Quality choice with reputation effects: Evidence from hospices in California

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Abstract

Hospices – firms that give palliative care to dying patients – form a large and growing industry in the US with significant implications for patient welfare and cost savings. Using data from California, I study how a hospice's quality choice is influenced by reputation concerns, and explore counterfactual policies to improve hospice quality. There is no price competition because Medicare pays hospices a fixed per-day rate for each patient, so hospices compete on reputation. A hospice's reputation is a stock of its past quality choices. Thus a hospice can build up its reputation stock over time by consistently choosing high quality. First I estimate a structural model of hospice choice by consumers, and find that hospice reputation has a strong effect on demand. Then I build a dynamic oligopoly model of hospices choosing quality to compete on reputation against rivals. This is used to recover the hospice cost function and conduct the following policy counterfactuals. As reputation becomes more persistent – for instance, through the creation of an online hospice rating system – hospices choose higher quality. Hospices also choose higher quality as Medicare prices increase, but the response depends on how differentiated they are in characteristics from rivals. Finally, a hybrid per-day per-visit hospice reimbursement scheme achieves the same quality with nearly 30% lower spending than the current per-day Medicare scheme.

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1 Introduction

Hospices give palliative care to dying patients by visiting them and helping with pain control and living arrangements. This is a useful industry to study for the following reasons. First, it is a large and growing industry - over 1.6 million Medicare patients used hospices in 2022, Medicare spent around $21 billion on hospice services in 2019, and the Affordable Care Act has sought to increase hospice usage. However, concerns have been raised about hospice quality across the US.[1] Improving hospice quality will result in improvement of hospice patient welfare, as well as cause many patients to switch away from ineffective and painful curative treatments. Second, the hospice industry is a regulated-price setting since Medicare reimburses hospices a fixed per-day rate for every patient. Regulated price settings are common in the US (like Medicare's DRG scheme) and across the world (such as in the UK, Germany and France), so the hospice industry can give insights on firm behavior and policy design for such markets. Third, it is a great setting for studying how reputation affects consumer and firm choices. In this context, the reputation of a hospice can be thought of as reflecting its past quality choices. A hospice can therefore choose to provide high quality of service to build up its reputation over time and attract consumers. Such reputation effects are also present in other healthcare markets, and hence studying hospices can shed light on quality choice in various healthcare settings.

Using firm-level data from California, I use a structural model of the hospice industry to show that hospices dynamically choose quality to build up reputation and attract consumers. This involves estimating consumer demand for hospices as well as the hospice cost function. Then, I use my model and estimates to explore counterfactual policies that can incentivize better hospice quality.

Hospice care is given to dying patients at their residences, where hospice staff administer pain medication and help with living arrangements. More visits by the hospice staff can be thought of as implying higher quality - it means the hospice is checking up on patients more and adjusting for day-to-day difficulties. Therefore, my measure of hospice quality is the average number of visits made by a hospice to its patients. There is no price competition because most hospice patients are covered by Medicare, and Medicare pays hospices a fixed per-day rate for each patient. This makes hospice reputation particularly salient for consumers. Hospices which have given higher quality care in the past are more likely to be known and referred within the community. This suggests that a hospice can build up its reputation by persistently choosing high quality over time, and use this improved reputation

[1] The Department of Health and Human Services has released a report citing numerous deficiencies in hospice quality: https://oig.hhs.gov/newsroom/media-materials/media-materials-2019-hospice/.

to attract more patients.

To study reputation and quality choice in this setting, I build a structural model of hospice demand by consumers and quality choice by hospices. Reputation of a hospice is defined to be a stock of its current and past quality choices. This reputation stock partially depreciates when moving from one period to next. On the demand side, each consumer makes a discrete choice from a set of hospices in her market. Her choice is influenced by hospices' reputations and characteristics. On the supply side, hospices play a dynamic game in an oligopoly setting where they choose quality every period. They take into account that higher quality will lead to increased reputation and market share but also higher cost per consumer.

I estimate this model using yearly hospice-level data from California for 2002-2018. A nested-logit discrete choice demand model is estimated following the inversion of Berry (1994) and allowing for persistent unobserved demand shocks. This lets me pin down the magnitude and persistence of hospice reputation for consumer choice. I then estimate a dynamic oligopoly model of quality choice which incorporates the reputation effects. The estimation method follows Bajari et al. (2007). This clarifies how forward-looking hospices choose quality over time in a strategic setting, and allows me to recover the hospice cost function.

The demand estimates show that reputation plays a significant role in consumer choice and depreciates at an annual rate of 53%. The hospice cost estimates show that an additional visit by a hospice costs around $200, for-profits enjoy an efficiency advantage over non-profits, and hospices in rural counties face higher cost of making visits than those in urban counties.

Using the estimated demand and cost parameters, I solve for hospices' equilibrium quality choices under various counterfactual policies. My first set of counterfactuals involves the persistence of a hospice's reputation. A policy that increases the persistence of a hospice's reputation - for instance, a review website that centralizes information on quality provision - leads to higher hospice quality. My second set of counterfactuals involves Medicare's reimbursement rates for hospices. I find that firms choose higher quality as Medicare price increases, but a firm's response depends on how differentiated it is in terms of characteristics compared to its rivals. My third set of counterfactuals involve changing the reimbursement scheme structure for Medicare. I compare the current per-day Medicare reimbursement scheme with a hybrid per-day and per-visit reimbursement scheme. The latter is found to achieve the same quality level but with nearly 30% lower Medicare spending.

Note that instead of modeling reputation formation as a complex process of belief updating, I approximate the reputation stock of a hospice as a parametric function of its past quality choices. This reputation stock enters a consumer's utility function and influences her choice of a hospice. This parametric approximation allows me to study reputation using only firm-level data and maintain computational tractability. It also allows me to be agnostic about the specific channel through which reputation operates. Consumers may care about reputation because hospice quality is not contractible, or because reputation is a good statistic for predicting future quality in the face of bounded rationality, or alternatively because it lets consumers infer the underlying efficiency or altruism of the hospice. I discuss these issues in more detail in Section 5.[2]

Contributions and related literature: I contribute to the empirical literature on reputation effects. To my knowledge I am the first to build and estimate a structural dynamic oligopoly model of reputation accumulation through quality choice. I also construct a novel way of measuring reputation using market share data. This is in contrast with other papers that measure reputation with user reviews; my approach avoids the econometric issues involving user reviews and allows reputation to be studied in settings where such review data are not available. There is a large empirical literature on reputation effects with most papers centered around online platforms; an example is Cabral and Hortaçsu (2010) who document patterns around seller reputation on eBay. See Tadelis (2016) for an extensive overview. There is much less work on reputation outside online platforms; one such paper is Jin and Leslie (2009) who study hygiene quality and reputation incentives in the context of restaurants. They document that chains and non-chains have different reputational incentives, franchised units have an incentive to free-ride, and there is regional variation in reputation incentives. Even fewer papers attempt to analyze reputation acquisition via a structural model of firms. Apart from myself, two papers which do so are Saeedi (2019) and Bai (2022), and below I explain how my model and estimation are quite distinct from theirs.

Second, this paper contributes to the literature on quality choice of healthcare providers by showing the importance of reputation for patients choosing medical providers as well as medical providers choosing quality. Papers on healthcare provider quality include Hackmann (2019), Lin (2015), Gaynor et al. (2013), and Wang (2022). Like Gaynor et al. (2013), I also add to the literature on how healthcare providers choose quality in a regulated-price setting.

Third, I contribute to a very sparse literature on hospices. I am the first to structurally estimate the supply-side of this industry. While healthcare providers such as hospitals and nursing homes have been studied extensively, hospices have seen relatively little work in the Economics literature. Prior work on the hospice industry include Chung and Sorensen (2018), who estimate a nested logit demand model to examine market expansion through hospice entry.

As previously mentioned, two other papers that estimate structural models of reputation

[2]Going by the theoretical literature on reputation effects, my model is closer to a hidden action model as opposed to a hidden information model.

are Saeedi (2019) and Bai (2022). Saeedi (2019) studies how eBay sellers choose quantity over time to qualify for Powerseller status or Registered-Store status. In contrast to my paper, her model assumes quality of sellers is exogenous and buyers are unaware of past buyers' experiences. A seller wants to be a Powerseller/Registered-Store to signal to consumers, and these badges are the "reputation mechanisms" she studies in her paper. Bai (2022) studies watermelon sellers using an experiment where some watermelons are laser-branded as a costly signal of quality. Unlike my paper, she does not assume that consumers have accurate knowledge of a seller's quality choice, and neither does she assume that sellers can precisely choose their quality. Her demand model explicitly accounts for consumer learning and beliefs. In contrast to this paper, she estimates a simplified supply side model of pricing and quality that does not account for competition, and given the lack of data cannot model long-term dynamics.

A strand of literature that this paper bears resemblance to is the advertising and brand management literature in marketing. Several structural papers in that field look at how firms spend money on advertising to build up their brand equity; see Dubé et al. (2005) and Borkovsky et al. (2017), and the references therein. This paper also adds to the literature on estimating dynamic games. I use the framework put forth in Ericson and Pakes (1995), and use estimation methods from Bajari et al. (2007) and Pakes et al. (2007). My paper has similarities with Benkard (2004), in that I use a nested-logit demand framework within a dynamic game of accumulation. While my paper is about reputation accumulation, Benkard (2004) is about accumulating experience levels. Finally, this paper has similarities with the dynamic investment literature in industrial organization; classic references are Olley and Pakes (1996) and Ericson and Pakes (1995).

2 Industry background

Hospices provide palliative care to terminally ill patients, the majority of whom die within 1 week to 3 months in my dataset. Patients who enroll in hospice typically no longer receive curative treatment. Most patients in the dataset are covered by Medicare, which reimburses hospices a fixed amount for every day the patient is enrolled. In return, hospice staff provide care to the patient by visiting her at her residence. The number of visits a hospice makes to its patient is a strong measure of the quality of service, and I claim that a hospice can build up its reputation by consistently providing higher quality over time.

2.1 Hospice care provision

Unlike other medical providers, hospices typically provide care at the residence of the patient, with different staff being responsible for different parts of care. Hospices employ several types of staff: registered nurses, licensed vocational nurses, home healthcare aides, physicians, social workers and chaplains. Of these, registered nurses, licensed vocational nurses and home healthcare aides (henceforth referred to altogether as hospice nurses) are responsible for the vast majority of patient visits. Physicians rarely make visits, and usually deal with reports on the patients from nurses. Social workers help the patient and her family with paperwork and choices, while chaplains make visits to a dying patient.

The hospice nurses 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.

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 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.

Hospice nurses 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.

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.

Medicare also distinguishes between different types of hospice care. Specifically, it draws a distinction between 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 Appendix A that of all the "days of care" provided by a hospice within each year, over 99% of it is dedicated to routine care.

2.2 Hospice selection by patients

After a patient with a terminal illness decides to no longer seek curative treatment, she and her family can choose to enroll into a hospice. How a hospice is chosen can vary. Sometimes a social worker at the hospital gives the patient a list of hospices, and suggestions on which to choose based on past experience; the same can be done by the patient's physician. The family can also search for hospices online (aided by online reviews and forums), or can rely on word-of-mouth from other families that have needed hospice services in the past.

When looking for advice on how to choose a hospice, a few suggestions are common. One is to choose hospices that are reputable and have served the community well over a long time.[3] Another is to choose a hospice that makes regular visits, is readily available for emergencies, and is ready to give care to patients with various complexities and circumstances. Additional suggestions include asking how the hospice will co-manage with and give respite to the primary caregiver.

These suggest several things. First, reputation matters - a hospice which has provided high quality of care in the past is more likely to be suggested by social workers, better known in the community and better reviewed than a hospice which has not. Such a hospice is more likely to be selected by a patient and her family, and so will have greater market share. This also suggests how information about a hospice's past quality choices can persist over time. Second, quality of care is strongly dependent on the number of visits that a hospice makes to a patient. 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 the case of an emergency. Such a hospice is also able to provide more respite to the patient's primary caregiver, which may be highly valued by the family. It is also likely that number of visits is correlated with the general effort of the hospice, and so with other unobserved dimensions of quality. While the above suggest that reputation and number of visits are important determinants of hospice choice, I estimate a demand model to check if that is indeed the case.

One potential criticism is that number of visits as a measure of quality does not capture

[3] Some websites which give suggestions on how hospices are chosen are listed in Appendix C.1 alongside relevant quotes. A representative quote from AmericanHospice.org reads:

"What do others say about this hospice? Get references both from people you know and from people in the field – e.g., local hospitals, nursing homes, clinicians. Ask anyone that you have connections to if they have had experience with the hospice and what their impressions are. Geriatric care managers can be a particularly good resource, as they often make referrals to hospices and hear from families about the care that was provided."

Similarly, HospiceFoundation.org states:

"Seek professional opinions. Ask clinicians, professional caregivers at nursing homes, geriatric care managers, or end-of-life doulas about their experience with a hospice. Talk to friends, family, and neighbors who have used hospice services and get their opinions about the experience with a provider."

the content of the visit itself. For instance, what if there's a hospice that makes many visits but does little per visit, while another hospice makes few visits but does a lot of useful work during each visit? Or what if one hospice trains its nurses better than another hospice? While these concerns might be relevant for other medical providers, for hospices they are less likely to be important. As explained above, hospice care is mostly low-skill care. The majority of it is giving pain medication, making adjustments to living arrangements, and helping out the patient with certain physical activities such as bathing. As such, it is unlikely that there will be great heterogeneity across hospices regarding what is done in a single visit. In my demand model I do allow for persistent unobserved hospice quality, which can control for characteristics like well-trained and better behaved nurses, but my supply side does not endogenize this as part of the hospice's choices.

