market. Fourth, I show that greater competition does not lead to incumbents lowering their per-visit costs or for higher-cost incumbents to exit the market. I also show that these results are

[2]I regress per-visit costs on number of hospices and various hospice and patient characteristics, using market size to instrument for number of hospices and controlling for market-level cost trends flexibly. This generates most of the results discussed here. I also use graphical methods to show the variation in the data that drives these results.

robust to controlling for patient characteristics that may influence visit costs. I use instrumental variables and control for cost trends, hospice characteristics, and patient characteristics to rule out confounders. Finally, I redo the analysis including Los Angeles county as well as restriting to smaller markets, and find qualitatively same results.

I find no evidence that reduction in per-visit costs leads to a decline in the quality of care. In fact, hospices with lower per-visit costs tend to make more visits to patients, which should improve patient experience. The cost reductions I document are not entirely driven by substituting cheaper home health aides for more expensive nurses. I also find evidence for reallocation of market share towards lower-cost providers in more competitive markets. Finally, I speculate about possible economic mechanisms that may be driving my results.

Contributions and related literature: First, I contribute to a small literature on how healthcare providers' costs evolve over time and with industry dynamics. My results connect to the general discussion in Cochrane (2015), who argues that competition in healthcare markets can drive down costs by improving efficiency of providers as well as improve quality of care. My results also connect to Chandra et al. (2016), who push back against the idea of "healthcare exceptionalism". Their paper argues that healthcare industry is similar to other industries in that higher quality hospitals see higher market share and growth. My paper contributes to this discussion by examining the cost side and showing that, similar to non-healthcare industries, increasing competition drives down costs over time.

In contrast to this paper, few papers in the Economics literature study the effect of competition on healthcare provider costs, and none study this question in the context of hospices. An advantage of studying hospices is that hospice services are simple and low-skill compared to other healthcare providers. Thus, there is less concern abut unobserved variation in type of services, patient case-mix, learning-by-doing, etc. Most papers studying competition in healthcare markets focus on prices and quality. Furthermore, papers studying healthcare provider costs and productivity often focus on hospitals, such as Gaynor et al. (2015).

Second, I contribute to the literature studying the effect of competition on efficiency, productivity, and reallocation. I do so by showing empirically that entry of low-cost producers play an important role in shifting average production costs across markets and over time. In contrast to most other papers in the literature, I focus on cost-based measures to study efficiency. There are advantages and disadvantages to this approach. The advantage is that this does not require me to make strong assumptions for estimation (such as those made in the production function estimation literature; see Olley and Pakes (1996) and subsequent literature), and such cost-based efficiency measures can be recovered directly from (often widely available) cost data. The disadvantage is that the cost data reflects accounting costs, and not economic costs. Increasingly, papers are leveraging cost data due to their richness and availability; see Igami et al. (2024). A key paper for my work is Backus (2020), who studies the effect of competition on pushing out low-productivity ready-mix concrete plants and forcing incumbents to become more productive. Other papers in this area include Collard-Wexler (2011), Collard-Wexler and De Loecker (2015), Fabrizio et al. (2007), Syverson (2004a), Syverson (2004b), Galdón-Sánchez and Schmitz (2002), Schmitz (2005), and Demirer and Karaduman (2025); see Syverson (2011) for a survey.

Third, I contribute to the literature studying differences between for-profits and non-profits in two ways. First, I contribute by studying cost differences between for-profit and non-profit hospices; very few papers in the Economics literature study cost differences between for-profit and non-profit healthcare providers. Second, many papers in the Economics and public health literature have compared for-profits and non-profits present in the same market, and found that for-profits provide lower quality in some settings. This is then used to argue against for-profits. In contrast, I show that entry decisions by for-profits and non-profits are critical to the analysis. In my setting, entry by for-profits (and lack thereof for non-profits) has led to for-profits serving significantly more patients than non-profits, thereby improving patient access to care. Thus, "static" analysis of for-profits versus non-profits is not correct: rather than comparing for-profits and non-profits already in the market, we need to consider that profit motives incentivize entry by for-profits, which improve access to care for patients. Several papers study and model entry decisions by non-profits versus for-profits in non-hospice settings; these include Ballou (2008), Cohen et al. (2013), Exley et al. (2023), Gayle et al. (2017), Grant et al. (2022), Harrison and Laincz (2008), Harrison and Seim (2019), Lakdawalla and Philipson (2006), Owens and Rennhoff (2014), and Philipson and Lakdawalla (2001).

Fourth, I contribute to a small literature on hospices in the Economics literature. I am the first to study the dynamics regarding entry, exit, and production costs in the hospice industry. I also combine insights from the palliative care literature to capture the shape and inputs into the hospice cost function. An earlier paper by myself (Alam (2025)), using the same setting and dataset, studies how hospices choose quality to accumulate reputation and compete, then simulates the impact of alternative Medicare hospice reimbursement schemes. An important paper is Chung and Sorensen (2018), who look at broad patterns of hospice entry across the US, then estimate a nested logit demand model to examine market expansion from hospice entry. Other prior work include Dalton and Bradford (2019), who study length of stay of patients in non-profit and for-profit hospices; and Gruber et al. (2023), who show that hospices save money for Medicare by offsetting alternative expensive care for Alzheimer's and Dementia patients.

Fifth, I contribute to the literature on entry-exit dynamics in Empirical Industrial Organization. This paper brings reduced-form evidence that can inform structural modeling approaches in the literature. Most papers in this literature combine structural methods with parametric assumptions to impute economic costs of firms. Papers in this area using structural estimation methods include Collard-Wexler (2013), Ericson and Pakes (1995), Igami (2018), Igami and Uetake (2020), and Ryan (2012); see Doraszelski and Pakes (2007) and Arcidiacono and Ellickson (2011) for overview.

2 Industry Background and Data

Hospice staff provide palliative care to terminally ill patients by visiting them at their residence. Patients who enroll in hospice typically no longer receive curative treatment. Most patients in the dataset are covered by Medicare or Medi-Cal, which pays hospices a fixed amount for every day the patient is enrolled. In this paper, I use a panel dataset of hospices in California for 2002-2018 containing information about visits, costs, patient volume, and other firm-level statistics. This allows me to back out estimates of per-visit cost and competition levels in each market-year. I define a market to be at the county level, and justify this decision with data on patient origins. This section closely follows an earlier paper by the author (Alam (2025)).

2.1 Hospice care provision

Hospices typically provide care at the residence of the patient[3]. Hospices employ several types of staff: registered nurses, licensed vocational nurses, home healthcare aides, physicians, social workers and chaplains. Nurses and home health aides make the majority of hospice visits.

The hospice staff make multiple visits to a patient throughout the patient's enrollment period. Administrators of a hospice decide the number of visits, and set up the schedule for each nurse. A day for a hospice nurse involves driving to several patients as determined by the administrator, giving them care, writing up reports for the hospice physician and administrator, and refilling supplies. From my interviews with hospice administrators and readings on the industry, hospice staff do not drive out from the hospice office to visit patients; rather, they start from their home and visit patients. Thus, the exact location of the hospice office does not directly influence driving time.

The care given by hospice nurses is relatively low-skill compared to other medical providers. Hospices are not responsible for curative treatment; they are tasked with pain management and ease-of-living for a dying patient. Examples of hospice care include administering pain medication, providing medical supplies like oxygen and bandages, dressing bedsores, giving physical and

[3] My dataset (and Medicare) distinguishes between different types of hospice care – routine care (which is the care described above), inpatient care (where a patient moves to an inpatient ward of a hospice for intense treatment) and continuous respite care (where the hospice takes over as the primary caregiver). The majority of patients in my sample are given routine care; I show in Table 23 that of all the "days of care" provided by a hospice within each year, over 99% are dedicated to routine care.

speech therapy, helping with bathing and feeding, temporarily substituting as the primary caregiver, tending to emotional and spiritual needs of the patient, and giving grief counselling to the family after the patient passes away.[4]

It is important to note that the hospice decides how many visits to make to each patient and what care is to be provided during each visit. As is explained below, the patient does not incur any additional cost for more visits, and so would plausibly like as many visits as possible.

For a patient covered by Medicare or Medi-Cal, hospice care is essentially free. There is no out-of-pocket cost for enrolling into or receiving visits from a hospice. The patient generally has to turn down curative treatment to enroll into hospice care via Medicare. For the hospice, enrolling a patient covered by Medicare or Medi-Cal results in the hospice getting paid a fixed rate for every day the patient is enrolled (i.e. a per-diem rate). The fixed rate is set exogenously and does not depend on the number of visits that the hospice staff makes.

2.2 Data

The main dataset comes from Home Health Agencies And Hospice Annual Utilization Reports compiled by California Department of Health Care Access and Information (HCAI). Hospices in California are required to submit yearly utilization reports to HCAI where they report firm-level statistics for the year. This includes measures such as current location, total number of patients, total visits per year (broken down by type of staff), hospice characteristics, aggregate characteristics of patient pool, cost breakdowns, etc. I collect and clean utilization reports of hospices for 2002-2018. I complement this with additional data sources on population sizes (by age), mortality rates, and Medicare hospice reimbursement rates for California over the same time period.

Since the cost data is critical to my paper, I now present additional details about these variables. The cost breakdown includes costs incurred for administrative and general services, cost of program supervision, cost of visiting services, costs for specific hospice services (such as drugs, transportation, etc.), and various other costs. See Figure 19 for the full list of cost variables.

I definite total cost of visits to be the sum of visiting services costs, hospice service costs (except costs of radiation therapy and chemotherapy), and "other program costs". I define "operating cost" to be the sum of general service costs - administrative and general, "other hospice service costs", program supervision costs – hospice program/team supervision (non-visit wages), and volunteer program costs.

[4]Hospice staff do not function as the primary caregiver of the patient - someone in the patient's residence (a family member if the patient resides at home, or a nurse if the patient resides in a nursing facility) has to be the primary caregiver. But hospice nurses assist the primary caregiver, and sometimes may substitute in for a period of time to give respite to the primary caregiver.

A market is defined to be at the level of a county.[5] Market size is constructed by multiplying the population size of each age for a market with the corresponding mortality rate; that is, market size is the expected number of deaths happening in a market in a year.

For this project, I drop Los Angeles county (LA) from my main analysis due to recent allegations of fraud in hospices located in LA. The chief complaints are that individuals may be opening up fake hospices that provide no service and bill Medicare for fraudulent claims. According to the state auditor's report, the problem appears to be localized in LA. The worry with including LA data in my analysis is that if there is widespread fraud in LA hospices, then their strategic decisions (and data reporting) may be more problematic. See Section I for discussion and links to reports. For completeness, I present results including LA in the Appendix.

After data cleaning, I have a panel dataset of 45 counties in California, with 700 county-years. The remaining counties do not observe hospice entry over my dataset's time period.

3 Descriptive Evidence

In this section, I present key descriptive statistics from the dataset. First, I show distributions of key variables such as per-visit costs and competition levels. Second, I show how the number of hospices have grown tremendously between 2002-2018, and that this growth is mostly driven by entry of for-profit hospices. Third, for-profits have improved patient access by serving more patients than non-profits, while non-profits have improved access by operating in small markets eschewed by for-profits. Fourth, I show that per-visit costs are highly persistent, which when coupled with the importance of visit costs in overall hospice costs, suggests that it may play an important role in market dynamics. Fifth, I show that per-visit costs are lower in counties with more hospices, which is the key pattern this paper aims to examine.

3.1 Summary statistics

Table 1 shows summary statistics of some of the key variables in my dataset. Notably, per-visit costs are around \$100 with significant dispersion across hospices. Total cost incurred from visits forms a significant share of a hospice's overall costs, with a median of 54%. There is little concentration in large markets, with a median HHI of 735.4.

To get a sense of the level of competition in the hospice industry, Table 2 shows the distribution

[5] While some hospices offer services to multiple counties, I can rule out clusters of counties as a market definition using data. Specifically, the dataset contains a breakdown of a hospice's patient pool by patients' counties of residence. Most of a hospice's patients originate from the county where the hospice is located. The only exception are Yuba and Sutter counties which have a large overlap of patients, and so I combine them into a single market. The number of county-years enumerated later reflect this alteration.

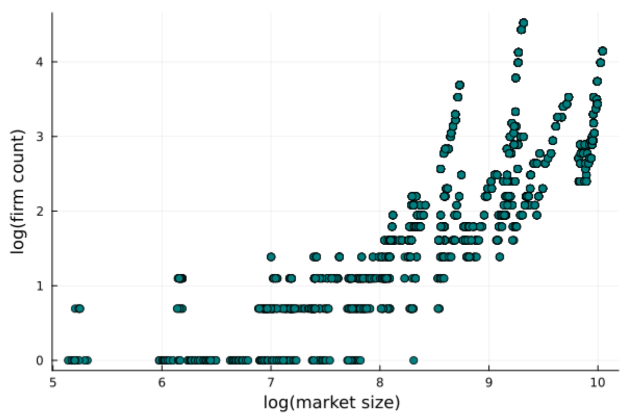
Table 1: Summary statistics

Variable	10%	25%	50%	75%	90%
Per-visit cost	63.58	81.47	108.78	144.46	186.24
Total visit cost / Total cost	0.36	0.47	0.57	0.66	0.76
Visits per patient-day	0.54	0.65	0.8	1.01	1.29
Average length-of-stay	37.09	44.39	53.71	65.39	79.77
Patients	38.0	92.0	246.0	488.0	832.4
Market share (%)	0.55	1.82	6.69	23.62	58.29
HHI	597.41	857.77	1604.35	3053.62	6169.71

Notes: For this table, "market share" denotes the within-hospice market share, i.e., the denominator is the total number of observed hospice patients, not the number of potential patients. HHI is calculated using within-hospice market shares.

of hospices across counties and years. A few large counties account for the majority of hospices in California. The number of hospices in these counties has been increasing over time.

Figure 1: Scatterplot of market size and number of hospices



Notes: Each point represents a county-year observation. Market size is measured as the expected number of deaths in that county-year.

I find that the number of hospices in a market is strongly positively correlated with the expected number of deaths in that market; see Figure 1 for a graphical illustration, and Table 16 for regression results. Thus, I will use the expected number of deaths in a market as an instrument for level of competition in regressions.

3.2 Market dynamics, For-profits, and Access to Hospice Care

To visualize market dynamics in the hospice industry, Figure 2 shows the evolution of entries, exits, and total hospices over time. The key takeaway is that the number of hospices in California

Table 2: Distribution of hospices across counties and years

County	2002	2009	2013	2017
San Bernardino	6	20	28	84
Orange	11	18	27	54
Ventura	5	17	23	34
Riverside	9	14	23	31
San Diego	11	15	19	29
Alameda	7	9	11	20
Sacramento	5	7	9	18
Santa Clara	6	7	12	14
Contra Costa	4	6	9	12
Fresno	3	4	6	10
San Mateo	3	4	5	9
Kern	3	8	8	8
San Joaquin	2	2	4	7
Santa Barbara	2	3	5	6
Sonoma	4	5	6	6
Placer	2	4	5	5
San Francisco	6	5	6	5
Shasta	1	2	2	4
Solano	2	2	3	4
Stanislaus	2	3	3	4
Butte	4	3	3	3
Imperial	1	1	1	3
Monterey	3	2	3	3
San Luis Obispo	1	2	3	3
Tulare	1	2	3	3
Sutter	2	2	2	3
El Dorado	2	2	2	2
Marin	1	1	2	2
Merced	2	3	2	2
Nevada	2	2	2	2
Amador	1	1	1	1
Humboldt	1	1	1	1
Kings	1	1	1	1
Mariposa	1	2	1	1
Mendocino	1	1	1	1
Napa	1	1	1	1
Santa Cruz	1	1	2	1
Siskiyou	2	3	3	1
Yolo	1	1	1	1
Lake	0	1	1	1
Tehama	0	1	1	1
Tuolumne	1	0	1	1
Inyo	0	0	0	1

Notes: Yuba and Sutter counties have a large overlap of patients, and so I combine them into a single market.

has been increasing rapidly over time, and is mostly driven by entry of for-profit hospices. Number of nonprofits has remained roughly the same since 2007. The total entries and exits in my dataset, broken down by for-profit status, are shown in Table 3, and corroborate the broad patterns from the graphs.

How has this growth affected patient access to hospice care? I argue that both for-profits and non-profits have improved patient access but in different ways.

