Learning and Efficiency in the Market for Physician Referrals

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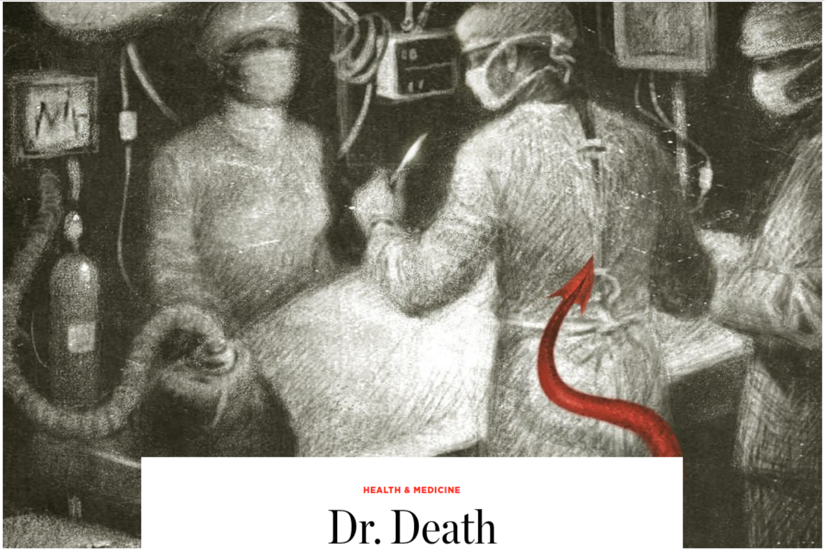
A (SAD/TERRIFYING) STORY



HEALTH & MEDICINE

Dr. Death

Plano surgeon Christopher Duntsch left a trail of bodies. The shocking story of a madman with a scalpel.

- Severely injured or killed 33 of 38 patients over 2+ years
- First doctor to be sentenced to life in prison for medical malpractice

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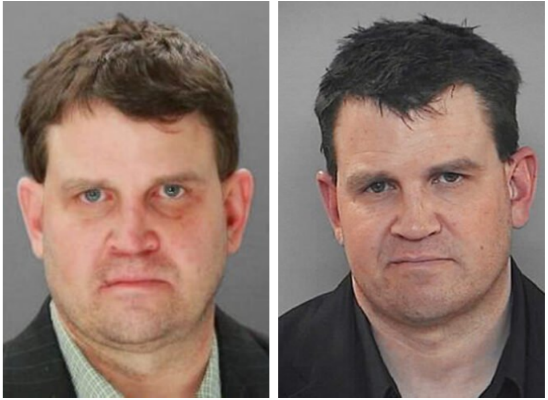

Duntsch grew accustomed to having his mug shot taken, whether for assault, DWI, or shoplifting.

ECONOMIC MOTIVATION

Physician referrals

- Service market where professionals with general skills (e.g., primary care) direct consumers to professionals with specialized skills
  - Substantial heterogeneity in prices and quality across specialists
  - Prices do not clear market in the short run

- Uncertainty about quality is a defining characteristic of most health care markets:

  Uncertainty as to the quality of the product is perhaps more intense here than in any other important commodity. (Arrow 1963, p. 951)

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- We use a structural learning model to measure the effects of uncertainty in physician referrals, and to simulate possible reallocations when there is better information about quality

Background on referrals

- Total physician/clinical services + hospital care: \$2.25 trillion
  - Primary care accounts for only 5% – 8%
    (Reiff et al. 2019, Reid et al. 2019, Martin et al. 2020)

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- Referrals have been increasing over time

	Rate per Visit		Annual Total	
	1999	2009	1999	2009
Referrals from primary care visits	5.8%	9.9%	22M	51M
Referrals among specialists	2.9%	7.3%	11M	38M
Patient self-referrals to specialists	6.0%	2.8%	51M	31M

(Barnett et al. 2012)

Background on referrals

- Referring physicians have large influence on choice of specialist
  (Freedman, Kouri, West, and Keating 2015; Chernew, Cooper, Hallock, and Scott Morton 2021)
- Referring physicians say patient outcomes and experiences matter
  (Schneider and Epstein 1996; Barnett, Keating, Christakis, O'Malley, and Landon 2012)