2.3 Payers and reimbursement schemes

Hospice services can be paid for by Medicare, Medi-Cal (California's Medicaid), private insurance, and various other payers. In my setting the overwhelming majority of patients are paid for by Medicare (see Table 1), and furthermore Medi-Cal's reimbursement is essentially the same as Medicare's. As a result, I focus my discussion on eligibility rules and reimbursement schemes for Medicare only.

For a patient covered by Medicare, hospice care is essentially free. There is no out-of-pocket cost for enrolling into or receiving visits from a hospice. Patients have to give a copay of up to $5 for outpatient drugs required for pain management. This means that the "price" of choosing a hospice does not vary across hospices in the patient's choice set, and moreover can be thought of as zero.

For the hospice, enrolling a patient covered by Medicare results in the hospice getting paid a fixed rate for every day the patient is enrolled (i.e. a per-diem rate). It is important to note that the fixed rate is set exogenously and does not depend on the number of visits that the hospice staff makes. To contrast extreme examples, if a patient enrolls in a hospice for 14 days, the hospice gets paid a fixed amount for each of those 14 days irrespective of how many visits they make.

The Medicare rate is determined as follows. Medicare sets a national per-diem rate that is split into a "labor component" and a "non labor component". Medicare also creates wage indices for each Metropolitan Statistical Area (MSA), such that a MSA with high wages will have a high wage index. The per-diem reimbursement rate of a hospice is the non-labor component and the labor component times the wage index of the hospice's MSA.[4]

Medicare allows the per-diem rate to vary substantially based on whether the care provided is routine home care, inpatient care, or continuous care. Medicare also lowers the per-diem rate for routine care if a patient is enrolled for more than 60 days.

Payer	% of patients
Medicare	83.7
Medi-Cal	7.37
Private insurance	6.37
Selfpay	1.65
Charity	0.82

Table 1: Percentage of total patients covered by each payer type.

3 Data

The dataset for this paper comes from firm-level data on hospices in California for 2002-2018. I use these data to construct firm-level measures of quality, defined to be average-visits-per-patient made by a hospice in a year. A market is defined to be at the level of a county, and I restrict my estimation to 28 counties. Total firms in a market range from 1 to 23, with moderate entry and little exit.

3.1 Data sources

The main dataset comes from Home Health Agencies And Hospice Annual Utilization Reports compiled by California Department of Health Care Access and Information (CHAI). Hospices in California are required to submit yearly utilization reports to CHAI 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, 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.

[4]To work out an example: for FY 2021, the labor component of routine home care is \$136.9, and the non-labor component is \$62.35. Suppose a hospice is in a county with a wage index of 0.8. The reimbursement rate of the hospice is approximately $136.9 \times 0.8 + 62.35 = \$171.87$. See Appendix C.2 for an example Medicare's reimbursement rates and its variation across counties.

3.2 Market definition

A market is defined to be at the level of a county. 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. This is reasonable since both the hospice and the patient have a strong preference to minimize distance - the patient wants to be close to the hospice so that she can benefit from quick visits during an emergency, and the hospice prefers serving nearby patients since it is less costly to travel to their residences. The only exception are Yuba and Sutter counties which have a large overlap of patients, and so I combine them into a single market. Market size is constructed by multiplying the population size of each age bracket for a market with the corresponding mortality rate.

I focus on 28 counties for my project.[5] While California has 58 counties, I have to drop the remainder for the following reasons. First, several counties do not see any hospice presence over the course of my dataset. Second, a few counties have a very large number of hospices (Los Angeles county has over 300). Markets with many small sellers have very different dynamics than those with few sellers. My model and estimation are oriented towards strategic interactions among small numbers of players and does not naturally accommodate such active markets.[6] Having few firms in a market also allows me to disentangle the competitive effects of rivals very clearly. Such sample selection is in line with many dynamic oligopoly papers such as Lin (2015) and Collard-Wexler (2013).

3.3 Measure of hospice quality

Following the discussion in Section 2.2, my measure of quality should reflect how often a hospice visits its patients. Recall that I have firm-level data; the dataset gives me total visits that a hospice makes to its entire pool of patients within a year and the number of patients it serves in the same year. Table 2 breaks down the ratio of total visits to patients for a hospice-year by staff type. It shows that nearly all visits are made by nurses and homemakers, and only these staff visits exhibit some variation across hospices and over time. Physicians and chaplains make very few visits, while social service workers seem to make a fixed number of visits across hospices. Therefore, I set my measure of quality to be the sum of nurse and homemaker visits divided by the number of patients. This is henceforth referred to as the

[5] A list of these counties can be found in Section A.5.

[6] In the IO literature, markets with many small sellers have sometimes been modeled using the oblivious equilibrium of Weintraub et al. (2008). A separate paper by myself aims to study hospice entry and exit for these active markets in California.

average-visits-per-patient that a hospice makes in a year.

	10%	**25%**	**50%**	**75%**	**90%**
Registered nurses	8.82	11.42	14.44	18.21	22.48
Licensed vocational nurses	0.0	0.0	0.64	4.43	8.9
Homemakers	5.39	7.69	11.24	16.85	24.21
Physicians	0.0	0.0	0.01	0.25	0.77
Social service workers	1.74	2.59	3.55	4.73	6.05
Chaplains	0.27	1.02	1.84	2.87	4.08
RN + LVN + Homemakers	17.17	21.88	27.83	37.66	52.48

Table 2: Distribution of visits by staff type for each hospice-year. The unit is visit per patient.

3.4 Summary statistics on competition and patients

I now present some summary statistics on competition and patient composition within my sample. The tables below and in the Appendix show distributions of various key variables; the main takeaways are as follows. First, the vast majority of hospices have over 100 patients. This assuages worries that my key measure of quality - average visits per patient- is mostly driven by patient severity, since we would expect that variations in patient severity would even out over a large number of patients over the course of the year. Second, the median firm count is 2 with the 75th percentile at 4, suggesting that an oligopoly setting is the correct mode of analysis instead of perfect competition. Third, while the total entry and exit over the 16 years of my data is significant, there is very little turnover in a market within an individual year. In my model, I will treat exit as effectively exogenous due to the lack of variation in my data. Fourth, the vast majority of patients have a length of stay between a week and 3 months; see Appendix A for more details. Finally, Appendix A also does a breakdown of patients by diagnosis, revealing that roughly half the patients are suffering from cancer.

	Min	**10%**	**25%**	**50%**	**75%**	**90%**	**Max**
firm count	1.0	1.0	1.0	2.0	4.0	7.0	23.0
entry count	0.0	0.0	0.0	0.0	0.0	1.0	5.0
exit count	0.0	0.0	0.0	0.0	0.0	1.0	3.0

Table 3: Distribution of market-level characteristics. Each observation is at the county-year level.

	10%	**25%**	**50%**	**75%**	**90%**
patients	63.0	149.0	289.5	511.75	765.0
market share	1.41	3.6	8.53	18.5	37.0

Table 4: Distribution of patients and market share. Each observation is at the hospice-year level.

Finally the data contains information on hospice-specific services and characteristics. These vary substantially across hospices, although there is little variation within a hospice over time. To give a snapshot, in 2017 there were 171 hospices in my dataset; of these, 12 had an inpatient unit, 15 offered special pediatric services, 2 offered adult day care services, and 95 were for-profit. The dataset also breaks down hospices by agency type: 110 hospices were free-standing, 27 also had a home-health unit, and 31 were hospital-based. I control for these characteristics in my demand estimation.

4 Structural model

To study and model reputation in this setting, I set up a structural model of demand and supply for the hospice industry. The demand side is a discrete-choice model that incorporates a measure of reputation of the hospice. The supply side is a dynamic oligopoly model where forward-looking hospices are choosing quality in a competitive setting. The remainder of the section details the equilibrium concepts and the timing of the dynamic game, and concludes with a discussion on reputation in my model.

4.1 Demand

The demand for hospices is modeled as a nested-logit discrete choice model, with a nest on hospices. A consumer can choose between any hospice present in the market in that period, or an outside option. The outside option of not choosing a hospice can be interpreted as the consumer continuing intense curative treatment, or choosing to be cared for by family/nursing home staff.

The utility of consumer i from choosing hospice j in period t is given by:

$$u_{ijt} = \alpha_{m(j)} + X'_{jt}\beta + \psi_{jt} + \xi_{jt} + \zeta_i + (1 - \sigma_n)\tilde{\varepsilon}_{ijt} \tag{1}$$

$$\xi_{jt} = \rho\xi_{jt-1} + \epsilon_{jt} \tag{2}$$

where $m(j)$ denotes the market in which hospice j is present and X_{jt} represents hospice characteristics[7]. The term ξ_{jt} denotes unobserved hospice-specific quality that is allowed to be serially correlated and vary over time. This can reflect factors like how connected the hospice is with physicians/nursing homes, advertising, and care quality beyond number of visits. The term ψ_{jt} is the reputation stock of hospice j in time t. Finally, $\zeta_i + (1-\sigma_n)\tilde{\varepsilon}_{ijt}$ reflect that this is a nested logit - there are two nests, one on all hospices and one on the outside option.

Reputation effect is incorporated as a stock transition equation:

$$\psi_{jt} = (1-\tau)\psi_{jt-1} + \eta a_{jt} \tag{3}$$

where a_{jt} is the average visits-per-patient made by hospice j in period t. Assuming $\psi_{j0} = 0$ (i.e. a new entrant has a reputation of zero), this can be rewritten as:

$$\psi_{jt} = \eta[a_{jt} + (1-\tau)a_{jt-1} + (1-\tau)^2 a_{jt-2} + \ldots]$$

That is, a firm's reputation is a discounted sum of its past choices of quality. I now offer a more thorough discussion on the modeling choices.

First, the nest on hospices (i.e. the inside options) allows for more flexible substitution patterns between hospices and the outside option relative to a simple logit with no nests. For instance, a high value of the nest parameter implies that should a consumer decide not to pick hospice j_1, she is more likely to pick another hospice j_2 instead of switching to the outside option; i.e. a consumer's preferences are positively correlated within the nest.

Second, the persistence of unobserved hospice-specific quality ξ_{jt} allows me to capture persistent unobservables in demand. One example could be that a hospice is well-connected with physicians and social workers in some hospitals and so get repeated referrals despite not choosing higher quality - this will manifest itself as the hospice having a high ξ_{jt} for many periods. Another example could be a hospice that has suffered a recent scandal such as elder abuse. Despite choosing high average visits-per-patient the negative publicity may last for several periods - this will manifest itself as the hospice having a low ξ_{jt} for many periods. Importantly, this allows for the fact that a hospice with persistent demand shocks will adjust its quality choices accordingly; for example, a hospice that predicts getting high draws of ξ_{jt} in the future may choose to lower its quality level in the current period. In addition, this allows for the possibility that a hospice with high ξ might face less entry because it is more difficult to compete against. In the demand estimation this means I build moments around

[7] The hospice characteristics are dummy variables for the following: hospice inpatient unit, pediatric program, bereavement services, day care for adults, for-profit status, free-standing hospice, home-health-based hospice, and hospital-based hospice.

ϵ_{jt} instead of ξ_{jt}; this follows Grennan (2013) and Lee (2013). The reasons behind why this is a more reasonable exclusion restriction are explained in Section 6.1.

4.2 Per-period profit and marginal cost function

The cost to a hospice for serving a patient depends on its quality choice, cost type and other characteristics. I impose the cost to be increasing linearly in the level of average-visits-per-patient.

The cost of serving each patient at quality a_j (henceforth referred to as marginal cost) is given by:

$$MC_j(a_j) = \gamma_0 + \Big(\gamma_{1,k(j)} + \gamma_{fp}FP_j + \gamma_{rural}RURAL_j\Big)a_j$$

where the terms in the bracket reflect the slope of the marginal cost function. The slope depends on 3 factors, and the economic intuition is that hospices with flatter slopes can raise quality and incur a smaller increase in cost per patient. The first term $\gamma_{1,k(j)}$ reflects how a firm's cost type affects the slope of its marginal cost function. The subscript $k(j)$ denotes that hospice j is of cost type k - a firm with a better cost type has a smaller $\gamma_{1,k}$ and so a flatter marginal cost function. This cost-type reflects variations in efficiency and altruism across hospices. In my baseline specification all firms have the same type; I also estimate an alternative specification where firms can be one of two types. The second term γ_{fp} allows the slope of for-profits to differ from those of non-profits. This is meant to capture systematic differences in efficiency and altruism across for-profits and non-profits. The last term γ_{rural} allows rural hospices to have different cost than urban hospices; anecdotal evidence suggests that rural visits are more costly because of worse infrastructure and longer driving distances.

In the dynamic game a period is defined to be a year. For the rest of this section the time subscript is suppressed for clarity.

