Quality choice with reputation effects: Evidence from hospices in California

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Motivation

Hospices provide palliative care to dying patients.

Useful to study because:

1. **Large industry, deficiencies in service quality**
2. **Insightful for regulated-price healthcare markets**
3. **Analyze quality choice under reputation effects**
    - Reputation of a firm reflects its past quality choices.
    - Current quality $\uparrow \implies$ reputation $\uparrow \implies$ future sales $\uparrow$

I show that hospices dynamically choose quality to build up reputation and attract consumers. Then I study counterfactual policies that incentivize better hospice quality.

Hospice industry

Hospices provide palliative care to dying patients.

- Serve patients at residences.
- Regular visits for pain-control, living arrangements.
- More visits $\implies$ higher quality.

> Hospice quality = Average visits-per-patient.

- Paid fixed rate per-patient per-day by Medicare.

Hospices

Reputation is an important driver of consumer choice.

- Quality not contractible: hospice unilaterally decides visits.
- Goodwill and name recognition $\rightarrow$ patient's choice.
- Good track record $\implies$ greater referrals, better known and reviewed $\implies$ greater market share.

Structural model

Estimate structural model of hospice industry using yearly firm-level data from California for 2002-2018.

> Reputation of a hospice = stock of its current and past quality choices, partially depreciates every period.

1. Demand: Consumers choose from set of hospices.
   - Influenced by hospice characteristics and reputations.
2. Supply: Hospices choose quality every year.
   - Dynamic oligopoly model.
   - Trade off improving reputation with higher cost.

Results: Estimation

Demand estimation:

1. Reputation plays important role in consumer choice.
   - Hospices which chose high quality **in the past** have higher **current** market share.
2. Reputation depreciates at annual rate of 53%.
   - Quality choices 4 years ago affect current market share.

Results: Estimation

Supply estimation:

1. Additional visit per patient costs the hospice around $200.
   - Includes staff wages, cost of medical supplies and operation.
2. For-profits more efficient than non-profits by $75-105 per visit.
3. Rural hospices suffer cost disadvantage of $18-30 per visit.

Results: Counterfactuals

Simulating effects of alternative policies:

1. Persistence of reputation $\uparrow \implies$ Quality $\uparrow$
   - E.g. review sites
2. Medicare prices $\uparrow \implies$ Quality $\uparrow$
   - Response varies with differentiation from rivals.
3. Compared to current per-day scheme, a hybrid per-day and per-visit scheme achieves same quality at nearly 30% lower Medicare spending.

Contributions

1. Estimate a novel structural model of reputation accumulation through quality choice.
2. Importance of reputation for i) patients choosing medical providers and ii) medical providers choosing quality.
3. Contribute to a very sparse literature on hospices, evaluate policies to improve outcomes.

Literature review

Contribute to the following strands of literature:

1. Effect of reputation on firms' choices: Tadelis (2016), Saeedi (2019), Bai (2022).
2. Quality choice by healthcare providers: Lin (2015), Hackmann (2019), Gaynor et al (2016).
3. Hospices: Chung and Sorensen (2018).
4. Brand equity and advertising: Dubé et al. (2005), Borkovsky et al. (2017).

Quality provision

Hospices typically provide care at residence of patient.

- Regular visits to patient.
- Hospice **unilaterally decides** how many visits to provide.

Type of care is relatively low-skill.

- No curative treatment.
- Pain management and ease-of-living.
- Content of visits similar across hospices.

Examples of hospice care

Reputation

How a hospice is chosen:

- Social worker at hospital.
- Patient's physician.
- Word-of-mouth from community and support groups.
- Online search.

Reputation

Key industry details:

1. Quality of care = total visits to patient.
    - More visits $\implies$ regular checkups and adjustments, symptom management, availability during emergencies.
2. Reputation drives consumer choice. Sources
    - Non-contractible quality, goodwill and name recognition.
    - Good track record $\implies$ greater referrals, better known and reviewed $\implies$ greater market share.
3. Past information on service quality can **persist and diffuse over time** via social workers, physicians, and surrounding community.