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- Specialist market shares are only weakly associated with quality
  (*Chapters:* Kolstad and Chernew 2009; Dranove 2011; Skinner 2011)
  (*AERs:* Chandra, Finkelstein, Sacarny, and Syverson 2016; Gaynor, Propper, and Seiler 2016)

Our approach

- Develop and estimate a structural learning model of referral decisions
  - Prior work on health care applies learning models to prescribing decisions (e.g., Crawford and Shum 2005; Ching 2010; Ferreyra and Kosenok 2011; Dickstein 2021)
  - Only vertical differentiation in our model (success rates)
- Model accounts for important barriers to reallocation beyond information:
  - Habit persistence (preference to refer to familiar specialists)
  - Capacity constraints of specialists (congestion effect)

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- Model accounts for important barriers to reallocation beyond information:
  - Habit persistence (preference to refer to familiar specialists)
  - Capacity constraints of specialists (congestion effect)
- Use model to quantify losses due to informational frictions
  - Simulate allocation and health outcomes under perfect information
  - Consider possible policies (e.g., perfect report cards? enforced experimentation?)
- Find that one-quarter of referrals would be reallocated under full information, still allowing for habit persistence and capacity constraints

Related literature

- Structural learning models have been widely applied to study product choice and related problems (Ching, Erdem, and Keane 2013)
- Many studies in economics and marketing have applied Bayesian learning models to prescribing decisions by individual physicians
  - New pharmaceutical drugs
    (e.g., Ching 2010; Ferreyra and Kosenok 2011)
  - Patient-specific drug matches
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- Other factors affecting referral choice:
  - peers from medical training
  - distance between offices
  - specialist gender, homophily
  - vertical integration

  (Sarsons, *ReStud* R&R 2025; Hackl, Hummer, and Prickner, *JHlthEcon* 2015; Richards-Shubik, Roberts, and Donohue, *JHlthEcon* 2022; Zeltzer, *AEJ:Applied* 2020; Baker, Bundorf, and Kessler, *JHlthEcon* 2016; Carlin, Feldman, and Dowd, *HlthEcon* 2016)

APPLICATION & DATA

DESIGN-BASED EVIDENCE

MODEL & IDENTIFICATION

ESTIMATION RESULTS

Application: joint replacement surgery

- About 500,000 hip replacements and 1,000,000 knee replacements per year in the US (and rapidly growing)
  - Expensive: \$23,000 mean ($\approx$ median) episode spending (\$12,500 std. dev.)
  - Some risk: 9.7% complications/rehospitalized, 0.6% die
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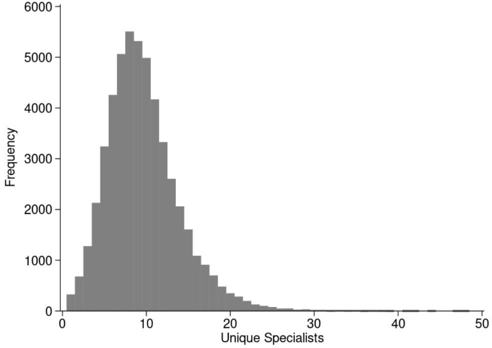
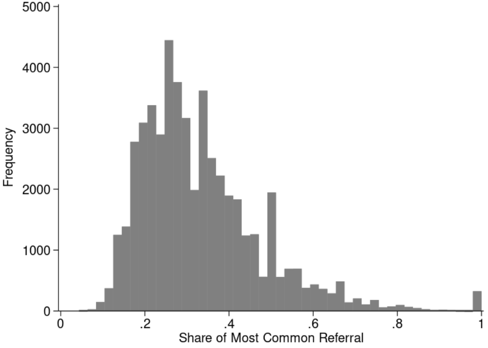
- Patients often referred by their primary care physicians (PCPs) to orthopedic surgeons (specialists) for the procedure
- Data: Medicare FFS claims from 2008 to 2018
  - Medicare covered approx. 50%/66% of all hip/knee replacements at the time
  - Referring physician (PCP) inferred from regular office visits over prior year (87% of surgeries are matched to a PCP)
  - Restrict to PCPs and orthopedic surgeons with sufficient volume
  - 2,014,300 surgeries, 10,500 surgeons, 51,700 PCPs in final sample summary stats