Combining the demand function with fixed Medicare prices and market size, the per-period profit of hospice j in market m choosing quality a_j is:

$$\bar{\pi}(a_j, \mathbf{a}_{-j}, \mathbf{x}_m; \theta) = M_m s_j(a_j, \mathbf{a}_{-j}, \mathbf{x}_m)\big[P_m^{MCAR} - MC_j(a_j)\big] \tag{4}$$

where $\mathbf{x}_m$ denotes the state variables in market m, $\mathbf{a}_{-j}$ denotes the vector of realized actions of all rival firms in the market, and M_m is the market size.[8] The price-per-patient P^{MCAR} is

[8]This requires calculating market share of all firms for a given state $\mathbf{x}_m$. This is done using the analytical formulae for nested logit. Let

$$\delta_{jt} = \alpha_m + X'_{jt}\beta + \sigma_n ln(s_{j|gt}) + \psi_{jt} + \xi_{jt}$$

calculated as the Medicare per-day rate for that period multiplied with the average length of stay of a patient in the data (60 days). This gives the predicted revenue that a single patient generates for a hospice given that period's Medicare price.

For the demand estimation I use the continuous measure of quality choice; however for estimating the supply side, I discretize quality choices into six tiers. This has the advantage of improving computational tractability (especially regarding counterfactuals) while still being a meaningful improvement of quality.

4.3 Dynamic choice of quality

The above demand and per-period payoff functions are incorporated into a dynamic oligopoly model to understand how hospices choose quality over time. This is modeled using the framework of Ericson and Pakes (1995).

The dynamic oligopoly is modeled as a discrete-time simultaneous-move game over an infinite horizon. Every period the incumbents decide what level of quality to provide. All consumers of a hospice receive the quality level chosen. Persistence of reputation means that current quality choices affect future sales, hence a forward-looking model is required; hospices also make this decision in a competitive setting, hence a model of strategic interaction is needed.

The incumbent's value function is:

$$V_j(\mathbf{x}_m, \epsilon_j^a; \theta) = \max_{a_j \in \mathcal{A}} \mathbb{E}\left[\bar{\pi}(a_j, \mathbf{a}_{-j}, \mathbf{x}_m; \theta) + \epsilon_j^a(a_j) + \beta V_j(\mathbf{x'}_m, \epsilon_j^{\prime a}; \theta) \middle| a_j, \mathbf{x}_m\right] \tag{5}$$

where θ is the set of structural parameters affecting a hospice's per-period payoff, ϵ_j^a is a vector of choice-specific errors for hospice j, and $\epsilon_j^a(a_j)$ is the choice-specific errors for hospice j choosing action a_j. The symbol $\mathcal{A}$ denotes the set of possible quality choices (recall that we discretize quality into six tiers for the supply side estimation), and a_j is the quality level chosen from this set. The choice-specific error terms are meant to capture unobservables affecting a firm's quality choice. In keeping with the literature and to help with tractability

where σ_n is the nest parameter that captures correlated preferences within the nest. Then the market share can be written as:

$$s_j(\boldsymbol{\delta}, \sigma_n) = \bar{s}_{j/g}(\boldsymbol{s}, \sigma_n)\bar{d}_g(\boldsymbol{\delta}, \sigma_n) = \frac{e^{\delta/(1-\sigma_n)}}{D_g^{\sigma_n}\left[\sum_g D_g^{(1-\sigma_n)}\right]}$$

where

$$D_g \equiv \sum_{j \in G_g} e^{\delta_j/(1-\sigma_n)}$$

in estimation, I assume these shocks to be $i.i.d$ and distributed Type-1 Extreme Value.

4.4 Assumptions on state transitions

In any period, the industry state comprises common-knowledge variables (own characteristics, rival characteristics, market characteristics) and private information (choice-specific structural errors ϵ^a). The industry state evolves due to a mix of firm decisions and exogenous transitions; below I list the assumptions I make on state transitions. The list of state variables and how their transitions are implemented during estimation are detailed in Section 6.2.1. The following mirrors the discussion in Lin (2015).

Let the vector of common knowledge state variables in the current period be $\mathbf{x}$. The vector of common knowledge state variables and private information is denoted as $\mathbf{s} = (\mathbf{x}, \epsilon^a)$. The state-to-state transition probability is $F(\mathbf{s}'|\mathbf{s}, \mathbf{a})$, where $\mathbf{a}$ denotes the vector of firm choices in the current period. Following Rust (1987), I make two assumptions on the state vector:

1. Additive Separability: This imposes that the choice-specific structural error ϵ^a enters the per-period payoff function additively, i.e. $\bar{\pi}(a_j, \mathbf{x}_m, \epsilon^a_j; \theta) = \bar{\pi}(a_j, \mathbf{x}_m; \theta) + \epsilon^a_j(a_j)$. This assumption was already made when writing out the incumbents' value function.

2. Conditional Independence: This comprises two assumptions. One, $\mathbf{x}'$ is independent of ϵ^a after conditioning on $(\mathbf{x}, \mathbf{a})$. Two, ϵ^a is *i.i.d.* and evolves independently of other state variables. Mathematically, this can be written as:

$$F(\mathbf{s}'|\mathbf{s}, \mathbf{a}) = F(\mathbf{x}', \epsilon^{a'}|\mathbf{x}, \epsilon^a, \mathbf{a}) = F(\mathbf{x}'|\mathbf{x}, \mathbf{a})F_\epsilon(\epsilon^{a'})$$

   where $F_\epsilon(\cdot)$ denotes the distribution of ϵ^a.

4.5 Equilibrium and Conditional Choice Probabilities

This section describes the equilibrium concept used and how that leads to the conditional choice probabilities (CCPs) predicted by the model. These CCPs will later be matched to observed probabilities to estimate the cost parameters. For this subsection, the notation for parameters is suppressed from the arguments for clarity.

I focus on pure-strategy symmetric Markov Perfect Equilibrium (MPE). Each firm's strategy thus depends only on the observed state variable and its private choice-specific shocks. Therefore a firm's strategy can be written as a mapping from states and choice-specific shocks to actions:

$$\sigma_j : \left(\mathbf{x}_m, \epsilon_j^a\right) \rightarrow \mathcal{A}$$

Let the vector $\sigma = \{\sigma_j\}_{\forall j}$ denote the strategy profile of all firms in a market. I now show how this can be used to construct CCPs.

The choice-specific value function of action a in state $\mathbf{x}_m$, $W_j(a, \mathbf{x}_m)$, is the net payoff to the hospice j from choosing action a before choice-specific shocks ϵ_j^a are observed. The ex-ante value functions $V_j(\mathbf{x}_m; \theta)$ can thus be written in terms of choice-specific value functions:

$$\begin{aligned} V_j\left(\mathbf{x}_m\right) &= \int V_j\left(\mathbf{x}_m, \epsilon_j^a\right) dG\left(\epsilon_j^a\right) \\ &= \int \max_{a_j \in \mathcal{A}} \left\{W_j\left(a_j, \mathbf{x}_m\right) + \epsilon_j^a\left(a_j\right)\right\} dG\left(\epsilon_j^a\right), \end{aligned} \tag{6}$$

The MPE is the strategy profile σ^* such that every firm is choosing the optimal strategy given the strategies of their rivals:

$$\sigma_j^*\left(\mathbf{x}_m, \epsilon_j^a\right) = \arg\max_{a_j \in \mathcal{A}} \left\{W_j\left(a_j, \mathbf{x_m}\right) + \epsilon_j^a\left(a_j\right)\right\} \tag{7}$$

Given this optimal strategy profile, the CCP of an action a_j taken by firm j can be written as:

$$\Psi\left(a_j \mid \mathbf{x}_m, \sigma^*\right) = \frac{\exp\left\{W_j\left(a_j, \mathbf{x}_m\right)/\sigma_e\right\}}{\sum_{a \in \mathcal{A}} \exp\left\{W_j\left(a, \mathbf{x}_m\right)/\sigma_e\right\}} \tag{8}$$

where σ_e is the logit scaling parameter of the Type-1 Extreme Value logit error ϵ^a.

4.6 Timing

Given the model above, the game's timing is as follows. For period t and market m:

1. Incumbents observe $\mathbf{x}_{mt}$ and all structural errors, and each make quality choices.
2. Reputation stock of each incumbent evolves.
3. Consumers observe $\mathbf{x}_{mt}$, reputation stocks, and structural errors, then choose a hospice.
4. Incumbents stay or exit the market.
5. Potential entrants observe $\mathbf{x}_{mt}$ and decide whether to enter or disappear.
6. All state variables evolve.

5 Discussion

I now offer a more thorough discussion on how reputation operates in my model and explain the motivations behind the reputation transition equation.

In my model hospices are competing against each other for consumers, and each consumer makes a discrete choice of which hospice to pick. I assume hospices have complete information about each other, i.e. they know each others' characteristics, types and past shocks. This is a reasonable assumption to make in my setting, because it is easy to imagine that hospices are carefully tracking their competitors over time. This means hospices do not use past choices of their rivals' to make inferences over anything. However, consumers do care about a hospice's reputation. Holding everything constant, a consumer is more likely to choose a hospice with high reputation over one with low. Given that this is the case, hospices have an incentive to persistently choose high quality over time and build up their reputation to attract consumers.[9]

Given this setting, why do consumers care about a hospice's reputation? A few reasons are:

1. A hospice with higher reputation has more goodwill and recognition in the community, and so is more likely to be referred to the patient. This has parallels with the intangible brand capital literature - for example Bronnenberg et al. (2022) talks at length about brand equity and reputation, and how these create an incentive for firms to repeatedly supply high quality over time. It also has parallels with reputation in a repeated game of quality choice under complete information.

2. To predict quality choice, consumers can track a firm's reputation alone instead of all possible state variables. As can be seen in the model above, quality choice is affected by factors such as unobserved demand shocks and hospice characteristics, all of which vary over time. Instead of keeping track of all these variables and their evolution, consumers can use reputation as a sufficient statistic of sorts.

   Here is an example to clarify this further. Suppose a hospice has gotten a large positive demand shock in the recent past. Since demand shocks are persistent, this means the hospice will likely get high demand shock this period too. These demand shocks will influence the quality choice of the hospice; maybe the hospice chooses low quality since

[9] Using the terminology from the theoretical literature on reputation, I am using a hidden action model of information (as opposed to hidden information). Hidden action models assume that quality is chosen by the firm and consumers try to predict a firm's quality choice with full information about its past choices. In contrast, a hidden information model assumes that a firm's quality is exogenously fixed, and the firm can choose to signal this quality type to consumers.

it is experiencing a bump in its demand through the shocks that will last for a while. Suppose also that the hospice had very favorable characteristics (X_{jt}) in the past that are likely to persist into the present period. Such characteristics will also influence the hospice's quality choice. Instead of keeping track of all these characteristics and shocks across hospices and over time, a consumer can just keep track of their past quality choices, which will contain the information from these persistent factors already. It might also be easier to keep track of reputation (by asking others about their impression of a hospice's recent performance) than something like demand shocks. It is also likely that demand shocks and hospice characteristics that aren't relevant to a patient's needs are observed with noise by that consumer, and so is even harder to track. Such information can also disappear or become harder to acquire with time.

3. A hospice with higher reputation may have persistently low cost or high altruism. In contrast to the above two explanations where hospices had the same cost function, suppose it were the case that hospices have differences in cost. This variation in cost can come from greater efficiency or altruism. Hospices can thus be of different cost types, and these types are not observed by consumers. In this setting, consumers will use reputation to infer a hospice's cost type. A hospice which has high reputation has consistently chosen high quality in the past, and may have persistently low cost (i.e. is high type). Such a high type hospice is more likely to provide high quality in the current period. There is an extensive theoretical literature on consumers using reputation to learn about the firm; see Fudenberg and Tirole (1991) for more details.

Another element of the model is that reputation depreciates at the rate of τ. This raises the question - why does reputation depreciate? There are several possibilities. One, information on quality choices disappears over time. This might be because of forgetting by the community. It could also be due to retirement or relocation of physicians, social workers, and community members. The patient's family is less likely to require a hospice soon after the patient passes away, so the fact that there are no repeat consumers (unlike online platforms) means information is less likely to persist. Another way of thinking about this is that information on past choices is still available but gets more costly to retrieve over time. Two, past quality choices may be less relevant over time. This is because past quality choice also represents old and outdated medical practice styles, technology, and medicine. An example is that a hospice nurse's visit 20 years ago had very different content compared to a hospice nurse's visit at present. Third, quality choices very far in the past reflect the hospice's demand shocks and characteristics that may no longer have any predictive power, since these are also changing over time.

Finally, note that my reputation transition equation includes current visit as well as past visits. This means that current period reputation - which influences hospice choice by a consumer - is affected by current quality choice. This seems to indicate that consumers observe current quality choice; if so, why would they need to predict current quality choice using past choices? First, I also estimate demand using a reputation transition equation that does not contain current visit and still find strong presence of reputation. Second, the decision to include current quality into reputation is mainly driven by the fact that my data is at the yearly level. This means information on current quality choice has time to diffuse through the community over the course of a year. Finally, it accounts for the possibility that a hospice might be able (to some extent) to convince a potential consumer about the level of quality they will provide.

6 Estimation

This section details how the structural model above is estimated. The demand model is estimated using two-stage GMM following the inversion technique of Berry (1994). The supply side is estimated using the method of Bajari et al. (2007) that matches simulated choices with observed choices.

