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

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Introduction

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  - Restricts supply but ensures minimum quality standards
- **Research Q':**
  - How do, empirically, outcomes depend on quantity and quality of physicians?
  - How to design licensing policies that balance this trade-off?
  - How is the design affected by migration?

This paper

- A simple novel framework for the quantity-quality trade-off
  - Planner's objective depends on the quality and quantity of labor

- Highlight empirical objects needed to quantify the consequences of *locally* changing stringency

- Estimate empirical counterpart in the context of physician licensing in Chile's public healthcare sector
  - Physician scarcity is a first-order policy concern
  - Licensing exam required has a simple policy design
  - Labor market rapidly changing in recent years due to migration

This paper

- The net effects on outcomes (access, mortality) from changing licensing stringency depends on the relationship between a few “sufficient statistics:”
  - Returns to quantity and quality in the production
  - Elasticity of quantity and quality w.r.t. licensing stringency

- We provide novel estimates for these objects using quasi-exogenous variation, accounting for potential equilibrium effects

- Main findings
  - Quantity and quality matter for health outcomes
  - Lowering the licensing threshold increases access, with no net effects on quality
    - Robust to large migration wave
    - Magnitudes muted in the long-run as exam can be retaken

Contributions

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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

Roadmap for today

1. **Setting and data**
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  - Referrals follow strict guidelines based on patient's address and diagnosis
- Wages based on public sector wage schedule (independent of score)
- Scarcity is a long-standing problem
  - $\approx$ 3 million people waiting for medical attention (15% of population)
  - $\approx$ 1/4 deaths in the country occur while waiting for medical attention

Medical licensing in Chile

- "Unique National Exam of Medical Competency" is a licensing exam aimed "to evaluate knowledge and abilities to practice general medicine"
  - Theory, 180 MCQ's (+ Practical, non-binding)
  - Scored 0-100, based on absolute performance
  - Passing score $= 51$
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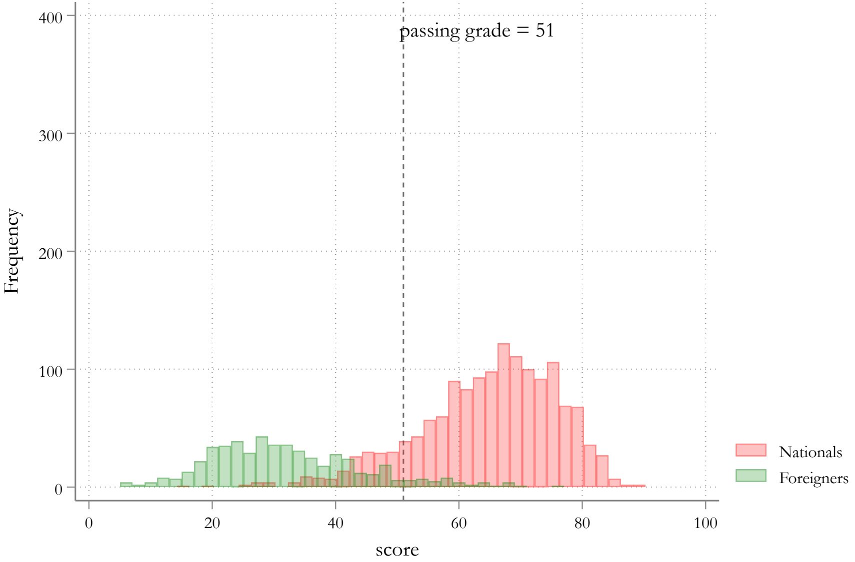
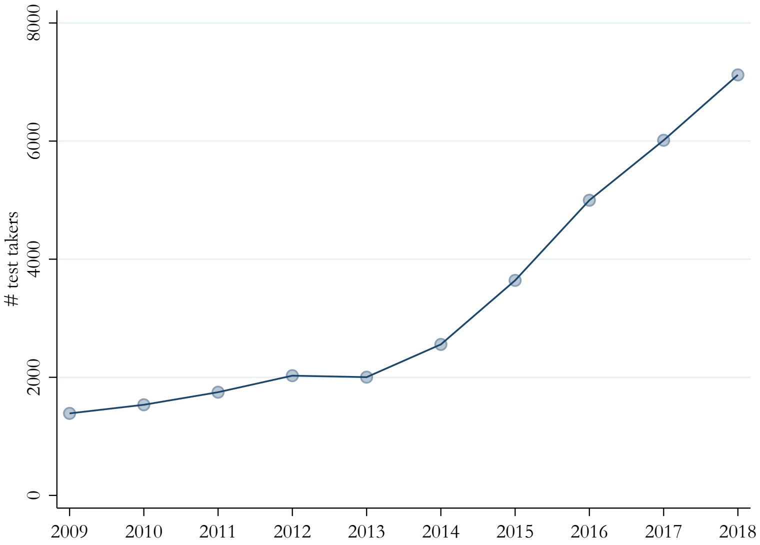
- Applied to graduate physicians in Chile and from abroad
  - Approval of exam implies automatic revalidation of foreign medical degree

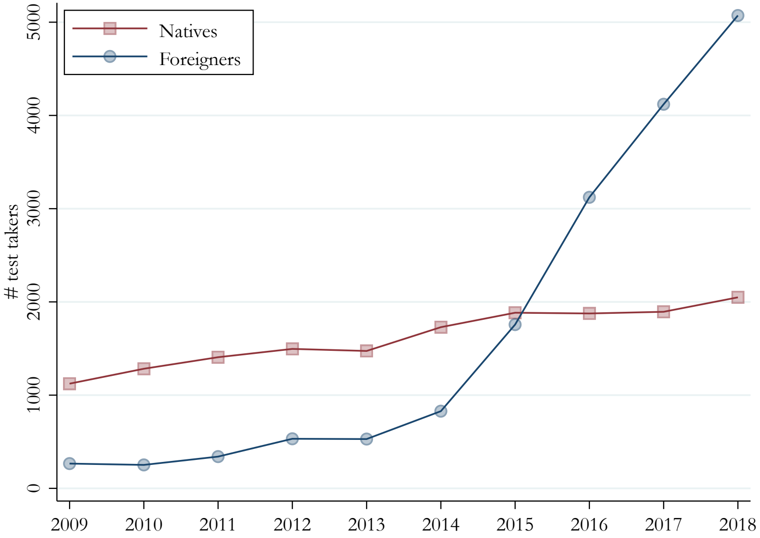
Licensing scores: 2013



Number of test-takers over time



Number of test-takers over time, by migration status



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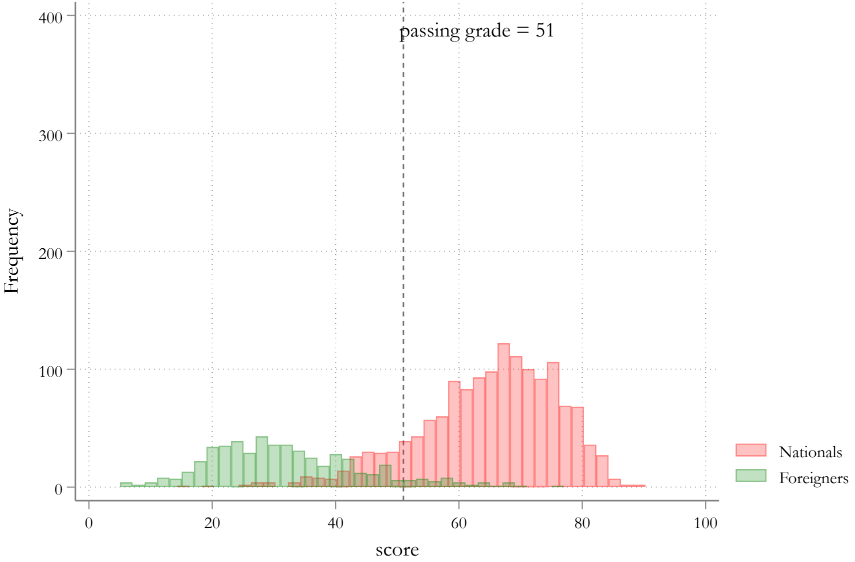
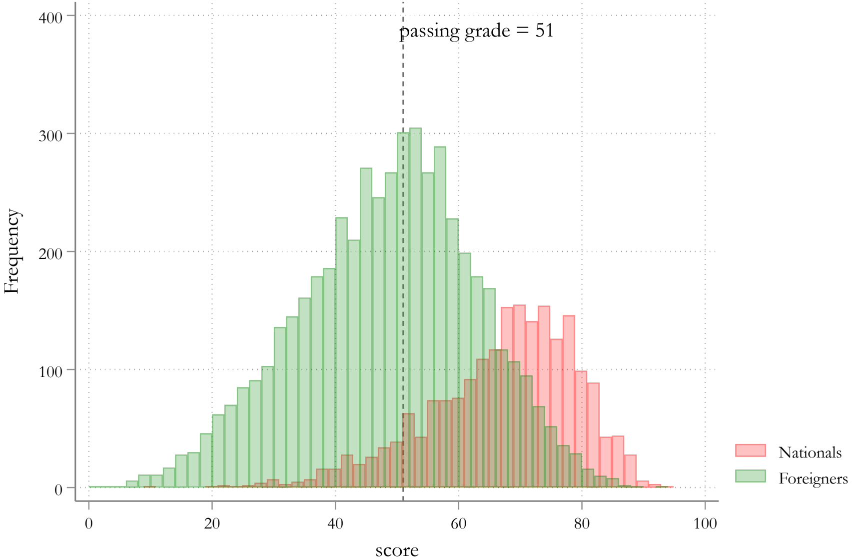