Reimbursement

Majority of patients in my data are paid for by Medicare.

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.

Reimbursement

Under Medicare:

1. Patient: hospice care is essentially free.
2. Hospice: paid a **fixed rate per-day** of patient enrollment.
    - Payment does **not** vary by number of visits.
    - Payment varies across counties and over time. Reflects a "national" rate and a cost index of the county.

Data

Data on hospices in California :

- Home Health Agencies And Hospice Annual Utilization Reports.
- Panel data on hospices at the **firm level**.
- Annual data covering 2002-2018.
- For each hospice-year: total patients served, total visits made by staff, hospice characteristics, etc.

Combine with: data on population sizes (by age), mortality rates, and Medicare hospice reimbursement rates.

Data

Market defined at county level.

- Can rule out broader market definitions using data.

Restrict attention to 28 counties.

- Some do not see hospice presence.
- Drop markets with > 24 hospices: numerical challenges and different industry dynamics.
- Sample selection in line with majority of IO papers using dynamic oligopoly models.

Data

$$\text{Measure of quality of a hospice} = \frac{\text{total visits}}{\text{total patients served}}$$

	10%	**25%**	**50%**	**75%**	**90%**
Visits-per-patient	17.17	21.88	27.83	37.66	52.48

Table 2: Distribution of average visits-per-patient.

Data

	Min	10%	25%	50%	75%	90%	Max
firm count	1.0	1.0	1.0	2.0	4.0	7.0	23.0

Table 3: Distribution of firm-count.

Entry and exit:

- Occur in 10% of county-years.
- Between 1 and 5.

Structural model: Demand

Demand model: Discrete choice (with outside option), nested logit.

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

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

- $\alpha_{m(j)}$ = county FE.
- X_{jt} = observed hospice characteristics.
- ψ_{jt} = hospice j's reputation.
- ξ_{jt} = Persistent unobserved hospice characteristic.
- ϵ_{jt} = innovation distributed independently with mean zero.

Structural model: Demand

Reputation follows a stock transition equation:

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

where a_{jt} = average-visits-per-patient by hospice j in period t.

Assuming $\psi_{j0} = 0$:

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

Combining:

$$u_{ijt} = \alpha_{m(j)} + X'_{jt}\beta + \xi_{jt} + \zeta_i + (1-\sigma_n)\tilde{\varepsilon}_{ijt} + \eta[\mathrm{a}_{jt} + (1-\tau)\mathrm{a}_{jt-1} + (1-\tau)^2\mathrm{a}_{jt-2} + \ldots]$$

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

Structural model: Supply

Intuition: marginal cost is increasing linearly in quality choice.

Cost of serving each patient at quality a_j:

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

- a_j = average visits-per-patient.
- $k(j)$ = cost-type of the hospice j.
- FP_j = For-profit status.
- $RURAL_j$ = Rural hospice indicator.

All patients of hospice j receive quality a_j.

Structural model: Supply

Hospice j's per-period profit:

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

- θ = cost parameters.
- $MC_j(a_j; \theta)$ = marginal cost of hospice j choosing quality a_j.
- x_m = state variable in market m.
- a_{-j} = actions of rivals.
- M_m = market size.
- $s_j(\cdot)$ = hospice j's market share.
- P^{MCAR} = Medicare per-day rate $\times$ 60 days.

Structural model: Supply

Quality choice decision:

- Dynamic game under competition.
- Simultaneous move.
- Discrete time (year).

For computational tractability:

- In supply side, I discretize quality choice into 6 tiers.

Hospice j's **choice-specific value function** for action a_j:

$$W_j(a_j, x_m; \theta) = \mathbb{E}\left[\bar{\pi}(a_j, x_m; \theta) + \beta V_j({x'}_m, {\epsilon'}_j^a\ ; \theta) \middle| a_j, x_m\right]$$

Value function

Structural model: Supply

To account for unobservables affecting quality choice:

- $\epsilon_j^a(a_j)$ = choice-specific shock for hospice j choosing a_j
- Distributed *i.i.d* T1EV.