6.1 Demand estimation

Using Berry (1994), the nested-logit discrete choice model can be rewritten in terms of market shares:

$$\begin{aligned} ln(s_{jt}) - ln(s_{0t}) = \alpha_{m(j)} + X'_{jt}\beta + \sigma_n ln(s_{j|gt}) + \xi_{jt} + \\ \eta[\mathrm{a}_{jt} + (1-\tau)\mathrm{a}_{jt-1} + (1-\tau)^2\mathrm{a}_{jt-2} + \ldots] \end{aligned}$$

where s_{jt} and s_{0t} represent the market shares of hospice j and the outside option respectively, and $s_{j|gt}$ is j's within-hospice market share. Recall that for flexibility we also allow the unobserved demand shocks to be persistent:

$$\xi_{jt} = \rho\xi_{jt-1} + \epsilon_{jt}$$

These equations are estimated simultaneously via two-step GMM. Endogeneity is an issue since the within-hospice market share $s_{j|gt}$ is mechanically correlated with unobserved demand shock ξ. Besides, it is likely that choice of visits is also correlated with ξ. As a result, I use instruments from Berry et al. (1995) (henceforth BLP IVs) and fuel prices. BLP IVs are standard instruments in the IO literature that use measure of competitiveness in product space to create variation in within-hospice market share and quality choice while being orthogonal to ϵ_{jt} in the ξ transition equation. In my setting, these are the sum of rivals and sums of rival characteristics. Fuel prices are cost shifters that also cause the same variation while being orthogonal to ξ. These instruments are multiplied with the error term ϵ_{jt} to give moment conditions for GMM.[10]

It is now clearer to see why building moments around ϵ_{jt} is giving me a better exclusion restriction. Without it, I would have to assume that level of competition in the market is orthogonal to the ξ of all incumbents. But that might not be true - if the incumbent has persistently high (or low) ξ, then that could affect entry/exit decisions and hence the level of competition in the market. By allowing for persistence, the claim is that level of competition is orthogonal to some residual term after accounting for persistence.

6.2 Estimation of dynamic oligopoly model

The two-stage estimator from Bajari et al. (2007) is used to estimate the cost parameters. The first stage involves getting reduced-form estimates of the firms' policy functions from the data, as well as state transition probabilities. In the second stage, these policy functions are used to conduct forward simulation and generate model-predicted conditional choice probabilities (CCPs, explained in section 4.5) for a given guess of cost parameters. Moment conditions are then constructed, and an optimizer searches to find cost parameter values that minimize the distance between model-predicted CCPs and observed probabilities.

6.2.1 First stage

State variables: The state variables that enter a hospice's value function are its characteristics and unobserved shocks, its rivals' characteristics and unobserved shocks, its lagged reputation, its rivals' reputations, Medicare rates, the share of its patients who are served at home or who are expected to stay over 180 days, market size, and identity of the county where it operates. Below I explain how I implement state transitions in my forward simulation.

For the estimation, I assume that a firm's characteristics do not change over time; this assumption generally matches observed patterns in the data. Firms' current period unobserved shocks (ξ) are imputed from the demand estimation; the estimated persistence rate

[10] This requires estimating a large number of parameters, including county fixed effects and coefficients on hospice characteristics. A trick to easing computational burden is to note that only τ and ρ enter nonlinearly, so I can concentrate out all the linear parameters and minimize over (τ, ρ).

is used to simulate it forward while drawing the errors (ϵ) from the econometric error distribution. Market size and Medicare rates follow an AR(1) process that is estimated from the data. Share of patients at home or staying over 180 days are drawn from the empirical distribution.

Firm types: Persistent firm-specific heterogeneity in cost can affect quality choice. For instance, a hospice can be more altruistic or efficient than its rivals, causing it to choose higher quality than would be predicted by the competitive environment in which it resides. To account for this, I run a regression of visit choices on hospice fixed effects, hospice characteristics, and market characteristics.[11] The fixed effects can then be interpreted as how much the firm deviates from the level of visits that would be predicted by the competitive environment. These hospice-specific fixed effects are divided into 2 tiers at the median; hospices with fixed effects in the first or second tier are called type 1 or 2 respectively. The intuition is that a hospice of a higher type is more efficient or altruistic, and so chooses higher quality than a hospice of a lower type in the same competitive environment. In one specification of my dynamic oligopoly estimation, I allow marginal cost to vary by hospice type; *a priori* a hospice of a higher type has lower marginal cost.

This now raises the question of what it means, in an economic sense, to have a higher type. In the previous paragraphs a higher type has been ascribed to greater efficiency or greater altruism. However, altruism is generally thought of as affecting preference and not cost. Ideally the hospice's objective function will contain an "altruism" term that accounts for the hospice caring about patient well-being alongside its profits, and the marginal cost function will be heterogeneous across hospices due to variation in efficiency. However, in my model an efficient versus an altruistic hospice behave similarly (they both choose higher quality than expected), and so it is not possible to distinguish between efficiency and altruism. Instead, I assume that the hospice maximizes profits, and allow the marginal cost to vary by type; the caveat being that a higher type is either more efficient, or its greater altruism is causing it to behave *as if* it is more efficient.

First-stage policy function: For the first stage of the Bajari et al. (2007) estimation method, I get an empirical estimate of the policy function by projecting visit choice on state variables. The visit choice is discretized into six tiers, and an ordered logit is estimated. The results are given in Table 5. I estimate the empirical policy function for a baseline specification where all hospices are the same cost type, and an alternative specification where hospices are either cost-type 1 or cost-type 2.

[11] The regressors include: rivals' reputation tiers, functions of rivals' characteristics, rivals' imputed demand shocks, own reputation stock, own characteristics, aggregate data on lengths of stay of own patients, share of patients who reside in their own home, firm age, share of patients with cancer, Medicare price, market size and fuel prices. Fixed effect of firms vary from -2 to 65; I set 33 to be the cutoff for type.

Given the restrictions due to sample size and variation in data, I estimate a parsimonious empirical policy function that captures the key state variables in a tractable manner. I discretize the range of reputation values into 3 tiers, and include the count of rivals within each tier. This captures the competitive effects on own quality choice from rivals' reputations, and as Table 5 shows I find this competitive effect to be significant. I also include own demand shock ξ_{jt} and own characteristics. I find that firms with more favorable demand shocks choose lower quality. For-profits choose higher quality compared to non-profits, holding everything else constant. Finally, I include the fraction of patients who stay over 180 days as well as those who are served at their home; the intuition being that longer-staying patients may mechanically push up average visits over a year, and home-based patients might need fewer visits since they have a dedicated caregiver. Both of these claims are held up in the estimates.

In addition, I try to be cognizant of the issues raised in Berry and Compiani (2020), namely that such empirical policy functions should ideally not suffer from having endogenous state variables. To that end, I include county fixed effects to absorb unobserved market-specific persistent shocks. In addition, the presence of own demand shocks ξ_{jt} imputed from the demand estimation should cover for much of the time-varying shocks facing a hospice. I also experiment with adding market size and Medicare rates but these are insignificant after the inclusion of county fixed effects. Since the Medicare rates capture the changing cost in an area over time for hiring healthcare workers, this seems to suggest that the county fixed effects are picking up much of the unobservable cost shocks impacting hospices.

Entry and exit: Entry and exit are infrequent in my data, so I implement entry and exit as exogenous transitions rather than endogenizing them as part of the firm's choice problem. In my forward simulation, entry by potential entrants into a market is modeled through an ordered logit specified in Table 6. Exit by a firm happens with a probability of 4% every period, which matches exit rates in my data.

6.2.2 Second stage

In the second stage, these first-stage policy functions and transition matrices are used in forward simulation to construct value functions. This combines methods discussed in Bajari et al. (2007) and Pakes et al. (2007).

A brief overview of the algorithm is as follows. Fix a guess of structural parameters θ. For every observed state $\mathbf{x}_t$ and hospice j (i.e. each observation in my hospice-level panel data), I estimate the choice-specific value function for each quality level. For quality choice a_j by hospice j in the current period, a single simulated path is constructed as follows:

1. The empirical policy function is used to predict quality choices by all firms, conditional

	No types	Time invariant
ξ_{jt}	-0.843	-0.996
	(0.114)	(0.117)
$X'_{jt}\beta$	0.355	-1.285
	(0.566)	(0.589)
Own reputation	2.902	2.997
	(0.203)	(0.209)
Count of rivals in first reputation tier	0.214	0.207
	(0.057)	(0.058)
Count of rivals in second reputation tier	0.244	0.245
	(0.042)	(0.042)
Count of rivals in third reputation tier	0.081	0.084
	(0.028)	(0.029)
For-profit	1.315	0.521
	(0.215)	(0.226)
Share of patients with 180+ days stay	0.167	0.178
	(0.012)	(0.012)
Share of patients with home residence	-0.020	-0.016
	(0.003)	(0.003)
Type 2		1.649
		(0.128)

Table 5: Ordered logit estimates of visit-choice policy function. Average visits-per-patient discretized into 6 bins of 0-15, 15-22, 22-29, 29-36, 36-43, and 43+ with open lower intervals and closed upper intervals. This table reports the results of ordered logit for the six quality tiers on own and rival characteristics. Estimates of county fixed effects and cutoffs suppressed.

on the market state $\mathbf{x}_t$.

2. The reputation stock of each firm updates based on its quality choice. Each incumbent receives a payoff.

3. The entry transition function is used to predict the number of potential entrants who apply for entry. These entries are implemented in the next period.

4. The empirical exit probabilities are used to predict whether any incumbent exits.

5. Using the state variable transition functions from first-stage, all state variables update. This includes unobserved demand shocks, market size, and Medicare rates.

6. The game moves to the next period, and I repeat this algorithm.

	Entry count
Firm count	-0.300
	(0.117)
Market size	0.001
	(3.461e-04)
Medicare price	-3.846e-04
	(2.423e-04)
County FE	Yes

Table 6: Ordered logit of entry count on market characteristics, used as entry transition function. This is constructed as follows. For each market-year, I calculate the total number of entries ("entry count"). Then I run an ordered logit of entry counts on market characteristics (market fixed effects, market size, Medicare price). I restrict the ordered logit to market-years with 3 or less entries; greater than 3 entries are very rare and give unintuitive results. Estimates of county fixed effects and cutoffs suppressed.

The above simulation is run for many periods until the discounted profit is driven close to 0; in my estimation I set this to be 80 periods. Summing together the discounted per-period payoffs gives me the total payoff from hospice j choosing quality a_j for a single simulated path. I repeat this simulation many times (currently 200 in my estimation) and average over the total payoffs. This gives me the choice-specific value function from choosing quality a_j in state $\mathbf{x}_t$ by hospice j. The choice-specific value function is denoted by $W(a_j; \mathbf{x}_t, \theta)$.

The choice-specific value functions are constructed for every quality $a \in \mathcal{A}$. These are then used to construct model-predicted choice probabilities $\hat{\Psi}(a_j|\mathbf{x}_t, \theta)$ from the structural model using Equation 8. The model-predicted choice probabilities say - given state $\mathbf{x}_t$, how likely is it that hospice j would choose action a_j, conditional on our guess of structural parameters θ.

Next, I describe how these model-predicted choice probabilities are used to estimate the hospice cost fuction. The intuition is that I search over the parameter space to find values of parameters θ that minimize the distance between predicted choice probabilities and observed choices.

The dynamic oligopoly model is estimated using two-step GMM. The model-predicted error term for observation n is given by:

$$\Xi_n(\theta) = a_n^{data} - \sum_{a_n \in \mathcal{A}} a_n \hat{\Psi}(a_n|\mathbf{x}_{mt(n)}^{data}, \theta)$$

where $\hat{\Psi}(a_n|\mathbf{x}_{mt(n)}^{data}, \theta)$ is the predicted choice probability for action a_n, θ is the guess of structural parameters, $mt(n)$ denotes the market-by-year that observation n occupies, and the superscript $data$ indicates that the value of the variable comes from the data. The error term measures how close the average model-predicted choice is to the observed choice. The instruments used in GMM are the variables in the first-stage empirical policy functions, giving us the moment conditions $E[Z'\Xi_n(\theta)]$. The intuition for this is that the model's predicted choices leverage the variables in the first-stage policy functions, and so at the true parameter values the model's prediction errors should be orthogonal to these variables. The resulting GMM optimization problem is:

$$\min_{\theta} \left[\frac{1}{N}\sum_{n} Z_n'\Xi_n(\theta)\right]' \hat{W} \left[\frac{1}{N}\sum_{n} Z_n'\Xi_n(\theta)\right]$$

This objective function is minimized to estimate cost parameters of hospices. Standard errors are calculated via block-bootstrapping. I sample blocks of county-year observations from my data with replacement until I match the total number of county-year observations in my dataset. Then I re-estimate the model on each bootstrap sample. I use the sample variance over all the resulting bootstrap estimates to calculate the standard errors for my cost parameters. This closely follows Wang (2022).

7 Results

7.1 Demand

Table 7 shows the results from the demand estimation. The reputation decay rate τ is estimated to be 0.53, which can be interpreted as saying 47% of a hospice's reputation transfers over to the next year. A positive value of η means that a hospice with higher past quality choices is more likely to be chosen by consumers; in other words, a hospice with higher reputation will have higher market share. The unobserved shocks are highly persistent (ρ), and consumer preferences within a nest are highly correlated (σ_n). The remaining values in Table 7 gives consumer preferences for hospice characteristics.

