Education Policy and the Quality of Public Servants

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DSE Conference
The University of Hong Kong
December 11th, 2025

Motivation

- Public servants are essential for **state capacity** and effective **public service delivery**
- The government struggles in the **competition for talent**
  - Rigid hiring rules and pay scales (Shleifer & Vishny, 1994)
  - Limited use of performance-based incentives (Holmstrom & Milgrom, 1987)
  - Scarce prospects for career development (Besley et al., 2022)
- High-skilled workers face a public sector **wage penalty** (Gindling et al., 2020)
- Many policies face barriers to **implementation at scale**
  - Wage-related policies: **fiscal constraints**
  - Incentive-based reforms: **rigid rules of the public sector**

This paper studies **the upstream role of higher education**

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Higher education finance

- Literature centers on the **equity** and **efficiency** of different funding instruments
  - Marginal effect of extra $ on **access** and **completion**
- Lack of evidence on the best tools to **attract talent into strategic fields**

Research Questions:

1. Is **education policy** an effective tool to recruit public servants?
   - Ex-post evaluation of a **Teacher Recruitment Policy**
2. What is the **most effective** design?
   - **Equilibrium** Model of Higher Education
3. Is education policy a **cost-effective** intervention?
   - Counterfactual simulation of **education** and **wage** policies

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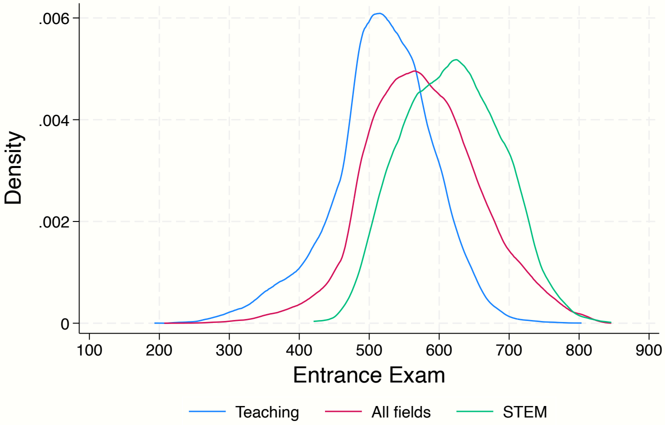
Teacher Recruitment Policy

Context

- During the 2000s Education was the most popular degree in Chile (15% of all enrollment)
- Average STEM student ≈ top 5% student at Teacher College

Figure: Scores at College Entrance Exam, by field, 2010



Teacher Recruitment Policy

- Established in 2011 in all public universities, **optional** for private universities (44 out of 60)
- Based on the scores at the National College Entrance Exam (scores 150-850)

  Incentives: students get **full funding** if score is above 80th percentile (600 points)

  Selectivity: colleges set a **cutoff** at the median (500 points)

- Financial incentives serve a **two-sided** purpose
  - Students: induce **self-selection** into teaching
  - Colleges: induce adoption of **selectivity** measures
- Low take-up: **two-thirds** of private universities **opted-out** of the policy.
  - Limits **crowding-out**, less **scholarship-eligible** vacancies

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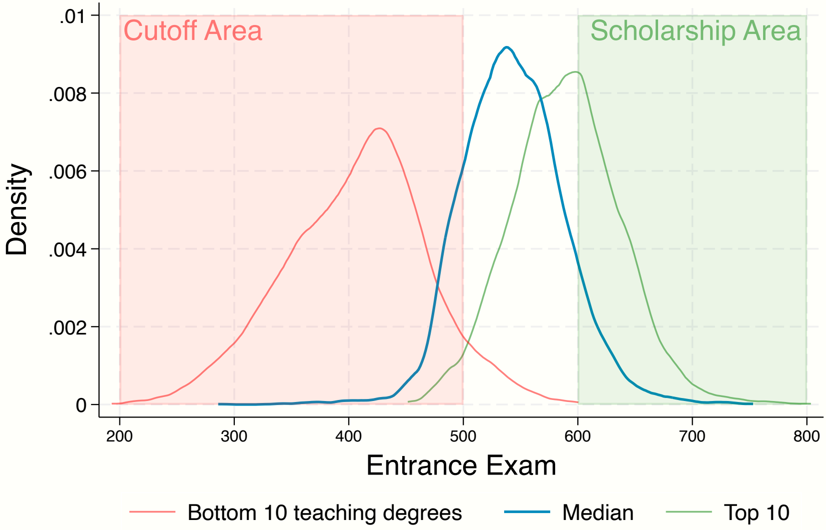
Figure: Scores at college entrance exam for different teaching degrees