Licensing scores: 2018 ‣ More data



Data: 2011-2019

- Novel admin employer-employee data for all 181 public hospitals in Chile
    - Occupation, wages, hours, nationality, demographics, university
- Individual-level discharge data in all public hospitals
    - Date and cause of admission, date of discharge or in-hospital death date, diagnosis, patient demographics
    - + universe of death records (post discharge)
- Licensing exam scores for all exam takers
- Exits from hospitals' waiting list
    - Health providers enter patients into waiting list for specialist consultations, surgeries, or specific procedures

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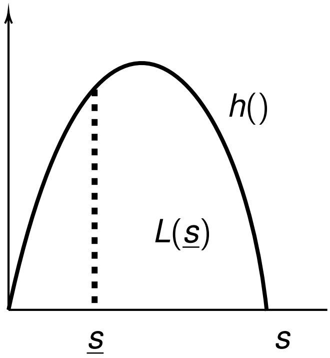

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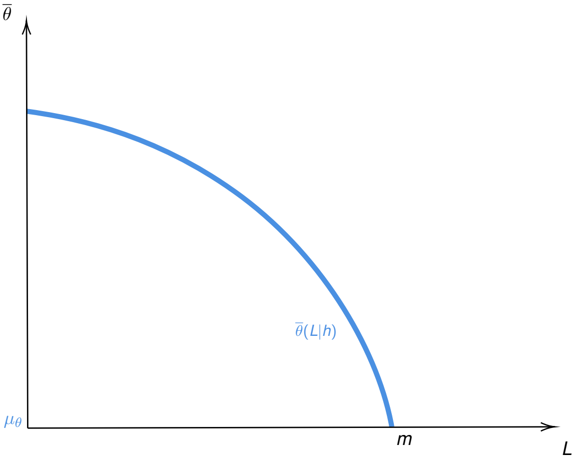

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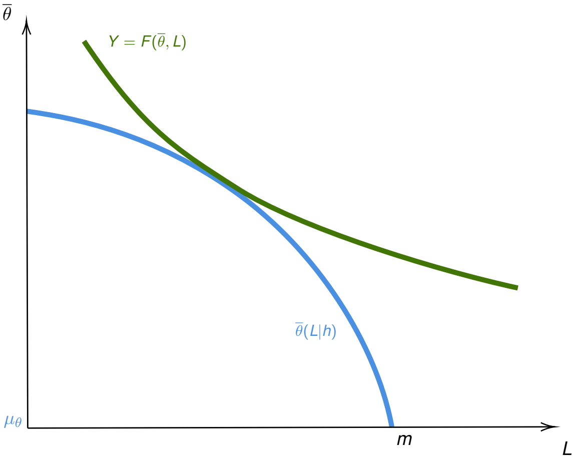

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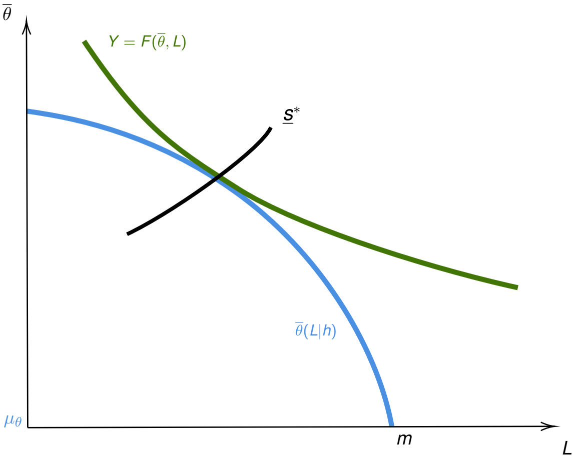

A simple licensing problem: Parametrization

- Parametrization
  - Quality index: $\bar{\theta}(\underline{s}) \equiv \mathbb{E}(\bar{\theta}|s > \underline{s})$
  - Production function: $Y = F(L(\underline{s}), \bar{\theta}(\underline{s})) = L^{\alpha_L} \cdot exp(\bar{\theta})^{\alpha_{\bar{\theta}}}$
  - Noisy test: $s = \theta + \epsilon$, where $\epsilon \sim N(0, \sigma_\epsilon^2)$ and $\theta \sim N(\mu_\theta, \sigma_\theta^2)$. $SNR \equiv \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2}$

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- Elasticity of outcome w.r.t. licensing threshold

$$\frac{1}{Y}\frac{\partial F}{\partial \underline{s}} = \underbrace{\alpha_L \cdot \frac{1}{L}\frac{\partial L}{\partial \underline{s}}}_{\text{quantity effect}} + \underbrace{\alpha_{\bar{\theta}} \cdot \left(\frac{\partial \bar{\theta}}{\partial \underline{s}}\right)}_{\text{quality effect}} = \underbrace{\frac{-m \cdot h(\underline{s})}{L}}_{\eta_L} \cdot \left(\alpha_L - \alpha_{\bar{\theta}} \cdot \underbrace{SNR \cdot (\mathbb{E}[\bar{s}|s > \underline{s}] - \underline{s})}_{-\tilde{\eta}_{\bar{\theta}}/\eta_L}\right)$$

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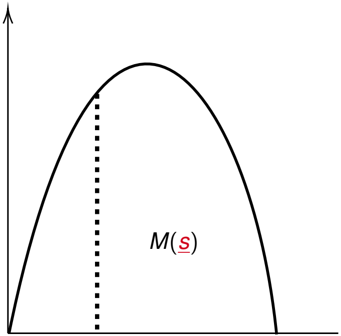
- Depends on
  - quantity elasticity, η_L: determined by mass at the margin
  - net effect per-marginal worker: > 0 as long as $\alpha_L / \alpha_{\bar{\theta}} > -\tilde{\eta}_{\bar{\theta}}/\eta_L$

Empirical Model, Overview



- m physicians. Scores are realized as a function of quality. $M(\underline{s})$ pass

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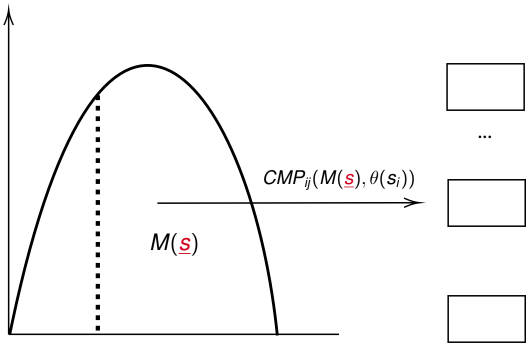

- Match with hospitals with probability CMP_{ij}; potentially endogenous

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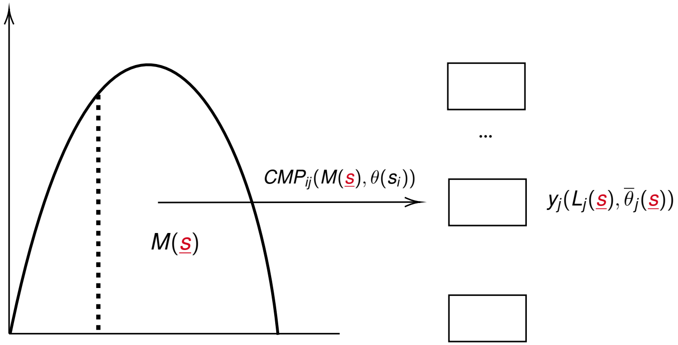

- Production is realized as a function of quality and quantity

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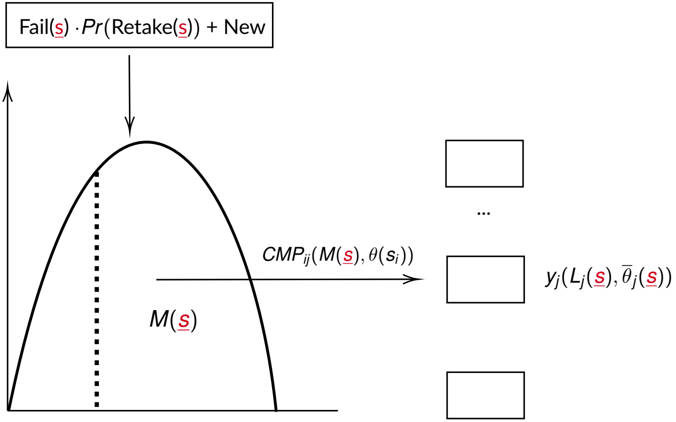
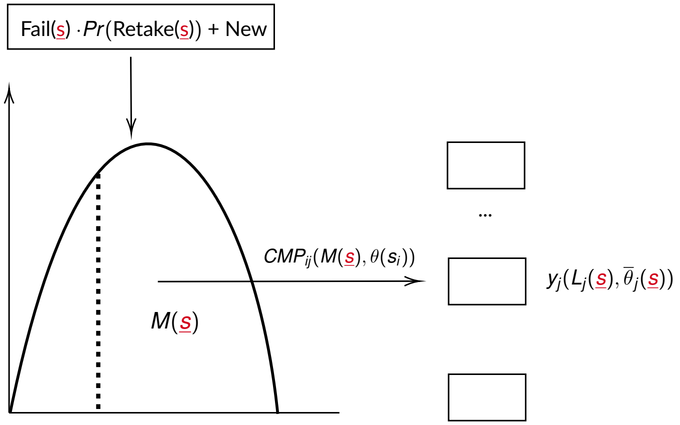


- Threshold affects set and distribution of retakers dynamically

Empirical Strategy, Overview



- Step 1: $\theta(s)$ from a model mapping $\theta \rightarrow s$ (includes retaking probability)