To more easily interpret the value of η and τ, Figure 1 shows an impulse response to convey the importance of reputation effects. The setting is a duopoly, where the visit choices by the two firms for each period t are given by:

$$\text{Quality by Firm 1} = \begin{cases} 22, & \text{if } t \leq 2 \\ 39, & \text{if } 2 < t \leq 6 \\ 22, & t > 6 \end{cases}$$

$$\text{Quality by Firm 2} = 22$$

	Demand
τ	0.530
	(0.156)
ρ	0.756
	(0.072)
σ_n	0.597
	(0.034)
η	0.012
	(0.003)
Hospice inpatient unit	0.011
	(0.112)
Pediatric program	0.223
	(0.071)
Bereavement services	0.008
	(0.037)
Day care for adults	0.038
	(0.169)
For-profit	-0.291
	(0.081)
Agency type: free-standing	-0.168
	(0.133)
Agency type: home health based	-0.287
	(0.152)
Agency type: hospital-based	-0.259
	(0.159)

Table 7: Results of demand estimation. Here τ denotes depreciation rate of reputation, ρ denotes persistence of unobserved hospice-specific demand shocks, σ_n is the nest parameter, and η is the impact of quality choice on the reputation stock this period. The demand model is estimated using 2-step nonlinear GMM with BLP IVs and fuel prices. Robust-standard errors in parentheses. County fixed effects are suppressed.

That is, firms 1 and 2 make identical quality choices except in periods 3-6, when firm 1 chooses higher quality. Figure 1 traces out the market share of firm 1; note that there is an outside option so the market shares of the two firms do not sum to 100. As firm 1 increases its quality in period 3, its market share rises, but reputation effects mean that its market share keeps rising in the next few periods even as it chooses the same quality level of 39. This shows how reputation accumulates over time. After period 6 it returns to the original quality choice of 22, but its market share remains elevated for 6 more years and gradually decays down to the original level. This illustrates how reputation decays over time if not maintained with high quality choices.

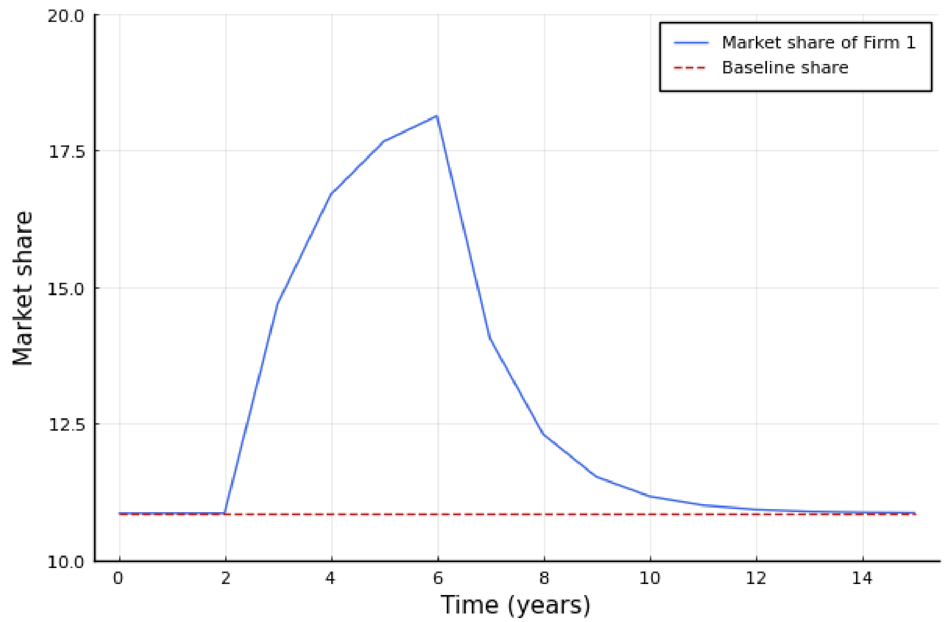


Figure 1: Impulse response in a duopoly setting to illustrate reputation accumulation. Firm 1 and 2 choose identical quality in every period except periods 3-6, when Firm 1 chooses higher quality. "Baseline share" denotes what Firm 1's market share would have been had it kept choosing Quality = 22 over the same period.

7.2 Supply

Table 8 gives the results of the dynamic supply estimation. The marginal cost should be interpreted as the cost per patient over their entire stay at a specified quality level; for instance, $MC(a_j = 30)$ gives the cost per patient when giving 30 visits to each patient. The estimation is done for two specifications, with and without cost types. Recall that for the dynamic supply estimation, the quality choices are discretized into 6 bins, each separated by roughly 7 visits. As a result, the slope coefficients (γ_1, γ_{fp}, γ_{rural}, γ_{12}) should be interpreted as the increase in marginal cost for 7 additional visits. In addition, I set $\gamma_0 = \gamma_1$. Across the two specifications the marginal cost of an additional visit is approximately \$191-220. For-profits enjoy an efficiency advantage worth \$76-105 per visit. Hospices operating in rural markets suffer from a cost disadvantage of \$17-29 per visit relative to urban hospices. For the specification with heterogeneous cost-types, type-2 hospices enjoy a cost advantage of \$84 per visit over type-1 hospices.

7.3 Robustness

I perform additional robustness checks not reported in the main text. Alternative demand specifications with firm fixed effects give very similar results. The impact of a firms' age

	No types	With cost-types
γ_1	1343.728	1541.100
	(32.311)	(48.872)
γ_{fp}	-740.676	-532.156
	(93.892)	(116.642)
γ_{rural}	125.534	206.063
	(54.289)	(74.825)
σ_e	5.018e+05	3.419e+05
	(95866.721)	(1.307e+05)
γ_{12}		-594.847
		(111.097)

Table 8: Results of supply estimation. Table shows the estimates for the marginal cost function $MC_j(a_j) = \gamma_0 + (\gamma_{1,k(j)} + \gamma_{fp} FP_j + \gamma_{rural} RURAL_j)a_j$, where a_j is the quality level, FP is for-profit-status, and $RURAL$ denotes whether the hospice is located in a rural county. This and the logit scaling parameter σ_e are estimated by forward-simulation using the method of Bajari et al. (2007). Standard errors (in parentheses) calculated via bootstrapping at the county-year level.

is already subsumed in my reputation transition equation (a firm who has lived longer has a larger number of past quality choices affecting its current reputation), but a demand specification that includes age as a hospice characteristic also finds the presence of reputation effects. I also re-estimate the demand model without allowing current quality choice to enter reputation this period and I continue to find the presence of reputation effects. Finally, I adjust my quality choice level by hospice-year measures of average lengths-of-stay for an alternative measure of hospice quality. My dataset contains information on the fraction of patients who enrolled for 0-7 days, 8-30 days, 31-90 days, 91-179 days, and 180+ days. I use this information to construct average lengths-of-stay for each hospice-year. An alternative measure of hospice quality could therefore be the ratio of total visits and total patients times average length-of-stay, i.e. average visits-per-patient-per-day. I estimate the demand model with this new quality measure and get very similar results.

8 Policy counterfactuals

Given the above estimates of the structural parameters, I can now conduct counterfactuals to investigate the effects of various policy environments.

8.1 Solving for equilibrium outcomes

To conduct counterfactuals I need to fully solve the model. This requires solving a nested fixed-point problem; more specifically, I need to calculate $\Psi(a_j|\mathbf{x})$, $\hat{v}(a_j, \mathbf{x})$ and $V(\mathbf{x})$ such that all 3 of the following equations simultaneously hold:

$$\Psi(a_j|\mathbf{x}) = \frac{e^{\hat{v}(a_j,\mathbf{x})/\sigma_e}}{\sum_{a\in\mathcal{A}} e^{\hat{v}(a,\mathbf{x})/\sigma_e}} \tag{9}$$

$$\hat{v}(a_j, \mathbf{x}) = \sum_{\mathbf{a}_{-j}\in\mathcal{A}_{-j}} \left\{ \left[\bar{\pi}(a_j, \mathbf{a}_{-j}, \mathbf{x}') + \beta V(\mathbf{x}') \right] F(\mathbf{x}'|\mathbf{x}, a_j, \mathbf{a}_{-j}) \prod_n \Psi(\mathbf{a}_{-j}[n]|\mathbf{x}) \right\} \tag{10}$$

$$V(\mathbf{x}) \quad = \quad \sigma_e \left[0.577216 + \ln \Big(\sum_{a_j\in\mathcal{A}} e^{\hat{v}(a_j,\mathbf{x})/\sigma_e} \Big) \right] \tag{11}$$

The first equation represents the CCP of hospice j. This gives the probability of hospice j choosing action a_j conditional on the state variables $\mathbf{x}$. This particular functional form arises because I assume the choice-specific errors to be distributed Type-1 Extreme Value, as is common in the IO literature. Since this error term is known to the firm but unknown to the econometrician, I can only derive choice probabilities from solving the model.

The second equation represents the choice-specific value function for hospice j with state variables $\mathbf{x}$ - prior to knowing the choice-specific structural errors, $\hat{v}(a_j, \mathbf{x})$ is hospice j's expected payoff from choosing action a_j when facing state variables $\mathbf{x}$. Forming this expectation requires integrating over several random variables. The last term shows that this expression requires integrating over rival actions, which is done using the CCP at equilibrium strategies. Intuitively, since this is a simultaneous-move game, when hospice j chooses an action this period it does not know its rivals actions, and so has to make predictions using the equilibrium strategies. The middle term shows that conditional on own choice and rival choices, the firm also needs to integrate over all possible values of state variables. The first term is then the current period payoff and continuation value conditional on state variables and rival choices.

The third equation is the ex-ante value function, which has the same intuition as the value function encountered in Section 4.5. Here I can write an analytical expression for this term because of the assumption of choice-specific error terms being distributed Type-1 Extreme Value.

I solve the model by iterating between the three equations until convergence. To ease computational burden, I solve for a simpler version of the model. First, I limit the number of firms to 3. This is a good approximation of the competitive environment in my data, since firm-count at the market-year level has a median of 2. Second, I do not allow for entry. This rules out firms acquiring reputation for entry deterrence. This is a reasonable assumption to make because I find no evidence of entry deterrence through reputation in my data, as well as because entry happens in less than 10% of market-year observations. Third, I do not allow for exit, again because of how infrequently it is observed in the data.

In my counterfactuals I also want to test if differentiated hospices react differently based on their characteristics and unobserved demand shocks. To be precise, I can rewrite the demand model as:

$$\begin{aligned} u_{ijt} &= \alpha_{m(j)} + X'_{jt}\beta + \psi_{jt} + \xi_{jt} + \zeta_i + (1-\sigma)\tilde{\varepsilon}_{ijt} \\ &= \Pi_{jt} + \psi_{jt} + \zeta_i + (1-\sigma)\tilde{\varepsilon}_{ijt} \end{aligned}$$

where $\Pi_{jt} = \alpha_{m(j)} + X'_{jt}\beta + \xi_{jt}$ reflects how much hospice j differentiates along non-reputation dimensions. A hospice with higher Π_j can be thought to have more favorable characteristics and persistent demand shocks than others. In my counterfactuals, I test whether hospices with different Π_j respond differently to policy changes. For the sake of clarity, I impose in my counterfactuals that a hospice's Π_j remains constant over time. This matches reality well, as I find that my estimated Π_{jt} from the demand model is highly persistent.

Counterfactual results are reported as follows. For a given policy experiment, I solve the nested fixed-point problem to obtain the CCPs $\Psi(\cdot|\mathbf{x})$. The CCP gives the probability of a firm making each action choice for any given state under the chosen policy experiment. I pick a starting point for a market, then simulate forward 1000 periods. I report the average quality choice by each firm over the simulation. To prevent my choice of initial conditions from contaminating the result, the first 200 periods are dropped; additionally I check by visual inspection to ensure that the industry has settled into its long-run state.

8.2 Counterfactual results

8.2.1 Increasing persistence of reputation

The first set of counterfactuals involve the persistence of reputation. From the perspective of understanding the model, it is important to know how firms would choose quality if reputation was more persistent, or if it decayed faster. From the perspective of policymaking, this can tell us whether policy changes that lead to greater reputation persistence can improve

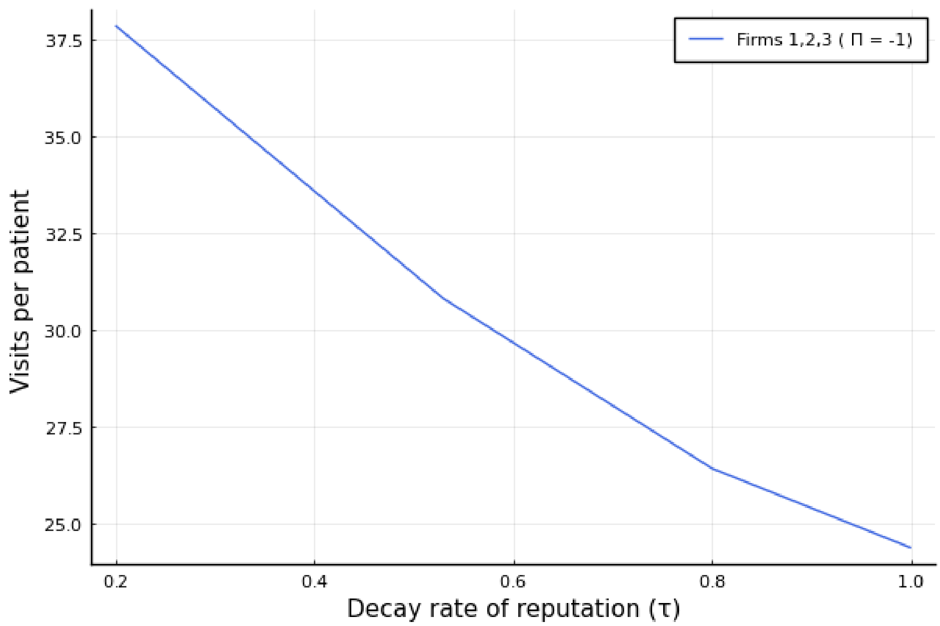


Figure 2: Average quality choice by undifferentiated hospices against reputation decay rates. This counterfactual studies three hospices competing in a hypothetical market. Π_j denotes the consumer valuation of non-reputation characteristics of hospice j. In this counterfactual I hold Π to be the same across all hospices, i.e. the hospices are undifferentiated in non-reputation characteristics. The three hospices choose nearly identical quality levels in equilibrium. As a result, the figure reports the average quality choices observed across all 3 firms over the simulations.

consumer welfare. For instance, in 2017 CMS launched Hospice Compare, a website that details quality information about hospices. Such review websites can aggregate and sustain information on hospices' quality choices for much longer and with greater accuracy, and can be thought of as helping reputation persist longer. Figure 2 looks at how the average visits-per-patient varies as reputation becomes less persistent. The counterfactual is done for 3 identical firms competing in a market. The takeaway is that quality choice falls as reputation decays faster. The intuition is that the marginal gain from increasing quality is smaller; since reputation is decaying more quickly, an increase in quality leads to a smaller increase in future sales, so it is no longer optimal to incur the higher cost from higher quality. This also highlights the importance of reputation in a regulated price environment; if reputation were not present, firms would choose much lower quality.