Referral concentration

Computed per PCP, using six years of data from 2013 to 2018



Mean = 9.6

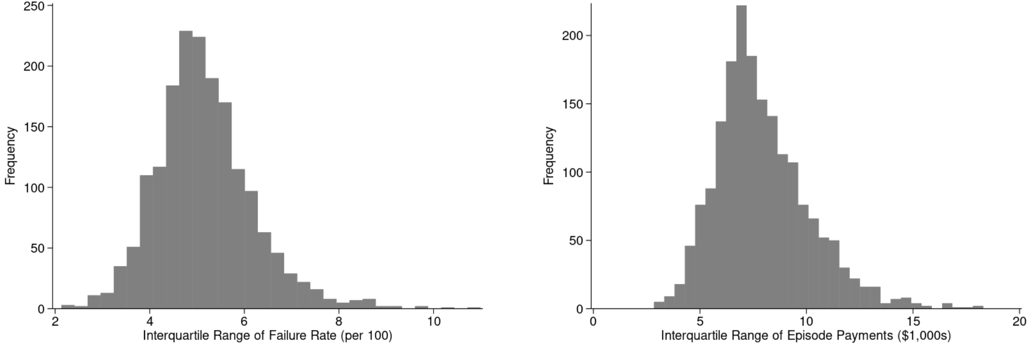


Mean = 0.33

Average number of specialists per HRR: 83
...and within 75 miles or 90th percentile of distance: 81

Heterogeneity in quality and cost

Interquartile ranges within markets of negative outcomes and episode spending



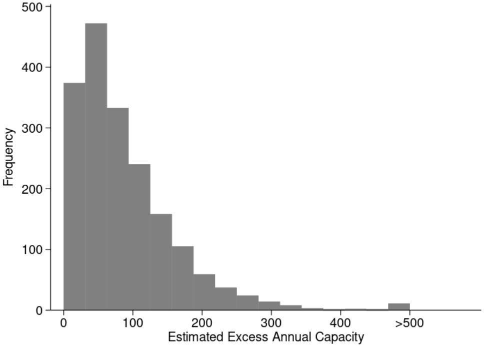
Average IQR = 0.046

Average IQR = $7,932

If some patients could be reallocated from worse to better specialists (75th to 25th percentiles of negative outcomes or episode spending), substantial improvements are possible.

Possible excess capacity among the top 25%

Totals by market x year; each specialist's capacity defined as their 75th pctile annual volume



There appears to be available capacity for better specialists to treat more patients.

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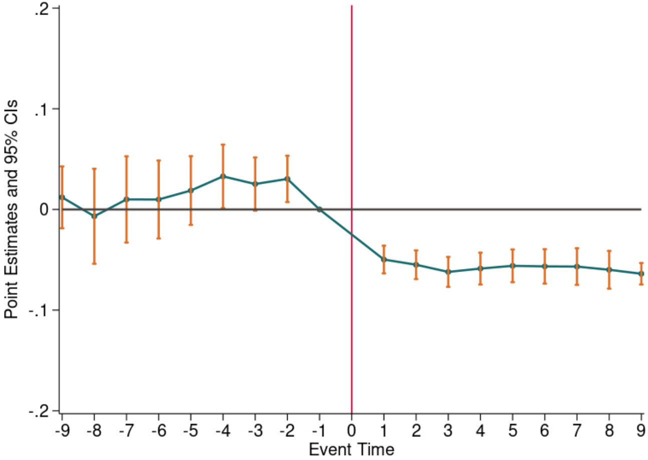
General Idea details

- Construct balanced panel of PCP-specialist pairs across quarters
- Compare referrals to same specialist among two types of PCPs:
  - PCPs whose patient(s) experienced a failure
  - PCPs whose patient(s) did not experience a failure
- Estimate stacked DD (Cengiz *et al.* 2019, QJE), stacked by the first, second, third, and fourth failure events per specialist

Event study of specialist's first failure event

Effect on referrals per quarter from PCP observing the failure vs. other PCPs, with specialist/quarter FEs



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PCPs refer a sequence of patients to a set of specialists, and learn about the quality of those specialists from the outcomes of their patients.