Empirical Analysis: Overview of results

- Are students reacting to financial incentives?
  - **RD Design:** sharp assignment rule to estimate effect of **scholarship eligibility** on enrollment
  - Probability of enrollment at a teacher college increased from 8% to 12%
- Quantifying composition effect
  - **DID:** Compare teachers that graduated from
    - Participating and Non-Participating degrees
    - Before and after policy implementation
  - Gains in **pre-college achievement**: 0.25 SD in college entrance exam scores
  - Gains in **teacher quality**: 0.11 SD in Teacher Value Added

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- Ex-ante, the **optimal policy** was not obvious:
  - **High** cutoff or **high** scholarship threshold $\rightarrow$ **low take-up** by private colleges
  - **Low** cutoff or **low** scholarship threshold $\rightarrow$ **negative composition** effect

- **What is the most effective design?**

  1. **Policy is a bundle of two components:**
     - Need to disentangle the relative importance of **financial incentives** vs **selectivity**
  2. **Both students (enrollment) and colleges (take-up, prices) react to the policy**
     - Account for **demand** and **supply-side** responses under alternative policy rules

Equilibrium Model of Higher Education

Model: Overview

- **Government** sets **education policy**: $\begin{cases} \bar{r} & \text{scholarship threshold} \\ \underline{r} & \text{cutoff} \end{cases}$
  - Direct impact on **preferences** and **choice sets** $\rightarrow$ enrollment $\rightarrow$ profits
- **Matching:** Deferred Acceptance algorithm (DA) (Gale & Shapley, 1962)
- **Colleges:** Maximize profits by deciding on **tuition** and **policy participation**
- **Students:** Maximize utility by choosing among **college-degree pairs**

- **Colleges:** Static Bertrand Differentiated product framework
  - For a specific **scholarship threshold $\bar{r}$** and **cutoff $\underline{r}$**

$$\textbf{Given } \{\bar{r}; \underline{r}\} : \begin{cases} \underline{\text{Continuous choice}}: & \text{Tuition } \boldsymbol{p_j} \text{ for } \underline{\text{every}} \text{ degree} \\ \underline{\text{Discrete choice}}: & \text{Policy participation } \boldsymbol{B_f} \in \{0; 1\} \ (f \text{ indexes colleges}) \end{cases}$$

$$\max_{B_f, \{p_j\}_{j \in \mathcal{F}_f}} \sum_{j \in \mathcal{F}_f} \Big(\Pi_j(p)\Big), \quad \Pi_j(p) \equiv \sum_{i \in \mathcal{I}} \Big(\pi_{ij}(\boldsymbol{p_j}, \boldsymbol{B_f}, \boldsymbol{\bar{r}}, \underline{\boldsymbol{r}}, .) \cdot [p_j - c_j]\Big)$$

- **Students:** Submit rank ordered lists based on utility

$$u_{ij} = V_{ij}\left(\delta_j, z_i, w_{ij}, \boldsymbol{p_j}(\boldsymbol{B_f}, \boldsymbol{\bar{r}})\right) + \eta_{ij}$$

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Equilibrium

- For the **demand** side of the market, the DA algorithm generates a **stable** matching.
- On the **supply** side, colleges jointly decide on **take-up** and **prices**
  - With **32** private teacher colleges, there are 2^{32} take-up combinations (over 4 billion)
  - Each one with its **own price equilibrium**
- Computing every payoff becomes intractable, both for **colleges** and the **econometrician**
- This paper proposes a **novel** approach:

Colleges concentrate their **bounded rationality** in their **close rivals**

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Equilibrium in k close rivals

Definition

- Players form beliefs about the actions of every player
- Given beliefs, they choose their best responses
- Players correctly track their **k closest rivals**, but may be wrong about distant competitors

- The number of close rivals $k \in 0 \ldots N$ determines how **sophisticated** players are.
  - if $\boldsymbol{k = 0}$ completely ignore strategic responses
  - if $\boldsymbol{k = N}$ then strategies are a Nash Equilibrium
- **Close rivals** are defined by the **cross-price demand sensitivity** $\frac{\partial s_j}{\partial p_k}$
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Value Added of Teaching Degrees

- The model allows to estimate the enrollment distribution under counterfactuals
- To measure changes in **teacher quality**, I need the **value added** of teaching degrees
- **Potential outcomes model**:
  - For student i who enrolls at $D_i = j$ when facing choice set Ω_i

$$E[Y_{ij}|X_i, \Omega_i, D_i = j] = \boldsymbol{\mu_j} + X_i\boldsymbol{\beta_j} + E[\epsilon_{ij}|X_i, \Omega_i, D_i = j]$$

- **Self-selection** into degrees based on potential outcomes implies $E[\epsilon_{ij}|X_i, \Omega_i, D_i = j] \neq 0$
- In K-12, usual assumption is $E[\epsilon_{ij}|X_i, \Omega_i, D_i = j, \boldsymbol{Y_{i,t-1}}] = 0$

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Multinomial Logit Selection Model

- Dubin & McFadden (1984)
- Condition potential outcomes on (unobserved) **preference shocks** $\boldsymbol{\eta_{ij}}$

$$E[Y_{ij}|X_i, \Omega_i, D_i = j, \boldsymbol{\eta_i}] = \mu_j + X_i\beta_j + \underbrace{\sum_{k\in\Omega_i} \omega_k \, \boldsymbol{\eta_{ik}}}_{\text{Selection on levels}} + \underbrace{\varphi \, \boldsymbol{\eta_{ij}}}_{\text{Selection on gains}}$$

  - Selection on **levels**: high-quality students have high taste for high-quality degrees
  - Selection on **gains**: specific match effect

- Conditional Independence Assumption: $E[\epsilon_{ij}|X_i, \Omega_i, D_i = j, \boldsymbol{\eta_i}] = 0$

Estimation

Estimation

Demand: Maximum Likelihood, embedding Nested Fixed Point Algorithm (Berry et al., 1995)

- Recover mean utilities $\boldsymbol{\delta_j}$ and (non-linear) preference parameters $\boldsymbol{\alpha}$
- DA: matching game $\equiv$ discrete choice model with personalized choice sets (Fack et al., 2019)

$$\mathcal{L}(\alpha, \delta) = \sum_{i=1}^{n} \sum_{j \in \Omega_i} \log \mathrm{P}\left(\mu_i^* \mid z_i, x_j, w_{ij}, \Omega_i \; ; \; \boldsymbol{\delta}, \boldsymbol{\alpha}\right)$$

- Prices are instrumented with the **exogenous** variation generated by the scholarship rule
- In a simplified model, it can be shown that:

$$\alpha_p = \frac{1}{J} \sum_{j \in \mathbb{J}} \frac{\lim_{r \to \bar{r}^+} \log \frac{s_{rj}}{s_{r0}} - \lim_{r \to \bar{r}^-} \log \frac{s_{rj}}{s_{r0}}}{p_j}$$

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Supply: Recover **marginal costs** by solving the colleges' first order condition

- Given preference parameters $(\boldsymbol{\delta}, \boldsymbol{\alpha})$, unique mapping for each college f

$$\boxed{\mathbf{S^f} + \boldsymbol{\Delta}^\mathbf{f}(\mathbf{P^f} - \boldsymbol{C^f}) = \mathbf{0}} \qquad \mathbf{S^f}\text{: market shares, } \boldsymbol{\Delta}^\mathbf{f}_\mathbf{jk} = \frac{\partial s_k(\boldsymbol{\delta}, \boldsymbol{\alpha})}{\partial p_j}\text{, } \mathbf{P^f}\text{: prices, } \mathbf{C^f}\text{: marginal costs}$$