1. For-profits: Over time, the share of patients treated by for-profits have grown tremendously, and now covers more than more hospice patients than non-profits (Table 2). Prior research

by Alam (2025) also finds market expansion effects of hospice entry to be significant.[6]

2. Non-profits: Non-profits have improved access by operating in smaller markets eschewed by for-profits. Table 4 contrasts the market size of i) counties with non-profits but without for-profits, and ii) counties with for-profits. The former has lower market size than the latter, suggesting that non-profits are willing to operate in smaller markets that for-profits may not find profitable enough, and therefore plays an important role in underserved areas. This is partly aided by donations; Table 5 shows that non-profits receive more donations-per-patient in counties with fewer hospices, suggesting that donations help non-profits operate in smaller markets.

Interestingly, 2006-2007 saw a large number of hospices (48 in total) switch from non-profit to for-profit status. This transition explains a large part of the patient share between the two types. These 48 hospices are spread out across 17 counties, and some may be part of larger chains transitioning to for-profit status. In total my data sees 65 transitions from non-profit to for-profit status, and 16 transitions from for-profit to non-profit status.

Table 3: Total entries, exits, and hospices.

Variable	**Value**
Total Exits	177
Total Entries	498
Total Unique Hospices	624

(a) Total entries, exits, and hospices.

For-profit Status	**Total Entries**	**Total Exits**
0	127	87
1	371	90

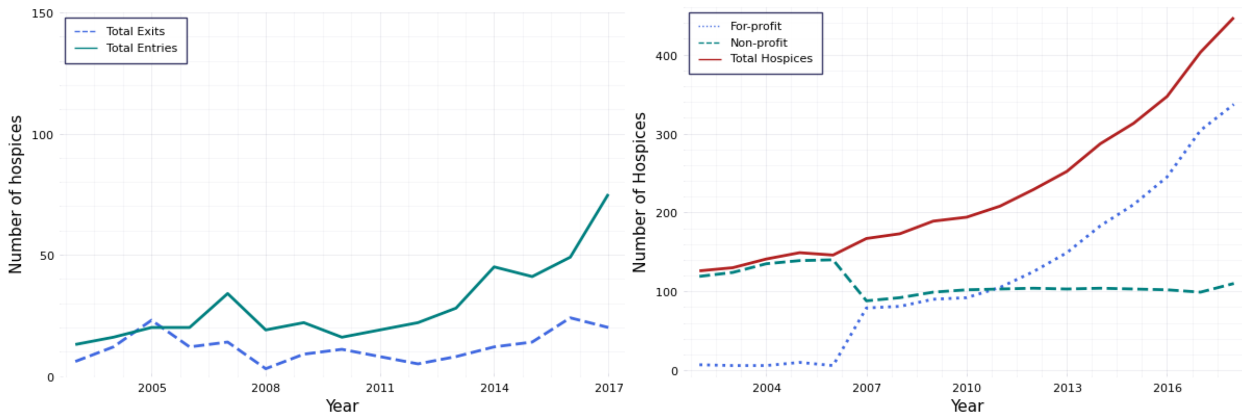
(b) Entries and Exits by for-profit status

3.3 Hospice costs and visits

Next, I examine the persistence of per-visit costs within a firm. I find that per-visit costs are highly persistent within a firm over time, with an autocorrelation coefficient of 0.95 (Table 6).

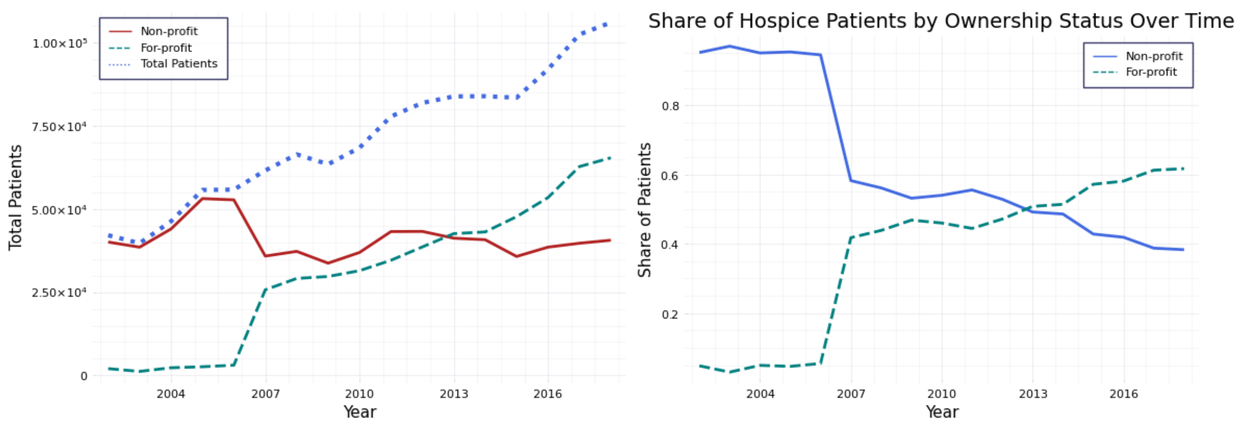
[6] To be rigorous: following Chung and Sorensen (2018), patient access should be tied to market expansion effects, i.e. does a new hospice entirely steal patients from other hospices, or does it bring in new patients who would not have otherwise enrolled in hospice care. This can be studied using the demand estimation method of Berry (1994) and checking if the nested logit parameter is significantly below 1, a strategy outlined by Chung and Sorensen (2018). Alam (2025) estimates a detailed demand model for hospices in California and indeed finds market expansion effect.

Figure 2: Time series plots of market dynamics.



(a) Total entries and exits by year

(b) Total hospices by year and for-profit status



(c) Total patients by year and for-profit status

(d) Share of total patients by year and for-profit status

Table 4: Market size by presence of for-profits.

Variable	**Counties without For-profits**	**Counties with For-profits**
Mean market size	2229.83	7067.76
Median market size	1207.7	5298.55

Notes: "Counties without For-profits" denotes counties which have non-profits but no for-profits. "Counties with For-profits" denotes counties which have for-profits (and may or may not have non-profits). Market size is measured in expected number of deaths per year.

This raises an important point. The high level of persistence means that current per-visit costs are a strong predictor of future per-visit costs. Since visit costs form a significant share of total costs (with a median of 54% from Table 1), this means that current per-visit costs have strong implications about future costs and profits. This makes it highly likely that per-visit costs affect entry and exit decisions of firms, which I corroborate in my empirical analysis. This analysis is

Table 5: Regression of donations per patient on competition level.

	Donations per patient
log(firm count)	-88.411***
	(10.727)
year Fixed Effects	Yes
Obs.	1,414

Notes: Robust standard errors in parentheses.

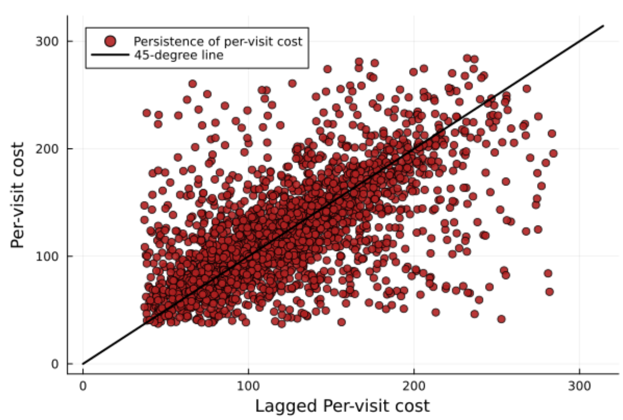
similar to Collard-Wexler (2011), who studies persistence of productivity in the ready-mix concrete industry, and argues that greater persistence of productivity means current productivity is a good indicator of future profits.

Table 6: Regression of current per-visit cost on lagged per-visit cost.

	Per-visit cost
Lagged per-visit cost	0.945***
	(0.007)
Obs.	2,712
R-squared	0.902

Notes: No intercept was included in the regression. Standard errors clustered at the county-level in parentheses.

Figure 3: Plot of current versus lagged per-visit costs.

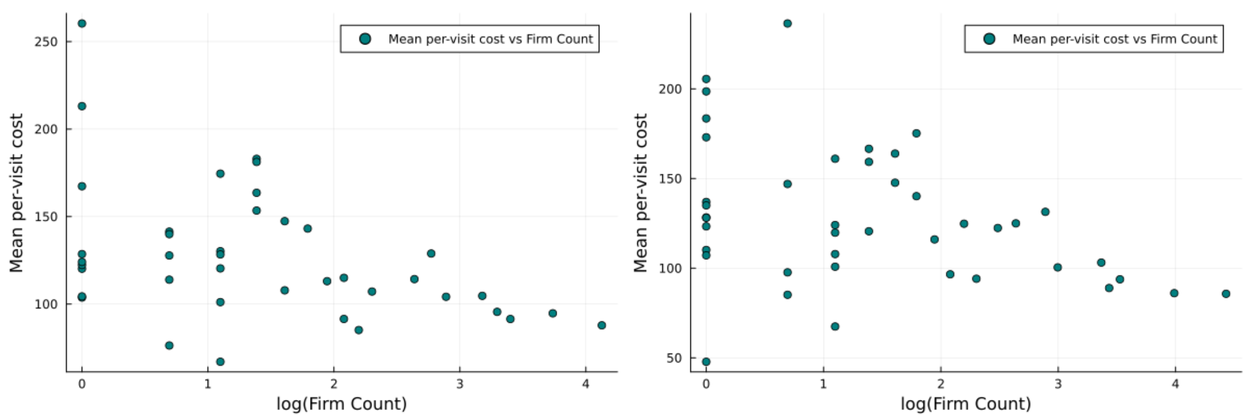


I find that hospices in more competitive markets make more visits-per-patient-day. This is shown in Figure 16 and Table 21, and is demonstrated carefully in Alam (2025). Visits-per-patient-day is a proxy for the quality of care and general effort provided by a hospice – a hospice which makes more visits is constantly checking and adjusting to the patient's condition, can manage symptoms better, and is likely to arrive quickly in case of an emergency.

Hospices which make more visits-per-patient-day also have greater market share – see Table 31 for a descriptive regression of patient volume on visits-per-patient-day, controlling for other factors. In more competitive areas, market share reallocates towards higher visits-per-patient-day hospices (Figure 17 and Table 22). This pattern is explored in more detail in an earlier paper by the author (Alam (2025)).

To motivate the research question of this paper, I plot various averages of per-visit costs (Figure 4). First, I plot county-level-mean of per-visit costs against county-level firm numbers for 2016 and 2017. Strikingly, I find that per-visit costs are lower in counties with more hospices. Second, I plot the year-level-mean of per-visit costs, and find that it is declining rapidly over time (Figure 5).

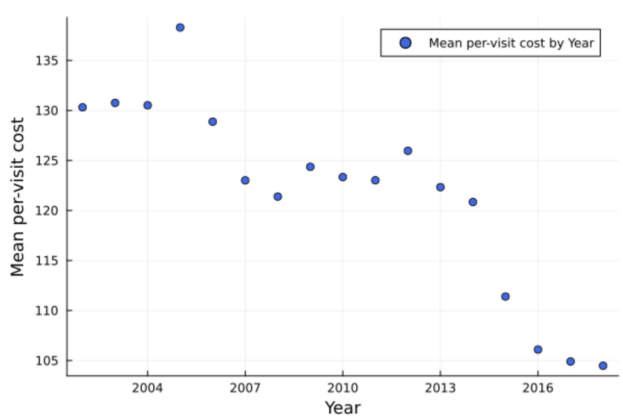
Figure 4: Variation in mean per-visit costs in the cross-section.



(a) Plot of county-level-mean of per-visit costs against county-level firm numbers for 2016.

(b) Plot of county-level-mean of per-visit costs against county-level firm numbers for 2017.

Figure 5: Plot of year-level-mean of per-visit costs over time.



4 Motivating evidence

In this section, motivated by Figure 4, I dig into the relationship between per-visit costs and competition. First, I regress per-visit costs on competition level to show that a negative relationship exists, and is robust to confounding factors. Second, I use a grouped-quantile IV regression to show that the distribution of per-visit costs shifts left with greater competition. Third, I hypothesize that the negative relationship may be driven by several economic mechanisms that subsequent sections will examine. Fourth, I present descriptive evidence about cost differences between for-profits versus non-profits, entrants versus incumbents, and exiting versus surviving hospices.

4.1 Regressions of per-visit costs

To see the link between per-visit costs and level of competition in my data, I regress per-visit cost on number of firms. While doing so, I attempt to control for possibe confounding factors:

1. Firms may be more likely to enter markets where costs are exogenously declining. I tackle this in two ways. First, I use market size (i.e. expected number of deaths in a market) as an instrument for competition levels. This is motivated by the idea that market size is a demand component that shifts the number of firms, and so is orthogonal to cost shocks. Second, I include polynomials of lags of market-level-mean per-visit costs as controls. Lags of market-level-mean per-visit costs help predict the trend of costs at the market level. The "polynomial of lags" functional form is motivated by the idea that firms and entrants are forming expectations about future costs based on past trends (which then influence dynamic decisions), so to capture such expectation formation without imposing any behavioral assumption, the function of lagged costs should be very general.

2. Cost functions may depend on quantity produced (reflecting economies or diseconomies of scale). Thus, as robustness checks, I include second-order polynomials of quantity in the regressions. I measure quantity via total patient days and total visits by hospices.[7]

[7] Given the industry details, economies of scale is more likely. Recall that hospice nurses usually start from their own home and drive out to multiple patient residences over the course of the day. If a hospice has more patients, that is more likely to reduce distance travelled to each patient (as subsequent visits are probably closer), resulting in economies of scale. Bensaid et al. (2022) finds evidence of economies of scale in the home health industry in France. In my estimation, I find some evidence of economies of scale: when I measure volume with total visits, I find per-visit costs to be somewhat declining in total visits.

Note that even if economies of scale were present but I did not control for it in my regressions, it would bias my coefficients in the opposite direction to what I find. If there are economies of scale, then greater competition (more firms) would lead to lower quantity per firm, which would increase per-visit costs. Thus, if I do not control for economies of scale, it would bias my coefficient on competition upwards (i.e. towards zero). Since I find a negative coefficient, this means that the true effect would be even more negative than what I estimate.

3. Third, I include operating cost as a control to account for additional factors of production that may affect the marginal cost of a visit.

Thus, the regression equation is:

$$log(c_{jt}) = \beta_m + \beta_f f_{m(j)t} + X'_{jt}\beta_x + \varepsilon_{jt} \tag{1}$$

where β_m are market fixed effects, $f_{m(j)t}$ is competition level (instrumented with expected number of deaths), X_{jt} are operating cost, second-order polynomials of one-year-lags and two-year-lags of market-level-mean per-visit costs, and other covariates.

Table 44 shows the results from 2SLS regression of per-visit costs on number of firms. The results suggest that markets with more firms have hospices with lower per-visit costs. I also perform robustness checks by measuring competition level with number-equivalent-HHI and find similar results (Section J.1).

4.2 Quantile analysis

While the 2SLS regression shows how the mean of the distribution of per-visit costs shifts with competition, I drill further into the data to examine changes in per-visit cost distributions as a result of competition. First, I illustrate the distribution of per-visit costs in three counties. Second, I run grouped-quantile regressions to rigorously show how the distribution of per-visit costs changes with competition. I find that increase in hospice competition shifts the distribution of per-visit costs left.

For a simple demonstration, Figure 6 plots smoothed densities of per-visit costs in years 2009 and 2018, during which time the level of competition increased substantially. It does so separately for three counties. This demonstrates how the distribution of costs change as level of competition rises. All 3 graphs show a similar pattern – as level of competition increases, the distribution of per-visit costs shifts left.

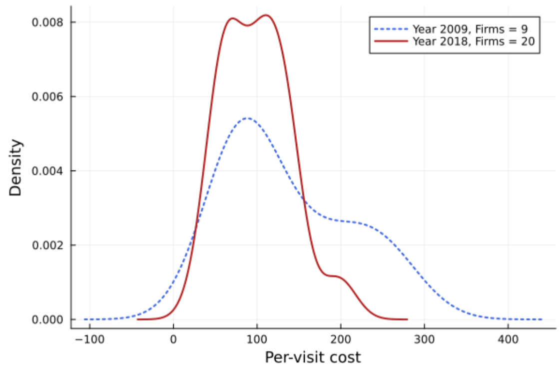
Next I run grouped-quantile regressions to measure how the distribution of per-visit costs changes with competition within my dataset. This follows the methods of Backus (2020), Chetverikov et al. (2016), and Larsen et al. (2023); see Section A.1 for details about implementation. I regress market-level quantiles on competition level in the market, using market size as an instrument for number of firms. Following Backus (2020), I use third-degree polynomials of the number of firms

An incorrect argument for number of hospices driving down per-visit costs is that more hospices mean greater concentration of hospice offices within a market, which reduces travel time between hospice office to patients. This is unlikely to be true. First, hospices do not drive out from their office to visit patients; rather, they start from their home and visit patients. Thus, the exact location of the hospice office does not directly influence driving time. Second, it would imply that costs of all hospices decline as more hospices enter. In my empirical analysis, I find that cost of entrants is lower than cost of incumbents.

