The Effects of Public Housing on Children: Evidence from a National Experiment in Colombia

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Motivation

- Poor children are more likely to become poor adults, especially in low- and middle-income countries
  - They are exposed to more sources of disadvantage and have fewer human capital investment opportunities (Currie and Vogl, 2013)
- Individual policies may be insufficient to address children's needs
- Promising interventions: "big push" policies (Balboni et al., 2022; Banerjee et al., 2015)
  - Involve more comprehensive approaches to improve children environments
  - Tend to be rare in deprived contexts

This Paper

- Investigates whether a big-push-style housing policy can break the intergenerational poverty trap
- Focuses on Colombia's **"Free Housing Program"**
  - 100,000 units granted *for free* to disadvantaged families (value: $22,000 USD)
  - Located in desirable areas of municipalities
  - Program was oversubscribed ⇒ 30% of units were randomized
- Studies the impact of winning a housing unit on **children's schooling outcomes**
  - Use admin and survey data to examine household-, neighborhood-, and school-level mechanisms

This Paper

- **This paper is part of a broad agenda evaluating the effects of housing on:**
  - Economic outcomes (Camacho et al. 2022): increases in household income, female LFP
  - Health and healthcare utilization (Duque et al. 2024): reductions in doctor visits and ER/hospitalizations due to respiratory problems and infections, and declines in adult mortality

What We Find:

- 4 years after winning the housing unit:
  - Educational outcomes:
    High school graduation (↑ 17%), years of schooling (↑ 0.5 yrs), enrollment in tertiary education (↑ 10%), test scores (↑ 0.09 SD)
  - Potential mechanisms:
    - School quality: children attend schools with ↑ value added
    - Neighborhood quality: families live in better and more central neighborhoods
    - Family-level mechanisms: ↑ durable goods, ↑ employment, ↑ income, and ↑ spending on educational goods and food

Literature

1. **Housing programs and children**
   - Developed countries:
     - *Housing assistance (subsidized rent, relocation)*:
       → Positive effects on children who benefit early- (Currie and Yelowitz 2000; Chetty et al. 2016; Chetty and Hendren 2018; Chyn 2018) rather than later-in-ife (Kling et al. 2007; Jacob et al. 2004, 2015)
       → Mechanism: improvements in neighborhood quality
   - Developing countries:
     - *Place-based interventions (e.g., slum upgrading, land titling)*:
       → Positive effects on self-reported outcomes and child's health
       Cattaneo et al. (2009), DiTella et al. (2007); Field (2007), Galiani et al. (2007), Galiani et al. (2017)
     - *Relocation policies (+ subsidized rent)*:
       → Minimal benefits on recipients: Location/generosity is key!
       Barnhardt, Field, Pande (2017), Franklin (2019), Picarelli (2019)

Literature

2. **"Big push" policies to break poverty traps**
   $\rightarrow$ Given nonlinearities in the dynamics of poverty, the size of the transfer is critical for pushing people out of poverty

   (Hirschman 1958; Murphy et al. 1989; Balboni et al. 2022; Banerjee et al. 2015, 2021)

- **Contribution:**
  $\rightarrow$ ***First experimental evidence on the effects of public housing relocation in a developing country on children's outcomes***

  $\rightarrow$ ***Show that housing can be a linchpin for big-push-type of interventions, with large intergenerational effects***

Outline

1. Program overview
2. Data and empirical approach
3. Results
4. Mechanisms
5. Conclusions

Outline

Colombia's "Free Housing" Program

- April 2012: President announces within two years 100,000 homes would be built and given to the disadvantaged for *free*
- Government allocated ∼2.2 billion USD to construction
  - per-housing unit cost set at ∼22,000 USD
- Projects to be located in desirable areas
  - *Bundle: housing + neighborhood amenities*
- Eligible groups: victims of violence, natural disasters, extreme poor
- Due to oversubscription, 30% of units assigned through lotteries (61,244 applicant families or 229,288 individuals)

Unit Quality

- End sample: 225 developments across 191 municipalities built between 2012-14
- Typical unit: two-bedroom apartment or row house
  - also furnished with basic appliances (e.g., stove)
  - basic services: electricity, gas, water
- Counterfactual unit: poorly-built, high-crime neighborhoods
  - e.g., in large cities, applicants typically lived in slums or "*comunas*" ($\sim$ Brazil's *favelas*)

Location of Housing Projects:

Example of applicant housing in Lorica, Cordoba, NE coast

Government housing project in Lorica, Cordoba, NE coast

Examples of large projects in Pasto and Bogotá

Lotteries

Outline

Administrative Data

1. Universe of housing lottery applicants: 2014+
   - Names and IDs of all household members (including children), beneficiary group, priority tier, date of application, application outcome, project ID, exact unit assigned, etc.
   - N=71,974 lottery applicants
2. "Census of the poor" (Sisben III): 2009-10
   - covers 60% of Colombia's population; used to target social programs
   - provides baseline demographic and socioeconomic characteristics

3. Universe of students in public schools: 2006-2019
   - indicates (i) enrollment status, (ii) graduation status
4. Universe of end-of-high school exam takers (ICFES): 2012-2019
   - mandatory exit exam taken by all HS graduates
   - used for university admissions
5. Universe of students in tertiary education (SNIES): 2012-2019
   - indicates enrollment status
6. Small survey to the lottery sample: 2020
   - self-reported outcomes: travel time to various ammenities, perceptions on neighborhood quality, etc.