Degree Value Added: Two-step control function approach

1. Estimate control functions $\boldsymbol{\lambda_j(X_i, \Omega_i, D_i)} = E[\eta_{ij} | X_i, \Omega_i, D_i = j]$
   - Closed-form expression, function of preference parameters (δ, α)
2. Estimate $\boldsymbol{\mu_j}$, $\boldsymbol{\beta_j}$ by OLS, plugging in $\boldsymbol{\lambda_j}$, adjusting inference with two-step score bootstrap Shrinkage

$$Y_{ij} = \boldsymbol{\mu_j} + X_i \boldsymbol{\beta_j} + \underbrace{\sum_{k \in \Omega_i} \omega_k \, \boldsymbol{\lambda_k(X_i, \Omega_i, D_i)}}_{\text{Selection on levels}} + \underbrace{\varphi \, \boldsymbol{\lambda_j(X_i, \Omega_i, D_i)}}_{\text{Selection on gains}} + \epsilon_{ij}$$

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Estimation

Close Rivals: Criterion function

- Combine market data and structural model
- Given estimated **preference parameters** and **marginal costs**, compute **profits**
- Simulate model assuming different levels of **strategic sophistication** (# of close rivals k)
- Select heuristic that best **rationalizes** the observed equilibrium

$$\arg\min_{k \in \{0,..,N\}} Q = \sum_{N} \sum_{j \in \mathcal{F}_f} \left(\hat{\Pi}_j(k) - \hat{\Pi}^*_j \right)^2$$

$\hat{\Pi}^*_j$	Estimated profits in **observed** equilibrium
$\hat{\Pi}_j(k)$	Estimated profits in **simulated** equilibrium with k **close rivals**

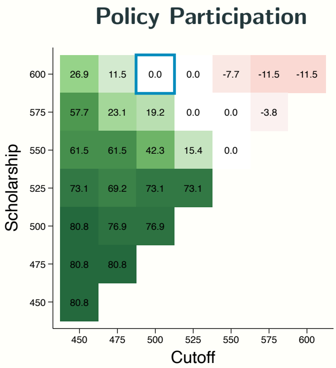
Counterfactuals

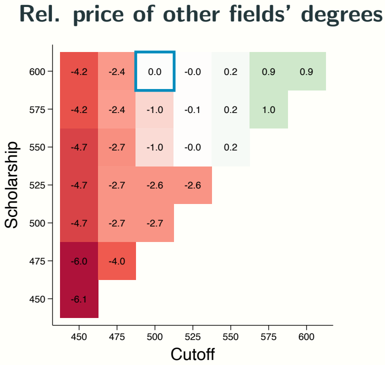
Counterfactuals

- **Education Policy**
  - I simulate a **grid** of scholarship-cutoff combinations
  - Each cell reports the % change with respect to the **baseline** policy
- **Wage Policy**
  - Data of graduates' wages at the **college-degree** level
  - Recover mean taste for wages by regressing δ_j on wage data
  - Heterogeneity captured in the non-linear demand parameters α

Counterfactuals: Supply-side responses

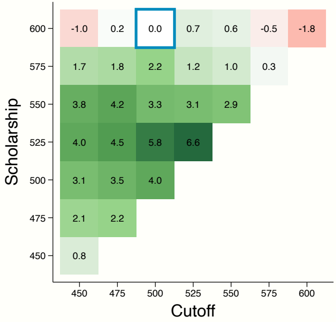
- Colleges react on **both** margin, ignoring either would lead to incorrect estimates





Counterfactuals: Sorting and labor market gains

Scores at College Entrance Exam



- Extreme policies **worsen composition**
- Gains (mostly) driven by **private colleges**