Optimal strategy of hospice j:

$$\sigma_j^*\left(\mathrm{x}_m, \epsilon_j^a\right) = \arg\max_{a_j \in \mathcal{A}} \left\{ W_j\left(a_j, \mathrm{x}_{\mathrm{m}}; \theta\right) + \epsilon_j^a\left(a_j\right) \right\}$$

Probability of hospice j choosing action a_j in state x_m is:

$$\Psi\left(a_j \mid \mathrm{x}_m; \theta\right) = \frac{\exp\left\{ W_j\left(a_j, \mathrm{x}_m; \theta\right) / \sigma_e \right\}}{\sum_{a \in \mathcal{A}} \exp\left\{ W_j\left(a, \mathrm{x}_m; \theta\right) / \sigma_e \right\}}$$

where σ_e = logit-scaling parameter for ϵ^a.

Structural model: Timing

For period t and market m:

1. Incumbents observe x_{mt} and structural errors, and make quality choices.
2. Reputation stock of each incumbent evolves.
3. Consumers observe x_{mt}, reputation stocks, and structural errors, then choose a hospice.
4. Incumbents stay/exit.
5. Potential entrants enter/stay out.
6. All state variables evolve.

Equilibrium

Estimation: Demand

$$u_{ijt} = \alpha_{m(j)} + X'_{jt}\beta + \xi_{jt} + \zeta_i + (1-\sigma_n)\tilde{\varepsilon}_{ijt} + \eta[a_{jt} + (1-\tau)a_{jt-1} + (1-\tau)^2 a_{jt-2} + \ldots]$$

Using the logit-share inversion of Berry (1994):

$$ln(s_{jt}) - ln(s_{0t}) = \alpha_m + X'_{jt}\beta + \sigma_n ln(s_{j|gt}) + \xi_{jt} + \eta[a_{jt} + (1-\tau)a_{jt-1} + (1-\tau)^2 a_{jt-2} + \ldots]$$

- s_{jt} = market share of hospice j.
- s_{0t} = market share of outside option.
- $s_{j|gt}$ = hospice j's within-hospice market share.

Estimation: Demand

$$ln(s_{jt}) - ln(s_{0t}) = \alpha_m + X'_{jt}\beta + \sigma_n ln(s_{j|gt}) + \xi_{jt} + \\ \eta[a_{jt} + (1-\tau)a_{jt-1} + (1-\tau)^2 a_{jt-2} + \ldots]$$

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

Estimated simultaneously with two-step GMM.

- Moment conditions built around ϵ_{jt}.
- Standard IO instruments: BLP IVs (sum of rivals and rival characteristics), fuel prices.

Estimation: Supply

Dynamic games estimation method of Bajari, Benkard and Levin (2007) used to recover hospice cost parameters.

1. Use forward simulation to approximate choice-specific value functions, derive model-predicted quality choices.
2. Choose cost parameters to match prediction with observed quality choices.

Estimation First stage Second stage

Results: Demand

$$u_{ijt} = \alpha_{m(j)} + X'_{jt}\beta + \xi_{jt} + \zeta_i + (1-\sigma_n)\tilde{\varepsilon}_{ijt} + \eta[a_{jt} + (1-\tau)a_{jt-1} + (1-\tau)^2 a_{jt-2} + \ldots]$$

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

	Demand
τ	0.530
	(0.156)
ρ	0.756
	(0.072)
σ_n	0.597
	(0.034)
η	0.012
	(0.003)

Results: Demand

	Demand
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)

Impulse response in duopoly

Results: Supply

$$MC_j(a_j) = \gamma_0 + \Big(\gamma_1 + \gamma_{fp} FP_j + \gamma_{rural} RURAL_j\Big) a_j$$

$$MC_j(a_j) = \gamma_0 + \Big(\gamma_1 + 1(type_j = 2)\gamma_{12} + \gamma_{fp} FP_j + \gamma_{rural} RURAL_j\Big) a_j$$

	No types	With cost-types
γ_1	1343.72	1541.10
	(32.31)	(48.87)
γ_{fp}	-740.67	-532.15
	(93.89)	(116.64)
γ_{rural}	125.53	206.06
	(54.28)	(74.82)
γ_{12}		-594.84
		(111.09)