8.2.2 Increasing Medicare rates

Healthcare providers have frequently complained that Medicare reimbursement rates are too low. To see how hospices react to higher reimbursement rates, my second set of counterfactuals study how hospice quality changes as the Medicare rate increases. Figure 3 reports a counterfactual where 3 identical firms make quality choices under different reimbursement rates. It can be seen that higher regulated prices lead to higher qualities being chosen by each firm. I also contrast the equilibrium quality choices at the estimated decay rate of 53% with those at a higher decay rate of 90%. I find that at a given Medicare rate, a higher decay rate results in lower quality. This further illustrates the importance of reputation effects when predicting quality choices at various Medicare reimbursement levels.

To see how hospice differentiation along non-reputation dimensions can influence results, Figure 4 reports the same counterfactual but this time Π_j varies between the three firms. Firms which have rivals closer to them in the product space (i.e. there is another firm with Π_j close to its own) react more strongly to an increase in price. In Figure 4a, Firm 1 is the only one with $\Pi = -2$, and does not react as much to an increase in price. In Figure 4b, Firms 1 and 3 both have $\Pi = -2$; this time, Firm 1 reacts more strongly to an increase in price.

8.2.3 Subsidizing individual visits

My final set of counterfactuals investigates alternative reimbursement schemes. The current reimbursement scheme involves Medicare paying hospices for every day a patient is enrolled, i.e. a per-day scheme. Since we want to achieve a target quality level at the lowest possible cost, a natural route to investigate is to tie part of the reimbursement to quality. To that end,

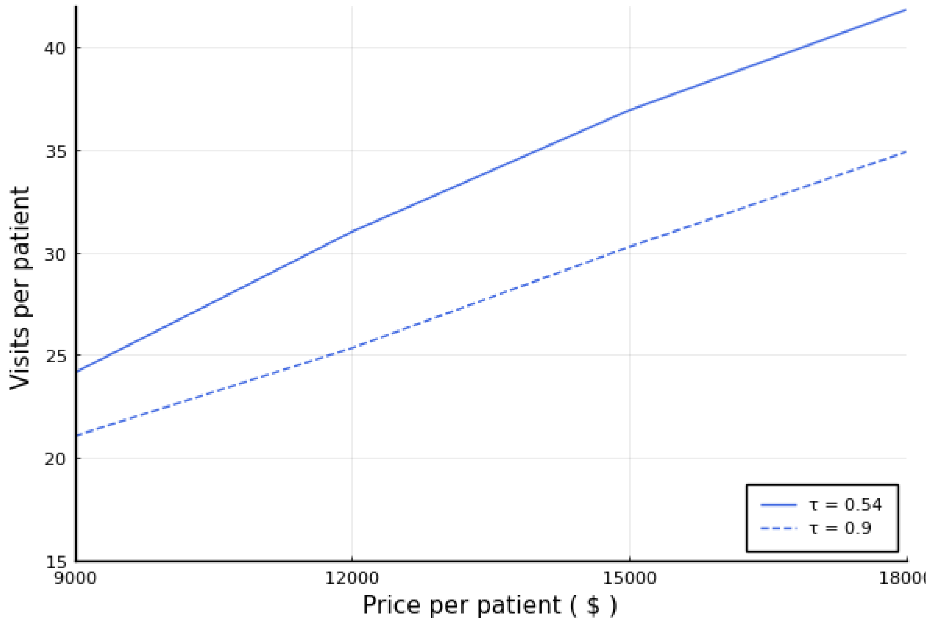
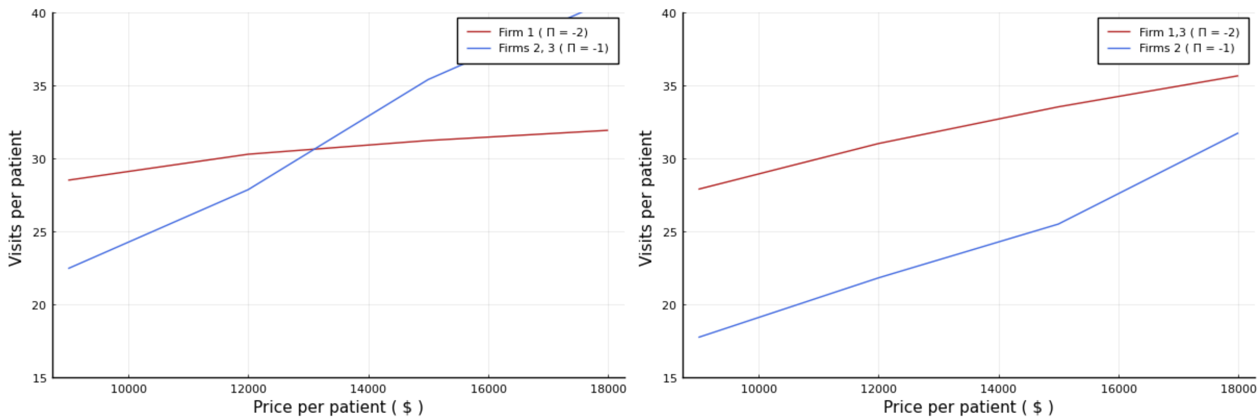


Figure 3: Average quality choice by undifferentiated hospices against increasing Medicare rates, at decay rates of 0.54 and 0.9. This counterfactual studies three hospices competing in a hypothetical market. Π_j denotes the consumer valuation of non-reputation characteristics of hospice j. In this counterfactual I hold Π to be the same across all hospices, i.e. the hospices are undifferentiated in non-reputation characteristics. The three hospices choose nearly identical quality levels in equilibrium. As a result, the figure reports the average quality choices observed across all 3 firms over the simulations.

I solve the model for hybrid per-day per-visit schemes. I progressively reduce the per-day rate and increase the per-visit rate while ensuring that under the new terms, the equilibrium quality choice remains at 29 visits-per-patient (the median visits-per-patient observed in my data). The results are shown in Table 9. The takeaway is that potential cost savings can be achieved by shifting weight from per-day to per-visit reimbursement. Note that how far I can increase the per-visit rate is limited by the estimated marginal cost of $200, since a per-visit rate exceeding the marginal cost will lead to hospices making unlimited visits to maximize profits.

8.3 Discussion

One caveat that should be kept in mind when interpreting the counterfactuals is that I show how different policy levers can be used to achieve a quality target, but do not specify what the quality target should be. This is because my demand model is silent about consumer valuation of visits. The thought experiment is that CMS has figured out the quality target through studies of their own, and can achieve said target with the policy instruments I have



(a) $\Pi_1 = -2$, $\Pi_2 = \Pi_3 = -1$

(b) $\Pi_1 = \Pi_3 = -2$, $\Pi_2 = -1$

Figure 4: Average quality choice by differentiated hospices against Medicare rates. This counterfactual studies three hospices competing in a hypothetical market. Π_j denotes the consumer valuation of non-reputation characteristics of hospice j. In this counterfactual I allow Π to differ across hospices. Hospices with larger Π have more advantageous non-reputation characteristics. Hospices with the same Π choose nearly identical quality levels in equilibrium.

Per-day rate	**Per-visit rate**	**Medicare cost (normalized)**
186.7	0.0	1.0
150.0	50.0	0.93
100.0	110.0	0.82
50.0	170.0	0.71

Table 9: Reimbursement schemes that lead to 29 visits-per-patient by three identical hospices. The rates are in US dollars. The total Medicare spending associated with each scheme is normalized with respect to the cost of the per-day scheme. The table is constructed as follows. In a hypothetical market with three undifferentiated hospices, a per-day rate of \$186.7 yields equilibrium quality choice of 29 visits-per-patient by each hospice. This costs Medicare a certain amount in spending, which I normalize to 1. The per-day rate is decreased and a per-visit subsidy is added on that results in an equilibrium quality choice of 29 visits-per-patient. The corresponding total Medicare spending is compared to that with only per-day rates.

detailed above.

A possible issue with subsidizing visits is that it could encourage spurious visits by hospices. While my model cannot allow for firms making spurious visits, it is interesting to think about how this might play out in the real world. First, since reputation effects are salient in this industry, a hospice that makes spurious visits can develop a bad reputation and lose future consumers, so reputation effects might rein in such issues. Second, Medicare can take additional steps to discourage spurious visits. It can adopt finer contract structures (such as reimbursing hospices for up to 3 visits a week). It can also enforce stronger monitoring.

9 Conclusion

Using firm-level data from California, I study quality choice by hospices, uncover the importance of hospice reputation for consumers, and explore counterfactual policies that can incentivize higher hospice quality. I build and estimate a structural model of consumer demand and hospice quality choice to do so. My measure of hospice quality is the average number of visits made by a hospice to its patients in a year, and I define reputation of a hospice to be a function of its current and past quality choices. As a result, a hospice can accumulate reputation over time by consistently choosing high quality. I use my structural model to quantify the importance of reputation for consumers choosing hospices and estimate the hospice cost function. Reputation plays an important role in consumer demand for hospices, and past reputation decays at an annual rate of 53%. The cost of an additional visit by a hospice to a patient is roughly $200, for-profits enjoy an efficiency advantage over non-profits, and rural hospices suffer from a cost disadvantage compared to urban hospices. Counterfactuals show that hospice quality increases with higher Medicare prices and greater persistence of reputation through review sites. I compare the current per-day Medicare reimbursement scheme with a hybrid per-day per-visit scheme, and find that the latter can incentivize the same level of hospice quality at lower cost.

There are several extensions that can be explored in future work. First, my counterfactuals shed light on how different regulations affect hospice quality choices, but they are silent on what the optimal regulation should be. For that, we would need to gauge how much the society values each hospice visit to a patient, then figure out the reimbursement scheme that incentivizes hospices to choose the socially optimal quality level. Future research could estimate the value of visits to patients, perform cost-benefit analysis, and pin down the optimal quality level for policies to target. Second, my dynamic oligopoly estimation does not allow for hospices to transition between different cost types. An alternative model of reputation could incorporate firms transitioning between cost types over time. This allows for the possibility that there are changes in management or personnel at a firm over time that influences the firm's quality choices. As a result, consumers use past quality levels to infer if such a transition has happened recently. This would involve incorporating a firm-specific unobservable in the cost function that changes via a Markov process. Dynamic oligopoly estimation in such a setting is extremely difficult; it would involve either fully solving the model or using a variant of Arcidiacono and Miller (2011) to try and estimate such unobserved firm-level heterogeneity. In any setting that is difficult; in a setting with multiple choices and without a terminal action, it might not be realistic to implement. Future research could aim at estimating a reputation accumulation model with type transitions in a computationally tractable manner.

A Additional summary statistics

A.1 Length of stay

Length of stay	% of patients
0-7 days	30.89
8-30 days	29.38
31-90 days	21.7
91-179 days	9.52
180+ days	8.51

Table 10: Distribution of patient length-of-stay.

In my dataset, I observe the number of patients in a hospice who stayed for i)0-7 days, ii) 8-30 days, iii) 31-90 days, iv) 91-179 days, v) 180+ days. Table 10 uses this data to construct the total number of patients in my dataset within each LOS bracket. Over 80% of the patients stay for less than 90 days.

To rule out the possibility that longer-staying patients are selecting into particular hospices, Table 11 shows the distribution of people within each LOS-bracket by hospice-year. For nearly all hospices, most of their patients stay for less than 90 days.

	10%	25%	50%	75%	90%
0-7 days	19.76	24.66	30.3	36.31	41.81
8-30 days	21.93	25.05	29.29	33.01	36.33
31-90 days	16.15	18.9	21.7	25.17	29.44
91-179 days	5.45	7.47	9.41	11.43	13.92
180 days	2.24	4.48	7.2	10.73	14.52

Table 11: Distribution of shares of lengths-of-stay of patients. Each observation is at the hospice-year level.

A.2 Disease category

Diagnosis	% of patients
Cancer	39.6
Heart	10.27
Dementia	13.57
Lung	6.39
Kidney	2.49
Brain stroke	4.47

Table 12: Percentage of hospice patients by diagnosis.

The dataset classifies the patients at a hospice by broad catergories of diagnosis. This allows us to see which diagnosis are more prevalent and whether hospices specialize in certain diagnosis over others. Table 12 shows that most hospice patients suffer from cancer; the second and third largest diagnosis categories are heart disease and dementia.