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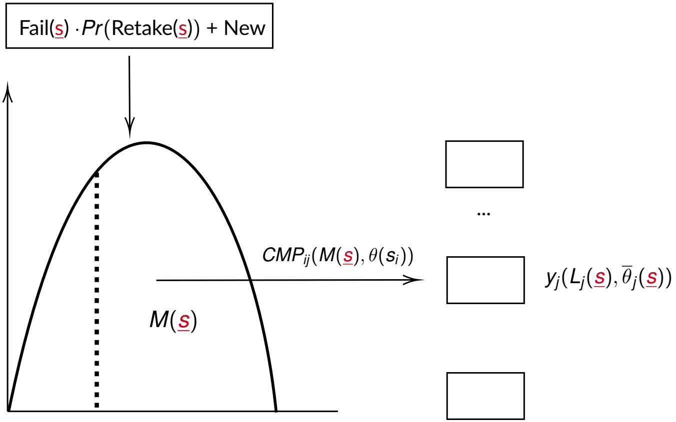

- Step 2: y_j; production function mapping inputs to outputs

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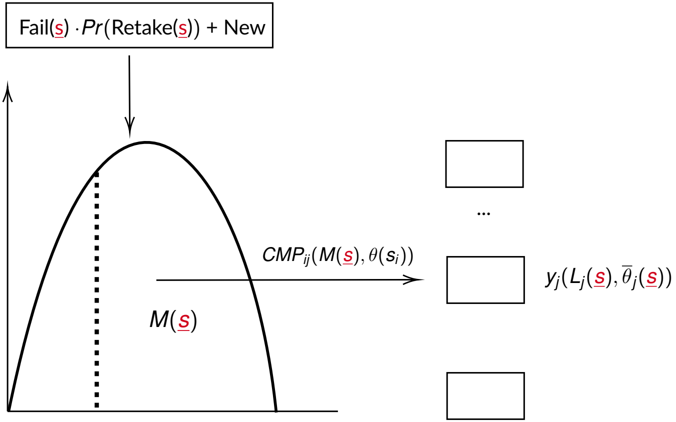

- Step 3: CMP_{ij}

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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

$$s_{in} = \theta_{i0} + \Gamma_{in} + \varepsilon_{in} \qquad \varepsilon_{in} \sim N\left(0, \sigma^2_{\varepsilon,\tau(i)}\right), \quad \theta_{i0} \sim N\left(\mu_{\theta,\tau(i)}, \sigma^2_{\theta,\tau(i)}\right)$$

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- Test-taking ability improves with exponential decay ▸ Score gains ▸ No quality gains

$$\Gamma_{in} = \sum_{k=0}^{n_i-1} \gamma_{0,\tau(i)} \cdot \exp(-\rho_{\gamma,\tau(i)} \cdot k) \quad n_i \geq 1$$

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

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

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: $\hat{SNR}_{\text{nationals}} = 0.65$; $\hat{SNR}_{\text{foreigners}} = 0.7$

✓ Can construct posterior given vector of scores $E(\theta_i | \mathbf{s}_i)$ ▸ Posterior

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Estimation: Production Function

- Outcome y^k depends on physician's quantity and quality:

$$y^k_{jt} = L_{jt}^{\alpha^k_L} \cdot exp(\bar{\theta}_{jt})^{\alpha^k_\theta} \cdot A^k_{jt} \cdot e^{\omega^k_{jt}} \cdot e^{\varepsilon^k_{jt}}$$

with ω^k_{jt} potentially known before input choices

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- We estimate the following regression leveraging panel data:

$$\ln(y_{jt}^k) = \alpha_L^k \ln(L_{jt}) + \alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} E(\theta_i | \mathbf{s}_i) + \underbrace{\gamma_t^k + \rho_j^k + \beta^k X_{jt} + \omega_{jt}^k}_{\ln(A_{jt}^k)} + \alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} \nu_{it} + \varepsilon_{jt}^k$$

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- Error term includes ω_{jt}^k and measurement error ν_{it}

Empirical Strategy: 2SLS

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

$$Z^L_{jt} = \sum_c \%\Delta\text{Test-takers}^c \times \text{share physicians}^c_{j,t-1}$$

$$Z^\theta_{jt} = \sum_c \Delta\text{Avg. Quality}^c \times \text{share physicians}^c_{j,t-1}$$

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$$Z_{jt}^{\theta} = \sum_{c} \Delta\text{Avg. Quality}^{c} \times \text{share physicians}_{j,t-1}^{c}$$

- 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

Outcomes

- $\mathcal{I}(L)$ is the set of patients treated
- $\Delta m_i(\bar{\theta}, L)$ is the value added of treatment for individual i
- Population health:

$$
\begin{aligned}
Y(L,\theta) &= \int_i m_{i0}\,di + \int_{i\in|\mathcal{I}(L)|} \Delta m_i(\bar{\theta}, L)\,di \\
&= \underbrace{|\mathcal{I}(L)|}_{\text{service rate}} \times \underbrace{\frac{1}{|\mathcal{I}(L)|}\int_{i\in|\mathcal{I}(L)|} \Delta m_i(\bar{\theta}, L)\,di}_{\text{treatment value added}} \quad (+\text{ Constant})
\end{aligned}
$$

We measure treatment value added as decrease in mortality (+ complications)

2SLS Estimates: The impact of physician on treatment value-added

	Mortality			In-hospital
	In-Hospital		30 days	Complications
	Ln death rate	Pred. death rate	Ln death rate	Ln complications rate
	(1)	(2)	(4)	(5)
Ln Physicians ($\hat{\alpha}_L$)	-0.82	0.12	-0.74	-0.97
	(0.31)	(0.08)	(0.27)	(0.26)
Avg. Physicians' Quality ($\hat{\alpha}_\theta$)	-0.04	-0.00	-0.04	-0.05
	(0.02)	(0.01)	(0.01)	(0.01)
Ratio ($\hat{\alpha}_L/\hat{\alpha}_\theta$)	19.00	-	17.61	19.39
	(5.69)	-	(5.01)	(4.23)
Case-mix Controls	Yes	No	Yes	Yes
Hospital and Year FEs	Yes	Yes	Yes	Yes
Observations	1,402	1,402	1,402	1,373
Mean Dep. var.	3.28	3.51	5.08	11.65
F-stat (First-stage)	21.97	34.50	21.97	21.15
Anderson-Rubin (χ^2) p-value	0.00	0.03	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.

▸ Other Inputs ▸ Alternative Model

The impact of physician quantity and quality on service rate

	Ln service rate	Ln inpatient surgeries	Ln exits from waiting list	
			Surgical	Medical
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	1.01	4.98	3.69	3.00
	(0.28)	(1.66)	(1.70)	(1.34)
Avg. Physicians' Quality ($\hat{\alpha}_\theta$)	0.01	0.11	-0.00	0.02
	(0.02)	(0.09)	(0.09)	(0.07)
Observations	1,402	744	738	942
Mean Dep. Var.	0.015	3,803	1,534	8,403
F-stat (First-stage)	21.97	12.16	9.85	15.83
Anderson-Rubin (χ^2)	0.000	0.000	0.000	0.000

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.

Roadmap for today

1. Setting and data
2. Empirical model
3. **Estimation**
   - Latent quality
   - Production function
   - **Sorting**
4. Policy counterfactual: Relaxing the licensing threshold
   - Short-run effect
   - Long-run effect

A model for CMP's

- Mass $M(\underline{s})$ of physicians pass test and seek jobs
  - Preferences over hospitals $u_{ij} = \tilde{\delta}_{ij} + \varepsilon_{ij}$, with $\varepsilon_{ij} \sim$ T1EV

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  - Preferences over physicians are vertical on quality $\hat{\theta}_i(s)$ ▸ Sorting Patterns
- Equilibrium (with fixed wages) satisfies pair-wise stability

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$\Rightarrow$ Choice-sets are determined by a set of cutoffs $\underline{\hat{\theta}}_j$ (Azevedo and Leshno, 2016)

$$CMP_{ij} = \frac{e^{\tilde{\delta}_{ij}} 1\{\hat{\theta}_i \geq \underline{\hat{\theta}}_j\}}{1 + \sum_{j'} e^{\tilde{\delta}_{ij'}} 1\{\hat{\theta}_i \geq \underline{\hat{\theta}}_{j'}\}} \approx \frac{e^{\tilde{\delta}_{ij}} \left[e^{-e^{\lambda(\hat{\theta}_i - \underline{\hat{\theta}}_j)}}\right]}{1 + \sum_{j'} e^{\tilde{\delta}_{ij'}} \left[e^{-e^{\lambda(\hat{\theta}_i - \underline{\hat{\theta}}_{j'})}}\right]}$$

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where $1\{\hat{\theta}_i \geq \underline{\hat{\theta}}_j\}$ depends on ratio of job seekers to vacancies ▸ Details

- $\frac{M_i^0(\underline{S})}{\kappa_j}$: Approved of similar quality to i: directly increases cutoffs
- $\frac{M_i^+(\underline{S})}{\kappa_j}$: Approved of higher quality than i: "trickle down" indirectly increases cutoffs