Counterfactuals

Simulate impact of different policies on hospice quality choice:

- Hypothetical market with 3 firms and no entry/exit.
- Calculate quality choices under different policies.
- Model solution method: Solving coupled fixed-point problem

To see if differentiated hospices react differently:

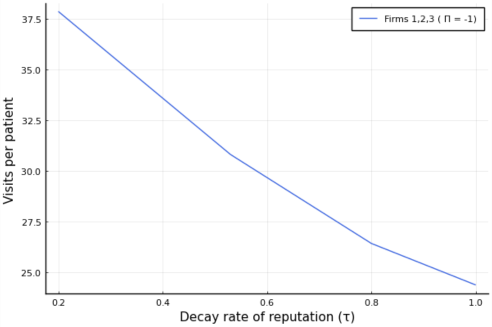
$$\begin{aligned} u_{ij} &= \alpha_{m(j)} + X_j'\beta + \psi_j + \xi_j + \zeta_i + (1-\sigma_n)\tilde{\varepsilon}_{ij} \\ &= \Pi_j + \psi_j + \zeta_i + (1-\sigma_n)\tilde{\varepsilon}_{ij} \end{aligned}$$

where $\Pi_j = \alpha_{m(j)} + X_j'\beta + \xi_j$ reflects how much hospice j differentiates along non-reputation dimensions.

Counterfactuals: reputation persistence

First set of counterfactuals involves the persistence of reputation.

Mimics policies like online review sites that make quality information widely available and easier to find.



Counterfactuals: Medicare prices

Medical providers have frequently complained that Medicare reimbursement rates are too low.

Study how hospice quality changes as Medicare rates increase:

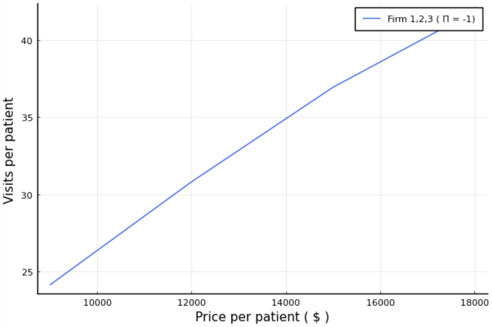
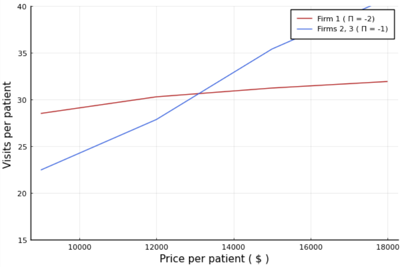


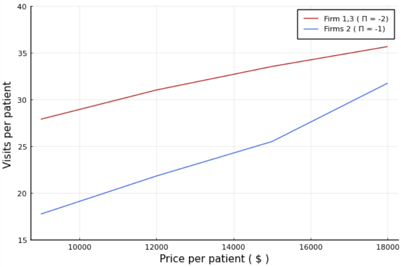
Figure 1: $\Pi_1 = \Pi_2 = \Pi_3 = -1.$

Counterfactuals: Medicare prices

With heterogeneous hospices:



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



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

Counterfactuals: Medicare prices

Comparison between static vs reputation setting:

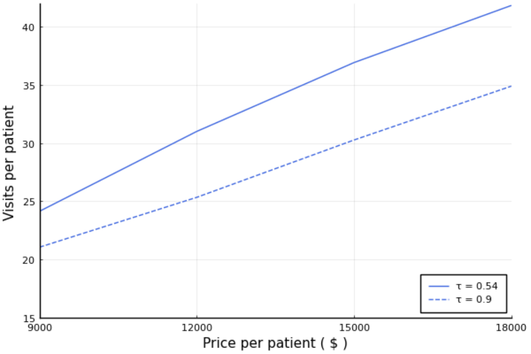


Figure 3: Average quality choice by hospice against increasing Medicare rates. $\Pi_1 = \Pi_2 = \Pi_3 = -1$.