Model specification

1. Each period t, the PCP i sends a patient (also t) to a specialist j from a fixed choice set J (choice indicators: D_{ijt})
   (also consider PCP i to specialist *practice* j)

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   - binary outcomes: $Y_{ijt} = 1$ (success) or 0 (failure)
   - quality: $q_j \equiv \Pr(Y_{ijt} = 1)$, *unknown to PCP*

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3. PCP's realized utility:

$$U_{ijt} \equiv \alpha Y_{ijt} + u(x_{ijt}) + f(e_{ijt}) + c(n_{jt}, z_j) + \xi_j + \epsilon_{ijt},$$

   - α – weight on patient outcomes (e.g., altruism)
   - $u(x_{ijt})$ – patient-specific factors (e.g., distance)
   - $f(e_{ijt})$ – prior experience with specialist (# patients, "familiarity")
   - $c(n_{jt}, z_j)$ – specialist current patient volume (congestion effect)
   - ξ_j – other demand factors (unobserved to econometrician)
   - ϵ_{ijt} – idiosyncratic shock

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- Model captures key features related to the potential to improve market allocations:
  - learning about quality
  - taste for familiarity
  - capacity constraints

Learning process
(ref: Gong 2025, Dickstein 2021)

- PCP beliefs about specialist quality: $q_j \sim \text{Beta}$

Learning process

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- PCP beliefs about specialist quality: $q_j \sim$ Beta
- Update based on patient outcomes:

$$m_{ijt} \equiv \mathrm{E}[q_j | (D_{ijs}, Y_{ijs})_{s=1}^{t-1}] = \frac{a_0 + \sum_{s=1}^{t-1} Y_{ijs}}{a_0 + b_0 + \sum_{s=1}^{t-1} D_{ijs}}$$

$$= \frac{a_0 + y_{ijt}}{a_0 + b_0 + e_{ijt}}$$

- a_0, b_0 – parameters of prior beliefs (mean $= a_0/(a_0 + b_0)$, "strength" $= a_0 + b_0$)
- $e_{ijt} = \sum_{s=1}^{t-1} D_{ijs}$ – number of past patients referred to j
- $y_{ijt} = \sum_{s=1}^{t-1} Y_{ijs}$ – successes among those patients

Referral decisions

- Myopic behavior:

$$\max_{j \in J} \mathrm{E}\left[U_{ijt} \middle| \ldots\right] = \max_{j \in J} \quad \alpha m_{ijt} + u(x_{ijt}) + f(e_{ijt}) + c(n_{jt}, z_j) + \xi_j + \epsilon_{ijt}$$

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- Forward-looking behavior: Gittins index solution (Gittins 1979)
  - Yields present discounted value of optimal expected returns from each specialist
  - Assumptions:
    1) one option is chosen at a time
    2) the unchosen options do not affect the current outcome
    3) the expected returns do not change for the unchosen options
    4) beliefs are independent across options
    (q_j fixed, no spillovers among surgeons $\implies$ 3 & 4)
  - Brezzi and Lai (2002) provide a closed-form approximation
  - Other terms are not dynamic (except f, where PDV is easy to compute)

Specification (myopic version)

$$\mathrm{E}\left[U_{ijt}|\ldots\right] = \alpha \overbrace{\frac{\rho\eta + y_{ijt}}{\eta + e_{ijt}}}^{m_{ijt}} + \overbrace{\pi x_{ijt}}^{u(x_{ijt})} + \overbrace{\sum_p \beta_p I(e_{p-1} \leq e_{ijt} < e_p)}^{f(e_{ijt})} + \overbrace{\gamma n_{jt}}^{c(n_{jt}, z_j)} + \xi_j + \epsilon_{ijt}.$$

(ρ – prior mean $= a_0/(a_0 + b_0)$, η – prior strength $= a_0 + b_0$)

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- Learning parameters:
  - Altruism (α): variation in success rates among specialists to whom a PCP has sent many patients in the past (ID at infinity) algebra
  - Prior mean (ρ): average success rate in market (rat'l expectations)
  - Prior strength (η): how the marginal effect of success (y_{ijt}) changes with experience (e_{ijt}); but there seems to be **low power so we fix it** at $\eta \in \{1, 5\}$