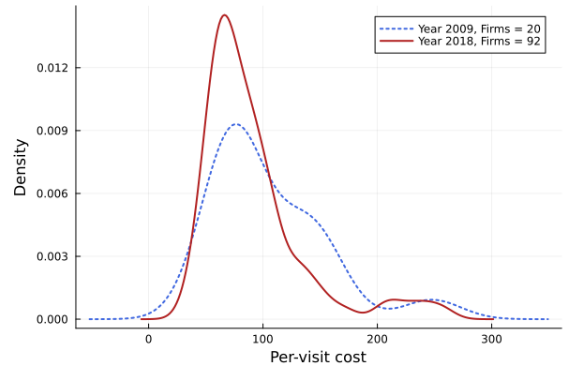
Table 7: Regression of per-visit costs on competition and controls.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	-0.125***	-0.123***	-0.129***	-0.104***
	(0.020)	(0.020)	(0.022)	(0.018)
Total patient days / 1000		0.001		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.038**	
			(0.011)	
Total Visits / 10,000 squared			0.000	
			(0.000)	
log(operating cost)	-0.008	-0.013	0.031*	-0.014
	(0.008)	(0.010)	(0.013)	(0.008)
Inpatient unit services				-0.032
				(0.045)
Pediatric program services				0.018
				(0.051)
Bereavement services for non-hospice survivors				0.090***
				(0.025)
Adult day care services				0.267*
				(0.104)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

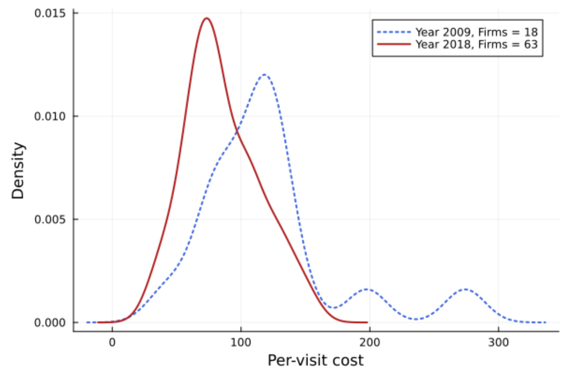
Notes: IV regression of log(per-visit cost) on log(firm count) with county fixed effects and controls. Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.



(a) Alameda



(b) San Bernardino



(c) Orange

Figure 6: Smoothed densities of per-visit cost in multiple counties.

to overcome an order-statistic bias. I include county fixed effects in all regressions, and every parameter is estimated separately for each quantile.

Let k denote the kth decile, and $\rho_{mt}^{(k)}$ be the kth decile of the market-level distribution of per-visit costs. The grouped-quantile regression equation is:

$$\rho_{mt}^{(k)} = \alpha_m^{(k)} + \alpha_f^{(k)} f_{mt} + X_{mt}' \alpha_x^{(k)} + g^{(k)}(n_{mt}) + \nu_{mt} \tag{2}$$

where f_{mt} is the level of competition and n_{mt} is the number of firms in the market. The semiparametric correction for the order statistic bias, $g^{(k)}(\cdot)$, is a third-degree polynomial of the number of firms in the market, and is estimated separately for each k. As a robustness check, I include market-level controls X_{mt} by having lags of market-level-mean per-visit costs. In Tables 8a and 8b, f_{mt} is log of number of firms.

The results are shown in Tables 8a and 8b (which additionally includes second-order polynomials of one- and two-year lags of market-level-mean per-visit costs). All regressions show that quantiles 10th to 70th shift left with more firms in the market, while results are more mixed for the higher quantiles. The effects are stronger at lower quartiles than higher quartiles.

Table 8: Grouped-quantile regressions of per-visit costs on competition.

Quantile	**Coefficient**	**S.E.**
0.1	-62.0691	47.1972
0.2	-57.7973	46.5341
0.3	-54.821	46.1504
0.4	-46.7867	45.9773
0.5	-39.649	46.1329
0.6	-30.7219	45.9584
0.7	-22.468	46.4914
0.8	-23.2499	47.4024
0.9	-23.9292	49.1447

(a)

Quantile	**Coefficient**	**S.E.**
0.1	-93.569	59.2587
0.2	-81.8432	59.0394
0.3	-72.2143	59.2026
0.4	-57.9146	59.4547
0.5	-47.2737	60.1173
0.6	-30.1996	59.828
0.7	-10.7681	60.5942
0.8	-3.16611	62.0975
0.9	3.44088	64.5013

(b)

Notes: Grouped-quantile IV regression of per-visit costs on competition, county fixed effects, and semi-parametric order-statistic bias correction. Table 8b also includes second-order polynomials of one-year-lag and two-year-lag of county-level-mean of per-visit costs. Robust standard errors are reported under S.E. See Section A.1 for details about implementation.

4.3 Discussion about economic mechanisms

Why does competition lower per-visit costs? I argue that the coefficient on competition in Table 44 could comprise three mechanisms:

1. Entry-composition effect: Greater competition occurs through entry of lower-cost firms, i.e. the composition of firms in the market shifts towards lower-cost firms.

2. Exit-selection effect: Greater competition forces higher-cost firms to exit the market.

3. Incumbent-treatment effect: Greater competition forces incumbents to lower their per-visit costs. This may be due to reduction in X-inefficiency or managerial slack; see Leibenstein (1966), Perelman (2011), and Backus (2020).

Each of these three mechanisms can lead to the coefficient on competition level being negative. Which of these mechanisms are present in the California hospice industry? The rest of the paper sheds light on this question.

4.4 Motivating evidence about mechanisms

I now present descriptive evidence about cost differences between for-profits versus non-profits, entrants versus incumbents, and exiting versus surviving hospices. This will also help clarify the variation in data that the next section's regression methods will use.

Table 9: Regression of per-visit costs on for-profit indicator and county-year fixed effects.

	log(per-visit cost)
For-profit	-0.219***
	(0.050)
County × Year Fixed Effects	Yes
Obs.	3,066

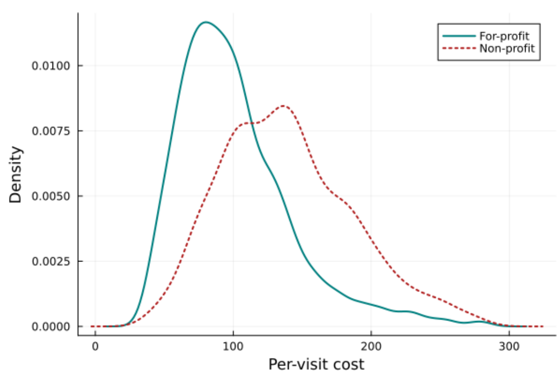
Notes: Standard errors clustered at county-level in parentheses.

4.4.1 Cost differences between for-profits and non-profits

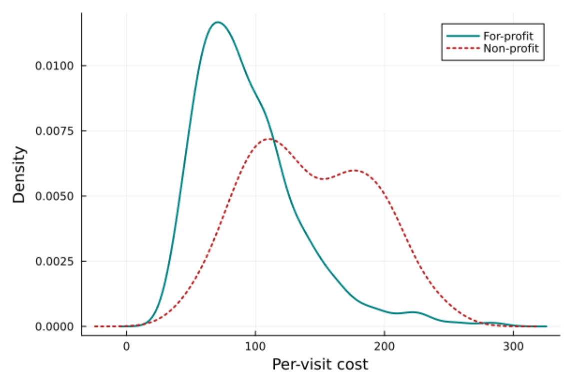
Since the growth in number of hospices is mostly driven by for-profit entry, I study whether for-profit hospices have lower per-visit costs than non-profits. I regress per-visit costs on for-profit status and county-year fixed effects. I also plot smoothed densities of per-visit costs broken down by for-profit status.

I find strong evidence that for-profit hospices have lower per-visit costs than non-profit hospices. See Table 9 for regression results, and Figure 7 for distribution of per-visit costs by for-profit status. The density plots show that for-profit hospices have a cost distribution that is shifted left relative to non-profits, indicating lower costs. I also plot the density for year 2017 separately alone to rule out possible across-year variation as a confounder and find the same result.

Figure 7: Density of per-visit costs by for-profit status.



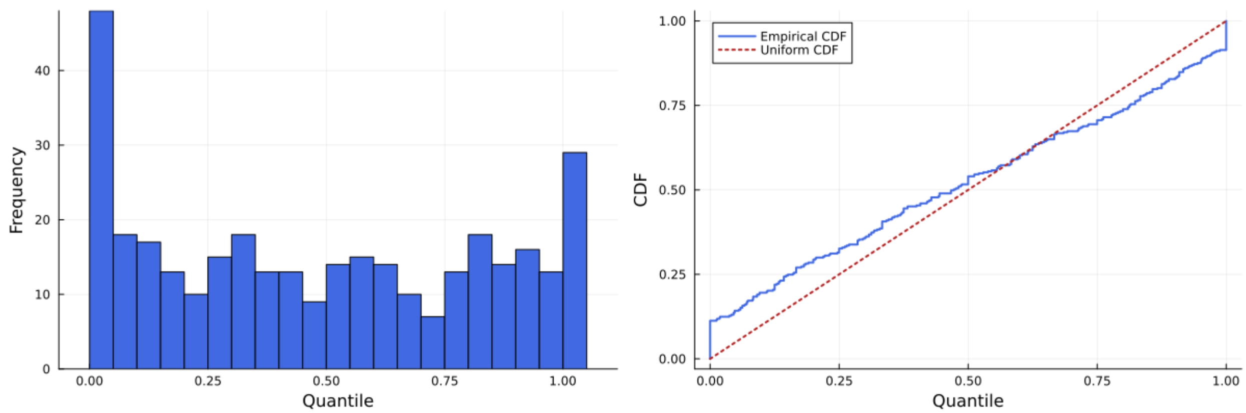
(a) Across entire dataset.



(b) For year 2017.

In Section 5, I will show that this conclusion holds on a set of comprehensive regressions over the full dataset.

Figure 8: Quantiles of per-visit costs of entrants in a county-year, using leave-one-out.



(a) Histogram.

(b) Cumulative distribution function.

Notes: These plots limit to markets with greater than 5 hospices for reliable quantile calculation.

4.4.2 Per-visit costs of entrants

For clarity, I first graphically study the costs of hospice entrants relative to incumbents. For each entrant, I compute the quantile of its per-visit cost in the empirical cost distribution of other hospices in the same county-year (excluding itself). This "leave-one-out" approach ensures that each hospice's quantile reflects its position among rivals and not include its own value. If entrants have low quantile values, it means they enter with costs lower than most incumbents; high quantile values indicate entrants with relatively high costs.

I illustrate my findings with the following graphs. First, I plot a histogram showing the frequency with which entrants fall into different quantiles of the rivals' cost distribution in the county-year. Second, I plot the cumulative distribution of these quantiles. This empirical CDF is compared to the CDF of a uniform distribution (the 45-degree line, which represents the benchmark of entrants randomly drawn from the county-year cost distribution). Together, these plots shed light on whether entrants are more efficient than incumbents: if the plots are skewed towards lower quantiles, then entrants tend to have lower costs than their local competitors. If the plots are more uniform, entrants are spread evenly across the cost spectrum. Figure 8 shows the results, limiting to markets with greater than 5 hospices for reliable quantile calculation; and Figure 15 limits to markets with greater than 10 hospices for robustness.

Both plots show that entrants tend to have lower per-visit costs than incumbents, as they are more likely to appear at lower quantiles. More specifically, this suggests entrants have lower per-visit costs than their rivals in the same county-year. Most striking is that entrants often have lower costs than all incumbents currently in the market, as illustrated by the histogram.

Next, I show suggestive evidence that later entrants have lower costs than earlier entrants. For each entrant, I calculate their mean per-visit cost over all years in my dataset, which I call their "mean lifetime per-visit cost". I regress the mean lifetime per-visit cost of a hospice on its entry time and other controls (Table 10). For the regression, I only include hospices entered after 2002 and those which never changed their for-profit status over my dataset. I measure entry time as the number of years since 2002 for Table 10. I find that later entrants have lower mean-lifetime per-visit costs than earlier entrants. To aid visualization, I plot the mean lifetime per-visit cost of hospices against their entry time in Figure 18, which also shows a downward trend.

In Section 5, I will show that this conclusion holds on a set of comprehensive regressions over the full dataset.

Table 10: Regression of mean lifetime per-visit cost on entry time and for-profit indicator.

	Mean lifetime per-visit cost	log(mean lifetime per-visit cost)
	(1)	(2)
Entry time	-1.204*	-0.016**
	(0.581)	(0.006)
For-profit	-15.404*	-0.137**
	(6.012)	(0.044)
County Fixed Effects	Yes	Yes
Obs.	425	425

Notes: Standard errors clustered at the county level in parentheses. Entry time is measured as number of years since 2002. For each entrant, I calculate their mean per-visit cost over all years in my dataset, which I call their "mean lifetime per-visit cost".

4.4.3 Per-visit costs of exiting hospices

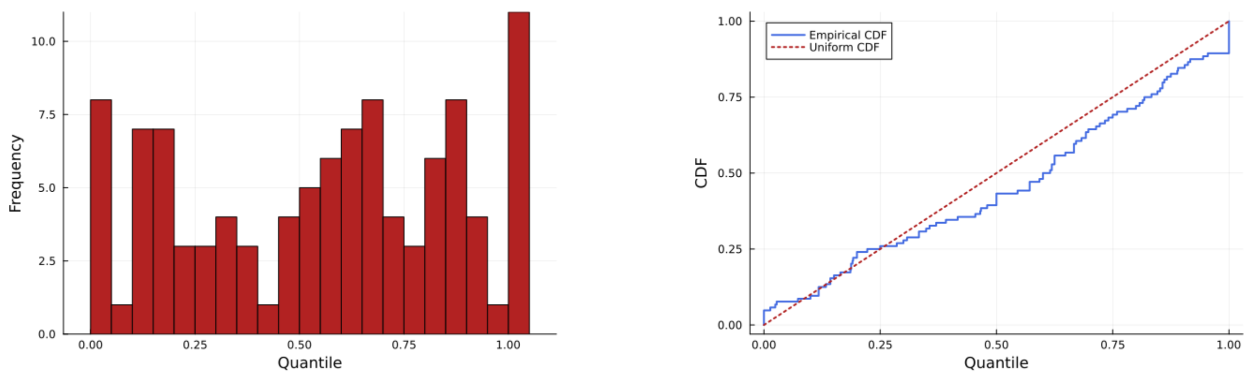
In this section I study if higher-cost hospices are more likely to exit. Since exiting the market may require the hospice to incur additional costs such as severance payments, for this section I calculate "per-visit costs" as total visiting services costs divided by total visits. The intuition is that costs on visits shouldn't vary based on whether the hospice will soon exit or not.

Similar to the analysis on hospice entrants, I first graphically study the costs of exiting hospices relative to its rivals. For each exiting hospice, I compute the quantile of its per-visit cost in the empirical cost distribution of other hospices in the same county-year (excluding itself). If an exiting hospice has low quantile values, it means they have costs lower than most incumbents, and vice versa.

I illustrate my findings with the following graphs. First, I plot a histogram showing the frequency with which exiting hospices fall into different quantiles of the rivals' cost distribution in the county-year. Second, I plot the cumulative distribution of these quantiles. This empirical CDF is compared to the CDF of a uniform distribution (the 45-degree line, which represents the benchmark of exits happening randomly across the county-year cost distribution). Together, these plots shed light on whether exiting hospices are less efficient than incumbents. If the plots are skewed towards higher quantiles, then exiting hospices tend to have higher costs than their rivals. Figure 9 shows the results, limiting to markets with greater than 5 hospices for reliable quantile calculation; and Figure 14 limits to markets with greater than 10 hospices for robustness.

The graphs suggest exiting hospices are slightly more likely to above-median in per-visit costs than their rivals. Most striking is that exiting firms often have higher costs than all incumbents currently in the market, as illustrated by the histogram. However, in contrast to the results for entrants, the results for exiting hospices is much weaker.

