Physicians' Occupational Licensing and the Quantity-Quality trade-off

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- Recent healthcare worker's migration increases role of licensing.
  - In US, # of foreign physicians Δ^+ 30% in last 20 years, now 20% of workforce
  - 2/3 in non-physician jobs, licensing plays a critical role (FED Minneapolis, 2022)

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  - Lowering the threshold would have positive net benefits for population health

▸ Contributions

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   - Input Elasticities
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  - Wage is based on public sector wage schedule (independent of exam score)

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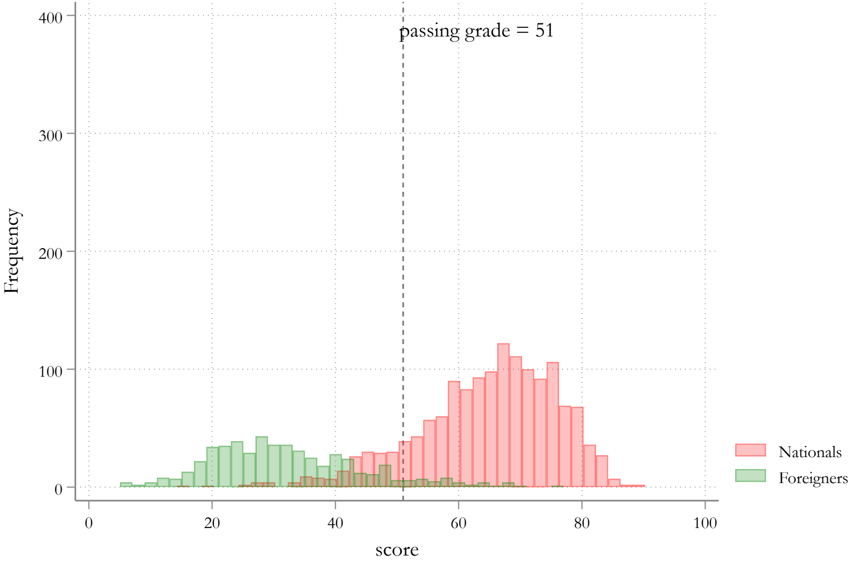
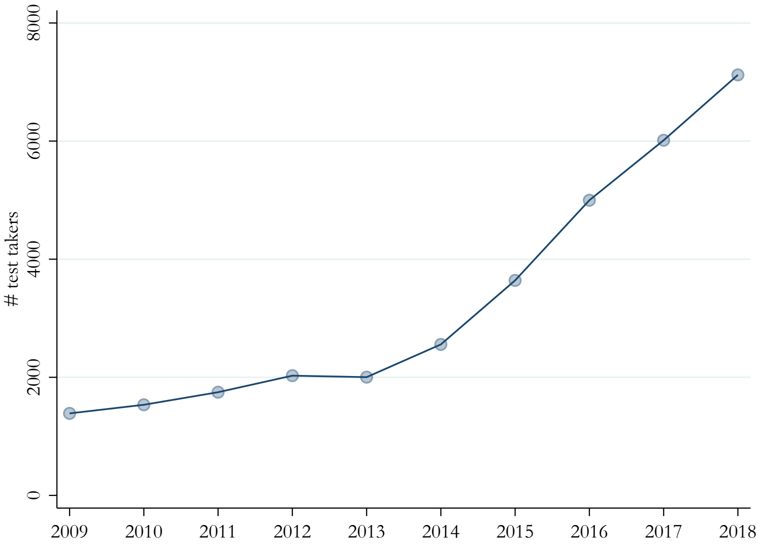
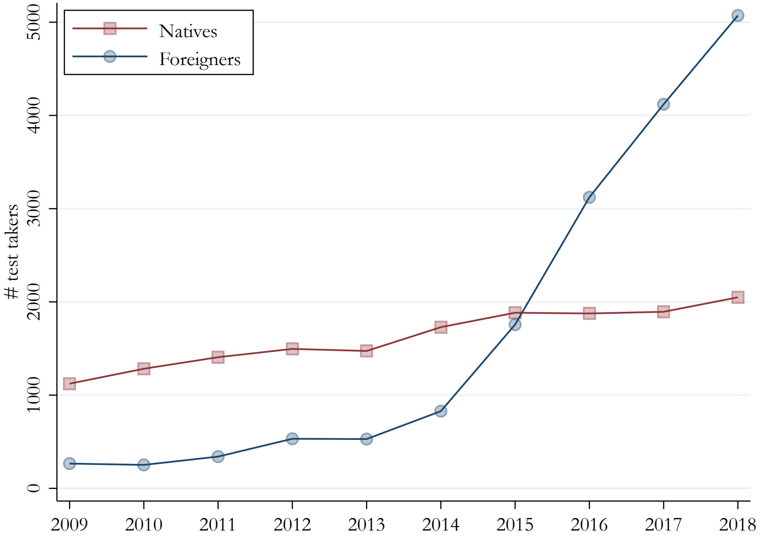


Number of test-takers over time



Number of test-takers over time, by migration status



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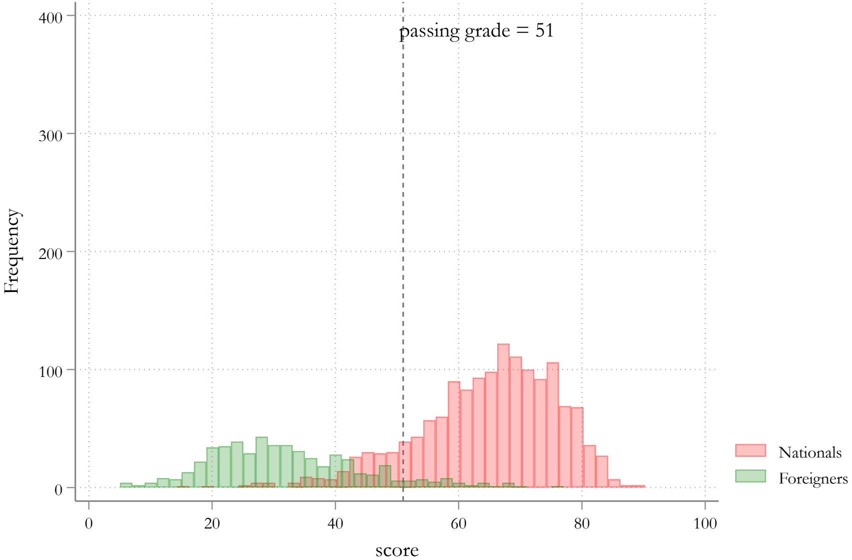
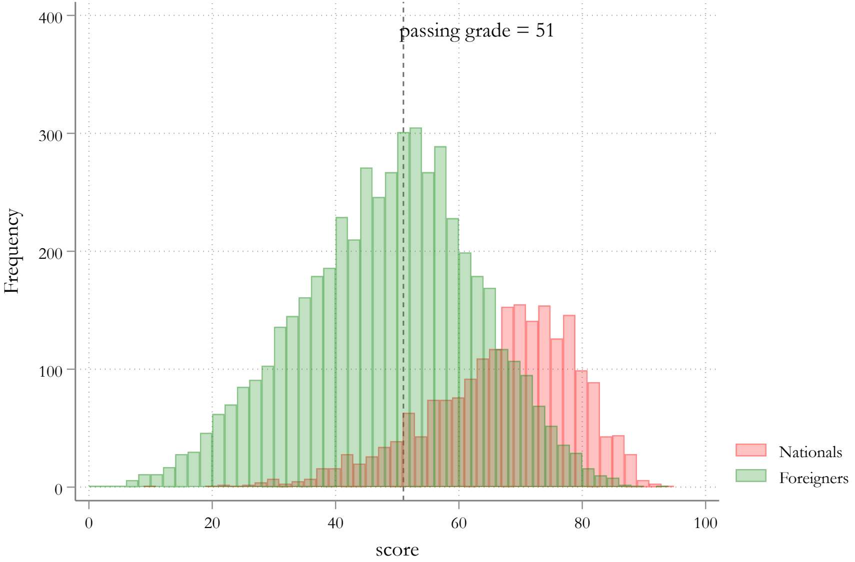


Licensing scores: 2018 ‣ More data



Scarcity is a long-standing problem and physicians remain scarce

- Currently, $\approx$ 3 million people waiting for medical attention (15% of population)
  - $\approx$ 1/4 deaths in the country occur while waiting for medical attention
- As of 2019, Chile had 17.5 physicians per 10,000 inhabitants
  - Half avg. of countries with comparable burden of diseases, injuries, & risk factors
  - Below minimum threshold to achieve effective Universal Healthcare coverage (Haakenstad et al. 2022)

Data: 2011-2019

- Novel admin employer-employee data for all 181 public hospitals in Chile
  - Occupation, wages, hours, nationality, demographics
- Registry of all physicians legally authorized to practice in Chile
  - title, date of issuance, and the name and country of the granting institution
- Licensing exam scores for all exam takers
- Individual-level discharge data in all public hospitals
  - Date of admission, diagnosis, patient demographics, date of discharge/in-hospital death,
  - + universe of death records (post discharge)
- Exits from hospitals' waiting list
  - Health providers enter patients into waiting list for specialist consultations, surgeries, or specific procedures

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A simple licensing problem

- Licensing technology based on threshold score $\underline{s}$. Output:

$$Y(\underline{s}) = F(L(\underline{s}), \mathring{\theta}(\underline{s}))$$

- The elasticity of the outcome with respect to the licensing threshold is

$$\frac{\partial Y}{\partial \underline{s}} \frac{1}{Y} \equiv \eta_{\underline{s}}^{Y} = \underbrace{\eta_{L}^{Y} \eta_{\underline{s}}^{L}}_{\text{Licensing Quantity Effect}} + \underbrace{\eta_{\mathring{\theta}}^{Y} \eta_{\underline{s}}^{\mathring{\theta}}}_{\text{Licensing Quality Effect}}$$

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$$\eta_{\underline{s}}^Y > 0 \iff \eta_L^Y / \eta_{\mathring{\theta}}^Y < \underbrace{-\eta_{\underline{s}}^{\mathring{\theta}} / \eta_{\underline{s}}^L}_{\equiv R(\underline{s})}$$

What primitives do elasticities depend on? Parameterization

- $lnY = \alpha_L lnL(\underline{s}) + \alpha_{\bar{\theta}}\bar{\theta}(\underline{s})$

- $s \sim h(\cdot)$
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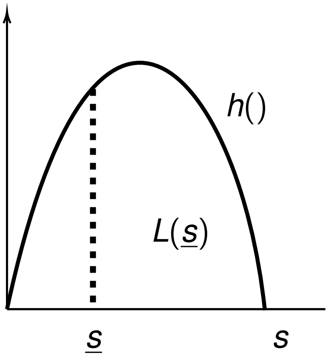

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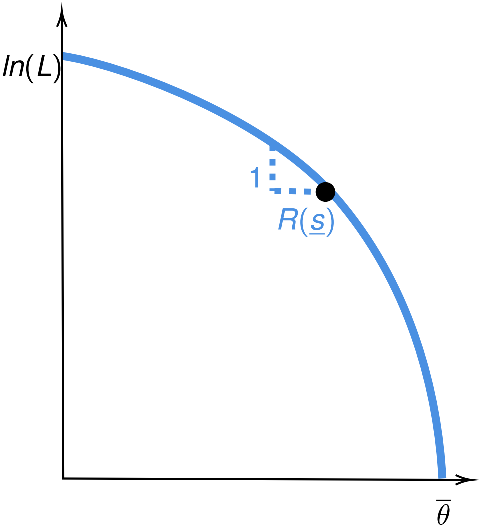

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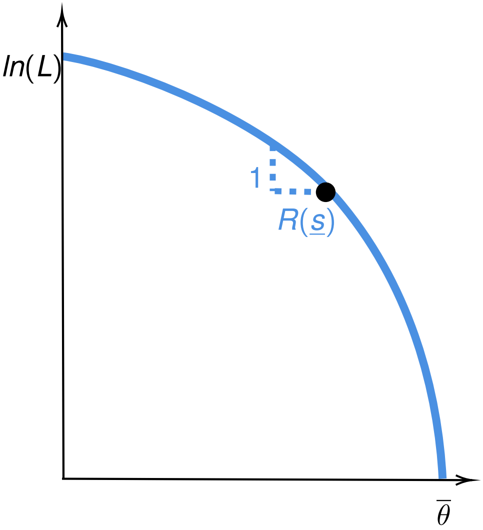

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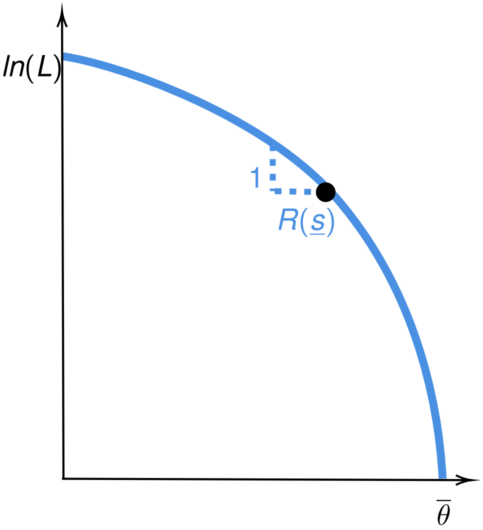
$$R(\underline{s}) \equiv -\frac{d\bar{\theta}/d\underline{s}}{dlnL/d\underline{s}} = \frac{\sigma^2_\theta}{\sigma^2_\theta + \sigma^2_\epsilon}\cdot(\mathbb{E}[s|s > \underline{s}] - \underline{s})$$



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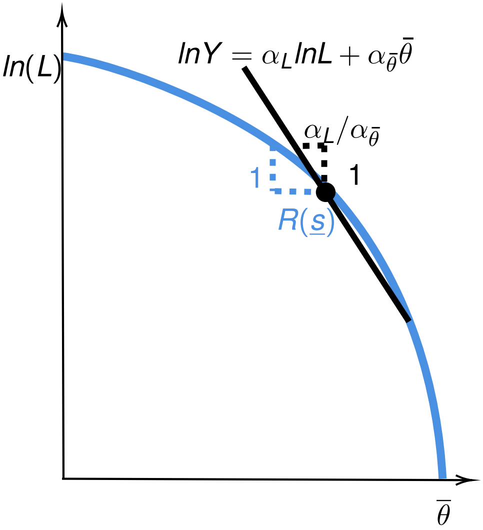

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  - net effect on *scores* per-marginal worker and precision of the signal
  - returns to quantity and quality

Main outcomes of interests: Access and quality

- Population health $Y(\underline{s})$ can be modeled as:

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$$\eta^Y_{\underline{s}} \simeq \eta^{\text{service rate}}_{\underline{s}} - \eta^{\text{mortality}}_{\underline{s}}$$

Roadmap for today

1. Setting and data
2. Empirical model
3. **Estimation**
   - **Input Elasticities**
   - Output Elasticities
4. Policy counterfactual: Relaxing the licensing threshold
   - Short-run effect
   - Long-run effect

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$\rightarrow$ Labor matching model
  - How do physicians match with hospitals?
  - How would matches change with a different threshold?