Counterfactuals: contract design

The following contract structures all achieve 29 average visits-per-patient:

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

Conclusion

1. Reputation $\rightarrow$ consumer choice and hospice quality.
2. Build structural model of reputation accumulation through quality choice, recover hospice cost function.
3. Policy counterfactuals:
   - Persistence of reputation $\uparrow$ and Medicare prices $\uparrow \implies$ hospice quality $\uparrow$.
   - A hybrid per-day and per-visit reimbursement scheme achieves the same quality as the current per-day scheme at nearly 30% lower spending.

Formula for value function

Incumbent's value function:

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

where $\epsilon_j^a(a_j)$ = choice-specific errors for hospice j choosing a_j

Back

Estimation: BBL 2007 overview

Two-stage estimator from Bajari, Benkard and Levin (2007) used to estimate the cost parameters.

First stage:

- Reduced-form estimates of firms' policy functions.
- Transition probabilities for state variables.

Second stage:

- First-stage results used to conduct forward simulation and generate model-predicted CCPs for a given guess of cost parameters.
- Find parameter values that match model-predicted and observed probabilities.

Estimation: Supply, First stage

Exogenous entry and exit rates based on empirical patterns.

Obtain empirical estimate of the policy function by projecting visit choice on state variables.

Infer cost-types using from FE regression on visit choices.

I discretize visit choice into six tiers and estimate an ordered logit with county FEs.

Back

Inferring type Entry and exit simulation

Estimation: Supply, First stage Back

	No types	With cost-types
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)

Estimation: Supply, Second stage Back

The dynamic oligopoly model is estimated using GMM.

The model-predicted error term for observation n is given by:

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

where $\hat{\Psi}(a_n | x_{mt(n)}^{data}, \theta)$ is the predicted choice probability for a_n.

Instruments used in GMM are the variables in the first-stage empirical policy functions.

The objective function is:

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

Estimation: Inferring types

One specification accounts for cost "type":

- Regress visit choices on hospice fixed effects, hospice characteristics and market characteristics.
- Hospices with FEs above median = Type 2
- Intuition: Type 2 hospices consistently choose higher quality than expected $\implies$ more **efficient/altruistic**.
  - Consumers may use reputation to infer cost type of hospices.
- In estimation, marginal cost can vary by hospice type.
  - *a priori* a hospice of a higher type has lower marginal cost.

BBL first stage

Estimation: Entry and exit BBL first stage

Exit: Firms exogenously exit the market with probability 4.1% (derived from data).

Entry: Potential entrants enter a market at the rate predicted by the following ordered logit.

	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

Structural model: Equilibrium

Firm's strategy is a mapping from states and choice-specific shocks to actions:

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

Restrict attention to:

- Pure, symmetric and anonymous strategies.
- Markov Perfect Equilibrium: Strategy depends on only current period payoff-relevant state variables and choice-specific shocks.

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Counterfactuals Back

Solve coupled fixed-point problem so that conditional choice probabilities and value functions of all hospices are simultaneously satisfied in the market.

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

$$\hat{v}(a_j,\mathrm{x}) = \sum_{\mathbf{a}_{-j}\in\mathcal{A}_{-j}} \left\{ \left[\bar{\pi}(a_j,\mathbf{a}_{-j},\mathrm{x}') + \beta V(\mathrm{x}') \right] \right.$$

$$\left. F(\mathrm{x}'|\mathrm{x},a_j,\mathbf{a}_{-j}) \prod_n \Psi(\mathbf{a}_{-j}[n]|\mathrm{x}) \right\}$$

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

Examples of hospice care

Examples of hospice care:

- Pain medication
- Medical supplies
- Dressing bedsores
- Giving physical and speech therapy
- Bathing and feeding
- Respite for primary caregiver.

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Choosing a hospice

- 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**. Anecdote and word of mouth won't paint a full picture but they are still valuable data points...
  How long has the hospice been in operation? If it has been around for a while, that's an indication of stability."

Choosing a hospice

- 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?"

Choosing a hospice

- 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."

Back

Impulse respond Back

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

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