Figure 9: Distribution of per-visit costs of exiting hospices



(a) (b)

Notes: Figures 9a and 9b plot the quantiles of per-visit costs of exiting hospices in a county-year, using leave-one-out. These plots limit to markets with greater than 5 hospices for reliable quantile calculation.

To accurately quantify whether exiting firms do in fact have higher costs, I regress the binary variable of "Exit" on per-visit costs and county-by-year fixed effects (Table 11).

The results show that higher per-visit costs are associated with a higher probability of exit. I also find that hospices with more patients are less likely to exit. (This is similar to Collard-Wexler (2011), who finds that firm size is negatively related to exit probability.) The low R-squared suggests that per-visit costs have low explanatory power when predicting exits. This is consistent with the empirical literature, which generally finds that exits are much harder to predict than other firm decisions.

Note that this regression does not say anything about the exit-selection effect of competition. The exit-selection effect says that competition forces higher-cost firms to exit, while the above regression says high cost firms are more likely to exit without controlling for competition. To

Table 11: Regression of exit indicator on patients and per-visit costs.

	Exit
log(patients)	-0.028***
	(0.005)
log(per-visit cost)	0.033**
	(0.011)
County × Year Fixed Effects	Yes
Obs.	2,653
R-squared	0.196
Adj. R-squared	0.042

Notes: Standard errors clustered at county-level in parentheses.

study exit-selection effect directly, I regress exit on interaction of competition level and per-visit costs, along with other controls (Table 24). While the coefficient on the interaction term is not statistically significant – which seems to rule out exit-selection effect – the regression lacks power in general. I will return to the exit-selection effect in the next subsection, and confirm via a different method that in fact exit-selection is absent in my data.

5 Empirical Analysis

I examine the factors that drive the negative relationship between per-visit costs and competition using linear regression methods. First, I show that for-profits have lower costs than non-profits. Second, I show that entrants have lower costs than incumbents, and successive entrants have lower costs than prior entrants. Third, I show that greater competition does not lead to incumbents lowering their per-visit costs or for higher-cost incumbents to exit the market. Finally, I show that these results hold even after controlling for patient characteristics that may affect per-visit costs.

I now return to the three effects that can cause the coefficient on level of competition to be negative in Table 44: entry-composition effect, exit-selection effect, and incumbent-treatment effect.

After including for-profit status and entry time measure, the coefficient on competition should be the sum of exit-selection effect and incumbent-treatment effect.[8] Each of these mechanisms have a negative effect on per-visit costs. In this paper, instead of trying to disentangle these two effects, I focus on the combined effect.

[8]This is similar to the argument in Backus (2020). In that paper, the author runs a causal regression of productivity on competition, instrumenting it with demand shifters. He argues that the resulting negative effect is driven by the sum of "selection effect" (lower productivity firms forced out by competition) and "treatment effect" (firms improving their productivity in response to competition). Unlike my paper, Backus (2020) does not address entry by new firms.

I run a IV regression of per-visit costs on competition level, for-profit status, and entry time:

$$log(c_{jt}) = \beta_m + \beta_f f_{m(j)t} + \beta_1 \text{For-profit} + \beta_2 \text{Entry time} + X'_{jt}\beta_x + \varepsilon_{jt} \tag{3}$$

I instrument competition level with market size (i.e. expected number of deaths in a market). The results of this regression will tell us if for-profits have lower costs than non-profits, if later entrants have lower costs than earlier entrants, and if there is any remaining effect of competition on per-visit costs after controlling for these two factors.

The results are shown in Table 12. Confirming the patterns from the previous section, I find that for-profits have lower per-visit costs than non-profits, and later entrants have lower per-visit costs than earlier entrants.

Strikingly, once I include for-profit status and entry time measure, the coefficient on competition level is no longer statistically significant and is close to zero. This suggests that the negative relationship between per-visit costs and competition is not driven by the incumbent-treatment effect or exit-selection effect of competition, but rather by the entry-composition effect. In turn, this entry-composition effect is driven by i) for-profit hospices have lower per-visit costs than non-profit hospices, and ii) later entrants have lower per-visit costs than earlier entrants.

Since the exit-selection effect seems to be very weak given these results as well as Table 24, another way to check for the presence of incumbent-treatment effect is as follows. I restrict the sample to firms which entered by 2002, and run the IV regression of per-visit costs on number of firms, for-profit status, and other controls. Without the presence of exit-selection effect, the coefficient on competition level should be only the incumbent-treatment effect.[9]

The results are shown in Table 18; once again, the coefficient on competition is not statistically significant and is close to zero.

Prior literature on palliative care (see Section H) has suggested that patient characteristics affect hospice costs. This raises the possibility that my results are driven by patient characteristics, if for-profits and later entrants are somehow primarily serving patients with characteristics that lead to lower per-visit costs.

To ensure that my results are not driven by patient characteristics, I rerun the previous regression while controlling for the following characteristics of a hospice's patient pool:

1. Share of patients with cancer diagnosis: Some papers in the literature suggest that cancer patients may incur higher palliative-care costs.

[9]If exit-selection effect were present, then even after conditioning on entry before 2002, there would be a "survivors' bias" (Backus (2020)) – firms with high cost shocks and facing greater competition will exit. Thus, even for hospices with entry time before 2002, we will be left with a selected sample where higher competition markets have hospices with lower costs. Without exit-selection effect, there is no such bias.

Table 12: Regression of per-visit costs on competition, for-profit status, and entry time.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.046	0.046	0.052	0.045
	(0.033)	(0.033)	(0.038)	(0.032)
For-profit	-0.182***	-0.184***	-0.183***	-0.183***
	(0.046)	(0.046)	(0.042)	(0.047)
Entry time	-0.016***	-0.016***	-0.018***	-0.015***
	(0.004)	(0.004)	(0.003)	(0.004)
Entry before 2002	-0.028	-0.025	-0.025	-0.037
	(0.039)	(0.039)	(0.040)	(0.040)
Total patient days / 1000		-0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.043***	
			(0.011)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.032**	-0.024*	0.010	-0.033***
	(0.010)	(0.012)	(0.013)	(0.009)
Inpatient unit services				-0.058
				(0.038)
Pediatric program services				-0.024
				(0.047)
Bereavement services				0.057**
				(0.021)
Adult day care services				0.261**
				(0.095)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

2. Average length of stay and share of patients with short length of stay (less than 7 days): Multiple papers in the palliative-care literature suggest hospice visits and resource-use follow a U-shaped pattern with respect to length of stay, i.e. patients receive more visits at the beginning and end of their stays than in the middle. This may mean that resource-use *during* a visit may be higher for patients at the beginning and end of their stays; if that is the case, then hospices with mostly short-stay patients may have higher per-visit costs.

3. Share of non-routine care days: These days may be more resource-intensive, and thus hospices with a higher share of non-routine care days may have higher per-visit costs.

4. Share of home-based patients: There are conflicting suggestions on whether patients in their own homes incur higher or lower costs than patients located elsewhere (such as nursing homes). Nursing-home-based patients may have lower costs since they already receive some care from the nursing home staff, but it may also mean they do not have a primary caregiver at all times, and so may lack care.

Even after including these covariates in Equation 3, the results are qualitatively the same as before; see Tables 13 and 19.

I check if these patterns can be explained by studying the skill-mix of visits across for-profits and later entrants. I define the "skill mix of visits" as the share of visits made by higher-skilled workers (RNs, LVNs, and physicians) out of all visits made by RNs, LVNs, physicians, and home health aides, i.e. it tries to capture if a hospice may be using home health aides to substitute for clinical staff visits.

I rerun Equation 3 with skill mix of visits as an additional control, and find that the results are qualitatively the same. Hospices with higher skill mix do have higher per-visit costs, and including the variable slightly reduces the magnitude of the for-profit's cost advantage.

I perform a variety of robustness checks. Robustness checks using alternative measures of entry time are reported in Section D. My results are also robust to not using an instrumental variables approach, see Table 17.

I also perform robustness checks by measuring competition level with number-equivalent-HHI and find similar results; see Section J.1.

While I leave out LA county for my primary analysis due to allegations of fraud, I rerun my main regressions including LA county in the data and find similar results. I also rerun my main regressions for markets with fewer than 50 firms, and markets with fewer than 30 firms. I continue to find similar results; see Section J.

Table 13: Regression of per-visit costs on competition, for-profit status, and entry time.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.065	0.066*	0.079*	0.064*
	(0.033)	(0.033)	(0.039)	(0.032)
For-profit	-0.156**	-0.158**	-0.159**	-0.158**
	(0.048)	(0.048)	(0.046)	(0.049)
Entry time	-0.016***	-0.016***	-0.017***	-0.015***
	(0.004)	(0.004)	(0.003)	(0.004)
Entry before 2002	-0.032	-0.028	-0.031	-0.040
	(0.042)	(0.042)	(0.043)	(0.044)
Share of patients w/ cancer	0.253*	0.258*	0.244*	0.262*
	(0.118)	(0.119)	(0.120)	(0.114)
Share of patients w/ <7 days LOS	-0.138	-0.134	-0.100	-0.154
	(0.116)	(0.114)	(0.111)	(0.115)
Average length of stay	-0.001	-0.001	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	0.041	0.116	0.397	0.102
	(0.299)	(0.288)	(0.291)	(0.290)
Share of home-based patients	0.066	0.065	0.045	0.071
	(0.037)	(0.038)	(0.042)	(0.036)
Total patient days / 1000		-0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.044***	
			(0.010)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.026*	-0.019	0.015	-0.026*
	(0.010)	(0.012)	(0.013)	(0.010)
Inpatient unit services				-0.067
				(0.038)
Pediatric program services				-0.037
				(0.048)
Bereavement services				0.060**
				(0.022)
Adult day care services				0.268**
				(0.097)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

6 Discussion

In this section, I discuss mechanisms and possible confounders, and present some additional evidence. First, I decompose the cost components to see which components are primarily declining in the face of higher competition. Second, reduction in per-visit costs does not appear to cause a decline in quality of care. Third, I discuss the economic mechanisms that may be driving my results.

6.1 Decomposing cost components

Since my dataset contains breakdown of firm costs, I examine which cost components are primarily driving the results. That is, as level of competition increases, which cost components are most responsible for the decline in per-visit costs?

In Section G, I run the regression in Equation 3 on each cost component (divided by number of visits). I find that for-profits have lower costs in "nursing care", "medical social services expenses", and "other visiting services". Later entrants have lower costs in "nursing care"; and higher costs in "medical supplies"and "physician services".[10]

6.2 Suggestive Evidence on Quality and Reallocation

While the focus of this paper is on hospice production costs, a natural question to ask is whether hospices with lower per-visit costs also provide lower quality of care. I perform a series of empirical checks that offer no suggestive evidence of a decline in quality.

First, I show that hospices with lower per-visit costs provide more visits-per-patient-day. I regress visits-per-patient day on per-visit costs and a variety of controls (Table 20), and find a strong negative effect. Visits-per-patient-day is a good proxy for the quality and effort exerted by the hospice. A hospice that visits its patients more often are checking up on them regularly and adjusting for day-to-day difficulties.I find strong evidence throughout my data that hospices that make more visits-per-patient-day also have greater market share (Table 31). I have previously shown that hospices in more competitive markets also make more visits-per-patient-day. Furthermore, in more competitive areas, market share reallocates towards higher visits-per-patient-day hospices (Figure 17 and Table 22). This suggests that patients value visits-per-patient-day.

[10]There are two points to note regarding interpreting the above results. First, I mention only outcomes which are statistically significant at 10% level or less. This should not be judged as inference on individual cost components, but rather as suggestive evidence on which cost components show a "strong" correlation. The regressions are meant to be descriptive, not causal, and do not make use of Multiple Hypothesis Testing corrections as a result. Second, firms may be trading off one cost component with another; for example, a firm may be reducing "nursing care" while raising "medical supplies" costs; this also makes interpretation of the individual cost-component regressions difficult.

These results suggest that hospices with lower per-visit costs are taking advantage of their lower costs to provide more visits-per-patient-day. This makes sense because there is no price competition betweeen hospices, so consumers should choose hospices based on quality. Thus, with more firms, the quality competition should intensify, and only firms with lower per-visit costs can afford to make more visits.[11]

Second, I see if higher per-visit cost hospices also attract more patients – this would suggest that higher cost hospices are more attractive to patients possibly due to higher quality. To do so, I run the following descriptive regression on patient volume. I regress patient volume (number of patients and total patient days) on visits-per-patient-day and per-visit costs (while controlling for hospice age, for-profit status, and other factors). I find that per-visit costs have no statistically significant effect (Table 31). This also suggests that hospices with higher per-visit costs are not necessarily attracting more patients, suggesting that per-visit costs are not proxying for quality.

That said, this is a descriptive regression, and it is possible that for-profit status and age are absorbing meaningful variation in the per-visit cost variable. In particular, the for-profit status variable has a strong negative effect on patient volume. However, note that the following is still true – after controlling for for-profit status and age, higher per-visit costs do not lead to higher patient volume. Thus, after controlling for for-profit status, changes in per-visit costs do not appear to affect patient volume, which may suggest they don't reflect quality differences.

Third, the institutional details suggest that a widespread quality reduction is unlikely. Since hospice care is effectively free for the vast majority of patients, hospices compete primarily on quality and reputation. This quality competition is more fierce in more competitive markets. Since low cost hospices generally enter more competitive markets, it would suggest they would have an incentive to raise quality, not lower it.

On reflection, it is difficult to measure if hospices are making small sacrifices in quality, and if so by how much. Part of the story for cost reduction is likely coming from hospices improving coordination, adopting better technology, improving management practices, reducing waste, and other efficiency improvements that do not affect quality. However, it is possible that some cost-cutting measures may be affecting quality in ways that are hard for me to detect.

It is also possible that the any decline in quality from cost reductions may matter little to patients. Hospices compete primarily over quality and reputation, and in more competitive markets, that competition is more intense. Thus, it is unlikely that the lower cost hospices are all sacrificing

[11] An alternative argument could be argued that hospices which spend little within a visit worsen the health of their patient, and so has to make up with lots more visits. I believe this is unlikely. Visits are the most costly part of hospice care, as it involves hiring nurses, paying for their travel, and the opportunity cost of their time to the hospice. Thus, it is unlikely that a hospice is incurring the cost of a visit and then shirking on care quality during that visit. It is also not economical to shirk on within-visit care quality and then make up with more visits, since the type of care provided during visits is low-skill, while the overall cost of a visit is very high. While it may be true of few hospices, it is unlikely to be a widespread phenomenon.

quality significantly, because they would lose market share to higher-quality rivals. Instead, it may be that patients do not value certain dimensions of within-visit quality as much, and so hospices may be cutting costs in those dimensions. The hospice may use those cost savings to provide more vists-per-patient-day, which patients do value highly according to data. This may explain why per-visit costs do not correlate positively with patient volume in Table 31.[12]

For instance, when I regress "skill mix of visits" on a variety of covariates (Section F), I find that later entrants are not more likely to choose a higher skill mix of visits, and for-profits are more likely to choose a lower skill mix. Does this necessarily mean a decline in quality? No – it may be that for-profits are using lower-skill workers (such as home health aides) to perform tasks that do not require clinical skill, while reserving clinical workers for medical tasks. Thus, the hospice may be optimizing its skill mix of visits to reduce costs without sacrificing quality.

To emphasize, this project is concerned about production costs in healthcare provider markets and how they evolve with entry-exit dynamics. If production costs are lowered by firms sacrificing quality, it does not go against the main findings of this paper. That said, this section provides suggestive evidence that quality is not being sacrificed to lower production costs.

6.3 Reallocation

As competition increases, is there reallocation from high cost hospices to low cost hospices? To study this, I regress share-weighted per-visit costs on number of firms. The share-weighted per-visit cost in a market-year is calculated by weighting each hospice's per-visit cost by its within-hospice-market-share in that county-year. Thus, if there is reallocation towards low-cost firms as competition increases, then we should see a negative relationship between share-weighted per-visit costs and number of firms.

I find a strong negative effect, i.e., market share gets reallocated towards low-cost firms as competition increases (Table 14). I plot the relationship in Figure 10 to aid visualization.