Estimation: Sorting

- We approximate CMP's with a multinomial logit form

$$CMP_{ijt} = \frac{e^{\tilde{\delta}_{ij}} 1\{\hat{\theta}_i \geq \underline{\hat{\theta}}_j(M_{it}/\kappa_{jt})\}}{1 + \sum_{j'} e^{\tilde{\delta}_{ij'}} 1\{\hat{\theta}_i \geq \underline{\hat{\theta}}_{j'}(M_{it}/\kappa_{j't})\}} \approx \frac{e^{\boldsymbol{\alpha}_j \boldsymbol{z}_{it} + \beta M_{it}/\kappa_{jt}}}{1 + \sum_{j'} e^{\boldsymbol{\alpha}_{j'} \boldsymbol{z}_{it} + \beta M_{it}/\kappa_{j't}}}$$

  with

$$\boldsymbol{z}_{it} = [\text{National}_i, \text{quality quartile}_i, \text{time}_t]$$

  and
    - $M_{it} = [M_{it}^0, M_{it}^+] = [\text{Test Takers}_{\text{range(i),t}}, \text{Test Takers}_{\text{range(k>i),t}}]$
    - $\kappa_{jt} = \text{Beds}_{jt}/\text{Stock of Physicians}_{j,t-1}$

- Options j: 29 hospital referral regions + outside op. (priv. sector, primary care)

CMP estimates ‣ More

	Alternative Models			Placebo
	(1)	(2)	(3)	(4)
Distance$_{ij}$	-2.646	-2.647	-2.638	-2.650
	(0.108)	(0.108)	(0.108)	(0.108)
$(M^0_{it} + M^+_{it})/\kappa_{jt}$	-0.124			
	(0.014)			
$(M^0_{it})/\kappa_{jt}$		-0.265	-0.293	
		(0.050)	(0.197)	
M^+_{it}/κ_{jt}		-0.022	-0.070	
		(0.037)	(0.043)	
M^-_{it}/κ_{jt}				-0.020
				(0.013)
Time Trend	Y	Y	N	N
Alt.-specific Year FE	N	N	Y	Y

Estimated by MLE
N = 428,760; J=30 options (14,292 individuals)
M^-_{it} = Test Takers$_{\text{range(k<i),t}}$, M_{it} = Test Takers$_{\text{range(k=i),t}}$ M^+_{it} = Test Takers$_{\text{range(k>i),t}}$
Test takers measured in 100's.
Distance measured in km.

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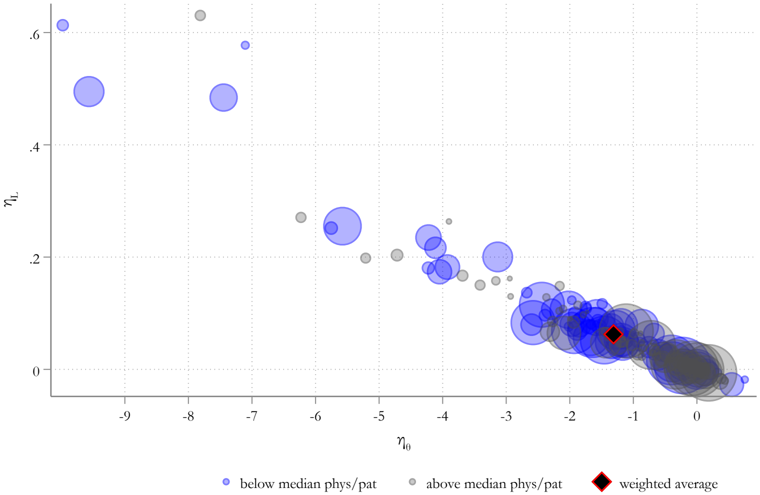
Elasticity of quantity and semi-elasticity of quality by hospital in ‘18

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



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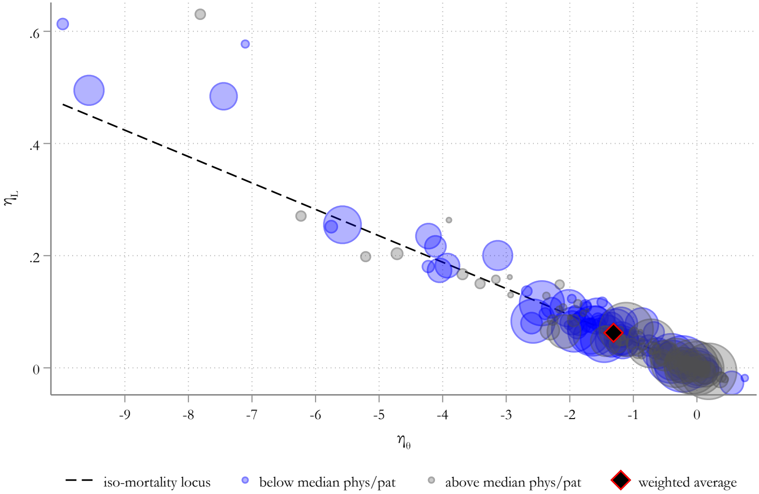

▸ Alternative Specification

Taking stock

- Outcome depends on service rate and 'value added' (-mortality)

$$Y(L,\theta) = \underbrace{|\mathcal{I}(L)|}_{\text{service rate}} \times \underbrace{\frac{1}{|\mathcal{I}(L)|}\int_{i\in|\mathcal{I}(L)|} \Delta m_i(\bar{\theta}, L)di}_{\text{treatment value added}}$$

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- On average, service rate increases when threshold is relaxed

$$\overline{\eta}^{\text{service rate}}_{\underline{S}} = \overline{\eta_{L_j,\underline{s}}} \cdot \alpha^{\text{service rate}}_{L} + \tilde{\eta}_{\bar{\theta}_j,\underline{s}} \cdot \cancelto{0}{\alpha^{\text{service rate}}_{\bar{\theta}}} \quad > \quad 0$$

Taking stock

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$$Y(L,\theta) = \underbrace{|\mathcal{I}(L)|}_{\text{service rate}} \times \underbrace{\frac{1}{|\mathcal{I}(L)|}\int_{i\in|\mathcal{I}(L)|} \Delta m_i(\bar{\theta}, L)di}_{\text{treatment value added}}$$

- On average, service rate increases when threshold is relaxed

$$\overline{\eta}_{\underline{S}}^{\text{service rate}} = \overline{\eta_{L_j,\underline{s}}} \cdot \alpha_L^{\text{service rate}} + \tilde{\eta}_{\bar{\theta}_j,\underline{s}} \cdot \cancelto{0}{\alpha_{\bar{\theta}}^{\text{service rate}}} \quad > \quad 0$$

- On average, mortality is unaffected when the threshold is relaxed

$$\overline{\eta}_{\underline{S}}^{\text{mortality}} = \overline{\eta_{L_j,\underline{s}}} \cdot \alpha_L^{\text{mortality}} + \overline{\tilde{\eta}_{\bar{\theta}_j,\underline{s}}} \cdot \alpha_{\bar{\theta}}^{\text{mortality}} = 0$$

Taking stock

- Outcome depends on service rate and ‘value added’ (-mortality)

$$Y(L,\theta) = \underbrace{|\mathcal{I}(L)|}_{\text{service rate}} \times \underbrace{\frac{1}{|\mathcal{I}(L)|}\int_{i\in|\mathcal{I}(L)|} \Delta m_i(\bar{\theta}, L)di}_{\text{treatment value added}}$$

- On average, service rate increases when threshold is relaxed

$$\overline{\eta}^{\text{service rate}}_{\underline{S}} = \overline{\eta_{L_j,\underline{s}}} \cdot \alpha^{\text{service rate}}_{L} + \tilde{\eta}_{\bar{\theta}_j,\underline{s}} \cdot \cancelto{0}{\alpha^{\text{service rate}}_{\bar{\theta}}} \quad > \quad 0$$

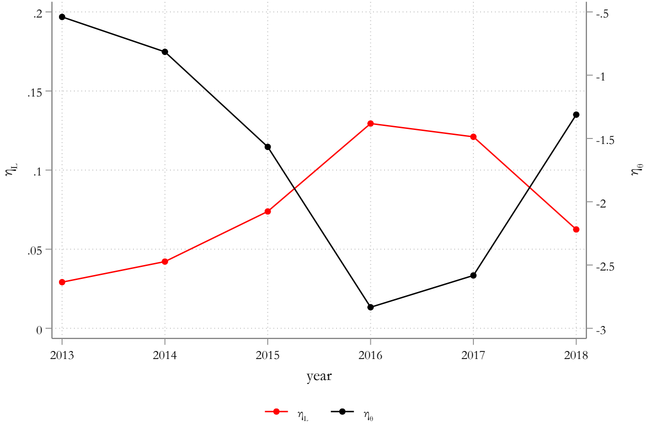
- On average, mortality is unaffected when the threshold is relaxed

$$\overline{\eta}^{\text{mortality}}_{\underline{S}} = \overline{\eta_{L_j,\underline{s}}} \cdot \alpha^{\text{mortality}}_{L} + \overline{\tilde{\eta}_{\bar{\theta}_j,\underline{s}}} \cdot \alpha^{\text{mortality}}_{\bar{\theta}} = 0$$

- Relaxing the threshold increases service rate and mortality is unaffected

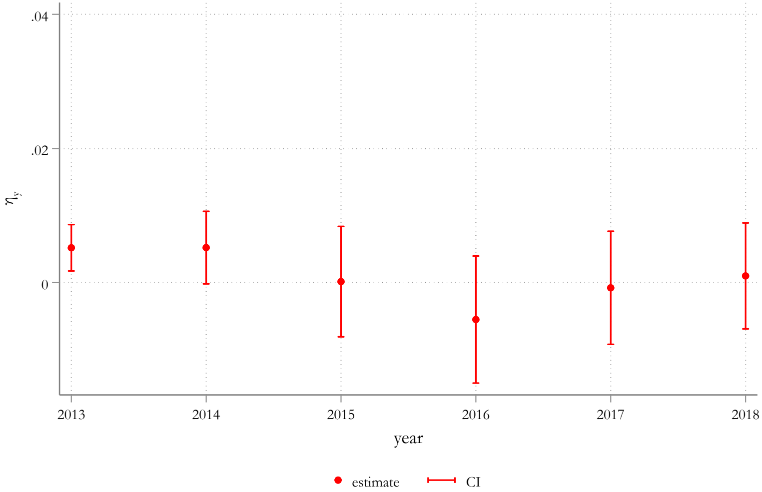
$$\Rightarrow \eta^{Y}_{\bar{s}} \simeq \eta^{\text{service rate}}_{\bar{s}} - \eta^{\text{mortality}}_{\bar{s}} > 0$$