Inferring unobserved quality from history of scores

- Physicians, indexed by i, belong to type $\tau \in \{N, F\}$.
- The score in attempt n is a noisy measure of quality and test-taking ability Γ_{in}

$$s_{in} = \theta_i + \Gamma_{in} + \varepsilon_{in}, \quad \theta_i \sim N\left(\mu_{\theta,\tau(i)}, \sigma^2_{\theta,\tau(i)}\right), \qquad \varepsilon_{in} \sim N\left(0, \sigma^2_{\varepsilon,\tau(i)}\right)$$

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- Retaking depends on average past score $\bar{s}_{in}$ and number of attempts ‣ Details

$$P(\text{retake}|\bar{s}_{in}, n_i, \tau(i)) = \frac{e^{\beta_{0,\tau(i)}+\beta_{n,\tau(i)}n_i+\beta_{s,\tau(i)}(\bar{s}_{in}-\underline{s})}}{1+e^{\beta_{0,\tau(i)}+\beta_{n,\tau(i)}n_i+\beta_{s,\tau(i)}(\bar{s}_{in}-\underline{s})}}$$

Estimation of latent quality

- Estimate retaking model with a logit ▸ Results

- Estimate scores model via SMM
  - Moments (by "type"): mean over attempts, mean of gains over attempts, cov. between attempts, variance of first attempt
  - Main result: $\widehat{SNR}_{\text{nationals}} = 0.65$; $\widehat{SNR}_{\text{foreigners}} = 0.7$

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✓ Can simulate evolution of mass of test takers in the long-run

Labor Market Matching

- How would physicians at the margin match with hospitals?

- Two main challenges:
  1. Predict matching outside the support of quality observed
  2. How matching prob. would change in counterfactual?
     - Lowering $\underline{s}$ increases number of lower-quality physicians seeking jobs
     - May impact eq. matching probabilities due to competition in labor market

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  - Approved of higher quality than *i*

‣ Vertical Sorting Evidence ‣ Fixed Wages Evidence

Estimation: Sorting

Approximate "Conditional Matching Probabilities" over 29 HRR + outside opt. as:

$$CMP_{ijt} = \frac{e^{v(x_{ijt})+g(M_t(\underline{s}),\kappa_{jt})}}{1 + \sum_{j'} e^{v(x_{ij't}))+g(M_t(\underline{s}),\kappa_{j't})}}$$

- $v(\cdot)$ captures physician and hospital preferences
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$$v(x_{ijt}) = \alpha^d \text{Distance}_{ij} + \alpha^h \overbrace{\text{Share}_{ijt-1}}^{\substack{\text{\% of phys from } i \text{ region} \\ \text{working in } j \text{ in } t-1}} +$$

$$\underbrace{\alpha_{jt} + \alpha_j^f \text{Foreign}_i + \alpha_j^q \mathbb{E}(\theta_i) + \alpha_j^{fq} \mathbb{E}(\theta_i) \times \text{Foreign}_i + \alpha_j^s \text{Specialist}_i}_{\text{290 coefficients}}$$

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$$g(M_t(\underline{s}),\kappa_{jt}) = (\beta_0 + \beta_r \text{Quality Rank}_j) \times \frac{M_{it}(\underline{s})}{\kappa_{jt}}$$

- $M_{it}(\underline{s}) = [M^0_{it}(\underline{s}), M^+_{it}]$ mass of physicians in and above i's quality range
- $\kappa_{jt} = \frac{\text{Beds}_{jt}}{\text{Stock of Physicians}_{j,t-1}}$
- Quality Rank$_j$: 3 terciles of quality distribution

Matching Probabilities Estimates

	Alternative Models			Placebo
	(1)	(2)	(3)	(4)
Distance_{ij}	-0.228	-0.228	-0.228	-0.228
	(0.014)	(0.014)	(0.014)	(0.014)
Share_{ijt-1}	0.651	0.651	0.653	0.652
	(0.146)	(0.146)	(0.146)	(0.146)
$(M_{it}^0)/\kappa_{jt}$	-0.637	-0.676	-0.726	
	(0.152)	(0.159)	(0.186)	
$(M_{it}^+)/\kappa_{jt}$		0.017	0.050	
		(0.021)	(0.038)	
$(M_{it}^-)/\kappa_{jt}$				0.022
				(0.019)
M interacted with Rank	No	No	Yes	No
Log likelihood	-15276.84	-15276.53	-15275.33	-15285.23

Notes: All include alternative-specific coefficients for the following variables: Year, Foreign indicator, physician's posterior quality, an interaction between Foreign indicator and posterior quality, and a Specialist indicator. $N \times J = 14,290 \times 30$

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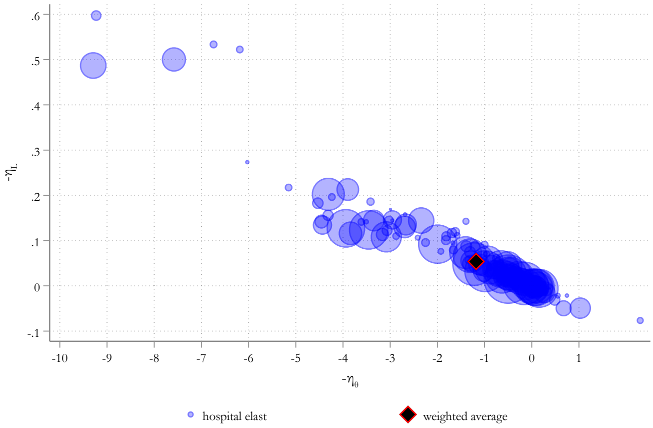
Short-run Elasticity of Quantity and Semi-elasticity of Quality in '18

$\eta_{L_j,\underline{s}}$ and $\tilde{\eta}_{\bar{\theta}_j,\underline{s}}$



- $\bar{R}(\underline{s}) = -\overline{\tilde{\eta}_{\bar{\theta}_j,\underline{s}}/\eta_{L_j,\underline{s}}} \simeq 24$

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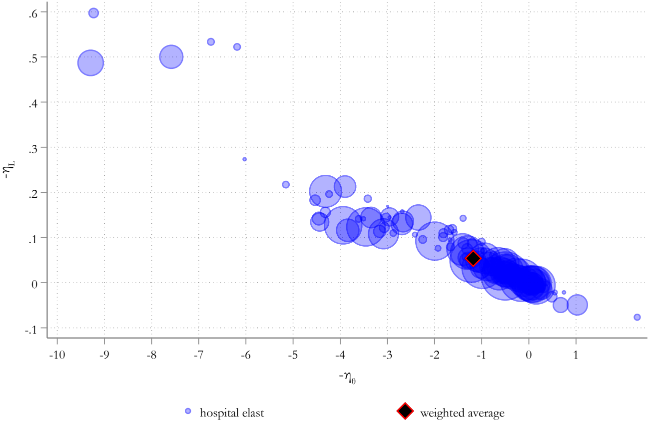

- $\bar{R}(\underline{s}) = -\overline{\tilde{\eta}_{\bar{\theta}_j,\underline{s}}/\eta_{L_j,\underline{s}}} \simeq 24$
- $|\eta_L|$ higher in (median split)
  - Low quality (46 %)
  - Low phys/pat (35 %)
  - North (26 %)

$R(\underline{s})$ approximation without CMPs

- Note that $R(\underline{s})$ is the quality effect per marginal (log) physician

$$R(\underline{s}) = \mathbb{E}[\theta | s > \underline{s}] - \theta(\underline{s})$$

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- Simple approx yields

$$\bar{R}(\underline{s}) = 21$$

$\rightarrow$ Can *approximate* sign of reform without estimation of CMPs
$\rightarrow$ Not enough to quantify *magnitude* of changes

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- For outcome k (access and quality), Cobb-Douglas production function:

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  - $\alpha_{\theta}^{k} \frac{1}{L_{jt}} \sum_{i \in J_t} \nu_i$: measurement error in phys' quality

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- For outcome k (access and quality), Cobb-Douglas production function:

$$lnY_{jt}^k = \alpha_L^k lnL_{jt} + \alpha_\theta^k \bar{\theta}_{jt} + A_{jt}^k$$

- Using the posterior; $\theta_i = E(\theta_i|\mathbf{s}_i) + \nu_i$ from the scores model:

$$\ln(Y_{jt}^k) = \alpha_L^k \ln(L_{jt}) + \alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} E(\theta_i|\mathbf{s}_i) + \rho_j^k + \gamma_{f(j)t}^k + \beta^k X_{jt} + \underbrace{\omega_{jt}^k + \alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} \nu_i + \varepsilon_{jt}^k}_{\mu_{it}}$$

- The error term μ_{jt}^k consists of three components:
  - ω_{jt}^k: an unobserved productivity shock potentially known before input choices
  - $\alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} \nu_i$: measurement error in phys' quality
  - ε_{jt}^k: an unobserved productivity shock that occurs after input decisions

Empirical strategy: 2SLS

- We leverage two shift-share (Bartik-like) instruments: Z_{jt}^{L} and Z_{jt}^{θ}
  (Altonji & Card 1981; Autor et al. 2013; Borusyak et al. 2022)

$$Z_{jt}^{L} = \sum_{c} \%\Delta\text{Test-takers}^{c} \times \text{share physicians}_{j,t-1}^{c}$$

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- The ***share*** component uses the (lagged) share of workers from region of training c that work at hospital j
- The ***quantity-shift*** component uses the % Δ in the number of elegible test-takers from region of training c
- The ***quality-shift*** component uses the Δ in the average quality of test-takers from region of training c

2SLS estimates on access to healthcare

	Ln service rate	Ln inpatient surgeries	Ln exits from waiting list	
			Surgical	Medical
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L^{\text{service}}$)	1.01	4.97	3.69	3.00
	[0.25]	[1.96]	[0.69]	[1.02]
Avg. Physicians' Quality ($\hat{\alpha}_\theta^{\text{service}}$)	0.01	0.11	-0.00	0.02
	[0.01]	[0.10]	[0.04]	[0.06]
Observations	1,402	744	738	942
Mean Dep. Var.	0.015	3,803	1,534	8,403
F-stat (First-stage)	22	12.3	9.9	15.9
Anderson-Rubin (χ^2)	0.000	0.000	0.000	0.000

Note: All include hospital FE and year FE and that vary with hosp. complexity, beds, inpatient case-mix controls (gender, origin, age, insurance). Exposure-robust standard errors clustered at the region of origin level in brackets (Borusyak et al., 2022).

▸ Decriptive Stats

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$$\hat{\alpha}_L^{\text{service rate}} / \hat{\alpha}_{\bar{\theta}}^{\text{service rate}} \to \infty$$

2SLS estimates on per-patient value added

	Mortality			In-hospital
	In-Hospital		28-days	Complications*
	Ln death rate	Pred. death rate	Ln death rate	Ln complications rate
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L^{\text{mortality}}$)	-0.83	0.13	-0.74	-0.58
	[0.19]	[0.11]	[0.20]	[0.23]
Avg. Physicians' Quality ($\hat{\alpha}_\theta^{\text{mortality}}$)	-0.04	-0.00	-0.04	-0.04
	[0.01]	[0.01]	[0.01]	[0.02]
Observations	1,402	1,402	1,402	1,402
Mean Dep. var.	3.284	3.494	5.075	3.272
F-stat (First-stage)	22	34.90	22	22
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Note: All include hospital FE and year FE that vary with hosp. complexity, beds, inpatient case-mix controls (gender, origin, age, insurance). Exposure-robust standard errors clustered at the region of origin level in brackets (Borusyak et al., 2022). *Complications include: infections, hemorrhage, sepsis.

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$$\hat{\alpha}_L^{\text{mortality}} / \hat{\alpha}_{\bar{\theta}}^{\text{mortality}} = 19$$

Taking a step back: How did the migration affect inputs and mortality?

$$Y_{jt} = \rho_j + \gamma_t + \beta Z^L_{jt} + \epsilon_{jt}$$

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$Y \equiv$	Ln # Physicians	Average Quality	Ln Death Rate
	(1)	(2)	(3)
Z^L_{jt}	0.028	-0.504	-0.002
	(0.003)	(0.033)	(0.006)
N	1,402	1,402	1,402

Taking a step back: How did the migration affect inputs and mortality?