What is the process by which market share gets allocated to lower-cost hospices? I argue that lower-cost hospices make more visits-per-patient-day (as shown earlier), and thus provide higher quality of care. Patients then choose these hospices, leading to higher market share. Table 31 regresses patient volume on visits-per-patient-day and per-visit costs (while controlling for hospice age, for-profit status, and other factors), and finds that visits-per-patient-day strongly correlate with volume, but per-visit costs have no statistically significant effect. This suggests that patients are

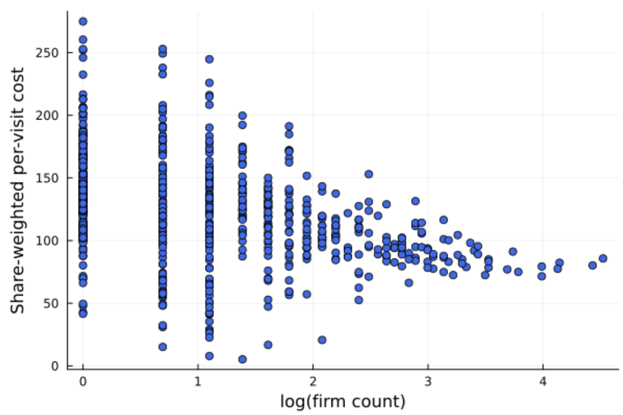
[12] This is similar to the ideas in Cochrane (2015): "My example industries do not cut costs by selling shoddy products or service. Instead, they provide consistent quality on the dimensions people turn out to really care about, and save on those that people don't really care about...How can health care emulate the quality improvement and cost reductions of these successful service oriented industries? My examples share a common thread: Intense competition. And, in particular, competition from new entrants, who put old companies out of business or force unwelcome and disruptive changes."

Table 14: Regression of share-weighted per-visit costs vs. number of firms

	Share-weighted per-visit cost	Share-weighted log per-visit cost
	(1)	(2)
log(firm count)	-17.261***	-0.331***
	(1.124)	(0.021)
Year Fixed Effects	Yes	Yes
Obs.	700	700

Notes: Robust standard errors in parentheses.

Figure 10: Scatter of share-weighted per-visit cost in a market-year by number of hospices.



Notes: Each point represents a county-year. The share-weighted per-visit cost is calculated for a county-year by weighting each hospice's per-visit cost by its within-hospice-market-share in that county-year.

choosing hospices based on visits-per-patient-day rather than per-visit costs (but see the caveats in the previous discussion).

6.4 Discussion on economic mechanisms behind firm decisions

In this section, I discuss possible economic mechanisms that may be driving my results, and provide some additional empirical evidence.

First, there is the question of how some hospices can attain cost reductions, apart from potential quality reductions (discussed elsewhere). Reading about hospice management online suggests it is a mix of improving coordination, monitoring and tracking costs, limiting unnecessary resource use or waste, adopting improved technology, intense bargaining over input prices, better management practices, etc.

What explains why later entrants have lower per-visit costs than past entrants? My preferred explanation is that with greater competition, firms need to compete more on quality (i.e. visits-per-patient-day), and increased visits-per-patient-day is more costly to provide. Only firms with lower per-visit costs can afford to make more visits while still being profitable. Thus, as competition goes up, the threshold level of cost that firms need to be below to enter the market goes down. This explains why earlier firms have higher costs, and per-visit costs decline with entry time. An alternative explanation on a similar note is that when considering entry into a market with already several hospices, an entrant will anticipate strong competition over patients, and therefore will need to have lower costs to maintain enough profits to justify incurring the entry cost.

It is also surprising that incumbents do not reduce costs when facing greater competition. I speculate that this has to do with organizational or managerial inertia that prevents incumbents from adjusting their cost structures.

Another puzzling fact is the absence of exit-selection effect. An explanation could be that the market for hospices is growing (rapidly in some counties), and such market growth may be sufficient to accommodate new and existing firms, even those with high costs.

Why do non-profits have higher costs than for-profits? There could be multiple reasons. The first is intrinsic motivation and salience – for-profits want to maximize profits, and so focus more on cost cutting; non-profits may have more altruistic objectives and have less pressure on maximizing profits. Second, non-profits may be partly funded by donations and enjoy tax advantages, and so they are less concerned about lowering costs to justify their operation.

To examine how important donations may be for non-profits, I study donations-per-patient of non-profits in my data. Table 15 plots the distribution of donations-per-patient at the hospice-year level. Surprisingly, I find that 40% of non-profit hospice-years have zero donations-per-patient. For more than 30% of non-profit hospice-years, donations-per-patient is greater than \$300. This is a sizeable amount, as the median per-visit cost is around \$100.

I also find that non-profits appear to have only a small tax advantage over for-profits. I study the distribution of taxes-per-patient for for-profits and non-profits. As expected, non-profits do not pay taxes in over 96% of observations. Surprisingly, over 70% of for-profit hospice-years also do not report paying taxes. Of the remainder that do, there is large variation ranging from \$18 per patient to hundreds of dollars per patient.

In Section B, I rule out the possibility that my finding of cost differences between non-profits and for-profits is driven by misreporting from non-profits.

7 Conclusion

I study the effect of entry-exit dynamics on hospice visit costs, and how it is influenced by the presence of non-profit and for-profit firms. Answering this will shed light on how competition may improve economic efficiency and lower skyrocketing healthcare costs in the United States. I use a panel dataset of hospices in California for 2002-2018 to construct hospice-level measures of per-visit costs and competition in market. Using linear and quantile regressions with instrumental variables, I show that per-visit costs are lower in counties with more hospices. I regress per-visit costs on number of hospices to show that a negative relationship exists, and is robust to confounding factors.

What drives the negative relationship between per-visit costs and competition? First, for-profits have lower costs than non-profits, and the entry of for-profits helps drive down overall costs in the market. Second, I show that entrants have lower costs than incumbents, and successive entrants have lower costs than prior entrants. Third, I show that higher-cost incumbents are more likely to exit the market. Fourth, I show that greater competition does not lead to incumbents lowering their per-visit costs or for higher-cost incumbents to exit the market, and that this is robust to controlling for patient characteristics. Finally, I find no evidence that reduction in per-visit costs leads to a decline in the quality of care.

The key policy insight is that entry barriers – such as the recently implemented Certificate-of-Need laws for hospices in Calfornia – can impede cost reductions from competition and also worsen patient access to care, since for-profits have improved access for patients.

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Online Appendix

A Estimation details

A.1 Quantile regression

This section follows similar descriptions in Larsen et al. (2023).

The grouped-quantile IV regression estimator closely follows Backus (2020), and has also been used in Chetverikov et al. (2016) and Larsen et al. (2023). It is appropriate for settings with group-level treatment (in my case, county-year competition) and micro data on outcomes within a group (in my case, firm-level per-visit costs).

In my setting, a group is a county-by-year cell, the treatment variable is county-by-year competition level, and micro data on outcomes corresponds to individual hospices in each county-year.

Since my quantile analysis focuses on deciles (10th percentile up to 90th percentile), this raises the question of how I calculate quantiles/deciles for markets with fewer than 10 firms. I use 2 methods to get around this:

1. I rerun the grouped-quantile IV regression but restrict the sample to county-years with at least 10 firms. The results are qualitatively the same.

2. I use the programming language *Julia*'s default setting for calculating quantiles, which uses linear interpolation between points following Hyndman and Fan (1996). This allows it to calculate quantiles even when there are fewer than 10 firms in a county-year.[13] See Figure 11 to see the exact description from Julia's documentation.

I regress market-level quantiles on competition level in the market. I instrument for competition level with market size, i.e. expected number of deaths. In additional robustness checks, I include second-order polynomials of one- and two-year lags of county-level mean of per-visit costs. I include county fixed effects in all regressions (similar to Larsen et al. (2023), who incorporate state fixed effects in their regressions). Note that every parameter is estimated separately for each quantile.

[13] The following examples serve as illustration of how *Julia* interpolates. For the vector [1,2,3,4,5], *Julia* calculates the 0th quantile to be 1, the 10th quantile to be 1.4, and the 25th quantile to be 2. For the vector [1, 2, 3], *Julia* calculates the 0th quantile to be 1, the 10th quantile to be 1.2, the 25th quantile to be 1.5, and the 50th quantile to be 2.

Figure 11: Julia documentation for calculating the pth quantile via interpolation.

Samples quantile are defined by `Q(p) = (1-γ)*x[j] + γ*x[j+1]`, where `x[j]` is the j-th order statistic of `v`, `j = floor(n*p + m)`, `m = alpha + p*(1 - alpha - beta)` and `γ = n*p + m - j`.

By default (`alpha = beta = 1`), quantiles are computed via linear interpolation between the points `((k-1)/(n-1), x[k])`, for `k = 1:n` where `n = length(v)`. This corresponds to Definition 7 of Hyndman and Fan (1996), and is the same as the R and NumPy default.

The keyword arguments `alpha` and `beta` correspond to the same parameters in Hyndman and Fan, setting them to different values allows to calculate quantiles with any of the methods 4-9 defined in this paper:

- Def. 4: `alpha=0`, `beta=1`
- Def. 5: `alpha=0.5`, `beta=0.5` (MATLAB default)
- Def. 6: `alpha=0`, `beta=0` (Excel `PERCENTILE.EXC`, Python default, Stata `altdef`)
- Def. 7: `alpha=1`, `beta=1` (Julia, R and NumPy default, Excel `PERCENTILE` and `PERCENTILE.INC`, Python `'inclusive'`)
- Def. 8: `alpha=1/3`, `beta=1/3`
- Def. 9: `alpha=3/8`, `beta=3/8`

Notes: Source url - https://docs.julialang.org/en/v1/stdlib/Statistics

Backus (2020) finds that such regressions suffer from an "order-statistic bias", which derives from the fact that some of the groups (county-years) have few firms present. He shows that the order-statistic bias is a nonlinear function of the number of firms, and thus including a flexible function of the number of firms in the grouped quantile regression fixes the bias. Following his method, I use third-degree polynomials of the number of firms to overcome the order-statistic bias.

With all this in place, I estimate the following grouped-quantile IV regression. Let k denote the kth decile, and $\rho_{mt}^{(k)}$ be the kth decile of the market-level distribution of per-visit costs.

$$\rho_{mt}^{(k)} = \alpha_m^{(k)} + \alpha_f^{(k)} f_{mt} + X_{mt}' \alpha_x^{(k)} + g^{(k)}(n_{mt}) + \nu_{mt}$$

where f_{mt} is the level of competition and n_{mt} is the number of firms in the market. The semiparametric correction for the order statistic bias, $g^{(k)}(\cdot)$, is a third-degree polynomial of the number of firms in the market, and is estimated separately for each k.

Similar to Backus (2020) and Larsen et al. (2023), estimating this involves a simple linear-regression (with IV) on market-level data for each quantile.

A.2 Smoothed density plots

Throughout the paper, I use smoothed density plots to visualize distributions of variables. These are kernel density plots, and for bandwidth use Silverman's rule.

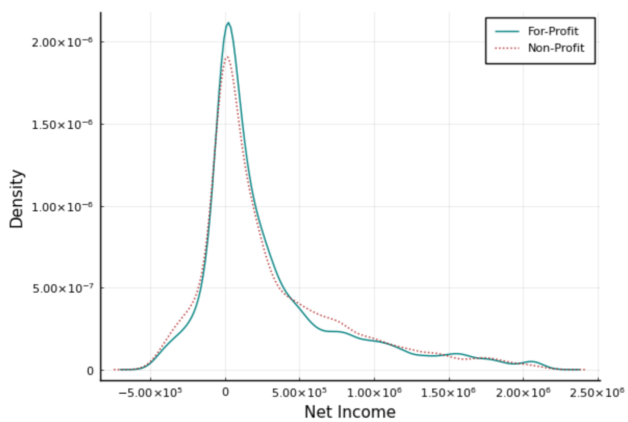
B Misreporting of costs by non-profits

One potential worry is that my finding of cost differences between non-profits and for-profits may be driven by misreporting from non-profits. If non-profits overstate their costs, then the true cost differences between non-profits and for-profits may be smaller than what I find. This may happen if non-profits have incentives to appear less profitable in order to receive donations or avoid scrutiny. (Interestingly, it has also been suggested that non-profits may have incentives to understate costs to appear efficient to donors and receive more donations.)

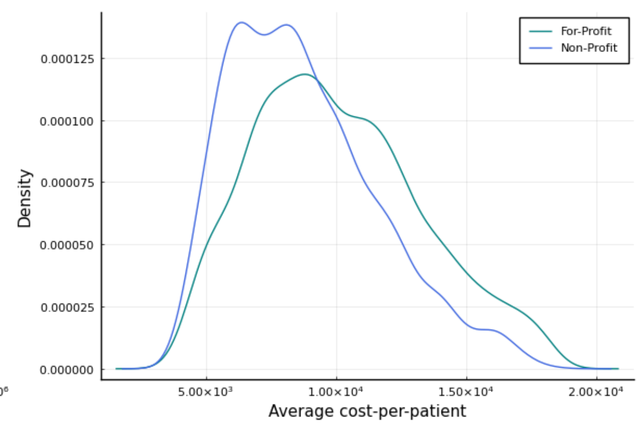
To rule out this possibility, I plot i) average cost-per-patient and ii) reported profits, of non-profits versus for-profits in Figure 12; also see Figure 13 for histograms.

I find distributions of for-profits and non-profits to be quite similar, and in particular do not find non-profits to systematically have lower profits or higher average cost-per-patient.

Figure 12: Distributions of reported profits ("net income") and cost-per-patient by for-profit status.



(a) Smoothed kernel density of reported profits, broken down by for-profit status.



(b) Notes: Smoothed kernel density of cost-per-patient, broken down by for-profit status.

Figure 13: Histograms of reported profits ("net income") and cost-per-patient by for-profit status.

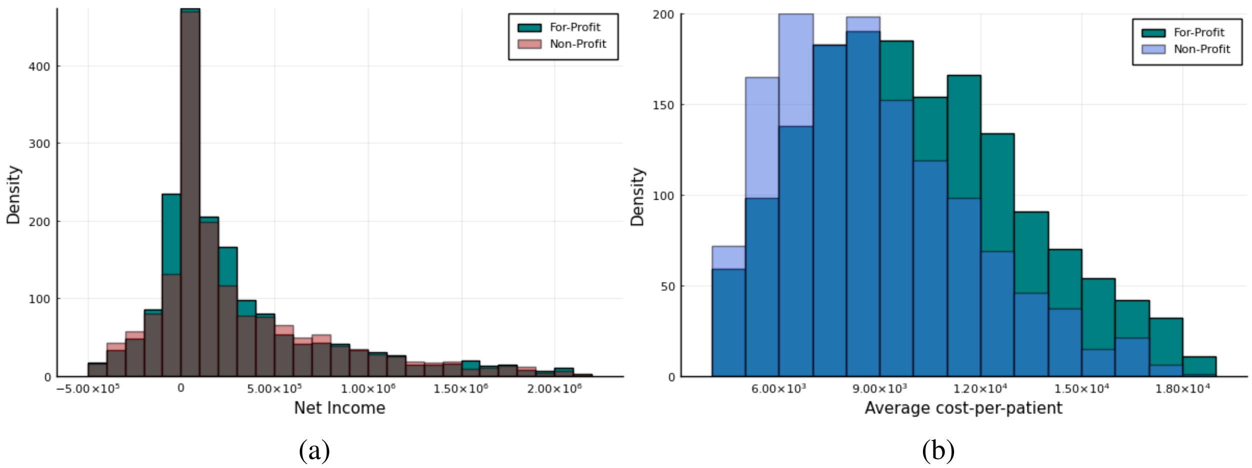
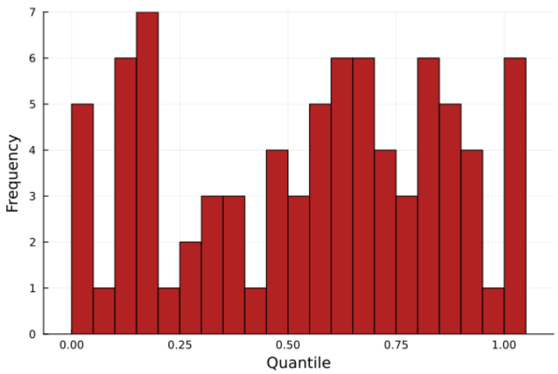


Table 15: Quantiles of donations-per-patient for non-profits.