Evolution of elasticities of quantity and quality



- Offsetting evolution of elasticities of quantity and quality
- U-shape: higher mass at margin but less vacancies over time

Evolution of elasticity of mortality at current cutoff, $\overline{\eta}_{S}^{\text{mortality}}$



- Elasticity of mortality w.r.t threshold has stayed constant over time

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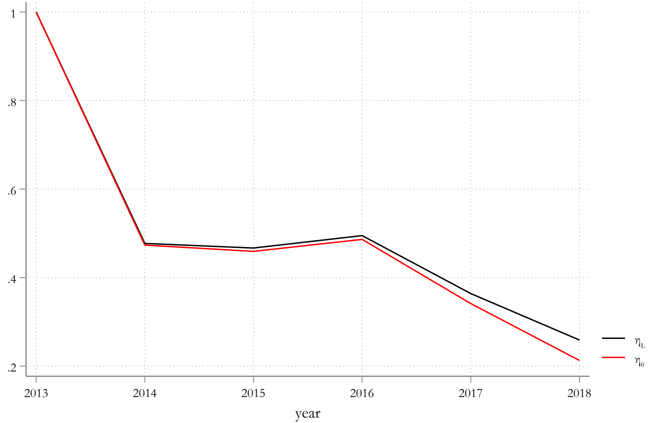
Dynamic policy effects

- 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: increasing 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?

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

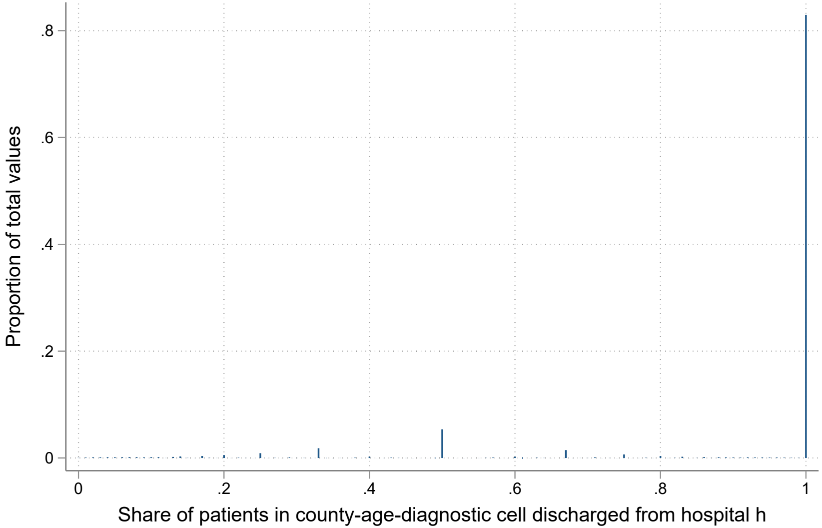
Referrals follow strict guidelines ‣ Back

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

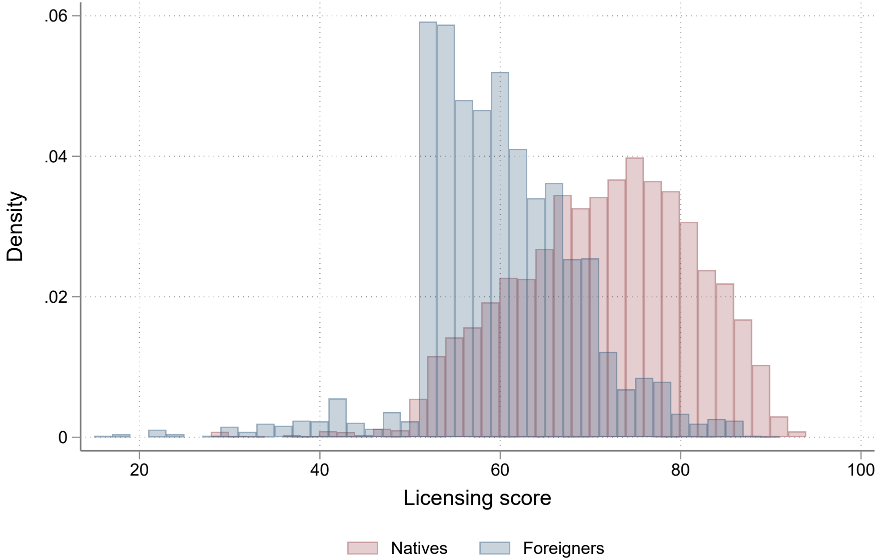
1. Complejo Hospitalario San José; **2.** Hospital Clínico De Niños Roberto Del Río; **3.** Instituto Nacional Del Cáncer Dr. Caupolicán Pardo Correa; **4.** Centro de Referencia de Salud Cordillera Oriente; **5.** Hospital Del Salvador; **6.** Instituto Nacional del Torax; **7.** Hospital de Niños Dr.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

Strict referrals

▸ Back

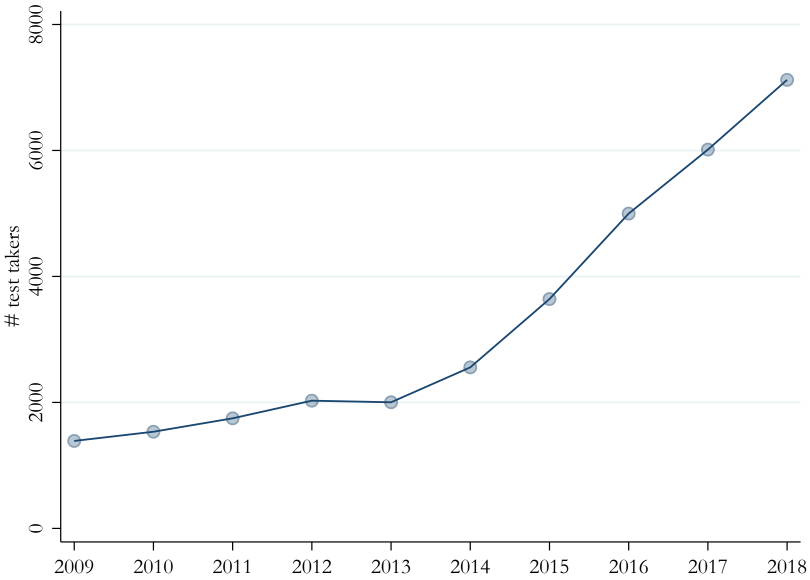


Licensing scores conditional on working in a public hospital ‣ Back



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:

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

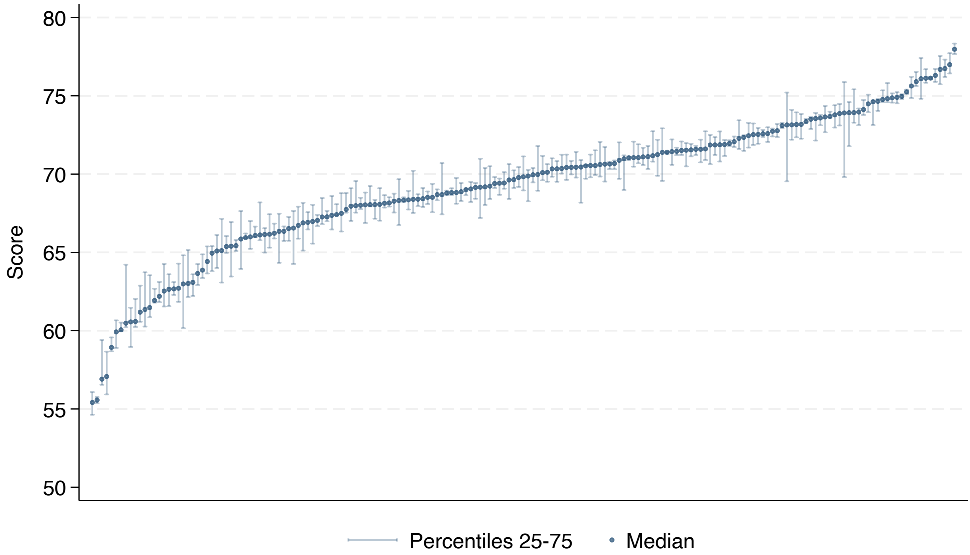
    - Cutoff in R is such that capacity equals L-phys. who prefer R + displaced L-phys. + displaced H-phys.