To see if hospices are specializing by diagnosis, or whether patients select into hospices by their diagnosis, Table 13 shows the distribution of patients of each diagnosis by hospice-year. This shows that most of a hospice's patients are suffering from cancer, heart disease or dementia, and there is no clear sign that a hospice gets most of its patients from one disease category alone.

	10%	25%	50%	75%	90%
Cancer	24.23	31.25	39.63	49.42	60.0
Non cancer	40.0	50.52	60.36	68.75	75.73
Heart disease	3.91	6.67	9.81	13.29	17.82
Dementia	3.33	6.5	11.72	18.03	25.0
Lung disease	2.61	4.27	6.18	8.46	11.12
Kidney	0.0	1.34	2.32	3.49	5.21
Liver	0.0	0.98	1.85	2.91	4.3
Brain stroke	0.0	1.53	3.48	5.89	8.96
HIV	0.0	0.0	0.0	0.13	0.46
Coma	0.0	0.0	0.0	0.0	0.35
Diabetes	0.0	0.0	0.0	0.0	0.44
ALS	0.0	0.0	0.26	0.61	1.03

Table 13: Distribution of shares of patients at a hospice per disease category. Each observation is at the hospice-year level.

A.3 Care type

	10%	25%	50%	75%	90%
Routine care	98.72	99.46	99.8	99.94	100.0
Inpatient care	0.0	0.0	0.04	0.23	0.69
Respite care	0.0	0.0	0.06	0.16	0.36
Continuous care	0.0	0.0	0.0	0.01	0.08

Table 14: Distribution of days of service provided for each hospice-year per care-type.

Medicare reimburses hospices with rates based on whether it provided routine care, inpatient care, respite care, and continuous care. Routine care has the lowest Medicare reimbursement rate, while other care types are much higher (see Figure 12).

The dataset divides the total days of care provided by a hospice into days providing each type of care. I calculate the fraction of care days in my dataset for each type of care. Table 14 shows that nearly all of a hospice's care days are for routine care.

A.4 Market definition

An important part of my analysis involves getting the market definition right for my setting. While I define my market to be at the level of a county, some papers on healthcare providers define markets at a larger level. Furthermore, some hospices advertise as being available for service in multiple counties at once. In my setting, I can rule out larger market definitions using my dataset. For each hospice, the dataset includes measures of the fraction of patients that arrive from each county. This allows me to isolate the fraction of a hospice's patients coming from the "home county" of the hospice (i.e. the county where the hospice is located) versus the fraction that is coming from an "away county". The distribution of home county share for each hospice in 2014 is shown in Figure 5. As this and Table 15 make clear, the vast majority of a hospice's patients arrive from the county where it is located. As a result, we define the relevant market to be at the county level.

	25%	**50%**	**75%**
Home county share	70.6	88.4	99.0

Table 15: Distribution of days of service provided for each hospice-year per care-type.

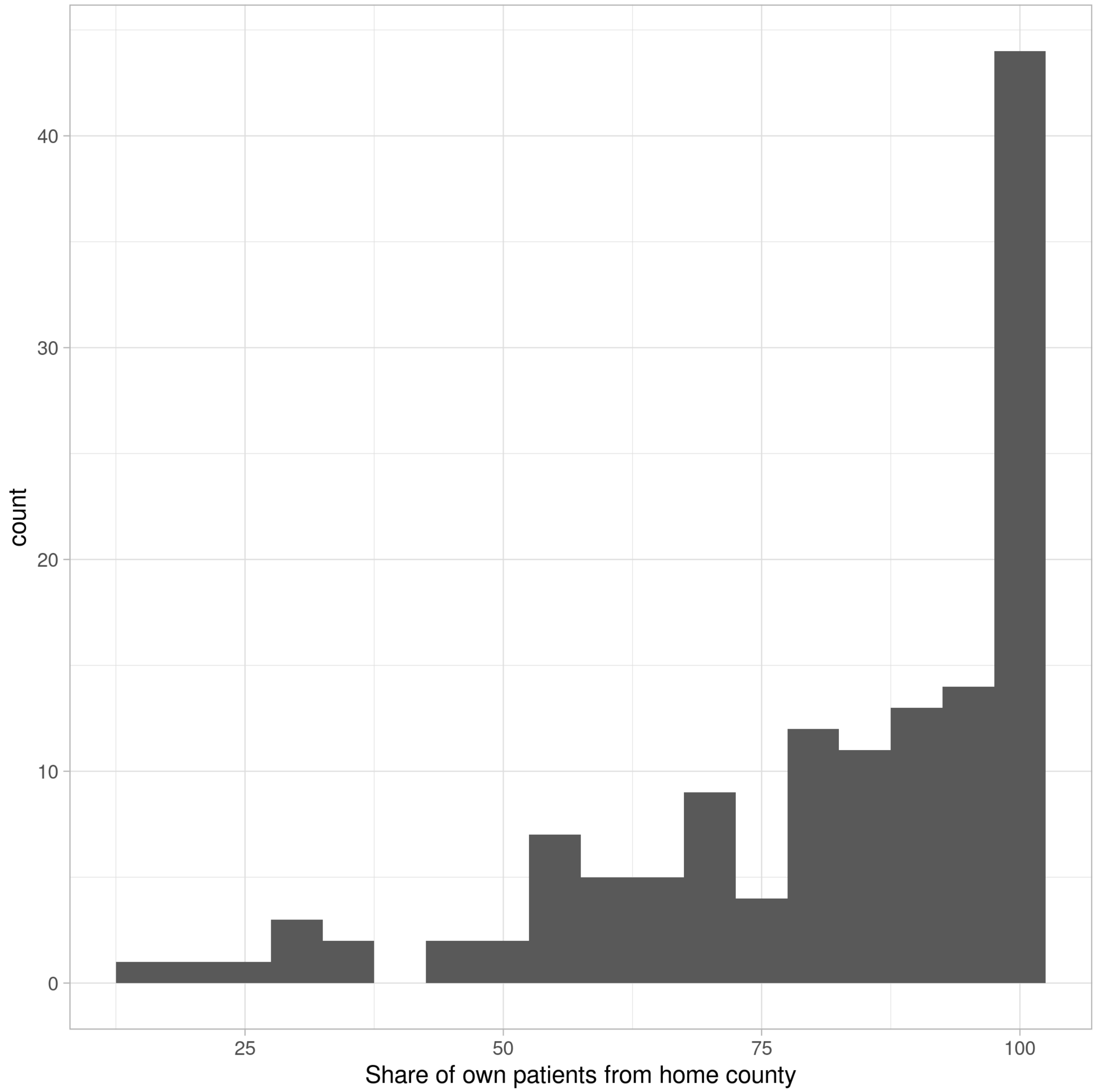


Figure 5: Histogram of home county share - percentage of a hospice's patients from the county where it is located - for hospices in 2014.

A.5 Statistics on firm count, entry, and exit

Table 6 shows the total firms in my dataset by year. Note that I focus on the following 28 counties in California:

Alameda, Contra Costa, Amador, Butte, San Joaquin, El Dorado, Fresno, Humboldt, Del Norte, Imperial, Kern, Kings, Lake, Madera, Marin, Mariposa, Mendocino, Merced, Monterey, Napa, Nevada, Placer, Sacramento, San Francisco, San Luis Obispo, San Mateo, Santa Barbara, Santa Clara, Santa Cruz, Shasta, Siskiyou, Solano, Sonoma, Stanislaus, Sutter, Tehama, Tulare, Tuolumne, Yolo.

Tables 6, 7, and 8 show the total number of firms in these counties over the years 2002-2018. As can be seen, the hospice industry has been growing over the past two decades. Most of the entry happens in Alameda, Contra Costa, Fresno, and Sacramento

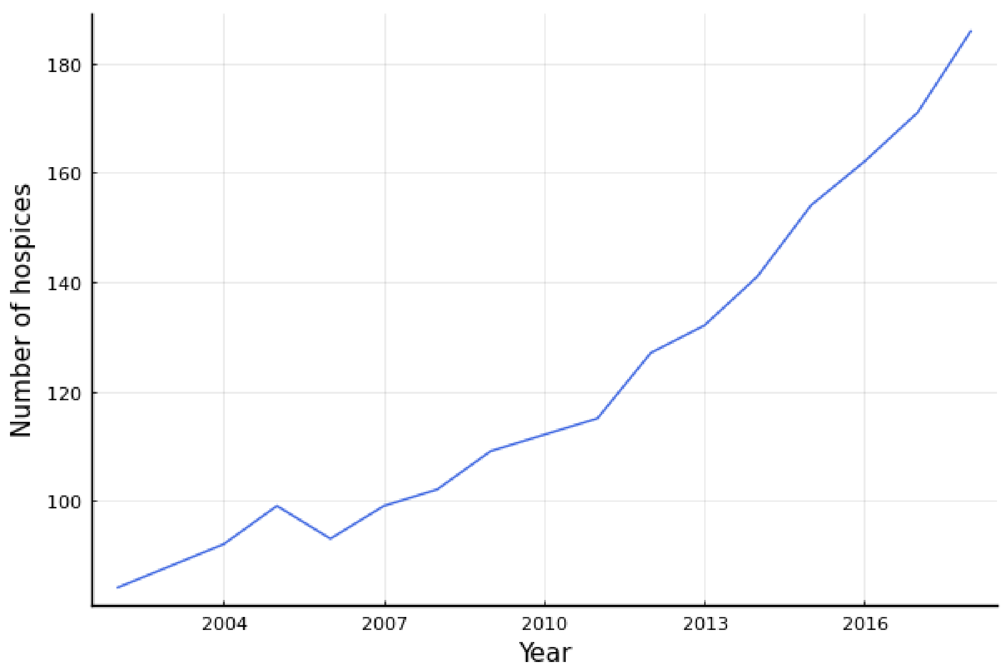


Figure 6: Plot of total firms in my dataset by year.

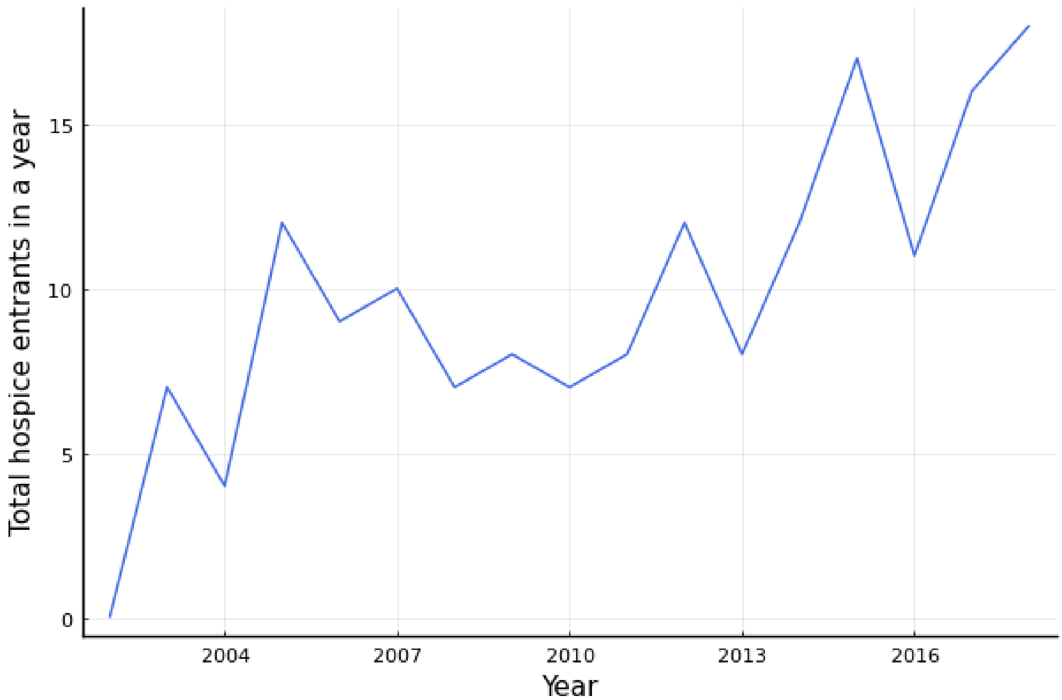


Figure 7: Plot of total hospice entrants in my dataset by year.

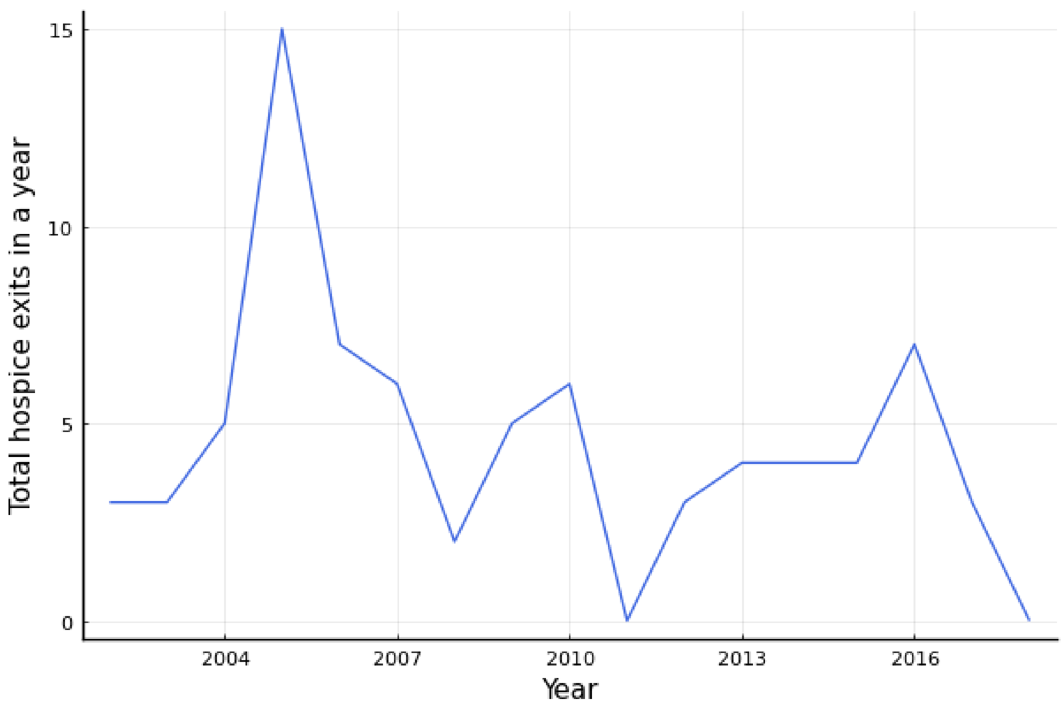


Figure 8: Plot of total hospice exits in my dataset by year.