1. Increased $ln(L)$, decreased $\bar{\theta}$:

$$R(Z) = -\frac{d\bar{\theta}}{dZ} / \frac{dln(L)}{dZ} = \frac{0.504}{0.028} = 18$$

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$$\frac{dln(Y)}{dZ} \simeq 0$$
$$= \alpha_L \frac{dln(L)}{dZ} + \alpha_{\bar{\theta}} \frac{d\bar{\theta}}{dZ}$$

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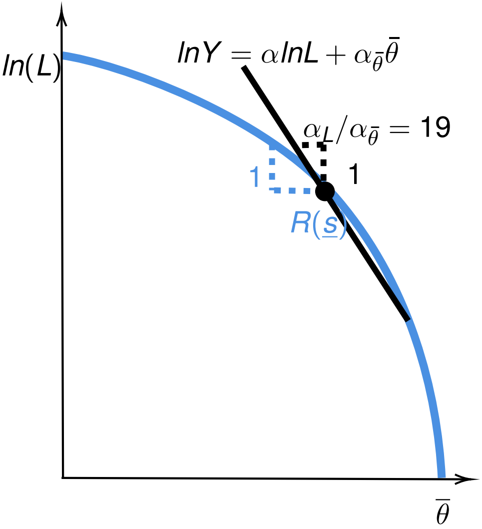
3. IV regression fits (mechanically)

$$\hat{\alpha}_L / \hat{\alpha}_{\bar{\theta}} = 19 \simeq -\frac{d\bar{\theta}}{dZ} / \frac{dln(L)}{dZ} = R(Z)$$

Migration shock identifies slope of iso-mortality



- Migration shock identifies slope of iso-mortality

Robustness Checks

- Validity of IVs:
  - Quantity and quality shocks do not predict predetermined hospital workforce or patient demographic variables (Borusyak et al., 2022) ‣ Go
  - Shares uncorrelated with changes in outcomes (Goldsmith-Pinkham et al., 2020) ‣ Go
  - IV does not have a direct effect on other inputs (e.g. nurses) ‣ Go
- Specification and Estimation of Production Function:
  - Estimates robust to any linear transformation of avg. quality (IV for meas. error)
  - Similar results using share of phys below median quality ‣ Go
  - Similar results using a translog production function ‣ Go

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   - **Short-run effect**
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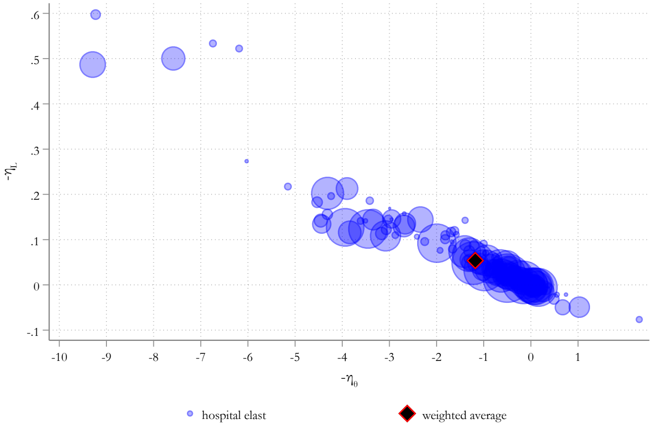
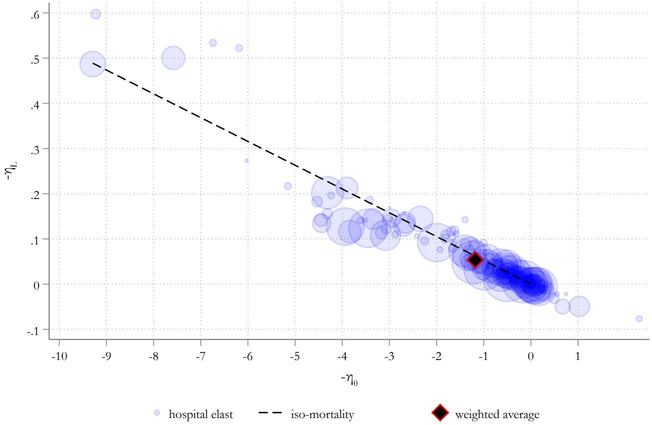
Policy counterfactual, 2018



- $\bar{R}(\underline{s}) = -\overline{\tilde{\eta}_{\bar{\theta}_j,\underline{s}}/\eta_{L_j,\underline{s}}} \simeq 24$

Policy counterfactual, 2018

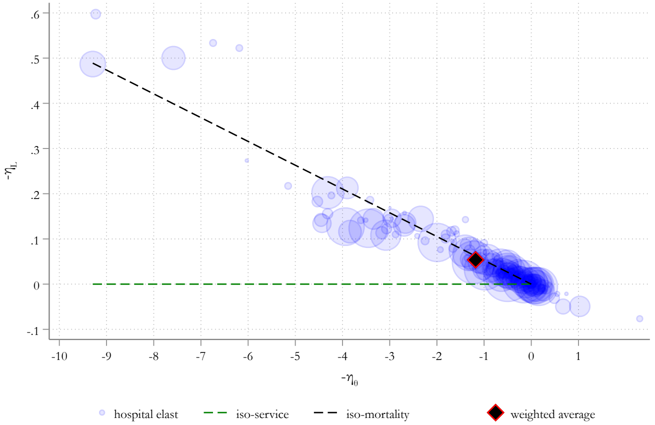
$$\eta_{\underline{s}}^{\text{mortality}_j} = \alpha_L^{\text{mortality}} \cdot \eta_{\underline{s}}^{L_j} + \alpha_{\bar{\theta}}^{\text{mortality}} \cdot \tilde{\eta}_{\underline{s}}^{\bar{\theta}_j}$$



- $\bar{R}(\underline{s}) = -\overline{\tilde{\eta}_{\bar{\theta}_j,\underline{s}} / \eta_{L_j,\underline{s}}} \simeq 24$
- $\dfrac{\alpha_L^{\text{mortality}}}{\alpha_{\bar{\theta}}^{\text{mortality}}} = 20 < 24$
  - policy slightly increases patient mortality

Policy counterfactual, 2018

$$\eta_{\underline{s}}^{\text{service}_j} = \alpha_L^{\text{service}} \cdot \eta_{\underline{s}}^{L_j} + \alpha_{\bar{\theta}}^{\text{service}} \cdot \tilde{\eta}_{\underline{s}}^{\bar{\theta}_j}.$$



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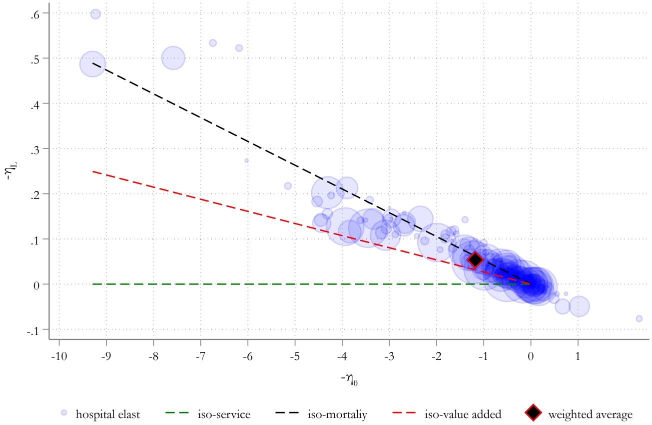
- $\dfrac{\alpha_L^{\text{mortality}}}{\alpha_{\bar{\theta}}^{\text{mortality}}} = 20 < 24$
- $\dfrac{\alpha_L^{\text{service}}}{\alpha_{\bar{\theta}}^{\text{service}}} \to \infty$
  - policy increases service

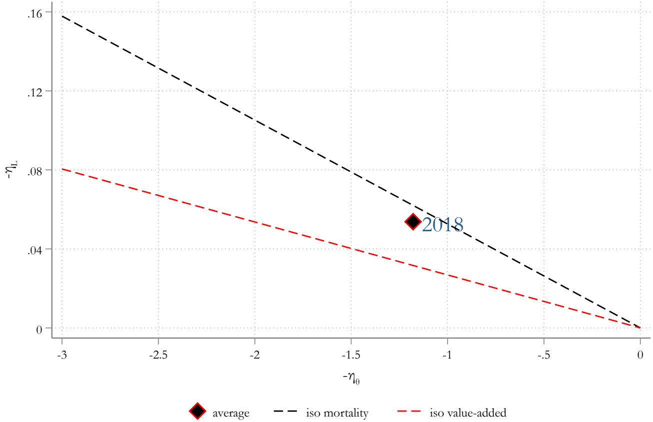
Policy counterfactual, 2018

$$\eta_{\underline{s}}^{\text{value added}_j} = (\alpha_L^{\text{service}} - \alpha_L^{\text{mortality}}) \cdot \eta_{\underline{s}}^{L_j} + (\alpha_{\bar{\theta}}^{\text{service}} - \alpha_{\bar{\theta}}^{\text{mortality}}) \cdot \tilde{\eta}_{\underline{s}}^{\bar{\theta}_j}.$$



- $\bar{R}(\underline{s}) = -\overline{\tilde{\eta}_{\bar{\theta}_j,\underline{s}}/\eta_{L_j,\underline{s}}} \simeq 24$
- policy slightly increases patient mortality
- policy increases service
- $\frac{\alpha_L^{\text{service}} - \alpha_L^{\text{mortality}}}{\alpha_{\bar{\theta}}^{\text{service}} - \alpha_{\bar{\theta}}^{\text{mortality}}} \simeq 37$
  - policy increases value added

Evolution of elasticities of quantity and quality



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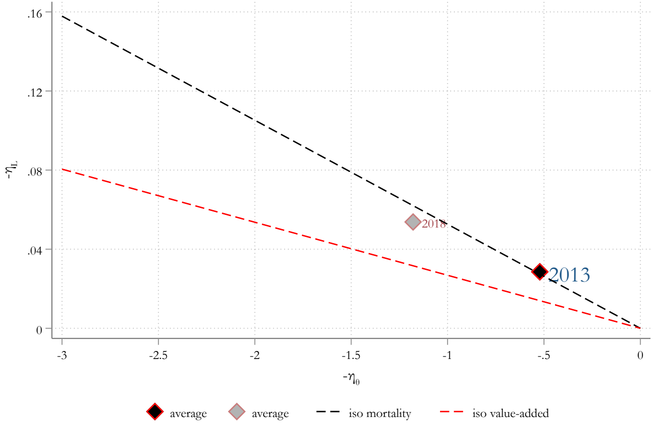

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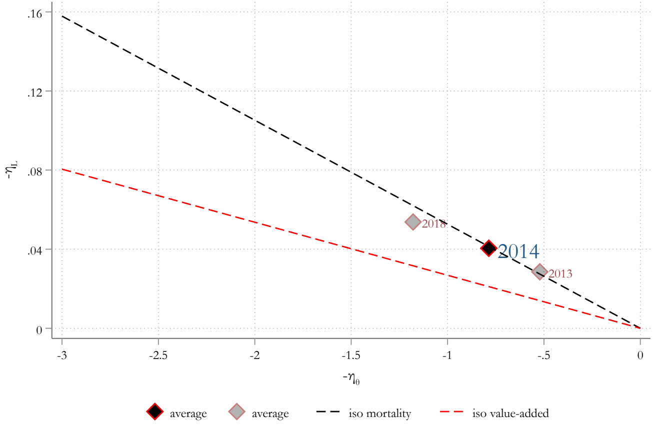

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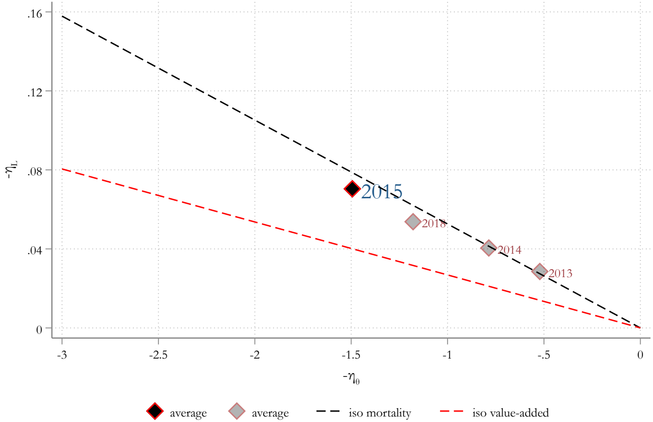

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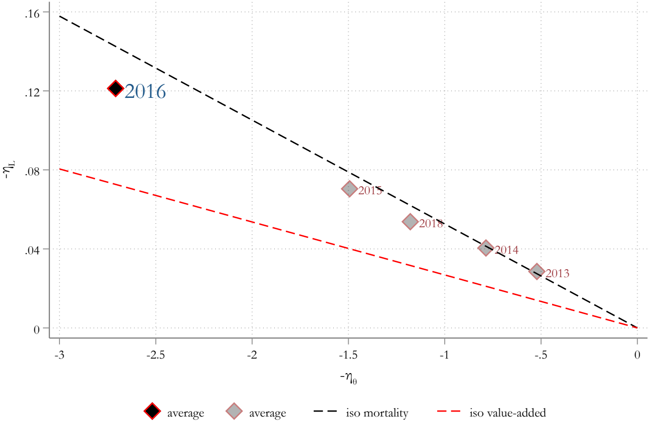

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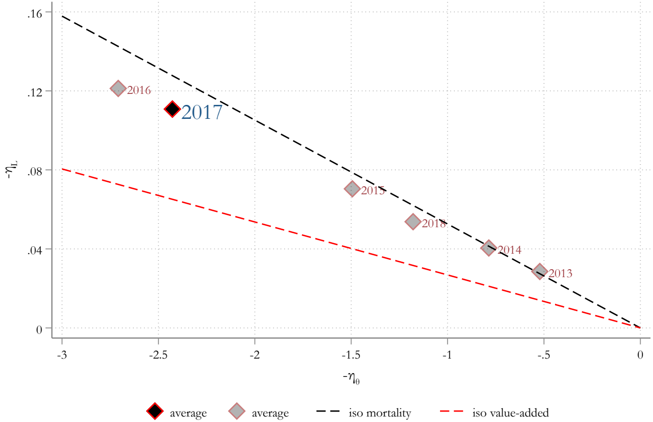