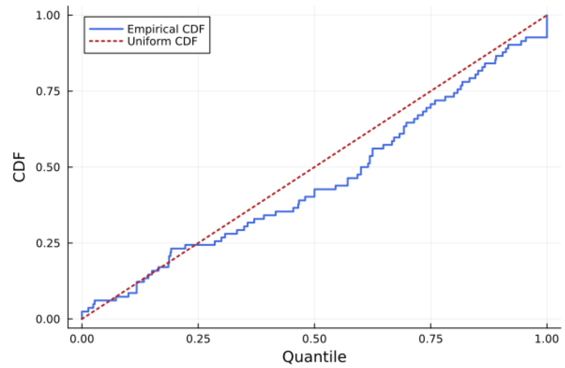
Quantile	Donations per Patient ($)
0.0	-41.37
0.1	0.0
0.2	0.0
0.3	0.0
0.4	13.31
0.5	93.11
0.6	227.2
0.7	382.56
0.8	676.45
0.9	1249.45
1.0	13068.4

C Miscellaneous

Figure 14: Distribution of per-visit costs of exiting hospices



(a)



(b)

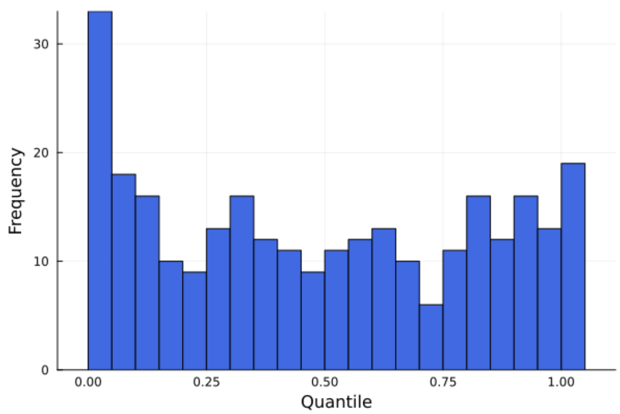
Notes: Figures 9a and 9b plot the quantiles of per-visit costs of exiting hospices in a county-year, using leave-one-out. These plots limit to markets with greater than 10 hospices for reliable quantile calculation.

Table 16: First stage of IV regression

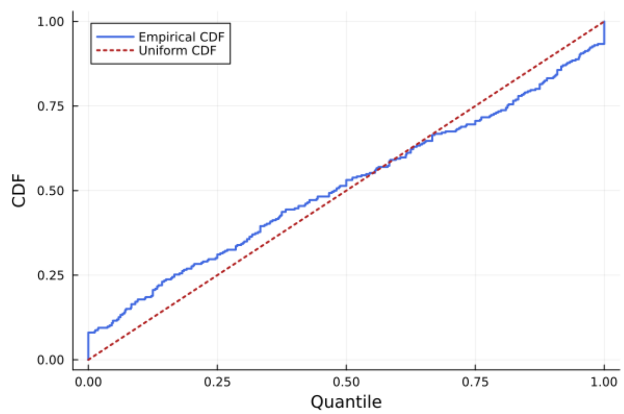
	log(firm count)			
	(1)	(2)	(3)	(4)
log(market size)	4.611***	4.606***	4.607***	4.605***
	(0.651)	(0.651)	(0.652)	(0.645)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

Notes: Controls are the covariates from the regressions.

Figure 15: Quantiles of per-visit costs of entrants in a county-year, using leave-one-out.



(a) Histogram.



(b) Cumulative distribution function.

Notes: These plots limit to markets with greater than 10 hospices for reliable quantile calculation.

Table 17: Cost-competition regression without instruments (OLS regression).

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.030	0.031	0.038	0.031
	(0.021)	(0.021)	(0.020)	(0.020)
For-profit	-0.153**	-0.154**	-0.156**	-0.155**
	(0.048)	(0.048)	(0.046)	(0.049)
Entry time	-0.014***	-0.014***	-0.015***	-0.013***
	(0.004)	(0.003)	(0.003)	(0.003)
Entry before 2002	-0.025	-0.021	-0.023	-0.033
	(0.043)	(0.043)	(0.044)	(0.045)
Share of patients w/ cancer	0.244*	0.249*	0.234	0.255*
	(0.119)	(0.121)	(0.122)	(0.115)
Share of patients w/ <7 days LOS	-0.159	-0.156	-0.125	-0.174
	(0.117)	(0.115)	(0.113)	(0.115)
Average length of stay	-0.001	-0.001	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	0.029	0.101	0.380	0.092
	(0.301)	(0.290)	(0.289)	(0.292)
Share of home-based patients	0.066	0.064	0.045	0.071
	(0.037)	(0.038)	(0.042)	(0.036)
Total patient days / 1000		-0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.044***	
			(0.010)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.025*	-0.018	0.016	-0.025*
	(0.010)	(0.011)	(0.012)	(0.009)
Inpatient unit services				-0.068
				(0.039)
Pediatric program services				-0.037
				(0.048)
Bereavement services				0.059*
				(0.022)
Adult day care services				0.261*
				(0.099)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

Notes: Standard errors clustered at the county level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 18: Regression of per-visit costs on competition and for-profit status, limited to hospices that entered on or before 2002.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.079	0.072	0.064	0.087
	(0.066)	(0.066)	(0.064)	(0.066)
For-profit	-0.099	-0.098	-0.107	-0.086
	(0.055)	(0.054)	(0.054)	(0.051)
Total patient days / 1000		-0.003		
		(0.001)		
Total patient days / 1000 squared		0.000**		
		(0.000)		
Total Visits / 10,000			-0.023	
			(0.013)	
Total Visits / 10,000 squared			0.000	
			(0.000)	
log(operating cost)	-0.068***	-0.048	-0.030	-0.084***
	(0.015)	(0.024)	(0.025)	(0.017)
Inpatient unit services				0.026
				(0.045)
Pediatric program services				0.135*
				(0.065)
Bereavement services				0.059
				(0.043)
Adult day care services				0.365***
				(0.058)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	891	891	891	891

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 19: Regression of per-visit costs on competition and for-profit status, limited to hospices that entered on or before 2002.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.100	0.097	0.092	0.104
	(0.079)	(0.079)	(0.077)	(0.081)
For-profit	-0.060	-0.061	-0.073	-0.050
	(0.051)	(0.052)	(0.051)	(0.049)
Share of patients w/ cancer	0.413	0.407	0.445	0.365
	(0.241)	(0.253)	(0.264)	(0.239)
Share of patients w/ <7 days LOS	-0.429*	-0.402*	-0.405	-0.430*
	(0.195)	(0.198)	(0.210)	(0.189)
Average length of stay	-0.004**	-0.004*	-0.003*	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	0.247	0.411	0.737	0.232
	(0.740)	(0.642)	(0.680)	(0.851)
Share of home-based patients	0.088	0.084	0.065	0.096
	(0.110)	(0.112)	(0.108)	(0.112)
Total patient days / 1000		-0.002		
		(0.001)		
Total patient days / 1000 squared		0.000		
		(0.000)		
Total Visits / 10,000			-0.022	
			(0.014)	
Total Visits / 10,000 squared			0.000	
			(0.000)	
log(operating cost)	-0.062**	-0.049	-0.028	-0.075***
	(0.018)	(0.026)	(0.026)	(0.020)
Inpatient unit services				0.004
				(0.043)
Pediatric program services				0.109
				(0.057)
Bereavement services				0.068
				(0.043)
Adult day care services				0.375***
				(0.063)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	891	891	891	891

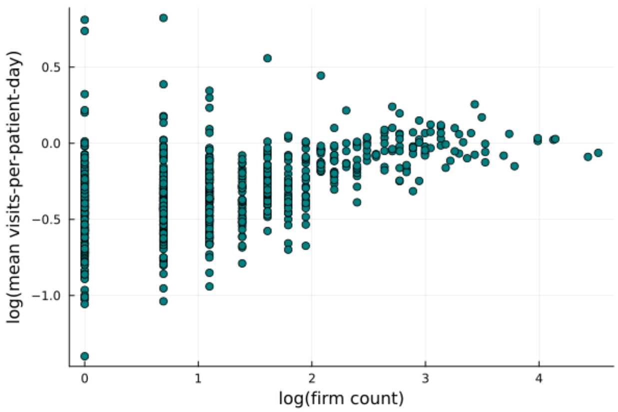
Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 20: Regression of visits-per-patient-day on per-visit costs and for-profit status.

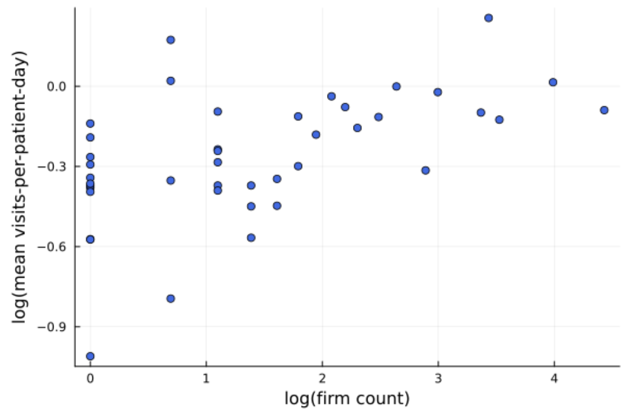
	Visits-per-patient-day
log(per-visit cost)	-0.214***
	(0.015)
For-profit	-0.005
	(0.022)
County Fixed Effects	Yes
Controls	Yes
Obs.	3,155

Notes: This is limited to observations with visits-per-patient-day below 1.5 to remove outliers. Standard errors clustered at county-level in parentheses. Controls are log of firm count, hospice inpatient unit indicator,pediatric program indicator, bereavement for non-hospice-survivors indicator, daycare for adult services indicator, for-profit status,and agency types indicators.

Figure 16: Variation in mean visits-per-patient-day over time and space.



(a) Plot of county-level-mean of visits-per-patient-day over the full dataset.



(b) Plot of county-level-mean of visits-per-patient-day for 2017.

Table 21: Regression of county-level-mean visits-per-patient-day on number of hospices.

	Mean visits-per-patient-day	log(mean visits-per-patient-day)
	(1)	(2)
log(firm count)	0.086** (0.028)	0.120** (0.036)
County Fixed Effects	Yes	Yes
Obs.	699	699

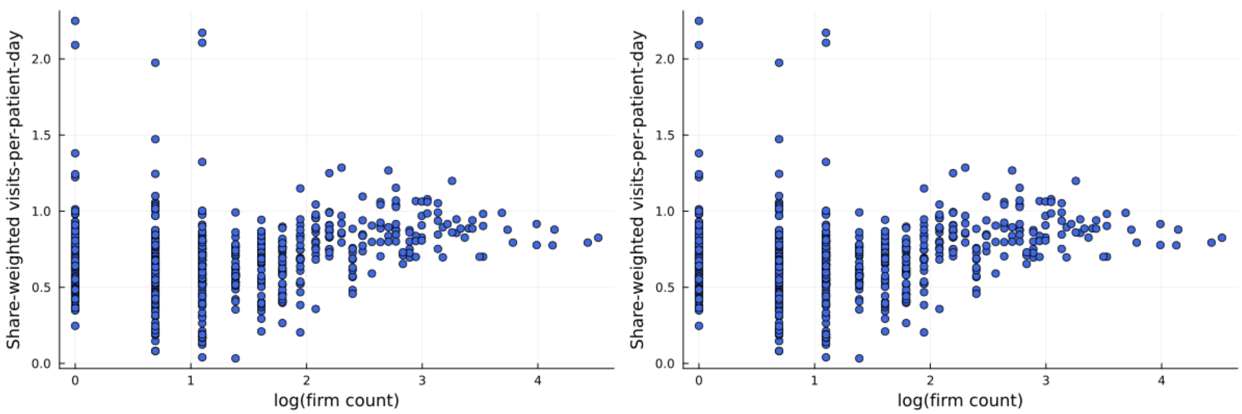
Notes: Each observation is a county-year. For the county-year, I calculate the mean visits-per-patient-day by averaging over all hospices in that county-year. Standard errors clustered at the county level in parentheses.

Table 22: Regression of share-weighted visits-per-patient-day on number of hospices.

	Share-weighted visits-per-patient-day	Share-weighted log visits-per-patient-day
	(1)	(2)
log(firm count)	0.047*** (0.008)	0.118*** (0.008)
Year Fixed Effects	Yes	Yes
Obs.	700	700

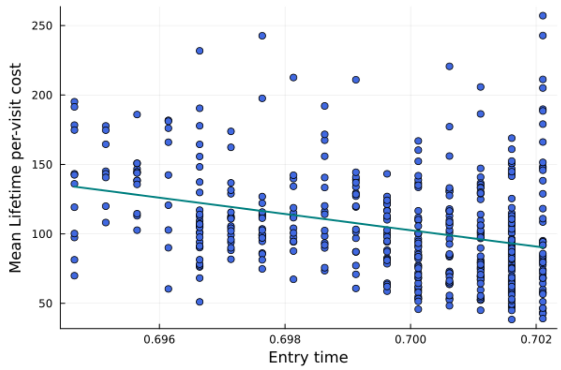
Notes: Each observation is a county-year. Standard errors clustered at the county level in parentheses.

Figure 17: Scatter of share-weighted visits-per-patient-day against firm count.

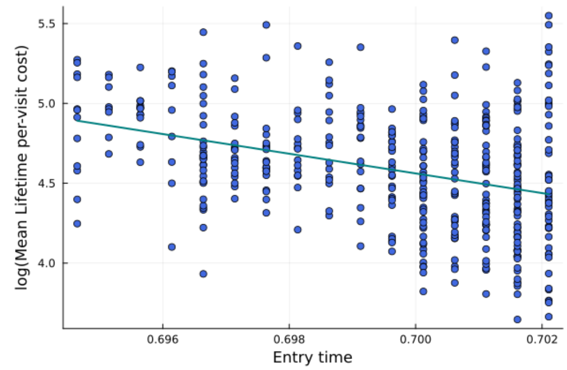


County	Total Exits	Total Entries	Total Unique Hospices
San Bernardino	32	117	124
Orange	25	76	88
Ventura	12	47	52
Riverside	13	38	47
San Diego	6	26	37
Sacramento	7	25	30
Alameda	6	19	26
Contra Costa	10	18	22
Santa Clara	6	16	22
San Mateo	4	13	16
Kern	5	11	14
Fresno	3	10	13
San Joaquin	4	10	12
Santa Barbara	3	8	10
Sonoma	5	7	11
Placer	2	5	7
San Francisco	5	5	11
Shasta	2	5	6
Marin	3	4	5
Stanislaus	2	4	6
Sutter	3	4	6
Mariposa	3	3	4
Santa Cruz	1	3	4
Tulare	1	3	4
Merced	2	2	4
Tehama	1	2	2
El Dorado	1	1	3
Kings	1	1	2
Mendocino	1	1	2
Monterey	1	1	4
Napa	1	1	2
Siskiyou	2	1	3
Yolo	1	1	2
Butte	1	0	4
Del Norte	1	0	1
Madera	1	0	1

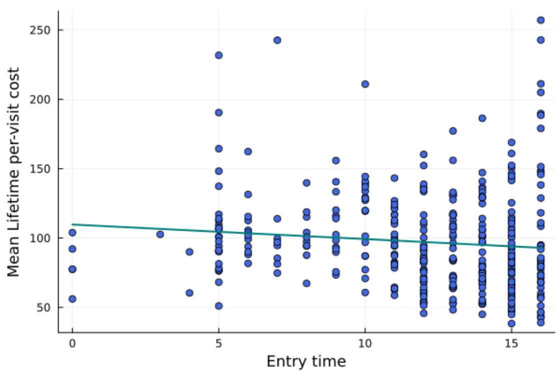
Figure 18: Scatterplot of mean per-visit costs versus entry time.



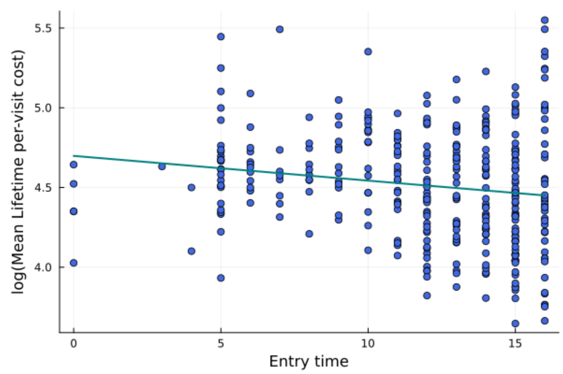
(a)



(b)



(c)



(d)

Notes: Each point is a unique hospice. The mean is calculated over the lifetime of the hospice, i.e. the mean per-visit cost for a specific hospice over all years observed in the dataset. Entry time is measured as number of years since 2002.

Figure 19: Snapshot of the "operating expense form".

DETAIL OF OPERATING EXPENSES
(do not input "$" signs, commas, or decimals; round up to whole dollar)
Use data from Medicare Cost Report where applicable.