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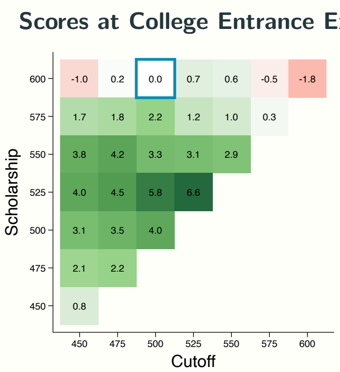

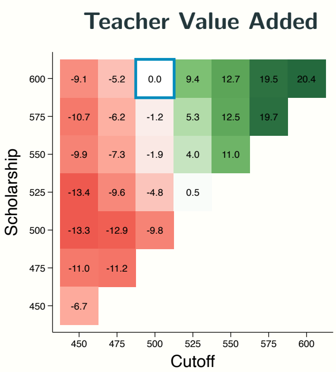

- Low-quality teacher colleges produce below-average **teachers**
- Even if they attract above-average **college students** Shares Cost DVA

Wage Policy

- Upon a wage increase, private universities have **no incentive** to raise admission standards
- Market shares **strongly** react to wage increases, students qualify to **other scholarships**

(1) Wage increase	(2) Market Shares	(3) Entrance Exam	(4) TVA	(5) $ Scholarships
5 %	10.76	0.84	-0.91	0.66
10 %	22.66	1.51	2.38	4.81
15 %	31.62	2.74	3.47	7.99
20 %	39.08	3.90	8.11	8.64
25 %	48.23	4.91	13.07	14.81
30 %	56.98	5.62	18.52	15.21
35 %	66.21	6.36	26.37	19.84
40 %	75.56	7.14	35.92	27.59
45 %	82.69	8.10	44.32	39.68
50 %	89.71	8.88	57.34	41.99

- What about **incumbent** teachers? Literature finds null effects (de Ree et al., 2018, Bau and Das, 2020)

Conclusion

Conclusion

- **Increasing the quality of public servants**
  - Scope for **education policy** when labor market conditions deter high-quality candidates
  - Focus on **teachers**, but similar context for other high-skilled public servants (nurses, social workers)
- **Accounting for colleges' endogenous responses**
  - Private colleges can be induced to increase **admission standards**, if properly **incentivized**
- **From High School Students, to College Students, to Teachers**
  - Recruitment policies should consider the intermediate step of **teacher training**
  - Maximize **pre-college achievement** of enrollees $\neq$ maximize **teacher quality**
- **General Framework, accommodates other settings**
  - Shortages, budget constraints, multiple policy instruments

Thanks!

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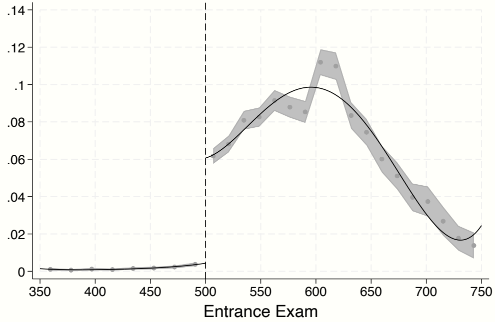
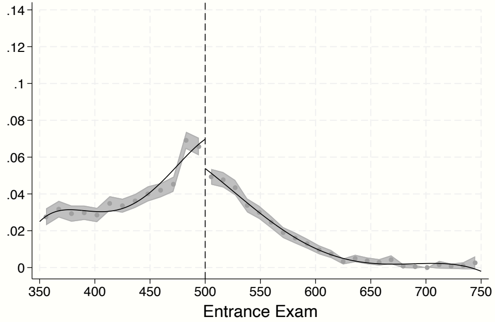
Appendix: RD Plot 500 points cutoff