A.6 Reimbursement rates

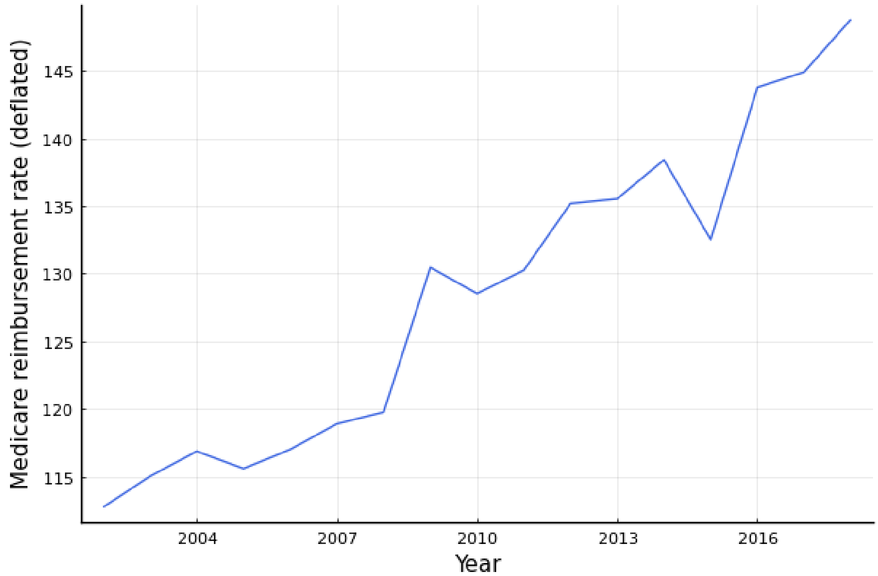


Figure 9: Medicare reimbursement rate (inflation-adjusted) for Kern county.

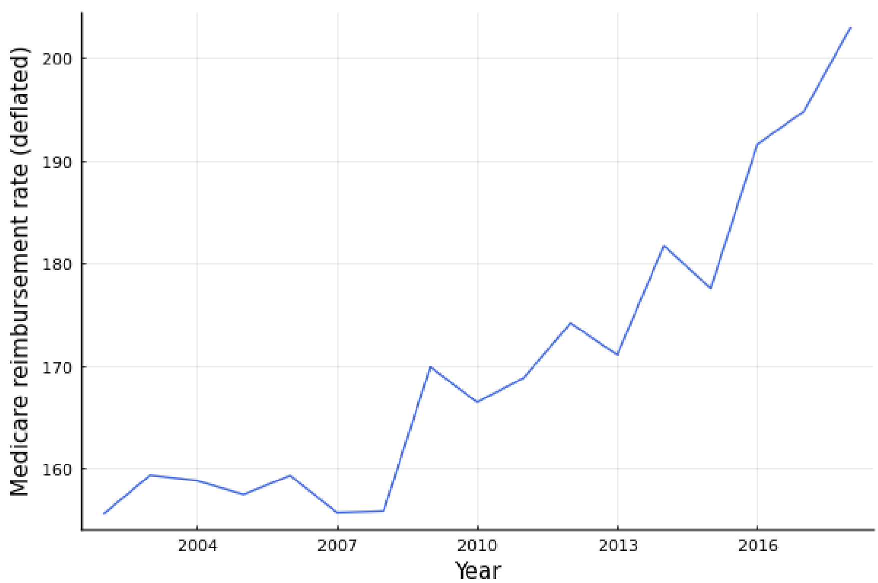
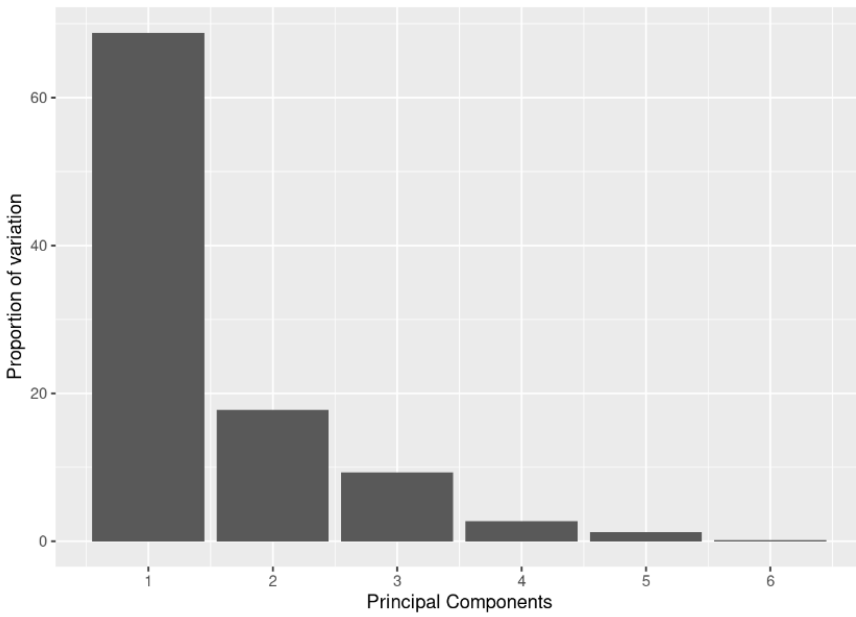


Figure 10: Medicare reimbursement rate (inflation-adjusted) for Alameda county.

A.7 Principal components analysis of visits by staff type



	PC1	PC2	PC3	PC4	PC5	PC6
rnpat	0.4223153	0.7939506	-0.3565230	0.2495343	0.0433376	0.0061776
physnpat	0.0151012	-0.0068927	-0.0221099	-0.0032503	-0.0416916	-0.9987426
socsvcspat	0.1317572	0.1580743	-0.1338480	-0.9503556	0.1912078	-0.0010246
lvnpat	0.1834381	-0.5006202	-0.8411163	0.0710564	0.0519645	0.0224485
homemkrpat	0.8730719	-0.3053850	0.3769924	0.0254161	0.0411040	0.0051643
chaplainpat	0.0903201	0.0269610	-0.0699097	-0.1698567	-0.9774627	0.0440833

Figure 11: Principal components analysis of visits by staff type. The staff types are (in order of presentation) Registered Nurse, Physician, Social service worker, Licensed Vocational nurse, Home-maker, and Chaplains. The PCA analysis shows that visits by RN, LVN and Home-makers explain nearly all the variation in visits by a hospice.

B Robustness check with length-of-stay adjustment

Most hospice patients die within 1 week to 3 months of enrollment. While I do not observe the exact length of stay of each patient, the dataset includes the fraction of total patients at a hospice who stayed for i)0-7 days, ii) 8-30 days, iii) 31-90 days, iv) 91-179 days, v) 180+ days. Using this measure, I construct the mean-length-of-stay at a hospice in a particular year. This is done by assuming that each patient in the LOS bracket stays until the midpoint of that bracket, e.g. a patient in 91-179 days bracket stayed for 135 days. Then, multiplying the fraction of patients in each LOS bracket with the midpoint of the LOS bracket and summing them together gives an estimate of the average length-of-stay for a hospice-year.

	10%	**25%**	**50%**	**75%**	**90%**
Average length-of-stay	34.34	43.33	51.35	59.98	68.88

Table 16: Distribution of average LOS across hospice-years.

An alternative measure of hospice quality could therefore be constructed by dividing the total number of visits with the number of patients *and* the mean LOS for that hospice-year. Such a measure could be described as the average visits-per-patient-per-day made by the hospice. This has the advantage that the quality measure is not affected by a few long-staying patients.

	10%	**25%**	**50%**	**75%**	**90%**
Average visits-per-patient-per-day	0.41	0.52	0.65	0.81	1.0

Table 17: Distribution of average visits-per-patient-per-day across hospice-years.

As a robustness check, I re-estimate my demand model with this new quality measure (see Table 18). I find very similar results, and in fact reputation has a lower depreciation rate (34%) compared to my main specification.

	Demand
τ	0.343
	(0.149)
ρ	0.820
	(0.069)
σ_n	0.583
	(0.039)
η	0.325
	(0.131)
Hospice inpatient unit	0.004
	(0.124)
Pediatric program	0.259
	(0.074)
Bereavement services	0.025
	(0.039)
Day care for adults	0.008
	(0.138)
For-profit	-0.197
	(0.095)
Agency type: free-standing	-0.205
	(0.149)
Agency type: home health based	-0.353
	(0.169)
Agency type: hospital-based	-0.336
	(0.182)

Table 18: Results of demand estimation with average visits-per-patient-per-day as quality measure.

C Miscellaneous

C.1 Relevant webpages

1. The raw datasets can be accessed here: data.chhs.ca.gov/dataset/home-health-hospice-annual-utilization-report-complete-data-set

2. Details about Medicare's reimbursement policy can be found here: https://www.medicare.gov/coverage/hospice-care.

3. Some websites which detail my claim on how hospices are chosen can be found in the following:

   - https://www.vitas.com/hospice-and-palliative-care-basics/when-is-it-time-for-hospice/how-to-choose-a-hospice-provider
   - https://www.cancer.org/treatment/end-of-life-care/hospice-care/how-to-find.html
   - https://www.health.harvard.edu/staying-healthy/choosing-hospice
   - https://hospicefoundation.org/End-of-Life-Support-and-Resources/Coping-with-Terminal-Illness/How-to-Choose
   - https://rainbowhospice.org/hospice-care/choosing-hospice/

4. Some quotes on how reputation should be considered when choosing a hospice are as follows.

   - AmericanHospice.org: What do others say about this hospice? Get references both from people you know and from people in the field – e.g., local hospitals, nursing homes, clinicians. Ask anyone that you have connections to if they have had experience with the hospice and what their impressions are. Geriatric care managers can be a particularly good resource, as they often make referrals to hospices and hear from families about the care that was provided... How long has the hospice been in operation? If it has been around for a while, that's an indication of stability."
   - HospiceFoundation.org: "Seek professional opinions. Ask clinicians, professional caregivers at nursing homes, geriatric care managers, or end-of-life doulas about

their experience with a hospice. Talk to friends, family, and neighbors who have used hospice services and get their opinions about the experience with a provider."

- Vitas.com: "Evaluate the hospice provider's history and reputation before you decide. How long has it been in business? ... What do other patients or families say about their experiences?"
- Caringinfo.org: "Most hospice programs use family satisfaction surveys to obtain feedback about their services so they can make improvements. Ask the hospice to share a summary of their family satisfaction scores for the last several months with you. You can also ask to see their latest state or Medicare inspection report to see if there are care provision problems. Finally, you could ask to see the hospice provider's list of complaints from the past 12 months."

C.2 Example of a hospice reimbursement scheme

LOCATION BY COUNTIES	ROUTINE HOME CARE DAYS 1-60 Revenue Code 0650	ROUTINE HOME CARE DAYS 61+ Revenue Code 0659	SERVICE INTENSITY ADD-ON (HOURLY) Revenue Code 0552	CONTINUOUS CARE (HOURLY) Revenue Code 0652	INPATIENT RESPITE CARE Revenue Code 0655	GENERAL INPATIENT CARE Revenue Code 0656
NATIONAL RATES	**$ 196.50**	**$ 154.41**	**$ 41.57**	**$ 41.57**	**$ 185.27**	**$ 758.07**
RURAL AREAS	$ 237.03	$ 186.26	$ 50.15	$ 50.15	$ 215.38	$ 903.74
ALAMEDA & CONTRA COSTA	$ 294.39	$ 231.33	$ 62.28	$ 62.28	$ 257.98	$ 1,109.87
BUTTE	$ 214.74	$ 168.74	$ 45.43	$ 45.43	$ 198.82	$ 823.63
FRESNO	$ 208.62	$ 163.94	$ 44.14	$ 44.14	$ 194.28	$ 801.64
IMPERIAL	$ 180.42	$ 141.77	$ 38.17	$ 38.17	$ 173.33	$ 700.28
KERN	$ 223.41	$ 175.56	$ 47.26	$ 47.26	$ 205.26	$ 854.78
KINGS	$ 206.61	$ 162.36	$ 43.71	$ 43.71	$ 192.78	$ 794.41
LOS ANGELES	$ 234.05	$ 183.92	$ 49.52	$ 49.52	$ 213.16	$ 893.02

Figure 12: Snapshot of Medicare reimbursement scheme in 2018. The reimbursement rate varies by county based on its Medicare wage index, and varies by the type of care provided.

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