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- Congestion effect (γ): identified using distances as instrument for referrals from other PCPs (Richards-Shubik *et al.* 2022)

Estimation

$$\mathrm{E}\left[U_{ijt} \middle| \ldots\right] = \alpha \frac{\rho\eta + y_{ijt}}{\eta + e_{ijt}} + \pi x_{ijt} + \sum_p \beta_p I(e_{p-1} \le e_{ijt} < e_p) + \underbrace{\gamma n_{jt} + \xi_j}_{\delta_{jt}} + \epsilon_{ijt}.$$

- Estimated separately in 306 geographic markets (HRRs)
  - Approach based on Bayer and Timmins (2007) spatial equilibrium model: spillovers among consumers who choose the same “location”
  - Similar to BLP demand estimation (with micro data), but congestion effect takes the place of a price

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1. Estimate multinomial logit with specialist-time fixed effects (δ_{jt})
   - split fixed effects into two time periods
   - impose $\alpha \geq 0$ via exponential transformation, $\alpha = e^{\tilde{\alpha}}$ (Fader et al. 1992)
2. Recover congestion effect using 2SLS regression of estimated fixed effects
   - $\hat{\delta}_{jt} = \gamma n_{jt} + \xi_j + v_{jt}$
   - instrument for n_{jt} is distances from *other* patients to specialist j

APPLICATION & DATA

DESIGN-BASED EVIDENCE

MODEL & IDENTIFICATION

ESTIMATION RESULTS

Parameter Estimates

Estimated separately within 306 HRRs; statistics weighted by number of patients per HRR.

	Myopic model				Forward-looking model			
Parameter	Mean	(SD/SE)	25th	75th	Mean	(SD/SE)	25th	75th
α (utility weight on outcome, *distribution across markets*)								
$(\eta = 1)$	0.277	(0.251)	0.094	0.337	0.371	(0.335)	0.131	0.476
$(\eta = 5)$	0.568	(0.548)	0.182	0.746	0.760	(0.757)	0.264	0.980
π (utility weight on distance, *distribution across markets*)								
$(\eta = 1)$	-0.0694	(0.0060)	-0.0822	-0.0519	-0.0696	(0.0058)	-0.0830	-0.0528
$(\eta = 5)$	-0.0698	(0.0062)	-0.0828	-0.0523	-0.0693	(0.0060)	-0.0830	-0.0522
γ (congestion effect per 100 patients, *single nationwide estimate*)								
$(\eta = 1)$	-0.265	(0.098)			-0.209	(0.068)		
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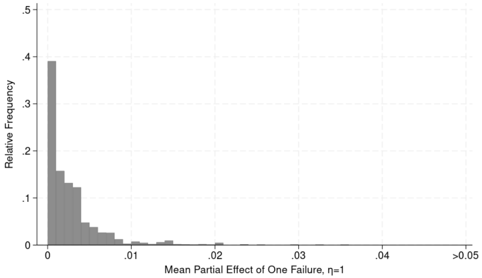
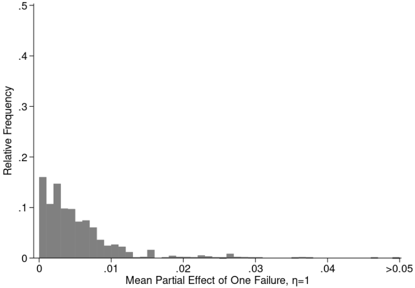
- $\bar{\alpha}/\bar{\pi}$ – success vs. failure is worth 4 miles (similar to other small estimates in the literature)
- γ – 100 patient increase in volume $\rightarrow \approx 20\%$ relative decrease in referral prob.