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

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

Box plot of quality by hospital

‣ Back



Elasticity of quantity

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

- 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

Licensing score imputation ‣ Back

- Before EUNACOM 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

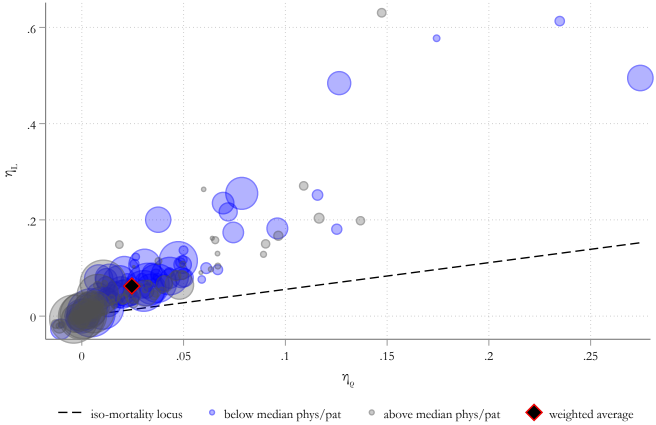
Descriptive Statistics: Hospital Characteristics

	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

Elasticity of quantity and semi-elasticity of quality by hospital

Back

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

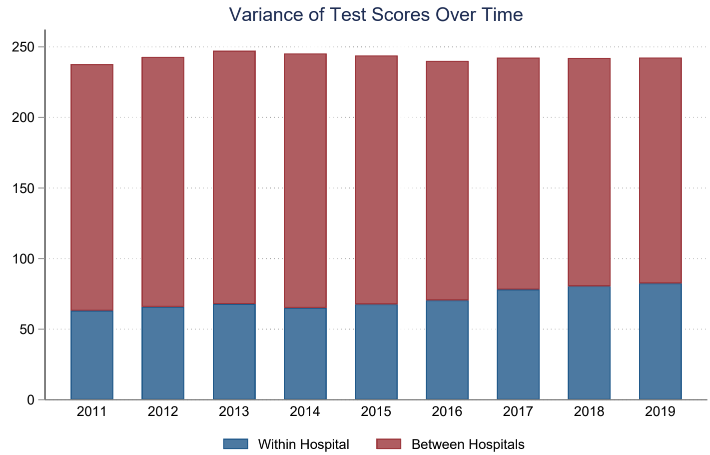


- Main result assuming that the quality index is equal to the share of physicians below median quality in the data.

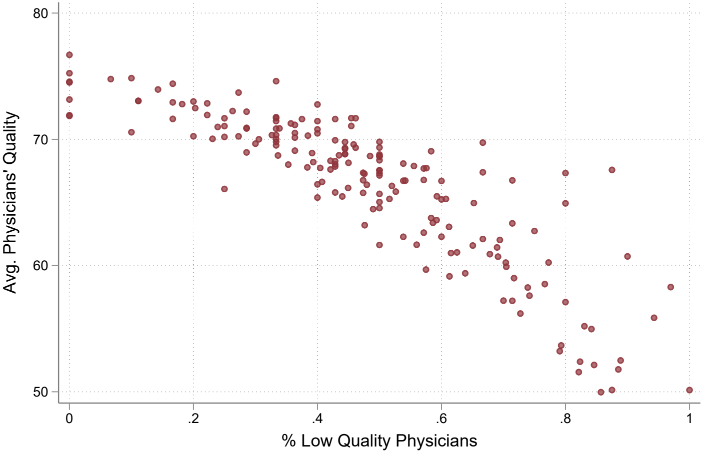
Descriptive Statistics: Patient and Hospital Characteristics

	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

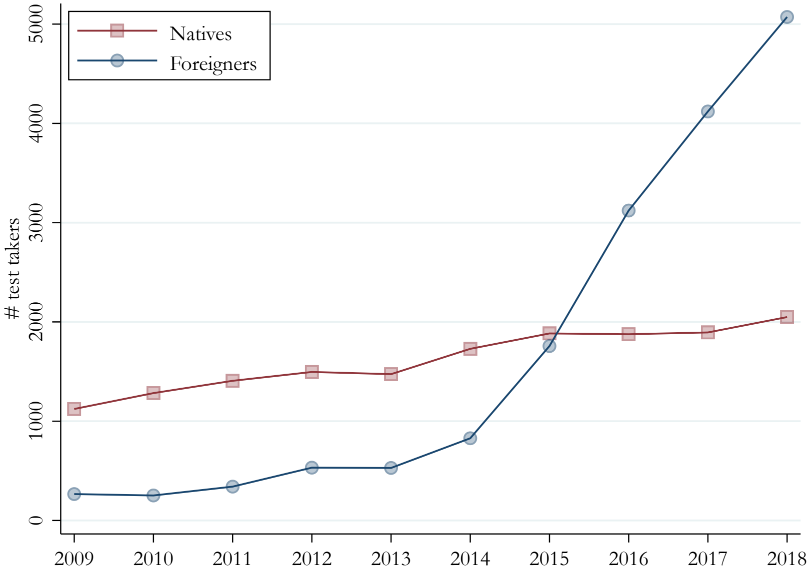


Descriptive Statistics: $\bar{\theta}$ and % Below $\bar{\theta}$



Number of test-takers over time, by migration status

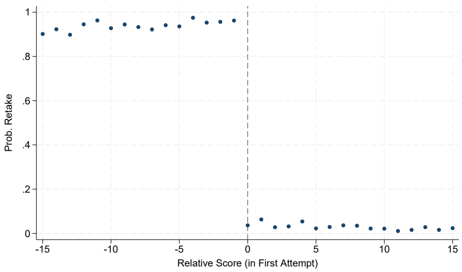
Back



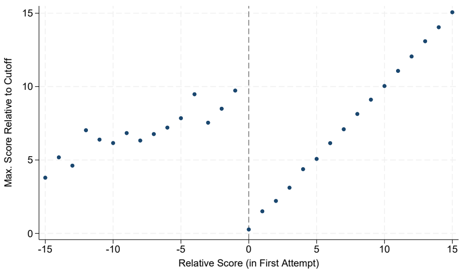
Disentangling test-taking ability and quality

- 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



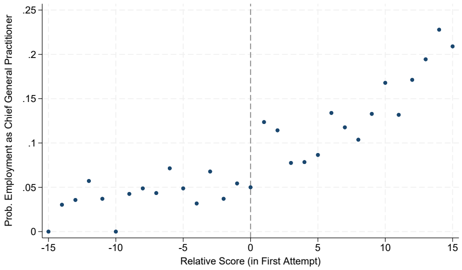
(a) Retaking Probability v.s. first score



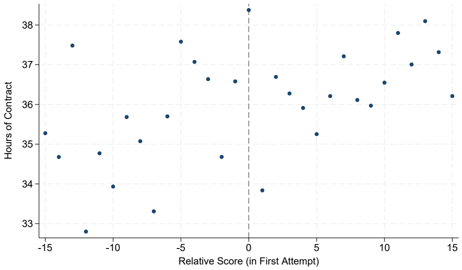
(b) Maximum achieved score v.s. first score

- 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

- Since we assumed that θ and ϵ are normally distributed, we can recover the posterior of quality for each physician given type-specific prior, SNRs, and their sequences of scores over attempts:

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

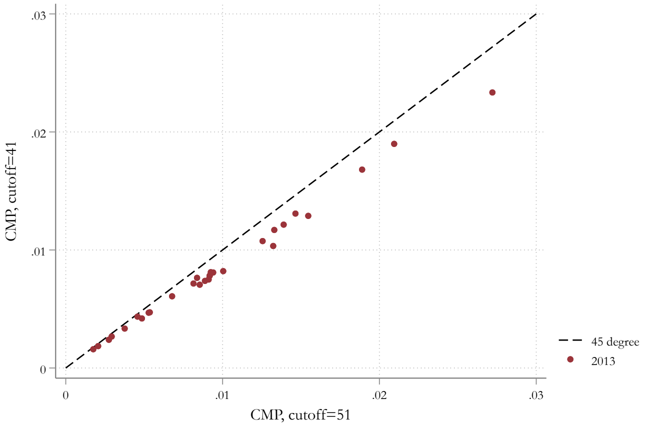
with

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

- The average quality of physicians in hospital j

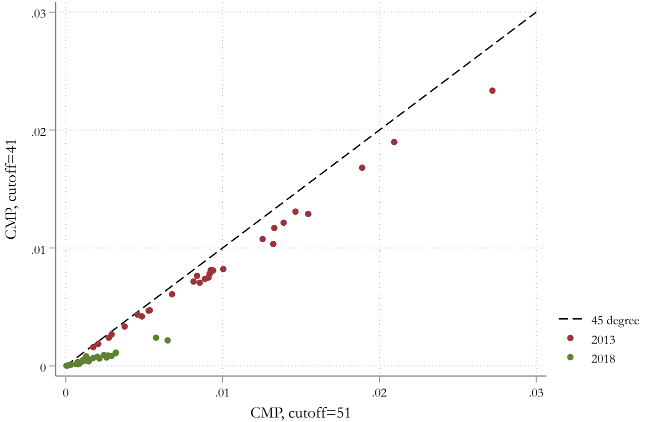
$$\bar{\theta}_j = \frac{1}{L_j} \left(\sum_{i \in j} E(\theta_i | s_i) + \nu_i \right)$$

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 $\bar{s}_{in}$ as:

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

- 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

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

with

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

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

where

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

The impact of physician quantity and quality on other outcomes

Back

	Ln predicted death rate	Ln complications rate	Ln exits waitlist	Ln surgery (inpatient)
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	-0.008	-0.798	3.426	4.238
	(0.048)	(0.259)	(1.091)	(1.324)
Avg. Physicians' Quality ($\hat{\alpha}_\theta$)	-0.048	0.574	-0.710	-0.970
	(0.034)	(0.184)	(0.754)	(0.852)
Case-mix Controls	Yes	Yes	Yes	Yes
Hospital and Year FEs	Yes	Yes	Yes	Yes
Observations	1,376	1,349	1,018	740
Mean Dep. Var.	3.49	11.65	10,386	3,819
F-stat (First-stage)	14.76	14	10.17	8.893
Anderson-Rubin (χ^2)	0.09	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. Complications include: infections, hemorrhage, and "other complications"