Figure 1: Enrollment at teacher colleges, 500 points cutoff

(a) Participant degrees



(b) Non-Participant degrees



Back

Appendix: RDD Estimates

Table 1: RD estimates of teacher enrollment

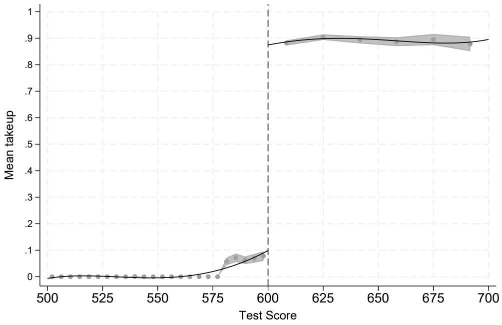
	Participant			Non-Participant		
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.05232***	0.03657***	0.02437***	-0.01779***	-0.00288	0.00121
	(0.00269)	(0.00633)	(0.00901)	(0.00306)	(0.00224)	(0.00075)
Cutoff	500	600	700	500	600	700
Observations	78258	42674	8752	105408	42674	16213
Bandwidth	44.1	36.3	26.5	61.4	36.1	45.7
Mean	.004	.086	.039	.067	.014	.000

Back

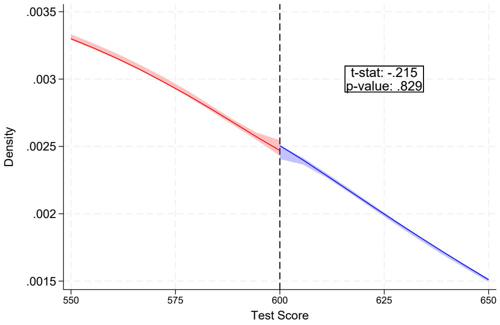
Appendix: RDD Robustness Checks

Figure 2: Robustness checks

(a) Scholarship takeup



(b) Manipulation test



Back

Appendix: RDD Placebo

Table 2: Placebo tests

	2011		2010	
	(1)	(2)	(3)	(4)
Enrollment	-0.00316	0.00010	-0.00302	-0.00063
	(0.00470)	(0.00786)	(0.00646)	(0.00527)
Cutoff	550	650	600	700
Observations	52540	20802	47246	11660
Bandwidth	67.8	29.2	50.2	38.4

Back

Appendix: RDD Field

Table 3: RD estimates by field, 600 points cutoff

	(1) Estimate	(2) SE	(3) Observations	(4) Bandwidth	(5) Baseline
Education (Participant)	0.0366***	(0.00633)	42674	36.3	.086
Education (Non-Participant)	–0.00288	(0.00224)	42674	36.1	.014
Not enrolled	–0.0148*	(0.00780)	46368	39.9	.198
Social Sciences	–0.0132***	(0.00503)	54236	46.2	.083
Business	–0.00181	(0.00493)	57034	48.9	.082
Farming	–0.000733	(0.00278)	61931	53.2	.023
Art and Architecture	–0.000730	(0.00359)	71132	61.4	.049
Basic Sciences	0.00130	(0.00356)	47811	40.9	.028
Law	–0.000570	(0.00368)	57638	49.1	.038
Humanities	–0.00140	(0.00191)	58173	50	.011
Health	–0.00503	(0.00602)	76918	66	.169
Technology	0.00153	(0.00765)	54236	46.2	.203

Back

Appendix: RDD Applying

Table 4: RD estimates of application at teacher colleges

	Any choice		First choice	
	(1)	(2)	(3)	(4)
Applied	0.01332	0.01568	0.03210***	0.02469***
	(0.00980)	(0.01263)	(0.00630)	(0.00872)
Cutoff	600	700	600	700
Observations	33800	8752	48264	8752
Bandwidth	28.9	26.8	41.2	26.9
Mean Below	.220	.098	.106	.039

Back

Appendix: RDD Retaking

Table 5: RD estimates of retaking PSU

	(1)	(2)
Retake	-0.00715	-0.01186
	(0.00758)	(0.01545)
Cutoff	600	700
Observations	58627	17009
Bandwidth	50.4	47.5
Mean Below	.228	.251