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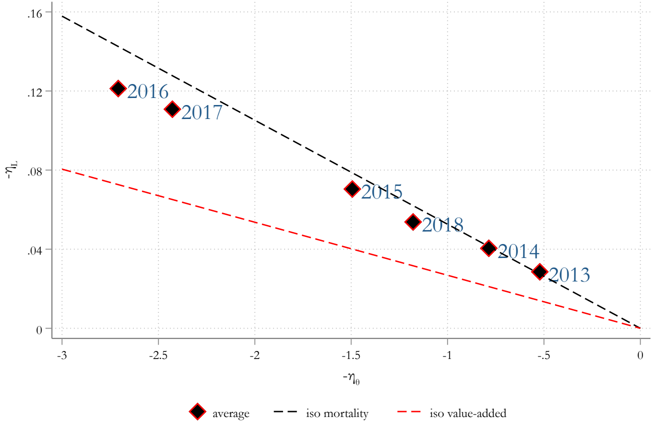
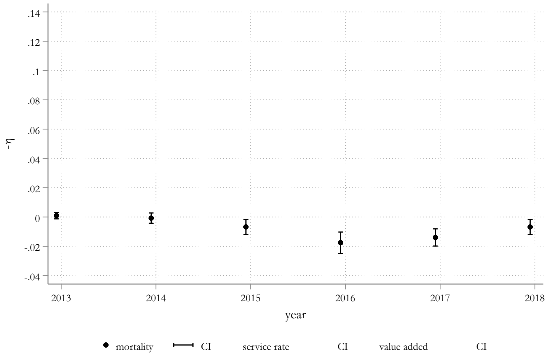


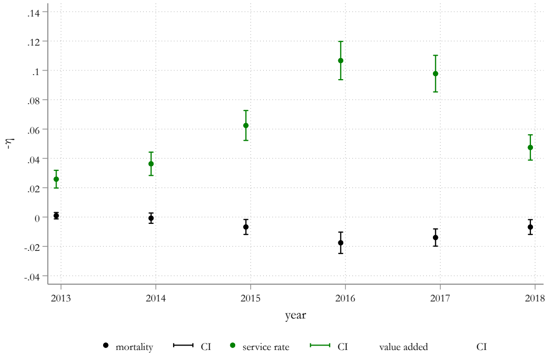
- Offsetting evolution of elasticities of quantity and quality
- Higher mass at the margin but higher stock and fewer vacancies over time

Net impacts on quality



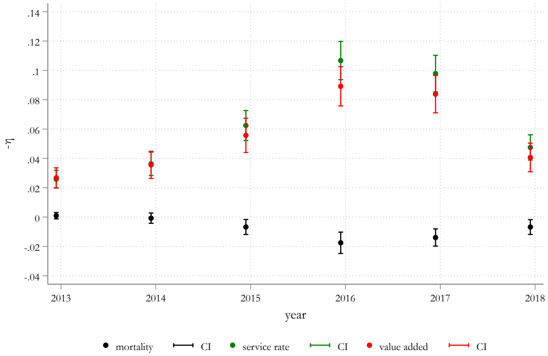
- Effects on per-patient mortality constant over time

Net impacts on quality and access



- Effects on per-patient mortality constant over time
- Effects on service rate maximal in 2016

Net impacts on quality, access, and value added



- Effects on per-patient mortality constant over time
- Effects on service rate maximal in 2016
- Effects on value added maximal in 2016

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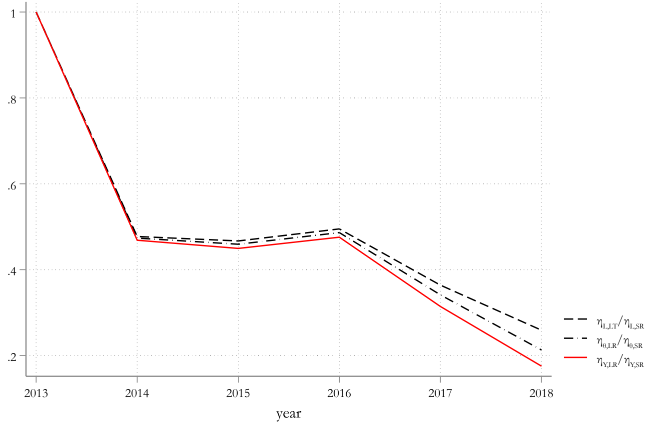
Dynamic policy effects

- What are the dynamic effects of permanently changing the licensing threshold?
- Key issue: retaking mitigates the relevance of the threshold over time
- In our sample, 83% of (first-takers) who fail in 2013 pass by 2018
- Strategy to quantify dynamic effects:
    1. Simulate individual histories for each cohort using the model of scores and retaking
    2. Compute yearly elasticities w.r.t. threshold (set permanently lower)

Simulated ratio between short and long term elasticities



- Retaking dampens long-run effects of the policy.
- However, policy has net positive effects even 5 years after

Concluding remarks

- We show that physician quantity and quality matter for health outcomes
- We provide a framework to include this tradeoff in the analysis of licensing policies
- We estimate sufficient statistics to quantify the effects of locally relaxing licensing thresholds on patient outcomes
- Policy implication: net benefits from lowering licensing threshold in Chile's public healthcare system.
- Next step: Can we improve policy impacts by optimally allocating marginal physicians to hospitals?

Comments and feedback

ataljp@econ.upenn.edu

Contributions

- **Physician quantity matters:** Carrillo & Feres 2019, Finkelstein et al. 2021, Clemens & Gottlieb 2014

  $\rightarrow$ Exogenous variation to show physician quantity matters for outcomes

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- **Occupational licensing:** (Friedman & Kuznets 1945; Friedman 1962; Kugler & Sauer 2005; Kleiner 2013; Kleiner 2016; Dillender 2024, Wiswall, 2007; Angrist & Guryan 2008, Larsen et al., 2023, Kleiner & Soltas 2023, Farronato et al., 2024, Sun and Li, 2024)

  $\rightarrow$ Provide a framework to understand the quantity/quality trade-off and evaluate the stringency of licensing policies in relevant health outcomes

▸ Back

Licensing Scores

Back

Year	# Tests	Average score	% Approved (score $\geq$ 51)	Average score if score $\geq$ 51	# Tests $\in [40-51)$
2009	1,389	71.8	92	74.3	87
2010	1,535	65.1	80	72.1	142
2011	1,748	66.6	81	73.3	160
2013	2,003	56.1	66	67.5	231
2014	2,557	55.8	65	67.5	335
2015	3,641	54.7	60	66.5	651
2016	4,999	53.0	54	66.9	1,012
2017	6,014	52.1	55	64.9	1,233
2018	7,121	53.9	58	65.0	1,552

Referrals follow strict guidelines

ESTABLECIMIENTOS ATENCIÓN SECUNDARIA Y TERCIARIA				
1	COMPLEJO HOSPITALARIO SAN JOSÉ		5	UAPO COMUNAL
2	HOSPITAL CLÍNICO DE NIÑOS ROBERTO DEL RÍO		6	COSAM COMUNAL
3	INSTITUTO PSIQUIÁTRICO DR. JOSÉ HORWITZ BARAK			
4	INSTITUTO NACIONAL DEL CÁNCER DR. CAUPOLICÁN PARDO CORREA			

SERVICIO DE SALUD														
COMUNA	Colina									Conchalí				
ESTABLECIMIENTO	109310 - Centro de Saud Familiar Colina	109316 - Centro de Salud Familiar Esmeralda	109416 - Posta Salud Rural Colorado	109417 - Posta Salud Rural Los Ingleses	109418 - Posta Salud Rural Las Canteras	109419 - Posta Salud Rural Santa Marta de Liray	109420 - Posta Salud Rural Chacabuco	109716 - Centro Comunitario de Salud Familiar Esmeralda	109810 - SAPU Colina	109302 - Centro de Salud Familiar Lucas Sierra	109308 - Centro de Salud Familiar Alberto Bachelet Martínez	109309 - Centro de Salud Familiar José Symon Ojeda	109314 - Centro de Salud Familiar Juanita Aguirre	109709 - Centro Comunitario de Salud Familiar Dr. José Symon Ojeda
PEDIATRÍA														
CARDIOLOGÍA PEDIÁTRICA	2	2	2	2	2	2	2	2		2	2	2	2	2
ENDOCRINOLOGÍA PEDIÁTRICA	2	2	2	2	2	2	2	2		2	2	2	2	2
ENFERMEDADES RESPIRATORIAS PEDIÁTRICAS	2	2	2	2	2	2	2	2		2	2	2	2	2
GASTROENTEROLOGÍA PEDIÁTRICA	2	2	2	2	2	2	2	2		2	2	2	2	2
GINECOLOGÍA PEDIÁTRICA Y DE LA ADOLESCENCIA	2	2	2	2	2	2	2	2		2	2	2	2	2
HEMATOLOGÍA ONCOLÓGICA PEDIÁTRICA	2	2	2	2	2	2	2	2		2	2	2	2	2
HEMOFILIA (SIN LÍMITE DE EDAD)	2	2	2	2	2	2	2	2		2	2	2	2	2
INFECTOLOGÍA PEDIÁTRICA	2	2	2	2	2	2	2	2		2	2	2	2	2
NEFROLOGÍA PEDIÁTRICA	2	2	2	2	2	2	2	2		2	2	2	2	2
NUTRICIÓN CLÍNICA DEL NIÑO Y EL ADOLESCENTE	2	2	2	2	2	2	2	2		2	2	2	2	2
NANEAS	2	2	2	2	2	2	2	2		2	2	2	2	2
MEDICINA INTERNA	1	1	1	1	1	1	1	1		1	1	1	1	1
CARDIOLOGÍA	1	1	1	1	1	1	1	1		1	1	1	1	1
NUTRICIÓN Y DIABETES	1	1	1	1	1	1	1	1		1	1	1	1	1
PROGRAMA MANEJO DE LA OBESIDAD	1	1	1	1	1	1	1	1		1	1	1	1	1
ENDOCRINOLOGÍA ADULTO	1	1	1	1	1	1	1	1		1	1	1	1	1
ENFERMEDADES RESPIRATORIAS ADULTO	1	1	1	1	1	1	1	1		1	1	1	1	1
GASTROENTEROLOGÍA ADULTO	1	1	1	1	1	1	1	1		1	1	1	1	1
HEMATOLOGÍA	1	1	1	1	1	1	1	1		1	1	1	1	1
VIH														
< 15 AÑOS	2	2	2	2	2	2	2	2		2	2	2	2	2
> 15 AÑOS	1	1	1	1	1	1	1	1		1	1	1	1	1
NEFROLOGÍA ADULTO	1	1	1	1	1	1	1	1		1	1	1	1	1
ONCOLOGÍA MÉDICA														
< 15 AÑOS	2	2	2	2	2	2	2	2		2	2	2	2	2
> 15 AÑOS (Derivación desde APS sólo con confirmación diagnóstica realizada)	4	4	4	4	4	4	4	4		4	4	4	4	4
REUMATOLOGÍA														
< 15 AÑOS	2	2	2	2	2	2	2	2		2	2	2	2	2
> 15 AÑOS	1	1	1	1	1	1	1	1		1	1	1	1	1

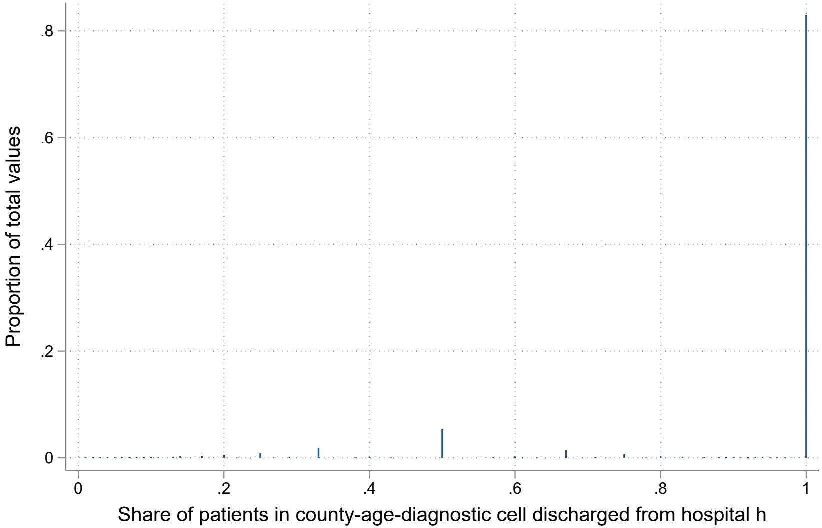
Referrals follow strict guidelines ▸ Back

Health Service Name	*Metropolitano Norte*		*Metropolitano Oriente*	
Primary Care	CESFAM Colina (1)	CESFAM Esmeralda (2)	CESFAM Aguilucho (3)	CESFAM La Faena (4)
Pediatrics				
Pediatric respiratory diseases	2	2	4	4
Internal Medicine				
Cardiology	1	1	5	4
Medical Oncology				
$<$ 15 years	2	2	7	7
$>$ 15 years	3	3	5	5
General Surgery				
Thoracic Surgery	3	3	6	6

1. Complejo Hospitalario San José; **2.** Hospital Clínico De Niños Roberto Del Río; **3.** Instituto Nacional Del Cáncer Dr. Caupolicán Pardo Correa; **4.** Centro de Referencia de Salud Cordillera Oriente; **5.** Hospital Del Salvador; **6.** Instituto Nacional del Torax; **7.** Hospital de Niños Dr. Luis Calvo Mackenna.