Other inputs ▸ Back

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

Other inputs ‣ Back

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

Other inputs

▸ Back

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

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

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  2. “Optimal mix” is independent of the average doctors’ quality in a hospital

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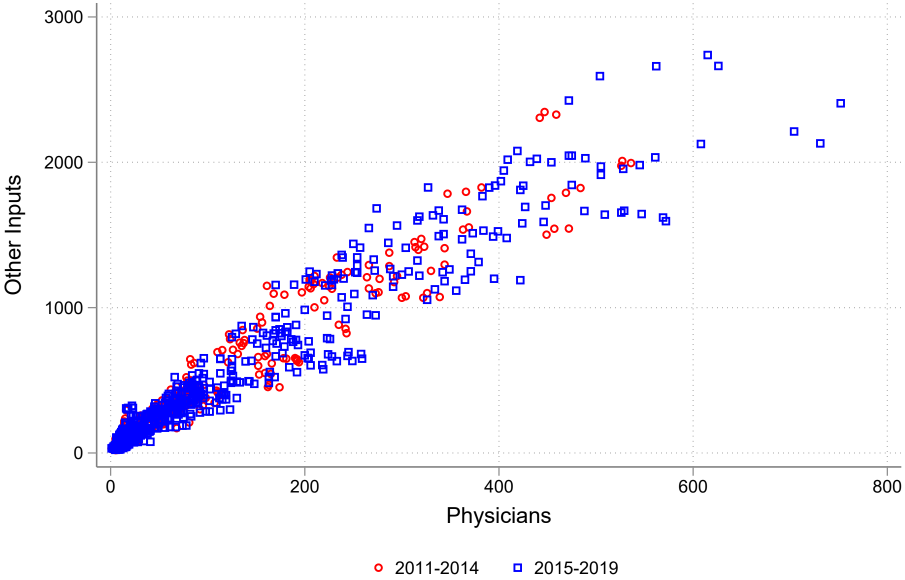
  2. "Optimal mix" is independent of the average doctors' quality in a hospital

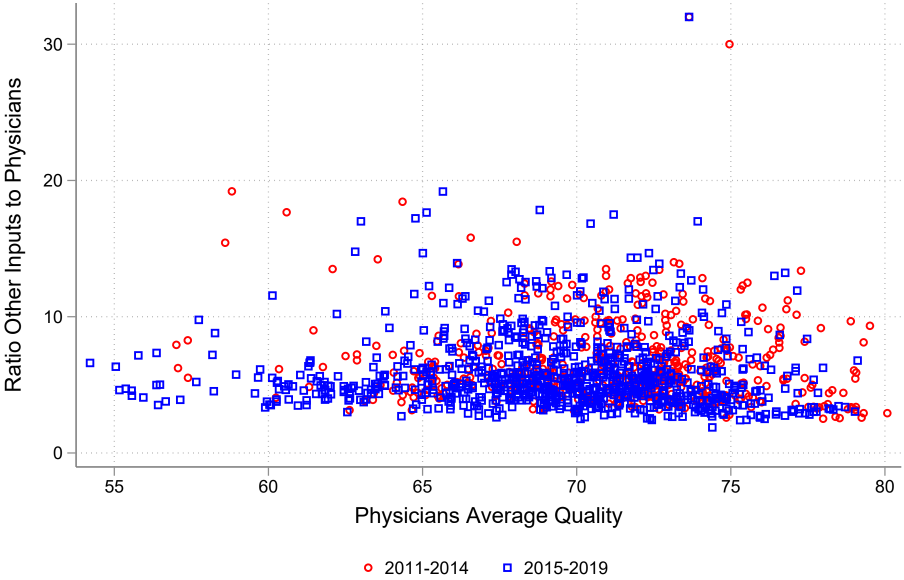
- We can assess these assumptions empirically

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 $O = e^c L^\gamma$: $\ln O = c + \gamma \ln L + \nu_i$,

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

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- Identification of the total effect of an extra doctor (i.e., $\tilde{\alpha}_L = \alpha_L + \alpha_O \gamma$) requires that $Cov(\nu_i, Z_i) = 0$
  - Or, simply put, that innovations in O_i do not correlate with the instrument

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- Does the instrument Z_i affects other inputs through a channel other than the increase in physicians?

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▸ Back

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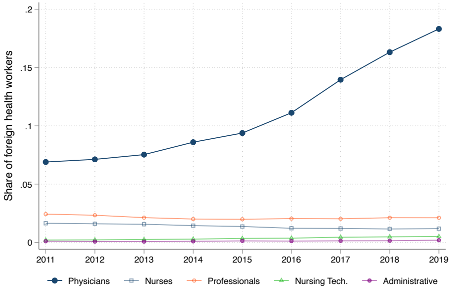
  - Or, simply put, that innovations in O_i do not correlate with the instrument

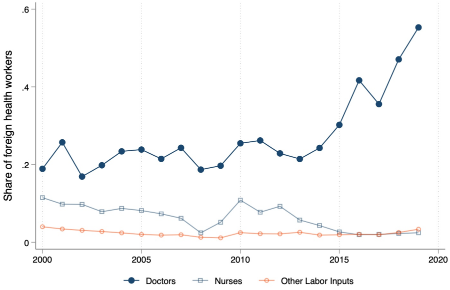
- Does the instrument Z_i affects other inputs through a channel other than the increase in physicians? Evidence suggests **no**

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

- A back-of-the-envelope calculation leveraging a set of auxiliary regressions suggests that $Cov(\nu_i, Z_i) \approx 0$
- The migration wave was most significant among doctors



(a) Stock Providers in Public Hospitals

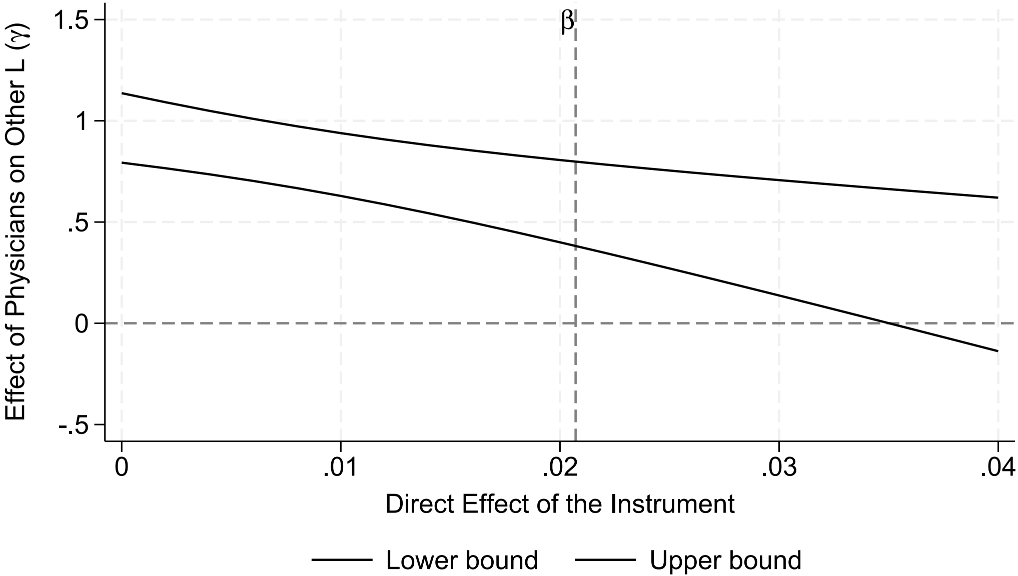


(b) Newly Registered Providers

Other inputs: Z_i does not affect other inputs directly

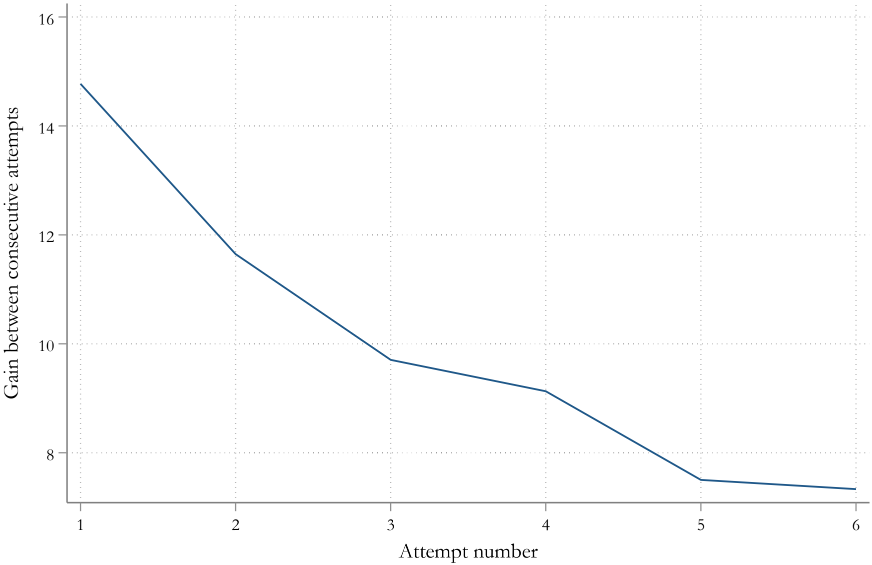
- Following Conley et al., (2012)
    1. Results are consistent with a direct effect of the instrument on other inputs equal to zero
    2. For the impact of physicians on other inputs to be zero, the direct effect of the instrument on other inputs should be implausible large (almost twice its reduced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