Partial Effect of Failures

Myopic model



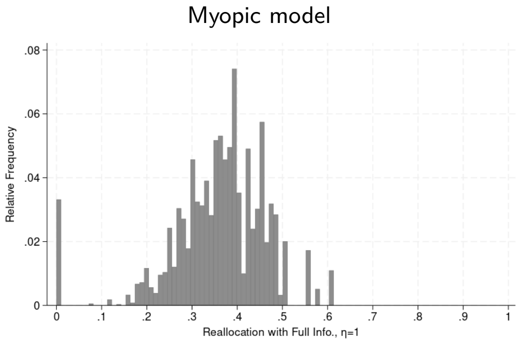
Forward-looking model

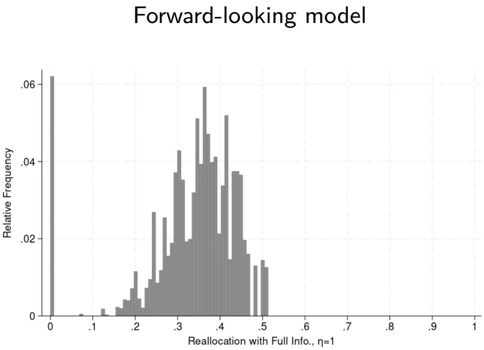


- Many markets with effectively no response to specialist failures
- Conditional on some response, mean reduction of 3-4% in referral probability
- Small but meaningful over the course of several referrals: translates to 3 weeks worth of surgeries per year for an average specialist (among our sample of patients).

Counterfactual: reallocation under full information

Distribution across markets of proportion of patients reallocated

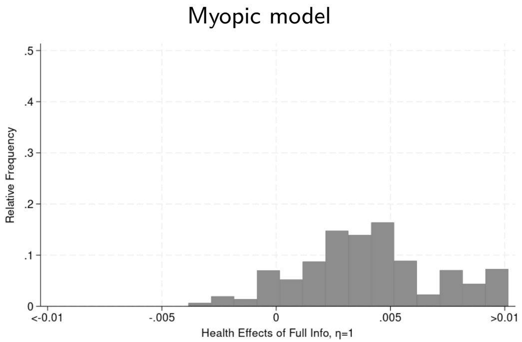


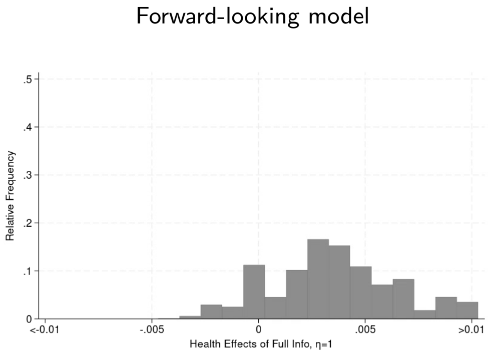


- Just over 25% of patients are referred to a different specialist on average (both models)
- Similar distributions, but somewhat more variation across markets under myopic model

Counterfactual: health outcomes under full information

Distribution across markets of change in success probability



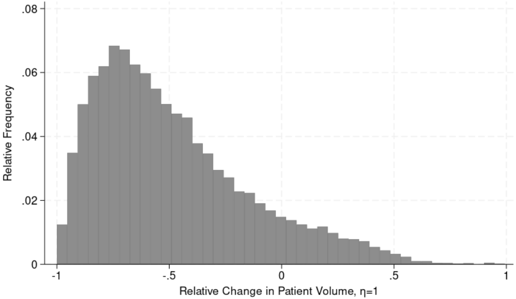


- Average improvement $\approx 4.5/1{,}000$ (both models); reducing failure rate by 5% (relative)
- About 750 fewer complications/readmissions (or deaths) per year in total

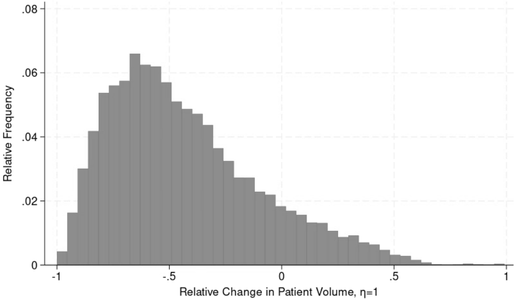
Counterfactual: specialist volume under full information

Distribution across markets of change in specialist volume, as a percentage of observed volume

Myopic model



Forward-looking model



- Aggregate reallocation away from low volume and toward high volume specialists
- Some specialists effectively forced to exit entirely