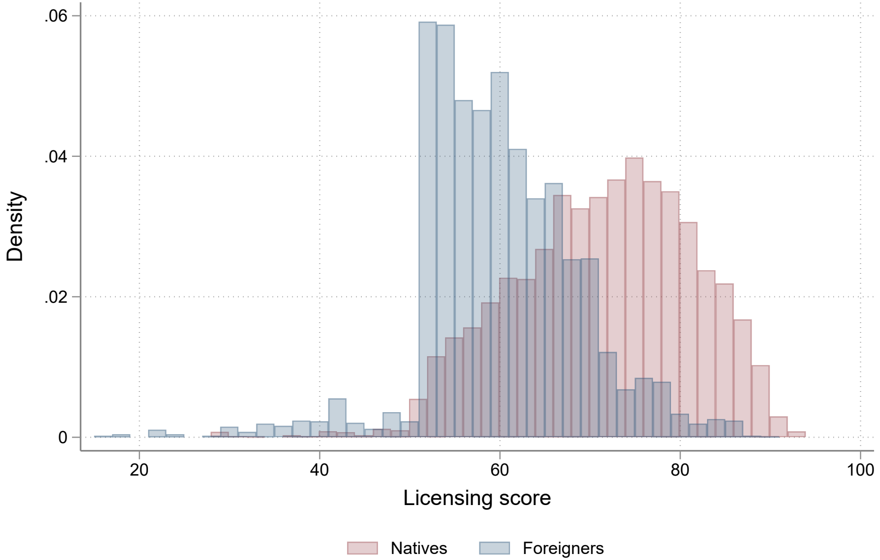
Strict referrals

‣ Back



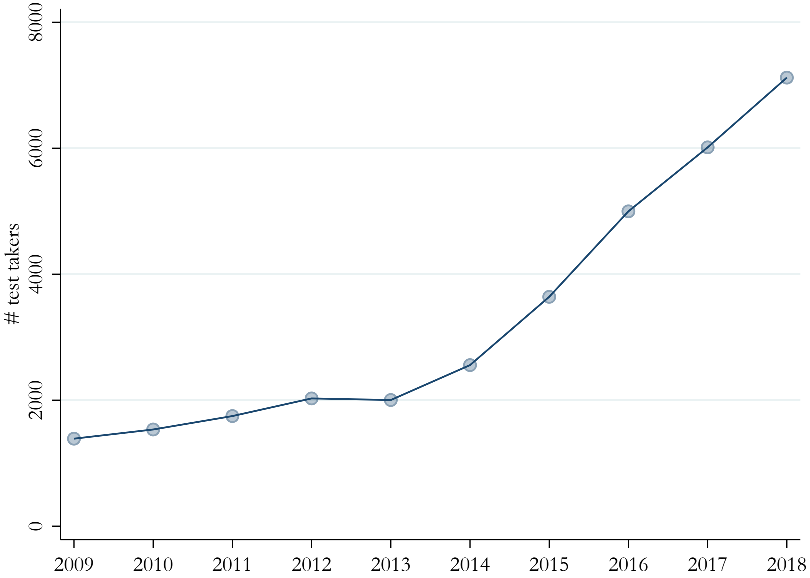
Licensing scores conditional on working in a public hospital

▸ Back



Number of test-takers over time

‣ Back ‣ By migration status



Empirical Model: CMP micro-foundation

- Two hospitals + outside option $(U, R, 0)$, and two physician quality tiers, (L, H) with mass M^H and M^U and tier-specific preferences
  - Cutoff in U is such that capacity equals mass of H-phys. who prefer U:

$$\kappa_U = M^H \underbrace{\left[\int_i Pr(u_{iU} > \max\{u_{iR}, u_{I0}\}|H)di\right]}_{\text{\% High-type top-pref is U}} Pr(\hat{\theta}_U < \hat{\theta}_i|H)$$

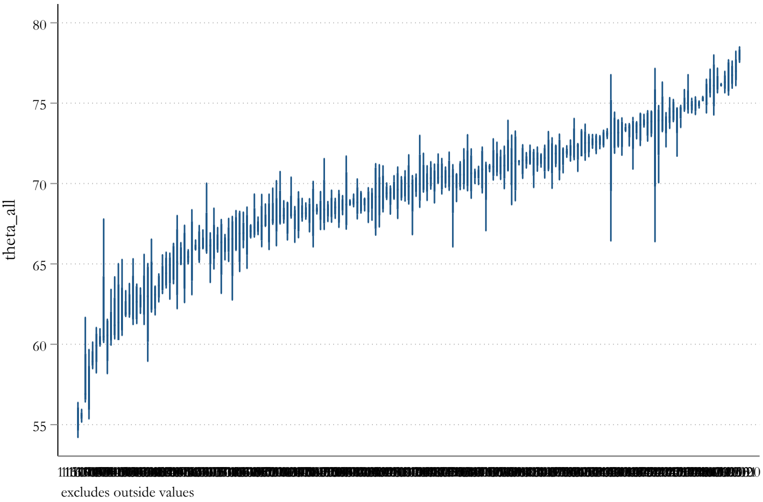
  - Cutoff in R is such that capacity equals L-phys. who prefer R + displaced L-phys. + displaced H-phys.

$$\kappa_R = M^L \left[\int_i \underbrace{Pr(u_{iR} > \max\{u_{iU}, u_{i0}\}|L)}_{\text{\% Low-type top-pref is R}} + \underbrace{Pr(u_{iU} > u_{iR} > u_{i0}|L)}_{\text{\% Low-type top-pref is U and second is R}} di\right] Pr(\hat{\theta}_R < \hat{\theta}_i|L)$$

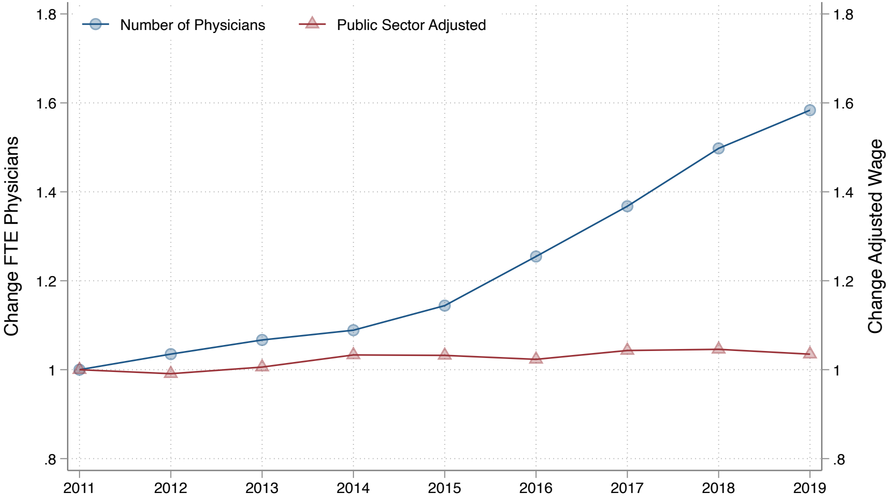
$$M^H \left[\underbrace{\int_i Pr(u_{iU} > u_{iR} > u_{i0}|H)}_{\text{\% High-type top-pref is U and second pref is R}} di\right] Pr(\hat{\theta}_R < \hat{\theta}_i < \hat{\theta}_U|H)$$

Box plot of quality by hospital

Back



60% increase in FTE physicians in public hospitals ▸ Back



Elasticity of quantity

$$\eta_{L_j,\underline{s}} = \frac{\underline{s}}{L_j}\left(\underbrace{-\int_X CMP_j(\underline{s}, X, M(\underline{s}))h(X,\underline{s})dX}_{\textit{Direct Effect} \ \frac{\partial L_j^{neq}}{\partial \underline{s}} < 0} + \underbrace{\int_{s \geq \underline{s}} \int_X \frac{\partial CMP_j\left(s, X, M(\underline{s})\right)}{\partial \underline{s}} h(X,s)dXds}_{\textit{General Eq Effect} \ \frac{\partial L_j^{eq}}{\partial \underline{s}} \ (+/-)} \right)$$

- Depends on:
  - The distribution of the marginal physicians at $\underline{s}$: $h(X, \underline{s})$
  - Their matching probabilities: $CMP_j(\underline{s}, X, M(\underline{s})), \forall j \in \mathcal{J}$
  - The general eq. effects of changing $\underline{s}$ on the matching probabilities
- Similar expressions for quality elasticity
  - Elasticity depends on SNR

Input elasticities estimates

	Labor elasticity $\eta_{\underline{s}}^{L_{jt}}$				Quality Semi-elasticity $\eta_{\underline{s}}^{\bar{\theta}_{jt}}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
high (phys/pat)$_{j,t-1}$	0.019			0.023	-0.294			-0.416
	(0.007)			(0.007)	(0.133)			(0.138)
high average score$_{j,t-1}$		0.033		0.029		-0.236		-0.163
		(0.006)		(0.006)		(0.135)		(0.126)
north$_j$			-0.025	-0.028			0.557	0.630
			(0.007)	(0.007)			(0.139)	(0.143)
mean dep. var.	-0.072	-0.072	-0.072	-0.072	1.401	1.401	1.401	1.401
N	1086	1086	1086	1086	1086	1086	1086	1086

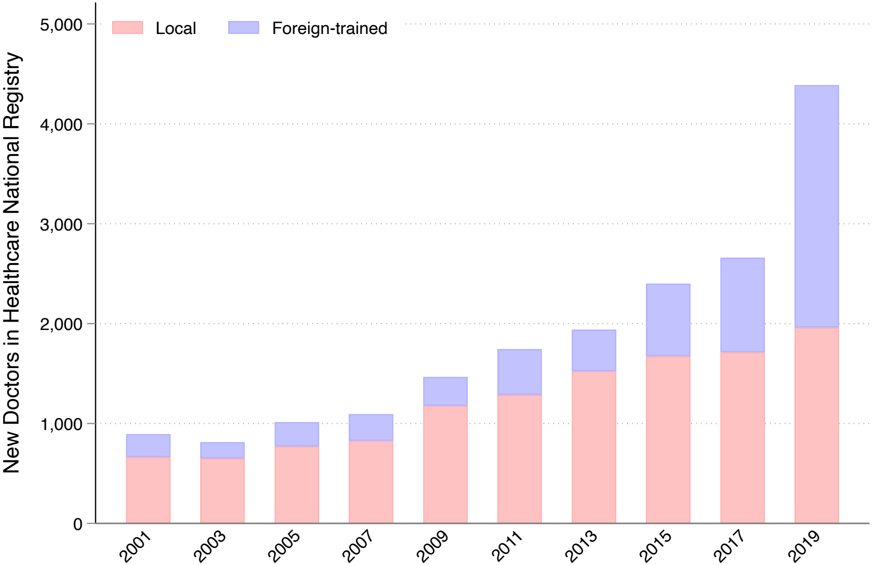
Back

Licensing score imputation ‣ Back

- Before the licensing exam there was a voluntary National Medical Examination (EMN)
  - Taken in Chilean medical schools btw 2003 to 2008
- Before the EMN:
  - Local medical graduates needed their Medical Surgeon Degree Examination
  - Foreign physicians had to pass a Foreign Medical Qualification Revalidation Examination

→ We don't observe licensing scores for all physicians working at a given hospital
  - Impute scores based on the score of other physicians from the same region who work in the same hospital

Registered Physicians ▸ Back



Descriptive Statistics: Hospital Characteristics,

▸ Back

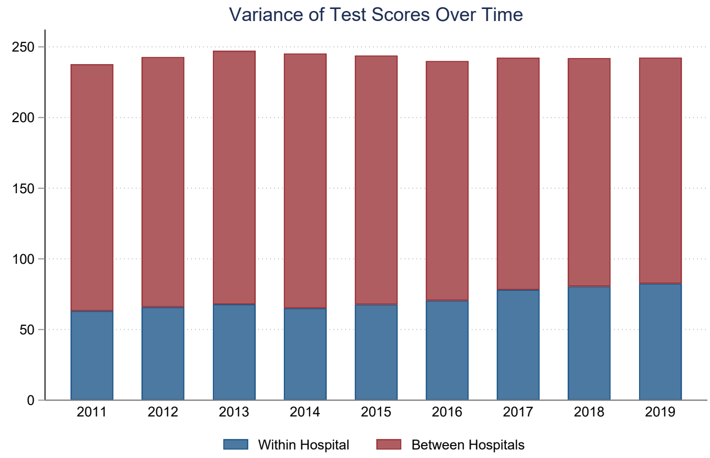
	Mean	Std. Dev.	Median (p50)	# of Obs.
	(1)	(2)	(3)	(4)
Hospital Characteristics:				
In-hospital Death Rate	3.28	1.82	2.92	1,402
Death Rate (1-month)	5.07	2.71	4.51	1,402
Service Rate (# Admissions/Beneficiaries)	0.02	0.02	0.01	1,402
Total Number of Surgeries	2,018	3,332	6.00	1,402
Length of Stay	4.03	5.66	3.00	1,402
Infection Rate	11.41	4.25	11.05	1,402
Physicians	77.64	119.64	20.00	1,402
Patients (# Admissions)	5,656	7,686	1,964	1,402

Descriptive Statistics: Patient and Hospital Characteristics

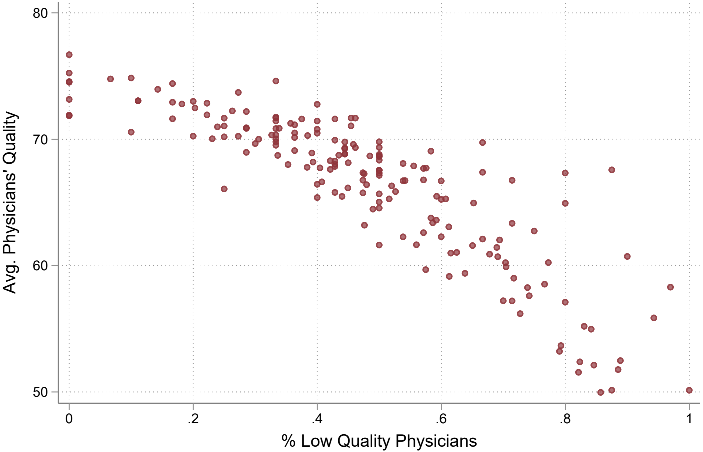
Back

	Mean	Std. Dev.	Median (p50)	# of Obs.
	(1)	(2)	(3)	(4)
Patient Characteristics:				
% Female	0.57	0.08	0.58	1,402
% Foreign	0.01	0.03	0.00	1,402
% Age $<$ 29	0.30	0.15	0.31	1,402
% Age $\in$ (30,29)	0.10	0.04	0.10	1,402
% Age $\in$ (40,49)	0.09	0.03	0.09	1,402
% Age $\in$ (50,59)	0.11	0.03	0.11	1,402
% Age $\in$ (60,69)	0.12	0.04	0.12	1,402
% Age $\in$ (70,79)	0.14	0.06	0.13	1,402
% Age $\in$ (80,89)	0.11	0.06	0.10	1,402
% Age $>$ 89	0.03	0.02	0.02	1,402
% Public Insurance	0.97	0.04	0.98	1,402