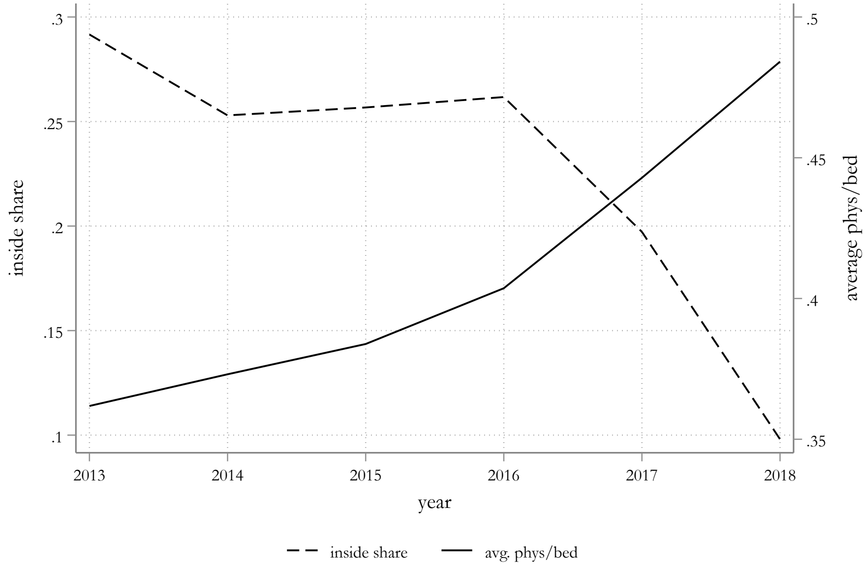
$$\hat{m}_k = \text{Observed moment } k$$
$$\bar{m}_k = \text{Simulated moment } k \text{ (average over simulations)}$$

Estimation Process:

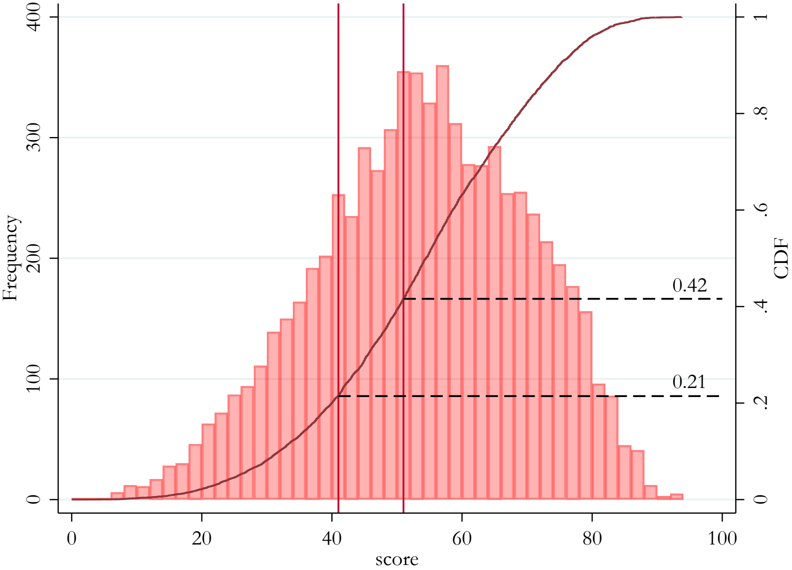
- Generate initial scores $s_{it} = \theta_i + \varepsilon_t$, with $\theta_i \sim N(\mu, \sigma_\theta^2)$ and $\varepsilon_t \sim N(0, \sigma_\epsilon^2)$
- Identify retakers: $s_{it} < s_c$
- Simulate retake scores: $s_{it+1} = \theta_i + \varepsilon_{t+1}$
- Compute simulated moments for each simulation
- 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 infra-marginals are nationals:

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

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

More on "sufficient statistics"

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

→ 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

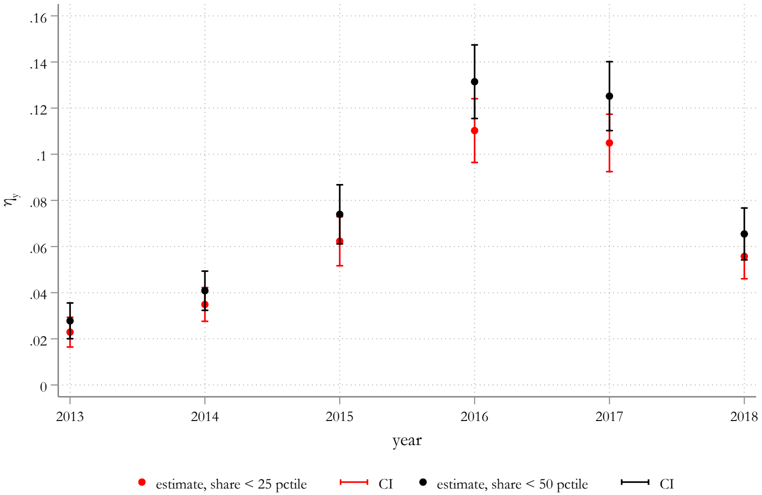
- We estimate a model of scores and retaking behavior

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

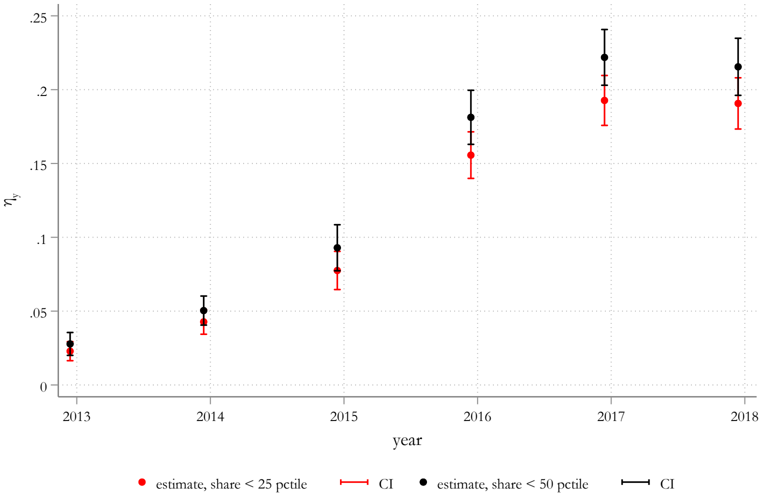
	Foreign	Nationals
nr. of attempts	-0.231	-0.163
	(0.020)	(0.059)
distance to cutoff	-0.036	-0.060
	(0.003)	(0.009)
Intercept	2.592	1.595
	(0.077)	(0.139)
N	8221	1340

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

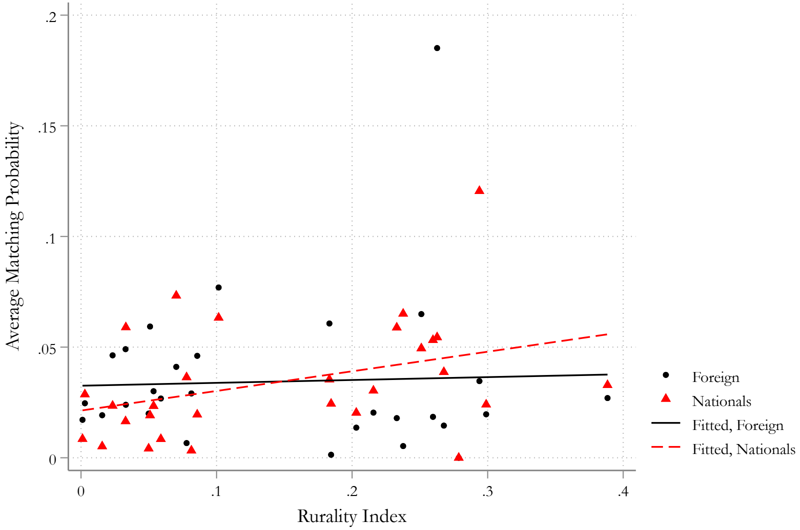
Evolution of elasticity at current cutoff, $\eta^{mortality}$, share model ‣ Back



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

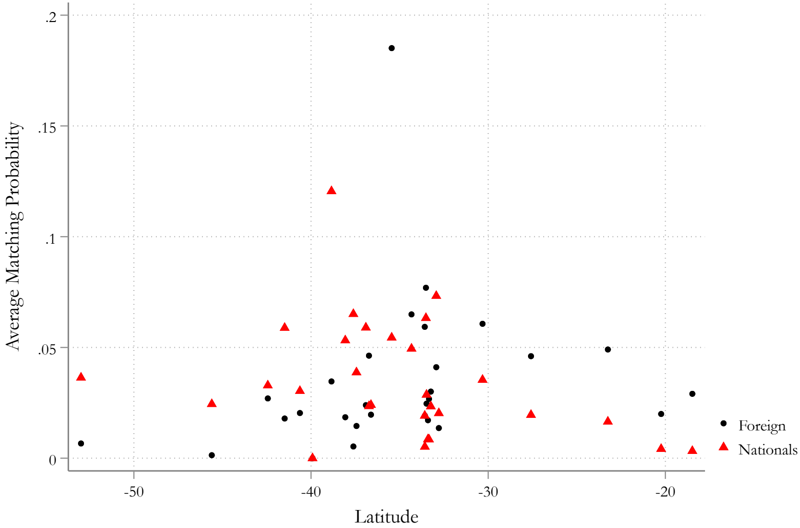


Matching Probability by Rurality ‣ Back



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