Summary

- Substantial quality and efficiency gains may be possible if referrals can be reallocated *within* geographic areas
- We estimate a structural learning model of referrals for major joint replacements
  - Key identifying variation for the learning process comes from differences in histories of patient outcomes *across* PCPs referring to the *same* specialists
- One of the first to quantify informational frictions in referrals
  - One-quarter of patients would be reallocated under perfect information
  - Small but meaningful improvements in quality
  - Reallocation from low to high volume specialists
  - Still allowing for other barriers from habit persistence and capacity constraints

THANK YOU

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APPENDIX SLIDES

Key summary statistics back

	(Baseline) 2008-2012	(Estimation) 2013-2018	Overall
Per patient (episode):			
90-day Readmission	0.081	0.066	0.072
	(0.272)	(0.249)	(0.259)
90-day Mortality	0.007	0.005	0.006
	(0.081)	(0.069)	(0.074)
90-day Complication	0.107	0.089	0.097
	(0.309)	(0.285)	(0.296)
Failure	0.109	0.091	0.099
	(0.312)	(0.288)	(0.298)
Episode spending	23,240	22,557	22,839
	(12,717)	(12,284)	(12,469)
Per PCP, per year:			
Total Referrals	3.809	4.398	4.134
	(2.940)	(3.478)	(3.261)
Unique Specialists	2.666	3.109	2.910
	(1.580)	(1.831)	(1.737)
Running values per PCP-specialist pair, over past five years:			
Total Referrals	- - -	4.445	- - -
		(10.453)	
Failure Rate	- - -	0.101	- - -
		(0.201)	

Event study

back

Effect on referrals per quarter from PCP "observing" the failure vs. other PCPs

- Create a quarterly panel of all PCP-specialist pairs with at least one referral between them (at any point)
- Capture failure events:
  - Failures for specialist j denoted $f = 1, ..., F_j$
  - Quarter of failures denoted $q_j(f)$, so that $q_j(1)$ denotes the quarter of first failure for specialist j,
  - $\underline{q}$ and $\overline{q}$ denote the first and last quarter of the analysis, respectively.
- Find all PCPs who ever refer to specialist j in relevant quarters, split into groups $k \in 0, 1$ based on failures
- Quarterly patients referred to specialist j from PCP type k, denoted $\bar{r}_{jkt}$.

Event study back

Effect on referrals per quarter from PCP "observing" the failure vs. other PCPs

With this notation and sample construction, we then estimate by OLS the following event study specification:

$$\bar{r}_{jkt} = \gamma_j + \gamma_t + \delta I(k=1) + \sum_{\substack{\tau=-9 \\ \tau\neq -1}}^{9} \lambda_\tau I(k=1, t=\tau) + \varepsilon_{jkt},$$

Identification of the myopic model

$$\alpha m_{ijt} + f(e_{ijt}) + u(x_{ijt}) + c(n_{jt}, z_j) + \xi_j + \epsilon_{ijt}$$

- Altruism parameter (α): marginal effect of success rate, in limit as $e \to \infty$ ("identification at infinity")

$$\alpha m_{ijt} = \alpha \frac{a_0 + \sum_{s=1}^{t-1} Y_{ijs}}{a_0 + b_0 + \sum_{s=1}^{t-1} D_{ijs}} = \alpha \frac{a_0 / e_{ijt} + \bar{y}_{ijt}}{(a_0 + b_0)/e_{ijt} + 1}$$

where $\bar{y}_{ijt} \equiv \sum_{s=1}^{t-1} Y_{ijs} / \sum_{s=1}^{t-1} D_{ijs}$ and $e_{ijt} \equiv \sum_{s=1}^{t-1} D_{ijs}$

- Strength of priors ($a_0 + b_0$): how the marginal effect of the success rate changes with experience (i.e., interaction)

$$\alpha m_{ijt} = \alpha \frac{a_0}{(a_0 + b_0) + e_{ijt}} + \alpha \frac{e_{ijt}}{(a_0 + b_0) + e_{ijt}} \times \bar{y}_{ijt}$$

- Prior mean ($\frac{a_0}{a_0+b_0}$): estimate outside the model, using average success probability in each market (then have a_0, b_0 separately)

back