Line No.		Total (1)
	General Service Cost Centers	
30	Administrative and General	
	Inpatient Care Service	
31	Inpatient – General Care	
32	Inpatient – Respite Care	
	Program Supervision	
35	Hospice Program / Team Supervision (Non-Visit Wages)	
	Visiting Services	
36	Physician Services	
37	Nursing Care	
38	Rehabilitation Services (PT, OT, Speech)	
39	Medical Social Services – Direct	
40	Spiritual Counseling	
41	Dietary Counseling	
42	Counseling – Other	
43	Home Health Aides and Homemakers	
44	Other Visiting Services	
	Hospice Service Cost Centers	
45	Drugs, Biologicals, and Infusion	
46	Durable Medical Equipment / Oxygen	
47	Patient Transportation	
48	Imaging, Lab, and Diagnostics	
49	Medical Supplies	
50	Outpatient Services (including ER Dept.)	
51	Radiation Therapy	
52	Chemotherapy	
53	Other Hospice Service Costs	
	Other Hospice Costs	
54	Bereavement Program Costs	
55	Volunteer Program Costs	
56	Fundraising Costs	
	Other Costs	
57	Other Program Costs*	
59	Total Operating Expenses	

* Program costs including community education and outreach program costs.

Notes: This is a screenshot of the operating expense form that hospices in California have to fill out each year for HCAI. Data from this form is used to compile the dataset used in this paper.

Table 23: Percent of visits by care type.

Variable	**10%**	**25%**	**50%**	**75%**	**90%**
Routine care	97.59	99.12	99.69	99.91	100.0
Inpatient care	0.0	0.0	0.07	0.37	1.13
Respite care	0.0	0.0	0.06	0.18	0.38
Continuous care	0.0	0.0	0.01	0.1	0.74

Table 24: Regression of exit including interaction of cost with competition.

	Exit
log(per-visit cost)	-0.004
	(0.027)
log(firm count)	-0.065
	(0.033)
log(patients)	-0.030***
	(0.006)
log(per-visit cost) x log(firm count)	0.010
	(0.008)
County Fixed Effects	Yes
Obs.	2,896
R-squared	0.029
Adj. R-squared	0.013

D Robustness checks with alternative entry time measures

Table 25: Entry time = entry order

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.083*	0.082*	0.098*	0.082*
	(0.033)	(0.033)	(0.042)	(0.032)
For-profit	-0.243***	-0.243***	-0.247***	-0.241***
	(0.041)	(0.042)	(0.039)	(0.043)
Entry time	-0.018**	-0.018**	-0.021**	-0.018**
	(0.006)	(0.006)	(0.006)	(0.005)
Entry before 2002	0.036	0.039	0.036	0.029
	(0.039)	(0.039)	(0.044)	(0.038)
Total patient days / 1000		0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.048***	
			(0.013)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.022*	-0.018	0.026	-0.023*
	(0.009)	(0.015)	(0.015)	(0.009)
Inpatient unit services				-0.026
				(0.038)
Pediatric program services				-0.004
				(0.046)
Bereavement services				0.036
				(0.020)
Adult day care services				0.115
				(0.093)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,093	3,093	3,093	3,093

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 26: Entry time = entry order

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.104**	0.104**	0.128**	0.103**
	(0.035)	(0.035)	(0.045)	(0.034)
For-profit	-0.214***	-0.214***	-0.221***	-0.214***
	(0.041)	(0.041)	(0.040)	(0.042)
Entry time	-0.018**	-0.017**	-0.021***	-0.017***
	(0.005)	(0.005)	(0.006)	(0.005)
Entry before 2002	0.033	0.036	0.030	0.026
	(0.040)	(0.040)	(0.044)	(0.039)
Share of patients w/ cancer	0.307*	0.312*	0.291*	0.314*
	(0.124)	(0.124)	(0.122)	(0.120)
Share of patients w/ <7 days LOS	-0.265*	-0.264*	-0.217	-0.276*
	(0.127)	(0.128)	(0.123)	(0.126)
Average length of stay	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	0.224	0.278	0.618	0.263
	(0.328)	(0.317)	(0.357)	(0.326)
Share of home-based patients	0.058	0.058	0.039	0.062
	(0.055)	(0.056)	(0.061)	(0.056)
Total patient days / 1000		0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.050***	
			(0.012)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.015	-0.012	0.032	-0.016
	(0.010)	(0.015)	(0.016)	(0.010)
Inpatient unit services				-0.040
				(0.040)
Pediatric program services				-0.020
				(0.046)
Bereavement services				0.040
				(0.021)
Adult day care services				0.131
				(0.098)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,093	3,093	3,093	3,093

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 27: Entry time = log(year of entry minus 2002 + 1)

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.068*	0.067*	0.081*	0.069*
	(0.032)	(0.032)	(0.039)	(0.032)
For-profit	-0.232***	-0.232***	-0.234***	-0.230***
	(0.041)	(0.041)	(0.038)	(0.042)
Entry time	-0.098**	-0.097**	-0.116***	-0.096**
	(0.034)	(0.032)	(0.030)	(0.032)
Entry before 2002	-0.072	-0.067	-0.093	-0.079
	(0.070)	(0.069)	(0.069)	(0.068)
Total patient days / 1000		0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.047***	
			(0.013)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.019*	-0.015	0.029	-0.020*
	(0.009)	(0.015)	(0.016)	(0.009)
Inpatient unit services				-0.029
				(0.038)
Pediatric program services				-0.005
				(0.045)
Bereavement services				0.040
				(0.020)
Adult day care services				0.124
				(0.097)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,093	3,093	3,093	3,093

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 28: Entry time = entry order

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.090*	0.090*	0.111*	0.090*
	(0.035)	(0.035)	(0.042)	(0.035)
For-profit	-0.203***	-0.203***	-0.208***	-0.204***
	(0.040)	(0.040)	(0.039)	(0.042)
Entry time	-0.093**	-0.091**	-0.113***	-0.090**
	(0.032)	(0.030)	(0.028)	(0.030)
Entry before 2002	-0.069	-0.063	-0.095	-0.075
	(0.069)	(0.068)	(0.067)	(0.068)
Share of patients w/ cancer	0.322*	0.326*	0.309*	0.328*
	(0.127)	(0.127)	(0.124)	(0.123)
Share of patients w/ <7 days LOS	-0.256*	-0.256*	-0.209	-0.269*
	(0.125)	(0.126)	(0.121)	(0.123)
Average length of stay	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	0.194	0.248	0.574	0.238
	(0.344)	(0.337)	(0.383)	(0.339)
Share of home-based patients	0.055	0.055	0.036	0.060
	(0.057)	(0.058)	(0.064)	(0.058)
Total patient days / 1000		0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.049***	
			(0.012)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.012	-0.009	0.035*	-0.013
	(0.010)	(0.015)	(0.017)	(0.010)
Inpatient unit services				-0.044
				(0.040)
Pediatric program services				-0.022
				(0.045)
Bereavement services				0.043*
				(0.021)
Adult day care services				0.140
				(0.102)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,093	3,093	3,093	3,093

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 29: Entry time = log(entry order)

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.082*	0.083*	0.099*	0.082*
	(0.032)	(0.033)	(0.040)	(0.032)
For-profit	-0.236***	-0.237***	-0.239***	-0.234***
	(0.040)	(0.041)	(0.037)	(0.042)
Entry time	-0.122***	-0.122***	-0.147***	-0.119***
	(0.033)	(0.034)	(0.035)	(0.031)
Entry before 2002	-0.067	-0.065	-0.089	-0.072
	(0.052)	(0.052)	(0.056)	(0.050)
Total patient days / 1000		-0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.050***	
			(0.013)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.023*	-0.017	0.026	-0.024*
	(0.009)	(0.015)	(0.016)	(0.009)
Inpatient unit services				-0.024
				(0.038)
Pediatric program services				-0.004
				(0.046)
Bereavement services				0.037
				(0.020)
Adult day care services				0.125
				(0.095)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,093	3,093	3,093	3,093

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 30: Entry time = entry order

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.102**	0.104**	0.129**	0.102**
	(0.034)	(0.034)	(0.043)	(0.033)
For-profit	-0.208***	-0.209***	-0.214***	-0.208***
	(0.040)	(0.040)	(0.039)	(0.041)
Entry time	-0.116***	-0.116***	-0.144***	-0.112***
	(0.031)	(0.031)	(0.033)	(0.029)
Entry before 2002	-0.064	-0.061	-0.092	-0.068
	(0.051)	(0.051)	(0.055)	(0.049)
Share of patients w/ cancer	0.311*	0.315*	0.294*	0.317*
	(0.126)	(0.127)	(0.124)	(0.123)
Share of patients w/ <7 days LOS	-0.266*	-0.265*	-0.219	-0.278*
	(0.127)	(0.127)	(0.123)	(0.126)
Average length of stay	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	0.235	0.301	0.643	0.274
	(0.327)	(0.315)	(0.355)	(0.324)
Share of home-based patients	0.055	0.055	0.035	0.059
	(0.055)	(0.056)	(0.061)	(0.056)
Total patient days / 1000		0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.052***	
			(0.013)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.016	-0.011	0.032	-0.017
	(0.011)	(0.015)	(0.017)	(0.011)
Inpatient unit services				-0.039
				(0.039)
Pediatric program services				-0.021
				(0.046)
Bereavement services				0.041
				(0.021)
Adult day care services				0.141
				(0.100)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,093	3,093	3,093	3,093

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

E Regression on patient volume

Table 31: Regression of patient volume on covariates.

	log(patients)
log(firm count)	-0.492***
	(0.107)
log(visits-per-patient-day)	0.342***
	(0.067)
log(per-visit cost)	-0.020
	(0.063)
For-profit	-0.448***
	(0.078)
log(age)	0.538***
	(0.035)
County Fixed Effects	Yes
Controls	Yes
Obs.	3,118

Notes: This is limited to observations with visits-per-patient-day below 1.5 to remove outliers. Standard errors clustered at county-level in parentheses. Controls are log of market size, hospice inpatient unit indicator,pediatric program indicator, bereavement for non-hospice-survivors indicator, daycare for adult services indicator, for-profit status,and agency types indicators.

F Regression on skill mix of visits

	Skill mix of visits	
	(1)	(2)
Share of patients w/ cancer	0.052	0.046
	(0.031)	(0.029)
Share of patients w/ <7 days LOS	-0.011	-0.005
	(0.036)	(0.036)
Average length of stay	-0.000	-0.000
	(0.000)	(0.000)
Share of non-routine care days	0.063	0.062
	(0.050)	(0.050)
Share of home-based patients	0.065***	0.063***
	(0.011)	(0.011)
Entry before 2002	0.001	0.002
	(0.011)	(0.011)
Entry time	0.001	0.001
	(0.001)	(0.001)
log(operating cost)	-0.009***	-0.009***
	(0.002)	(0.002)
For-profit	-0.036***	-0.032***
	(0.006)	(0.006)
log(firm count)	0.011	0.010
	(0.009)	(0.009)
log(per-visit cost)		0.024*
		(0.010)
County Fixed Effects	Yes	Yes
Obs.	3,314	3,314

Notes: "Skill mix of visits" is the share of visits made by higher-skilled workers (RNs, LVNs, and physicians) out of all visits made by RNs, LVNs, physicians, and home health aides. Standard errors clustered at county-level in parentheses.

Table 33

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.063*	0.064*	0.077*	0.061*
	(0.031)	(0.031)	(0.037)	(0.030)
For-profit	-0.144**	-0.146**	-0.146**	-0.147**
	(0.047)	(0.047)	(0.045)	(0.047)
Entry time	-0.016***	-0.016***	-0.018***	-0.015***
	(0.004)	(0.004)	(0.003)	(0.004)
Entry before 2002	-0.033	-0.029	-0.032	-0.040
	(0.041)	(0.041)	(0.041)	(0.043)
Skill mix of visits	0.332*	0.346*	0.366*	0.342*
	(0.148)	(0.152)	(0.149)	(0.152)
Share of patients w/ cancer	0.236*	0.240*	0.224	0.248*
	(0.116)	(0.117)	(0.117)	(0.112)
Share of patients w/ <7 days LOS	-0.132	-0.127	-0.093	-0.149
	(0.112)	(0.110)	(0.106)	(0.111)
Average length of stay	-0.001	-0.001	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	0.030	0.118	0.394	0.095
	(0.296)	(0.284)	(0.287)	(0.287)
Share of home-based patients	0.043	0.040	0.019	0.046
	(0.039)	(0.040)	(0.044)	(0.038)
Total patient days / 1000		-0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.045***	
			(0.010)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.023*	-0.014	0.020	-0.022*
	(0.010)	(0.012)	(0.012)	(0.010)
Inpatient unit services				-0.071
				(0.039)
Pediatric program services				-0.047
				(0.048)
Bereavement services				0.060**
				(0.021)
Adult day care services				0.245**
				(0.083)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

Notes: Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs. Standard errors clustered at county-level in parentheses.

G Regression on individual cost components

The controls in the following regressions are: share of patients with cancer, share of patients with length of stay less than or equal to 7 days, average actual length of stay, share of non-routine care days, share of patients served at home, entry in 2002 indicator, entry time measure, log of operating costs, for-profit status, lagged county-level-mean slope of per-visit costs (and its square) up to two lags.

	Drug, biologicals, and infusion
log(firm count)	-5.176***
	(0.770)
For-profit	0.446
	(0.788)
Entry time	0.128
	(0.115)
Entry before 2002	1.294
	(0.876)
County Fixed Effects	Yes
Controls	Yes

	Durable medical equipment
log(firm count)	-1.828*
	(0.794)
For-profit	-0.080
	(0.612)
Entry time	0.076
	(0.056)
Entry before 2002	-0.211
	(0.768)
County Fixed Effects	Yes
Controls	Yes

	Patient transportation
log(firm count)	0.048
	(0.105)
For-profit	0.115
	(0.095)
Entry time	0.003
	(0.011)
Entry before 2002	0.172
	(0.089)
County Fixed Effects	Yes
Controls	Yes

	Imaging, lab, and diagnostics
log(firm count)	0.029
	(0.072)
For-profit	0.036
	(0.029)
Entry time	-0.003
	(0.007)
Entry before 2002	-0.056
	(0.053)
County Fixed Effects	Yes
Controls	Yes

	Medical supplies
log(firm count)	0.100
	(0.423)
For-profit	0.070
	(0.473)
Entry time	0.190***
	(0.044)
Entry before 2002	1.168*
	(0.444)
County Fixed Effects	Yes
Controls	Yes

	Outpatient services
log(firm count)	1.877
	(1.888)
For-profit	-0.442
	(0.434)
Entry time	-0.132
	(0.118)
Entry before 2002	-0.036
	(0.219)
County Fixed Effects	Yes
Controls	Yes

	Physician services
log(firm count)	1.892**
	(0.660)
For-profit	-0.693
	(0.563)
Entry time	0.139*
	(0.063)
Entry before 2002	-0.941
	(0.505)
County Fixed Effects	Yes
Controls	Yes

	Nursing care
log(firm count)	14.870***
	(3.425)
For-profit	-13.290***
	(3.202)
Entry time	-1.783***
	(0.402)
Entry before 2002	-0.984
	(3.451)
County Fixed Effects	Yes
Controls	Yes

	Rehabilitation services expenses
log(firm count)	-3.105
	(2.868)
For-profit	-0.449
	(0.314)
Entry time	0.070
	(0.120)
Entry before 2002	0.340
	(0.791)
County Fixed Effects	Yes
Controls	Yes

	Medical social services expenses
log(firm count)	3.048
	(2.605)
For-profit	-3.803**
	(1.315)
Entry time	-0.025
	(0.203)
Entry before 2002	3.418
	(1.959)
County Fixed Effects	Yes
Controls	Yes

	Spiritual counseling
log(firm count)	0.406
	(0.581)
For-profit	-0.167
	(0.327)
Entry time	-0.060
	(0.050)
Entry before 2002	-0.563
	(0.372)
County Fixed Effects	Yes
Controls	Yes

	Dietary counseling
log(firm count)	0.030
	(0.103)
For-profit	-0.053
	(0.038)
Entry time	-0.009
	(0.005)
Entry before 2002	-0.040
	(0.044)
County Fixed Effects	Yes
Controls	Yes

	Counseling services (other)
log(firm count)	0.470
	(0.565)
For-profit	-0.473
	(0.276)
Entry time	0.042
	(0.027)
Entry before 2002	0.555
	(0.508)
County Fixed Effects	Yes
Controls	Yes

	Home health aides and homemakers
log(firm count)	0.417
	(0.948)
For-profit	-0.183
	(0.770)
Entry time	-0.140
	(0.072)
Entry before 2002	-0.736
	(0.749)
County Fixed Effects	Yes
Controls	Yes

	Other visiting services
log(firm count)	3.226*
	(1.423)
For-profit	-4.388**
	(1.395)
Entry time	-0.099
	(0.193)
Entry before 2002	-1.080
	(1.719)
County Fixed Effects	Yes
Controls	Yes

	Other program costs
log(firm count)	-1.928
	(3.313)
For-profit	1.364
	(1.500)
Entry time	-0.299
	(0.314)
Entry before 2002	-3.263
	(2.443)
County Fixed Effects	Yes
Controls	Yes

H Useful references and links from the palliative care literature

Some papers that helped inform this paper are Gibson et al. (2013) and Huskamp et al. (2008), among others.