Descriptive Statistics: Variance of Test Scores Over Time



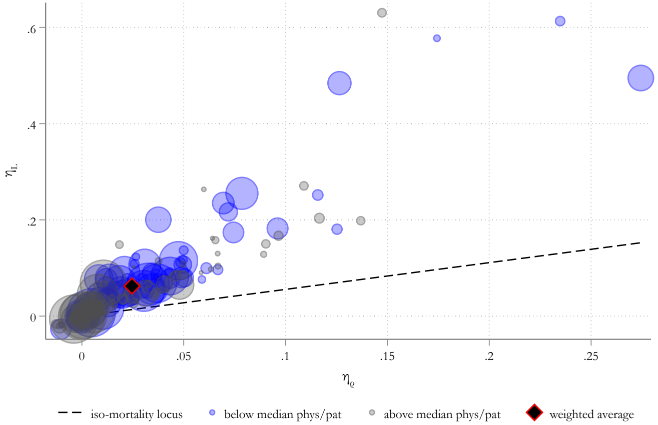
Descriptive Statistics: $\bar{\theta}$ and % Below $\bar{\theta}$



Elasticity of quantity and semi-elasticity of quality by hospital

▸ Back

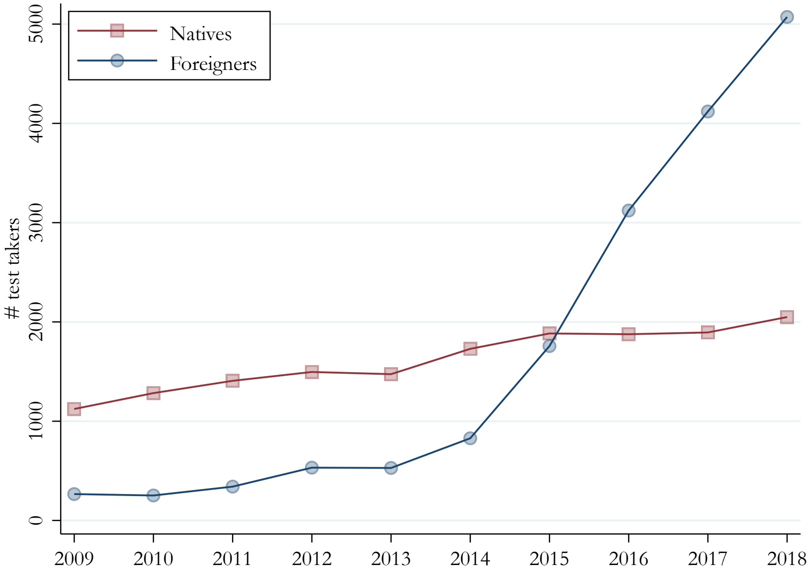
$\eta_{L_j,\underline{s}}$ and $\tilde{\eta}_{\rho_j,\underline{s}}$



- Main result assuming that the quality index is equal to the share of physicians below median quality in the data.

Number of test-takers over time, by migration status

‣ Back

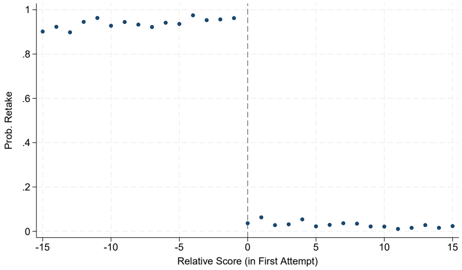


Disentangling test-taking ability and quality

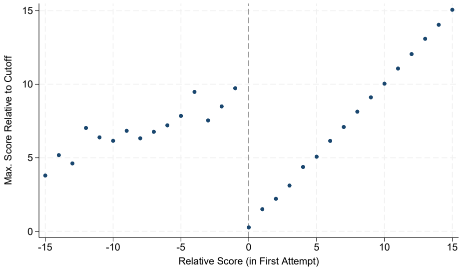
- Are score improvements due to increased test-taking ability (preparation) and/or due to improvements in quality?

- We leverage the discontinuity in retaking around the cutoff to show that retakers do not differ in outcomes that proxy for quality

More retaking and large score gains to the left of the cutoff



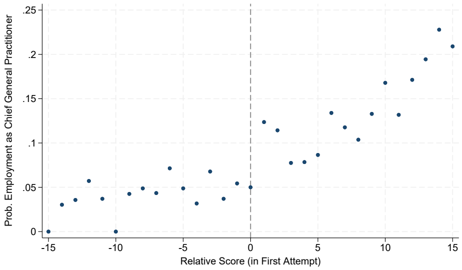
(a) Retaking Probability v.s. first score



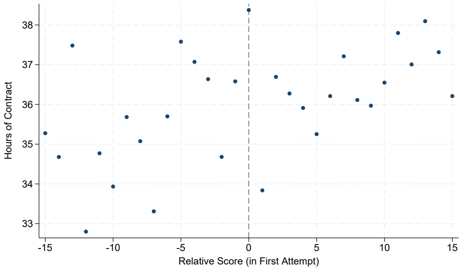
(b) Maximum achieved score v.s. first score

- Score gains in panel b) are a combination of gains in test-taking ability, gains in quality, and selection around cutoff (Gilraine and Penney, 2021)

No discernable differences in proxies for quality around cutoff ▸ Back



(c) Appointed Chief General Practitioner



(d) Hours of Contract

$\Rightarrow$ No differential effects in quality proxies suggest no quality gains due to retaking

Posterior quality ‣ Back

- Using normality assumption of θ and ϵ:

$$\mathbb{E}[\theta_i \mid s_{i0}, s_{i1}, \ldots, s_{in}] = \mu_{\theta,\tau(i)} + \frac{\sigma^2_{\theta,\tau(i)}}{\sigma^2_{\varepsilon,\tau(i)} + (n+1)\sigma^2_{\theta,\tau(i)}} \left(\sum_{t=0}^{n} (s_{it} - \Gamma_{t,\tau(i)} - \mu_{\theta,\tau(i)}) \right)$$

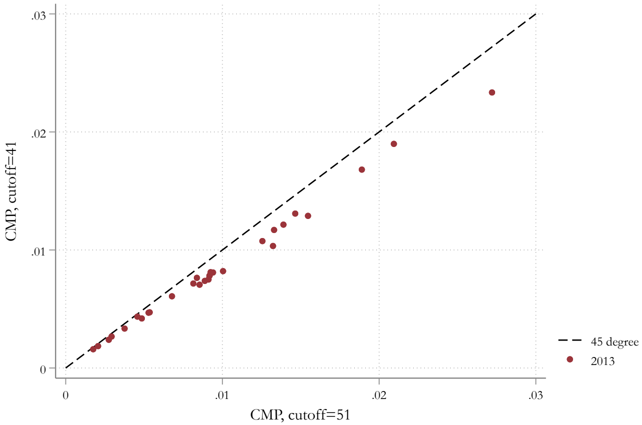
with

$$\theta_i = \mathbb{E}(\theta_i | s_i) + \nu_i$$

- The average quality of physicians in hospital j

$$\bar{\theta}_j = \frac{1}{L_j} \left(\sum_{i \in j} E(\theta_i | s_i) + \nu_i \right)$$

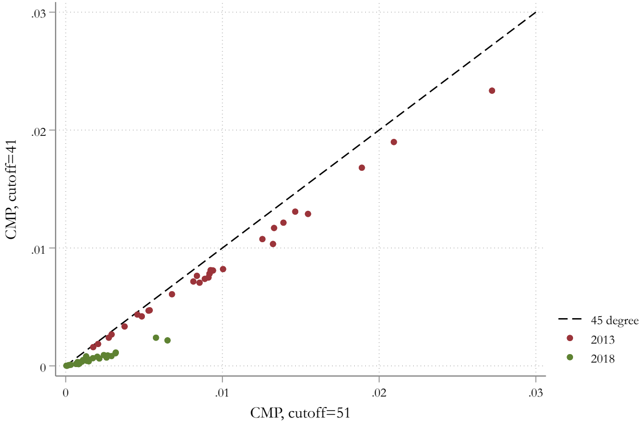
CMP estimates



The x axis shows probabilities under current cutoff. The y axis shows probabilities under a cutoff of 41, where the mass of low-quality physicians increases and generates displacement to the outside option.
In 2013, Average Nr Test takers / vacancies = 24.

CMP estimates

▸ Back



The x axis shows probabilities under current cutoff. The y axis shows probabilities under a cutoff of 41, where the mass of low-quality physicians increases and generates displacement to the outside option.
In 2013, Average Nr Test takers / vacancies = 24.
In 2018, Average Nr Test takers / vacancies = 750.

The impact of physician quantity and quality ‣ Back

	Service Rate	Death Rate		
	(Adm./Pop.)	In-Hospital		30 days
	Ln service rate	Ln death rate	Asinh resid. death rate	Ln death rate
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	0.940	-0.753	-0.499	-0.695
	(0.256)	(0.300)	(0.219)	(0.268)
% Low Quality Physicians ($\hat{\alpha}_\theta$)	-0.047	0.585	0.521	0.568
	(0.181)	(0.213)	(0.181)	(0.190)
Case-mix Controls	Yes	Yes	No	Yes
Hospital and Year FEs	Yes	Yes	Yes	Yes
Observations	1,376	1,376	1,403	1,376
Mean Dep. var.	0.016	3.301	0.009	5.086
F-stat (First-stage)	14.76	14.76	21.85	14.76
Anderson-Rubin (χ^2) p-value	0.00	0.00	0.00	0.00

Case-mix Controls include patients' demographics (share of female, share of foreign, share of inpatients in each of 8 age groups and in each of 5 types of insurance). We also control for beds per capita in each referral region.

Retaking decision: micro-foundation ▸ Back

- We specify the retaking probability for a physician of type τ who fails the exam in attempt n ($s_{in} < \underline{s}$) and has average past score $\underline{s}_{in}$ as:

$$P(\text{retake}|\underline{s}_{in}, n_i, \tau(i)) = \frac{e^{\beta_{0,\tau(i)}+\beta_{n,\tau(i)}n+\beta_{s,\tau(i)}(\underline{s}_{in}-\underline{s})}}{1+e^{\beta_{0,\tau(i)}+\beta_{n,\tau(i)}n_i+\beta_{s,\tau(i)}(\underline{s}_{in}-\underline{s})}}$$

- Follows from a dynamic model of (costly) retaking with learning about quality from the sequence of scores ▸ Details
- The model predicts that:
  - $\beta_{s,\tau} < 0$: Retaking prob. decreases with distance between average scores (signal) and passing threshold
  - $\beta_{n,\tau} < 0$: Conditional on scores, the passing probability is decreasing on the number of attempts due to (i) decay in score gains and (ii) decreasing variance of posterior quality

Retaking decision: micro-foundation ▸ Back

- Consider a dynamic model of physicians re-taking decisions
- At attempt n_i, a physician of type $\tau(i)$ with initial quality θ_{i0} and given preferences $\tilde{\delta}_i$ retakes if

$$V_{rt}\left(n_i, \underline{s}_{in_i-1}, \tau(i); \tilde{\delta}_i, M/\kappa\right) \geq V_{0t}\left(n_i, \underline{s}_{in_i-1}, \tau(i); \tilde{\delta}_i\right) \tag{1}$$

with

$$V_{rt}\left(n_i, \underline{s}_{in_i-1}, \tau(i); \tilde{\delta}_i, M/\kappa\right) = \underbrace{-c_r}_{\text{Retaking cost}} + \underbrace{\mathbb{P}\left(s_{in} \geq \underline{s} | n_i, \underline{s}_{in_i-1}, \tau(i)\right)}_{\text{Passing probability}} \underbrace{\log\left(\sum_j e^{\tilde{\delta}_{ijt}} 1\{\hat{\theta}\left(s_{in}, \tau(i)\right) \geq \underline{\hat{\theta}}_j\left(M_t/\kappa_{jt}, \tilde{\delta}_t\right)\}\right.}_{\text{Expected Labor market value}}$$

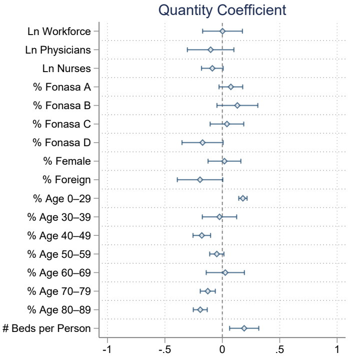
$$\left(1 - \mathbb{P}\left(s_{in} \geq \underline{s} | n_i, \underline{s}_{in_i-1}, \tau(i)\right)\right) \underbrace{\beta \max\{V_{rt+1}\left(n_i+1, \underline{s}_{in_i-1}, \tau(i); \tilde{\delta}_i, M/\kappa\right), V_{0t+1}\left(n_i+1, \underline{s}_{in_i-1}, \tau(i); \tilde{\delta}_i\right)\}}_{\text{Continuation value}}$$

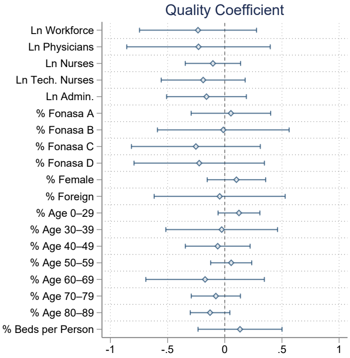
where

$$\mathbb{P}\left(s_{in} \geq \underline{s} | n_i, \underline{s}_{in_i-1}, \tau(i)\right) = \mathbb{P}\left(\underbrace{\hat{\theta}_{in}\left(\underline{s}_{in_i-1}, \tau(i)\right)}_{\text{Posterior quality in attempt } n_i} + \underbrace{\Gamma_{in_i}\left(n_i, \tau(i)\right)}_{\text{Gains to the test}} + \varepsilon_{in_i}\left(\tau(i)\right) \geq \underline{s}\right) \tag{2}$$