Back

Appendix: Empirical Bayes Shrinkage

- Value Added parameters $(\hat{\mu}, \hat{\beta})$ are **unbiased** but **noisy**
- To reduce sampling variance: **hierarchical empirical Bayes shrinkage**
  - Define $\theta_j = (\hat{\mu}_j, \hat{\beta}_j)$ as a random draw from a degree-level mixing distribution
  - Hyperparameters $\hat{\boldsymbol{\chi}}_{\boldsymbol{\theta}}$ and $\hat{\boldsymbol{\Sigma}}_{\boldsymbol{\theta}}$ are its mean and variance, $\hat{\boldsymbol{\Upsilon}}_{\boldsymbol{j}}$ the sampling covariance matrix

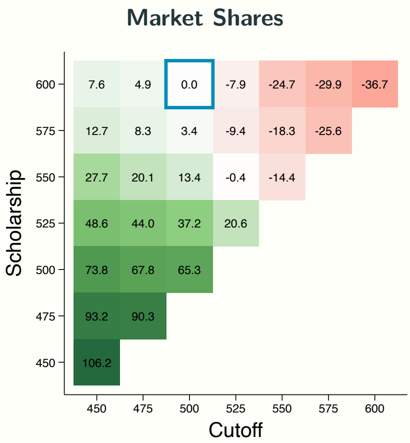
$$\hat{\boldsymbol{\chi}}_{\boldsymbol{\theta}} = \frac{1}{J}\sum_{j}\hat{\theta}_j \quad ; \quad \hat{\boldsymbol{\Sigma}}_{\boldsymbol{\theta}} = \frac{1}{J}\sum_{j=1}^{J}(\hat{\theta}_j - \hat{\chi}_\theta)(\hat{\theta}_j - \hat{\chi}_\theta)' - \hat{\Upsilon}_j \quad ; \quad \hat{\boldsymbol{\Upsilon}}_{\boldsymbol{j}} = E[(\hat{\theta}_j - \theta_j)(\hat{\theta}_j - \theta_j)'|\theta_j]$$

- Subtracting $\hat{\Upsilon}_j$ removes **excess variance** in the noisy $\hat{\theta}_j$ due to **sampling error**, leading to a consistent estimate of the cross-degree variability of latent θ_j.
- EB posterior predictions:

$$\theta_j^* = (\hat{\Upsilon}_j^{-1} + \hat{\Sigma}_\theta^{-1})^{-1}(\hat{\Upsilon}_j^{-1}\hat{\theta}_j + \hat{\Sigma}_\theta^{-1}\hat{\chi}_\theta)$$

Back

Appendix: Counterfactual Market Shares

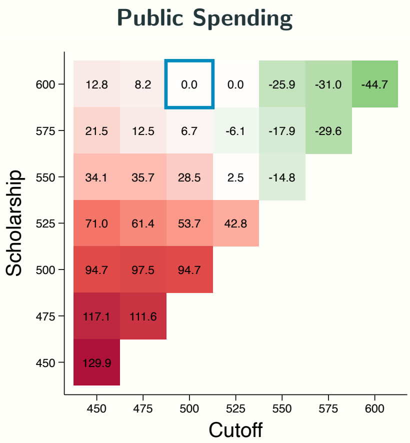


Back to Gains

Back to Scores

Back to TVA

Appendix: Counterfactual Public Spending

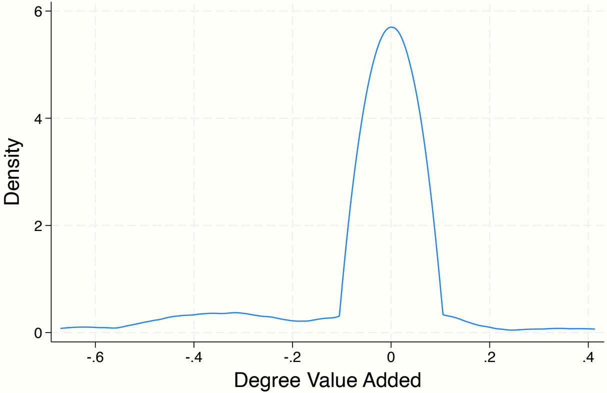


Back to Gains

Back to Scores

Back to TVA

Appendix: Degree Value Added



Back