Useful links:

1. https://www.milliman.com/en/insight/hospice-medicare-margins-analysis-of-patient-and-hospice-characteristics-utilization-an
2. https://www.medpac.gov/wp-content/uploads/import_data/scrape_files/docs/default-source/reports/Mar10_Ch02E_APPENDIX.pdf
3. https://allianceforcareathome.org/wp-content/uploads/NHPCO_Hospice_Staffing_Framework.pdf
4. https://allianceforcareathome.org/wp-content/uploads/PC_Staffing_grab-go.pdf
5. https://www.medpac.gov/wp-content/uploads/import_data/scrape_files/docs/default-source/contractor-reports/the-medicare-hospice-payment-system-a-preliminary-consideration-of-potential-refinements.pdf

I Entry restrictions and fraud in California hospice industry

1. Entry restrictions (initial): https://hospicenews.com/2021/10/05/california-passes-major-hospice-reform-laws/
2. Entry restrictions (extension till 2024): https://hospicenews.com/2022/12/01/new-california-law-further-tightens-hospice-license-oversight/
3. Entry restrictions (extension till 2027): https://www.cdph.ca.gov/Programs/CHCQ/LCP/Pages/AFL-25-04.aspx
4. Report from California State Auditor: https://information.auditor.ca.gov/reports/2021-123/index.html
5. Press release by California Attorney General: https://oag.ca.gov/news/press-releases/confronting-hospice-fraud-attorney-general-bonta-launches-public-awareness?utm_medium=email&utm_source=govdelivery

J Robustness checks for main results

J.1 With number-equivalent HHI

Table 34: Regression of per-visit costs on competition, for-profit status, and entry time. Competition measured as number-equivalent HHI calculated using within-hospice market share.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
Total patient days / 1000		0.002		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.040**	
			(0.011)	
Total Visits / 10,000 squared			0.000	
			(0.000)	
log(operating cost)	-0.007	-0.012	0.034*	-0.014
	(0.008)	(0.010)	(0.013)	(0.008)
Inpatient unit services				-0.034
				(0.045)
Pediatric program services				0.020
				(0.052)
Bereavement services for non-hospice survivors				0.090***
				(0.025)
Adult day care services				0.269*
				(0.100)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 35: Regression of per-visit costs on competition, for-profit status, and entry time. Competition measured as number-equivalent HHI calculated using within-hospice market share.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(Number-equivalent HHI)	0.053	0.057	0.071	0.053
	(0.048)	(0.050)	(0.056)	(0.047)
For-profit	-0.187***	-0.189***	-0.187***	-0.187***
	(0.045)	(0.046)	(0.042)	(0.047)
Entry time	-0.116***	-0.119***	-0.138***	-0.110***
	(0.029)	(0.028)	(0.027)	(0.028)
Entry before 2002	-0.097*	-0.099*	-0.116*	-0.102*
	(0.048)	(0.047)	(0.045)	(0.048)
Total patient days / 1000		-0.001		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.044***	
			(0.011)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.031**	-0.022	0.010	-0.032**
	(0.011)	(0.012)	(0.013)	(0.010)
Inpatient unit services				-0.056
				(0.037)
Pediatric program services				-0.026
				(0.047)
Bereavement services				0.057**
				(0.021)
Adult day care services				0.261*
				(0.099)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 36: First stage of IV using number equivalent HHI.

	log(Number-equivalent HHI)			
	(1)	(2)	(3)	(4)
log(market size)	3.311***	3.301***	3.326***	3.304***
	(0.481)	(0.479)	(0.480)	(0.476)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,114	3,114	3,114	3,114

J.2 Limited to markets with fewer than 50 firms

Table 37: Regression of per-visit costs on competition, for-profit status, and entry time. Limited to markets with fewer than 50 firms.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	-0.125***	-0.125***	-0.127***	-0.102***
	(0.023)	(0.024)	(0.028)	(0.022)
Total patient days / 1000		0.001		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.041**	
			(0.012)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.011	-0.012	0.033*	-0.020*
	(0.010)	(0.012)	(0.015)	(0.009)
Inpatient unit services				-0.018
				(0.045)
Pediatric program services				0.021
				(0.052)
Bereavement services for non-hospice survivors				0.091**
				(0.028)
Adult day care services				0.272*
				(0.104)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	2,766	2,766	2,766	2,766

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 38: Regression of per-visit costs on competition, for-profit status, and entry time. Limited to markets with fewer than 50 firms.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.057	0.059	0.064	0.057
	(0.042)	(0.042)	(0.050)	(0.041)
For-profit	-0.190***	-0.193***	-0.189***	-0.191***
	(0.047)	(0.047)	(0.043)	(0.048)
Entry time	-0.015**	-0.016**	-0.016***	-0.015**
	(0.005)	(0.005)	(0.004)	(0.005)
Entry before 2002	-0.026	-0.026	-0.022	-0.036
	(0.040)	(0.040)	(0.041)	(0.040)
Total patient days / 1000		-0.001		
		(0.001)		
Total patient days / 1000 squared		0.000		
		(0.000)		
Total Visits / 10,000			-0.045***	
			(0.011)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.035**	-0.023	0.011	-0.038***
	(0.011)	(0.014)	(0.014)	(0.010)
Inpatient unit services				-0.048
				(0.040)
Pediatric program services				-0.024
				(0.048)
Bereavement services				0.059*
				(0.023)
Adult day care services				0.269**
				(0.093)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	2,766	2,766	2,766	2,766

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 39: Regression of per-visit costs on competition, for-profit status, and entry time. Limited to markets with fewer than 50 firms.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.075	0.077	0.089	0.075
	(0.044)	(0.044)	(0.054)	(0.043)
For-profit	-0.162**	-0.164**	-0.164**	-0.163**
	(0.050)	(0.050)	(0.048)	(0.051)
Entry time	-0.015**	-0.015**	-0.016***	-0.014**
	(0.005)	(0.004)	(0.004)	(0.004)
Entry before 2002	-0.028	-0.027	-0.026	-0.038
	(0.043)	(0.043)	(0.043)	(0.044)
Share of patients w/ cancer	0.239	0.245	0.234	0.254*
	(0.126)	(0.127)	(0.127)	(0.122)
Share of patients w/ <7 days LOS	-0.199	-0.193	-0.154	-0.214
	(0.120)	(0.118)	(0.115)	(0.119)
Average length of stay	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	-0.030	0.056	0.326	0.026
	(0.316)	(0.304)	(0.304)	(0.308)
Share of home-based patients	0.073	0.071	0.050	0.077
	(0.047)	(0.048)	(0.051)	(0.045)
Total patient days / 1000		-0.001		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.046***	
			(0.011)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.027*	-0.017	0.017	-0.029*
	(0.011)	(0.014)	(0.015)	(0.011)
Inpatient unit services				-0.060
				(0.040)
Pediatric program services				-0.036
				(0.049)
Bereavement services				0.063**
				(0.023)
Adult day care services				0.274**
				(0.094)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	2,766	2,766	2,766	2,766

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

J.3 Limited to markets with fewer than 30 firms

Table 40: Regression of per-visit costs on competition, for-profit status, and entry time. Limited to markets with fewer than 30 firms.

Table 41: Regression of per-visit costs on competition, for-profit status, and entry time.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	-0.115***	-0.116***	-0.113**	-0.089**
	(0.031)	(0.031)	(0.032)	(0.030)
Total patient days / 1000		0.000		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.044**	
			(0.014)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.014	-0.013	0.033*	-0.024**
	(0.009)	(0.014)	(0.016)	(0.009)
Inpatient unit services				-0.014
				(0.045)
Pediatric program services				0.020
				(0.053)
Bereavement services for non-hospice survivors				0.097**
				(0.030)
Adult day care services				0.287**
				(0.098)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	2,461	2,461	2,461	2,461

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 42: Regression of per-visit costs on competition, for-profit status, and entry time. Limited to markets with fewer than 30 firms.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.101*	0.106*	0.115*	0.102*
	(0.049)	(0.049)	(0.056)	(0.047)
For-profit	-0.198***	-0.202***	-0.198***	-0.198***
	(0.049)	(0.048)	(0.044)	(0.050)
Entry time	-0.016*	-0.017**	-0.018**	-0.016**
	(0.006)	(0.005)	(0.005)	(0.006)
Entry before 2002	-0.014	-0.015	-0.012	-0.027
	(0.044)	(0.043)	(0.045)	(0.045)
Total patient days / 1000		-0.002		
		(0.001)		
Total patient days / 1000 squared		0.000		
		(0.000)		
Total Visits / 10,000			-0.048***	
			(0.013)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.040***	-0.023	0.011	-0.043***
	(0.011)	(0.016)	(0.016)	(0.010)
Inpatient unit services				-0.044
				(0.041)
Pediatric program services				-0.030
				(0.048)
Bereavement services				0.062*
				(0.026)
Adult day care services				0.283**
				(0.086)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	2,461	2,461	2,461	2,461

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 43: Regression of per-visit costs on competition, for-profit status, and entry time. Limited to markets with fewer than 30 firms.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.118*	0.123*	0.142*	0.119*
	(0.051)	(0.052)	(0.061)	(0.050)
For-profit	-0.172**	-0.176**	-0.175***	-0.173**
	(0.052)	(0.051)	(0.049)	(0.052)
Entry time	-0.016*	-0.016**	-0.017**	-0.015*
	(0.006)	(0.005)	(0.005)	(0.006)
Entry before 2002	-0.014	-0.014	-0.015	-0.027
	(0.047)	(0.047)	(0.048)	(0.049)
Share of patients w/ cancer	0.225	0.234	0.230	0.246*
	(0.123)	(0.125)	(0.124)	(0.120)
Share of patients w/ <7 days LOS	-0.224	-0.211	-0.155	-0.241
	(0.140)	(0.138)	(0.134)	(0.142)
Average length of stay	-0.002**	-0.002*	-0.002*	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Share of non-routine care days	-0.084	0.017	0.281	-0.031
	(0.342)	(0.331)	(0.329)	(0.329)
Share of home-based patients	0.052	0.049	0.026	0.055
	(0.063)	(0.063)	(0.065)	(0.061)
Total patient days / 1000		-0.001		
		(0.001)		
Total patient days / 1000 squared		0.000		
		(0.000)		
Total Visits / 10,000			-0.049***	
			(0.013)	
Total Visits / 10,000 squared			0.001	
			(0.000)	
log(operating cost)	-0.033*	-0.019	0.016	-0.035**
	(0.012)	(0.016)	(0.016)	(0.012)
Inpatient unit services				-0.055
				(0.041)
Pediatric program services				-0.042
				(0.048)
Bereavement services				0.066*
				(0.026)
Adult day care services				0.287**
				(0.085)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	2,461	2,461	2,461	2,461

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

J.4 Results with LA county included

Table 44: Regression of per-visit costs on competition and controls.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	-0.090**	-0.089**	-0.094**	-0.084***
	(0.027)	(0.028)	(0.028)	(0.023)
Total patient days / 1000		0.002		
		(0.002)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.041***	
			(0.010)	
Total Visits / 10,000 squared			0.001*	
			(0.000)	
log(operating cost)	0.000	-0.010	0.037***	-0.003
	(0.006)	(0.006)	(0.009)	(0.007)
Inpatient unit services				-0.056
				(0.030)
Pediatric program services				-0.015
				(0.050)
Bereavement services for non-hospice survivors				0.071***
				(0.018)
Adult day care services				0.191
				(0.160)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	5,085	5,085	5,085	5,085

Notes: IV regression of log(per-visit cost) on log(firm count) with county fixed effects and controls. Standard errors clustered at county-level in parentheses. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 45: Grouped-quantile regressions of per-visit costs on competition.

Quantile	Coefficient	S.E.
0.1	-43.3189	13.6307
0.2	-37.2306	13.3458
0.3	-32.8515	13.1767
0.4	-28.7941	13.0962
0.5	-22.56	13.1887
0.6	-15.1261	13.2179
0.7	-8.18223	13.5214
0.8	-1.34242	14.0879
0.9	6.66969	14.9671

(a)

Quantile	Coefficient	S.E.
0.1	-50.066	15.4714
0.2	-42.3478	15.3888
0.3	-36.2643	15.4396
0.4	-31.0552	15.5433
0.5	-24.7463	15.7815
0.6	-15.8003	15.8384
0.7	-6.39695	16.2494
0.8	2.47288	17.022
0.9	11.5009	18.1128

(b)

Notes: Grouped-quantile IV regression of per-visit costs on competition, county fixed effects, and semi-parametric order-statistic bias correction. Table 8b also includes second-order polynomials of one-year-lag and two-year-lag of county-level-mean of per-visit costs. Robust standard errors are reported under S.E. See Section A.1 for details about implementation.

Table 46: Regression of per-visit costs on competition, for-profit status, and entry time.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.022	0.021	0.033	0.018
	(0.020)	(0.021)	(0.022)	(0.020)
For-profit	-0.158***	-0.157***	-0.161***	-0.163***
	(0.033)	(0.033)	(0.031)	(0.033)
Entry time	-0.012**	-0.011**	-0.014***	-0.011**
	(0.004)	(0.004)	(0.004)	(0.003)
Entry before 2002	-0.001	0.002	0.002	-0.007
	(0.031)	(0.032)	(0.033)	(0.032)
Total patient days / 1000		0.001		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.048***	
			(0.009)	
Total Visits / 10,000 squared			0.001*	
			(0.000)	
log(operating cost)	-0.020*	-0.020**	0.020*	-0.019*
	(0.008)	(0.007)	(0.008)	(0.009)
Inpatient unit services				-0.071**
				(0.025)
Pediatric program services				-0.056
				(0.046)
Bereavement services				0.043**
				(0.014)
Adult day care services				0.184
				(0.160)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	5,085	5,085	5,085	5,085

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.

Table 47: Regression of per-visit costs on competition, for-profit status, and entry time.

	log(per-visit cost)			
	(1)	(2)	(3)	(4)
log(firm count)	0.030	0.029	0.044	0.026
	(0.020)	(0.021)	(0.024)	(0.021)
For-profit	-0.135***	-0.134***	-0.137***	-0.141***
	(0.032)	(0.032)	(0.031)	(0.032)
Entry time	-0.012***	-0.011***	-0.014***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Entry before 2002	-0.006	-0.002	-0.004	-0.011
	(0.033)	(0.033)	(0.035)	(0.034)
Share of patients w/ cancer	0.185*	0.187*	0.163*	0.197**
	(0.070)	(0.070)	(0.070)	(0.070)
Share of patients w/ <7 days LOS	-0.118*	-0.119*	-0.094	-0.122*
	(0.054)	(0.054)	(0.054)	(0.054)
Average length of stay	-0.000	-0.000	-0.001*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Share of non-routine care days	-0.137	-0.126	0.007	-0.101
	(0.111)	(0.110)	(0.147)	(0.110)
Share of home-based patients	0.134**	0.134**	0.127**	0.135**
	(0.039)	(0.038)	(0.046)	(0.038)
Total patient days / 1000		0.001		
		(0.001)		
Total patient days / 1000 squared		-0.000		
		(0.000)		
Total Visits / 10,000			-0.047***	
			(0.010)	
Total Visits / 10,000 squared			0.001*	
			(0.000)	
log(operating cost)	-0.012	-0.013*	0.027**	-0.011
	(0.008)	(0.006)	(0.008)	(0.008)
Inpatient unit services				-0.072**
				(0.025)
Pediatric program services				-0.066
				(0.046)
Bereavement services				0.043**
				(0.015)
Adult day care services				0.196
				(0.164)
County Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	5,085	5,085	5,085	5,085

Notes: Standard errors clustered at county-level in parentheses. Entry time is measured as number of years since 2002. Controls are second-order polynomials of lags of market-level-mean per-visit costs.