Robustness: Shock Balance Test

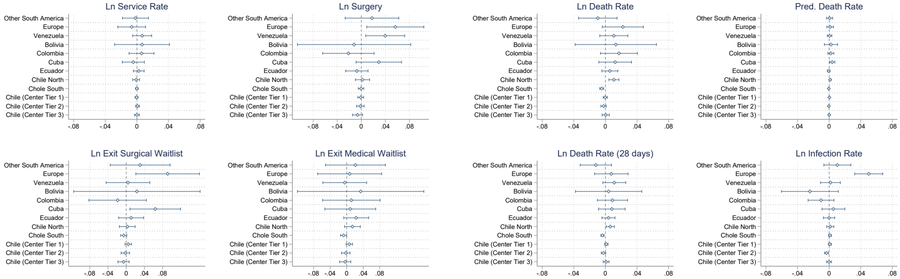
▸ Back





Robustness: Share Balance Test

▸ Back



Robustness: Alternative Measure of Quality ▸ Back

Panel A: Access

	Ln service rate	Ln inpatient surgeries	Ln exits from waiting list: Surgical	Ln exits from waiting list: Medical
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	0.98	4.36	3.71	2.94
	(0.25)	(1.29)	(1.32)	(1.19)
% Low Quality Physicians ($\hat{\alpha}_\theta$)	-0.05	-1.00	0.05	-0.17
	(0.18)	(0.80)	(0.78)	(0.82)
Observations	1,376	740	736	934
Mean Dep. Var.	0.0155	3,819	1,537	8,467
F-stat (First-stage)	16.25	10.33	9.29	9.96

Panel B: Quality

	Mortality: In-Hospital: Ln death rate	Mortality: In-Hospital: Pred. death rate	Mortality: 28-days: Ln death rate	In-hospital Complications: Ln complications rate
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	-0.68	0.13	-0.61	-0.45
	(0.28)	(0.07)	(0.25)	(0.27)
% Low Quality Physicians ($\hat{\alpha}_\theta$)	0.49	0.03	0.48	0.48
	(0.20)	(0.06)	(0.18)	(0.19)
Observations	1,376	1,376	1,376	1,376
Mean Dep. var.	3.30	3.50	5.09	11.65
F-stat (First-stage)	16.25	21.57	16.25	15.46

Robustness: Alternative Production Function ‣ Back

	Ln Death Rate		Ln Service Rate	
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	-0.83	0.43	1.01	1.08
	(0.31)	(1.64)	(0.29)	(1.34)
Avg. Physicians' Quality ($\hat{\alpha}_\theta$)	-0.04	0.07	0.01	0.01
	(0.02)	(0.15)	(0.02)	(0.12)
Interaction ($\hat{\alpha}_{L\theta}$)		-0.02		-0.00
		(0.03)		(0.03)
Observations	1,402	1,402	1,402	1,402
Model	2SLS	2SLS	2SLS	2SLS
Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Mean dep var	3.28	3.28	0.015	0.015
First-stage F-stat	22	2.332	22	2.332
Translog Quantity and Quality Impacts:				
Quantity Impact		-1.280		0.987
		(0.460)		(0.309)
Quality Impact		-0.010		0.008
		(0.002)		(0.001)

Reduced Form Impact of Quantity Instrument

	Ln Death Rate	Ln # Physicians	Average Quality
	(1)	(2)	(3)
Z_{jt}^{L}	-0.002	0.028	-0.504
	(0.006)	(0.003)	(0.033)
Observations	1,402	1,402	1,402
$\hat{\alpha}_{L}^{\text{mortality}}$			-0.828
$\hat{\alpha}_{\theta}^{\text{mortality}}$			-0.0419

Other inputs ‣ Back

- If there is complementarity between the number of doctors and other inputs
  - $O = e^c L^\gamma$

Other inputs ▸ Back

- If there is complementarity between the number of doctors and other inputs
  - $O = e^c L^\gamma$

$\rightarrow$ $Y = AL^{\alpha_L} e^c (L^\gamma)^{\alpha_O}$

Other inputs ‣ Back

- If there is complementarity between the number of doctors and other inputs
  - $O = e^c L^\gamma$

  $\rightarrow$ $Y = AL^{\alpha_L} e^c (L^\gamma)^{\alpha_O}$

  $\rightarrow$ $lnY = \phi + \underbrace{(\alpha_L + \gamma\alpha_o)}_{\tilde{\alpha}_L} lnL$

Other inputs

Back

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  - $O = e^c L^\gamma$

$\rightarrow$ $Y = AL^{\alpha_L} e^c (L^\gamma)^{\alpha_O}$

$\rightarrow$ $lnY = \phi + \underbrace{(\alpha_L + \gamma\alpha_o)}_{\tilde{\alpha}_L} lnL$

- Impact of physicians on outcome of interest, $\tilde{\alpha}_L$, is a bundled effect:

Other inputs

Back

- If there is complementarity between the number of doctors and other inputs
  - $O = e^c L^\gamma$

  $\rightarrow$ $Y = AL^{\alpha_L} e^c (L^\gamma)^{\alpha_O}$

  $\rightarrow$ $lnY = \phi + \underbrace{(\alpha_L + \gamma\alpha_o)}_{\tilde{\alpha}_L} lnL$

- Impact of physicians on outcome of interest, $\tilde{\alpha}_L$, is a bundled effect:
  - direct effect of an extra doctor α_L
  - indirect effect from the increase in other inputs $\gamma\alpha_o$

Other inputs ▸ Back

- If there is complementarity between the number of doctors and other inputs
  - $O = e^c L^\gamma$

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- Impact of physicians on outcome of interest, $\tilde{\alpha}_L$, is a bundled effect:
  - direct effect of an extra doctor α_L
  - indirect effect from the increase in other inputs $\gamma\alpha_o$

- Two underlying assumptions are:
  1. There is complementarity between physicians and other inputs at hospital level
  2. “Optimal mix” is independent of the average doctors’ quality in a hospital

Other inputs ‣ Back

- If there is complementarity between the number of doctors and other inputs
  - $O = e^c L^\gamma$

  $\rightarrow$ $Y = AL^{\alpha_L} e^c (L^\gamma)^{\alpha_O}$

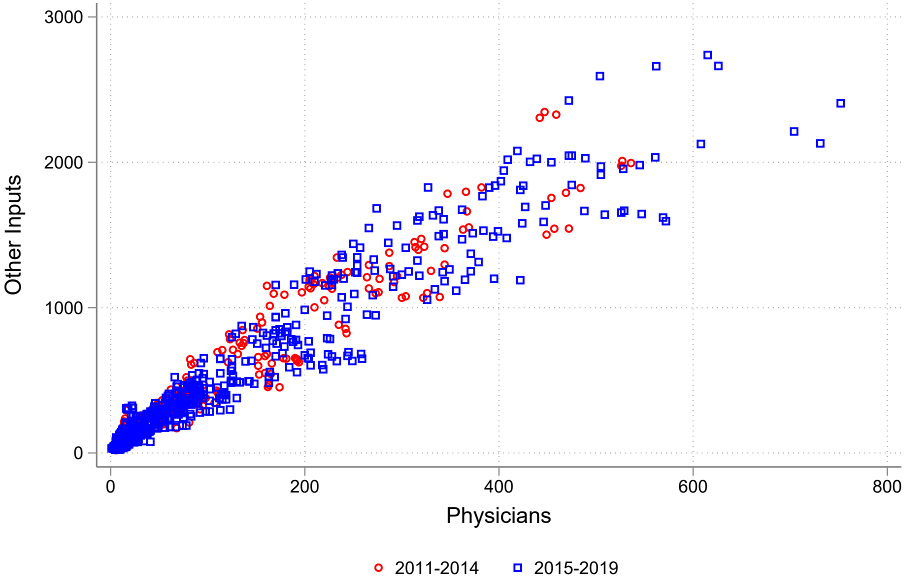
  $\rightarrow$ $lnY = \phi + \underbrace{(\alpha_L + \gamma\alpha_o)}_{\tilde{\alpha}_L} lnL$

- Impact of physicians on outcome of interest, $\tilde{\alpha}_L$, is a bundled effect:
  - direct effect of an extra doctor α_L
  - indirect effect from the increase in other inputs $\gamma\alpha_o$

- Two underlying assumptions are:
  1. There is complementarity between physicians and other inputs at hospital level
  2. "Optimal mix" is independent of the average doctors' quality in a hospital

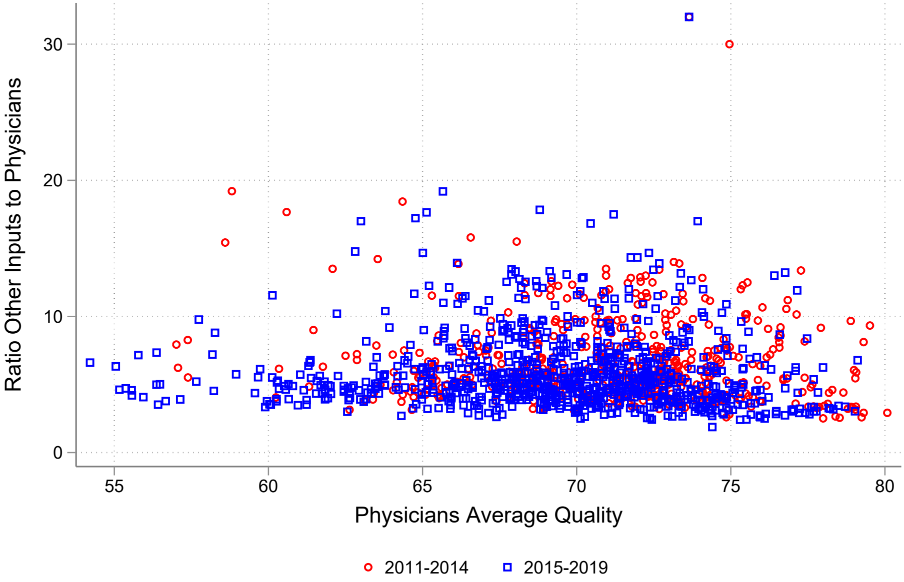
- We can assess these assumptions empirically

Other inputs: complementarity between physicians and other inputs



Other inputs: “optimal mix” is independent of quality

Back



Other inputs: Identification ▸ Back

- Using the empirical analog of $O = e^c L^\gamma$: $\ln O = c + \gamma \ln L + \nu_i$,

$$\tilde{\alpha}_L^{2SLS} = \alpha_L + \alpha_O \gamma + \alpha_O \frac{Cov(\nu_i, Z_i)}{Cov(L_i, Z_i)}$$

Other inputs: Identification ▸ Back

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  - Or, simply put, that innovations in O_i do not correlate with the instrument

Other inputs: Identification

Back

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Other inputs: Identification

▸ Back

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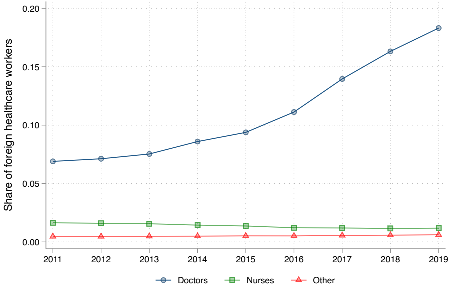
- Does the instrument Z_i affects other inputs through a channel other than the increase in physicians? Evidence suggests **no**

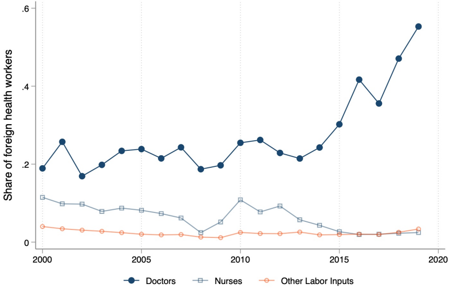
- A back-of-the-envelope calculation leveraging a set of auxiliary regressions suggests that $Cov(\nu_i, Z_i) \approx 0$

Other inputs: Z_i does not affect other inputs directly ▸ Back

- The migration wave was most significant among doctors



(a) Stock Providers in Public Hospitals

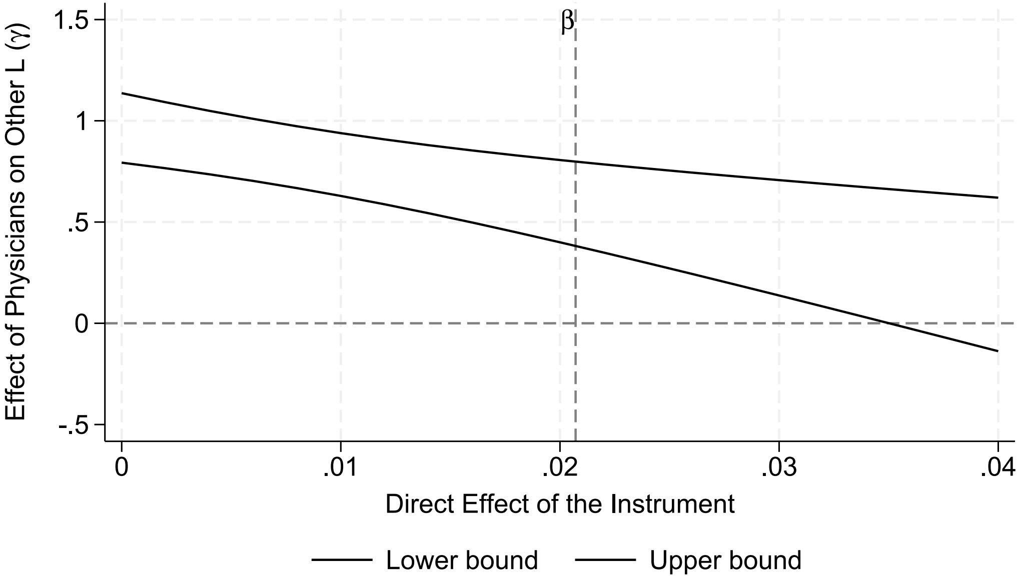


(b) Newly Registered Providers

Other inputs: Z_i does not affect other inputs directly

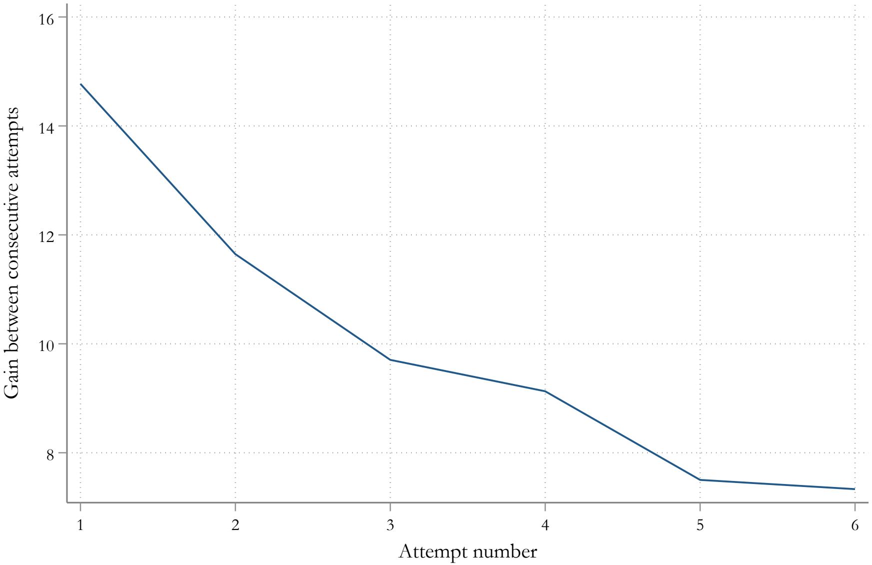
- Following Conley et al., (2012)
  1. Results are consistent with a direct effect of the instrument on other inputs equal to zero
  2. For the impact of physicians on other inputs to be zero, the direct effect of the instrument on other inputs should be implausible large (almost twice its reduced form impact β)

Other inputs: Z_i does not affect other inputs directly ‣ Back



Score gains over attempts

▸ Back



Objective Function and Estimation Process ‣ Back

Objective Function:

$$\min_{\mu,\sigma_\theta,\sigma_\epsilon} \left(\frac{1}{n_s} \sum_{k=1}^{n_s} (\hat{m}_k - \bar{m}_k) \right)^2$$

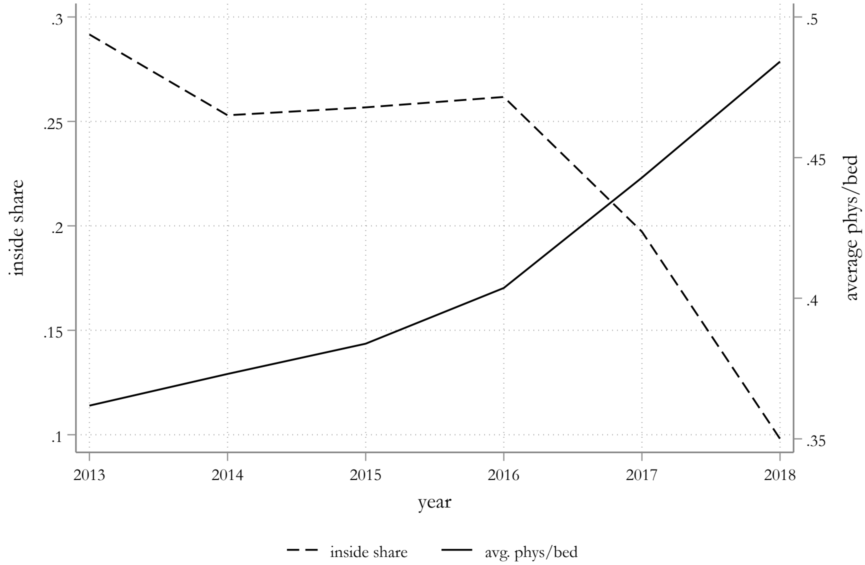
where:

$$\hat{m}_k = \text{Observed moment } k$$
$$\bar{m}_k = \text{Simulated moment } k \text{ (average over simulations)}$$

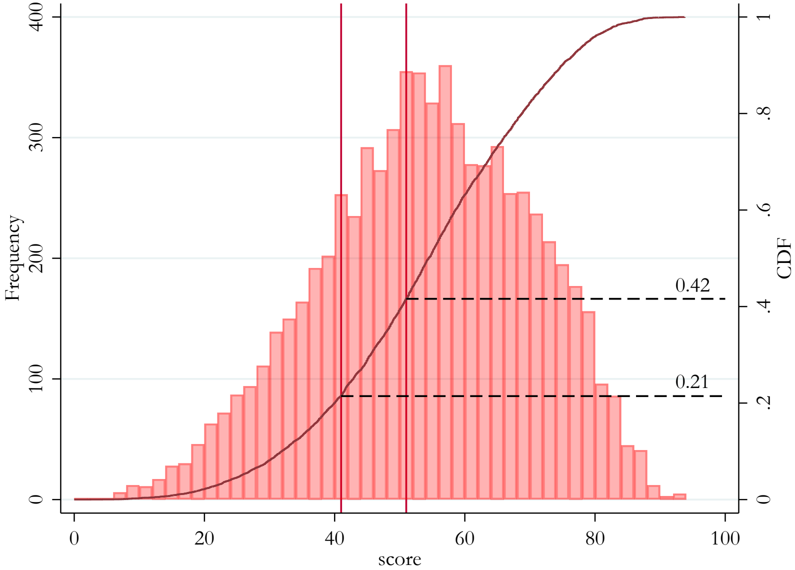
Estimation Process:

- Generate initial scores $s_{it} = \theta_i + \varepsilon_t$, with $\theta_i \sim N(\mu, \sigma_\theta^2)$ and $\varepsilon_t \sim N(0, \sigma_\epsilon^2)$
- Identify retakers: $s_{it} < s_c$
- Simulate retake scores: $s_{it+1} = \theta_i + \varepsilon_{t+1}$
- Compute simulated moments for each simulation
- Average simulated moments over multiple simulations
- Minimize the distance between observed and simulated moments

Inside Share ▸ Back



More physicians enter the system: $M \to M + \Delta M$



More on “sufficient statistics”

- “per marginal physician” effect of lowering threshold is positive iff

$$\begin{aligned}\alpha_L/\alpha_\theta &> -\tilde{\eta}_{\bar{\theta}}/\eta_L \\ &= \mathbb{E}[\theta|s > \underline{s}] - \theta(\underline{s})\end{aligned}$$

- As most marginals are foreigners and most supra-marginals are nationals:

$$\mathbb{E}[\theta|s > \underline{s}]_j \simeq \underline{s}_{\text{nationals}} + SNR_{\text{nationals}} \cdot (\underline{s}_{\text{nationals},j} - \underline{s}_{\text{nationals}})$$

$$\theta(\underline{s}) \simeq \underline{s}_{\text{foreigners}} + SNR_{\text{foreigners}} \cdot (\underline{s} - \underline{s}_{\text{foreigners}})$$

More on "sufficient statistics"

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$\rightarrow$ Estimates of SNRs and "raw moments" from score distribution are "sufficient statistics" for the "per-physician" effect of lowering threshold in hosp. j

$\rightarrow$ Independent of labor-market assumptions (CMPs)

▸ Back

Table: Passing rate among those who fail in 2013, 2013 cohort

Year	Pass (%)	Cumulative (%)
2014	25	25
2015	28	53
2016	14	67
2017	11	78
2018	5	83

Dynamic policy analysis

▸ Back

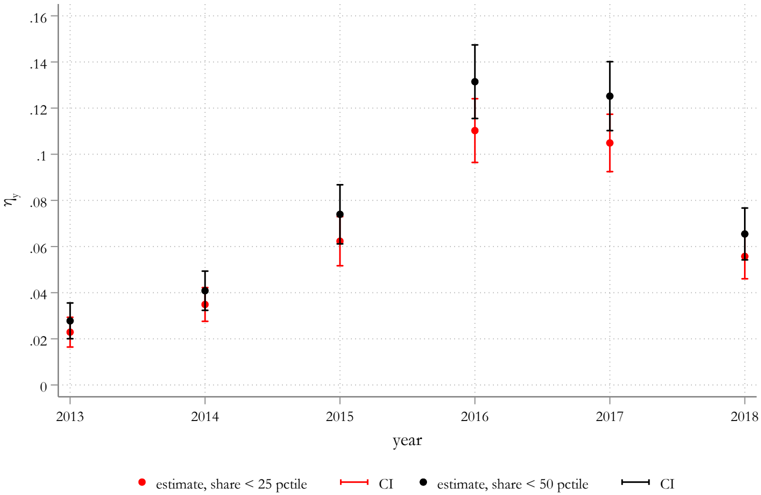
- We estimate a model of scores and retaking behavior

$$\mathit{logit}(P(\text{retake}_t)) = \alpha_\tau + \beta_{1,\tau}\text{nr. of attempts}_t + \beta_{2,\tau}\text{distance to cutoff}_t$$

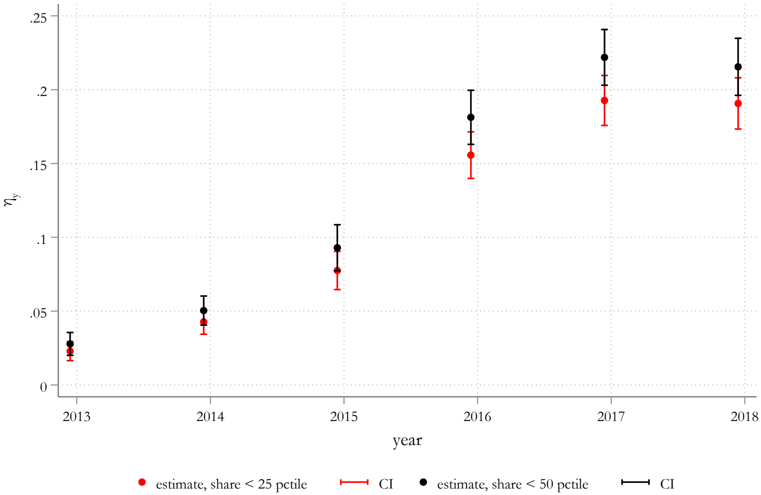
	Foreign	Nationals
nr. of attempts	-0.231	-0.163
	(0.020)	(0.059)
distance to cutoff	-0.036	-0.060
	(0.003)	(0.009)
Intercept	2.592	1.595
	(0.077)	(0.139)
N	8221	1340

- We simulate individual histories for each cohort $c \in [2013, 2018]$
- We compute yearly elasticities to the 2013 (and beyond) threshold

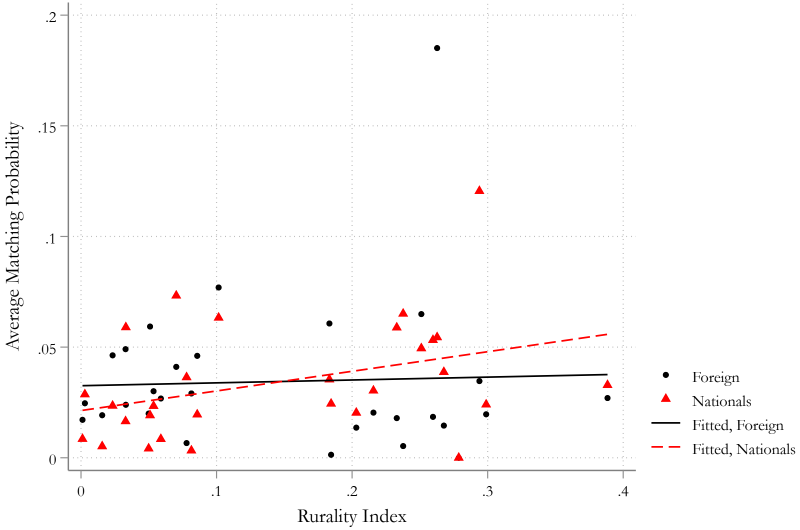
Evolution of elasticity at current cutoff, $\eta^{mortality}$, share model ▸ Back



Evolution of elasticity at current cutoff, $\eta^{mortality}$, share model ▸ Back

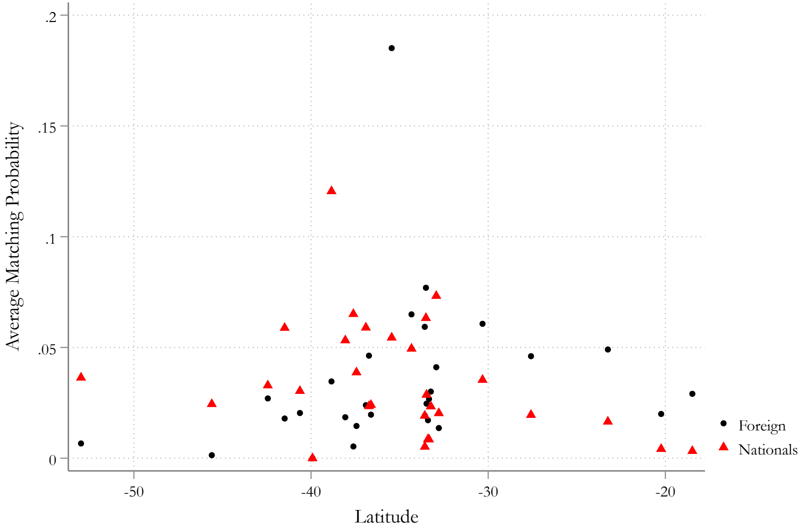


Matching Probability by Rurality ‣ Back



Matching Probability by Latitude

▸ Back



Long-term passing rates

Simulated passing year for 2013 cohort

year	$\underline{s} = 51$		$\underline{s} = 41$	
	pass	cumulative	pass	cumulative
2013	86.0	86.0	94.0	94.0
2014	6.8	92.8	3.5	97.5
2015	1.4	94.2	0.7	98.2
2016	0.3	94.6	0.2	98.4
2017	0.1	94.6	0.0	98.4
2018	0.1	94.7	0.1	98.5