Outcomes and Sample of Interest

- Key outcomes: High school graduation, ICFES score
- So need children to have reached 'graduation age'
- Restrict sample to:
  - Children who were aged 15 or below at *1st* lottery application
    - By law, students are allowed to drop out of school at age 16
  - Children who in 2019 (our last year of data) were old enough to have finished HS (age 18)
- N = 15,026 children

Empirical Approach

1. Compare outcomes for children in families who won vs. lost the housing lottery

$$y_i = \alpha + \beta D_i + \delta X_i + LC_i + \epsilon_i \, , \tag{1}$$

where:

- Y_i: outcome of child i
- D_i: indicator for whether child's i's family won *first* lottery they applied for
- X_i: vector of individual controls (sex, age at lottery FE, parental education, etc.)
- LC_i: housing project-by-lottery FE
- ϵ_i: error term; clustered at the project-municipality level

Covariate Balance (I)

	Treatment	Control	Test of Equality (p-value)
Age at Lottery	13.86	13.83	0.00
Female	0.49	0.50	0.13
Household Head Characteristics:			
Age at child's birth	27.91	27.74	0.20
Married	0.51	0.53	0.55
Employed	0.50	0.51	0.83
High school education	0.27	0.26	0.14
Some tertiary educ.	0.13	0.14	0.14
Household Size	5.80	5.82	0.24
Pre-Lottery House Characteristics:			
Urban	0.75	0.79	0.92
# Rooms	2.79	2.77	0.22

Covariate Balance (II)

	Treatment	Control	Test of Equality (p-value)
# bathrooms	0.88	0.89	0.20
Has shower	0.51	0.53	0.32
Access to Services:			
Electricity	0.94	0.95	0.81
Water/sewage	0.77	0.81	0.03
Cable TV	0.21	0.16	0.35
Trash Collection	0.71	0.78	0.99
Some tertiary educ.	0.13	0.14	0.14
Household Size	5.80	5.82	0.24
Household Wealth:			
Has fridge	0.43	0.43	0.61
Has washing machine	0.11	0.11	0.93
# children	3,917	11,109	15,026

Outline

The program improved access to local services

Post-Lottery Distance (in minutes) to Selected Locations

	Public Transport Station	School	Grocery Store	Park	Hospital or Clinic
Won Lottery	-10.403***	-2.652**	-10.698**	-6.778***	-7.214***
	(1.842)	(1.060)	(5.247)	(1.584)	(2.602)
Cont. mean (min)	22.41	21.46	27.89	19.54	31.74
# Observations	2,563	2,563	2,563	2,563	2,563

First-Stage: Effect of Winning Lottery on Living in Housing Unit

- Public housing take-up was very high
- Lottery winners have resided in housing units for 4 years

	Full sample		Education sample	
	Ever winning housing unit	Years in public housing (to 2019)	Ever winning housing unit	Years in public housing (to 2019)
	(1)	(2)	(3)	(4)
Won Lottery	0.82***	4.22***	0.80***	4.21***
	(0.02)	(0.12)	(0.02)	(0.11)
Observations	60,042	60,042	15,026	15,026
% treated	0.28	0.28	0.26	0.26

Effect of Winning Lottery on Children's Education (Intent-to-Treat)

Impact of Winning First Housing Lottery on:	No Controls (1)	Demographic Controls (2)	Control Mean (3)	# of Observations (4)
Years of education	0.567*** (0.081)	0.511*** (0.075)	9.00	15,026
High School graduation	0.077*** (0.018)	0.067*** (0.017)	0.42	15,026
Took ICFES	0.077*** (0.015)	0.065*** (0.014)	0.47	15,026
Enrolled in tertiary education	0.018** (0.008)	0.014* (0.007)	0.14	15,026

Effect of Winning Lottery on Children's Education (Intent-to-Treat)

Impact of Winning First Housing Lottery on:	No Controls (1)	Demographic Controls (2)	Control Mean (3)	# of Observations (4)
ICFES Score	0.030 (0.025)	0.025 (0.028)	-0.36	7,447
ICFES Score (Math)	0.007 (0.027)	0.004 (0.027)	-0.42	7,447
ICFES Score (Reading)	0.045* (0.029)	0.040 (0.029)	-0.41	7,447

Correction for selection

- Because housing increases Icfes-test taking, lottery winners and losers' Icfes scores are not directly comparable (i.e., there is selection into the test)
- Following Angrist, Bettinger, and Kremer (2012):
  1. Create "artificial" Icfes score by assigning observed scores at or above a particular value (e.g., decile) to all who obtained a score below this point as well as nontakers
  2. Estimate OLS and censored Tobit models
- By assuming normality and that nontakers would have scored below the artificial censoring point, this method provides consistent treatment effects on latent scores of all students

OLS and Tobit Selection-Corrected Estimates of the Effects of Public Housing on ICFES Score (Intent-to-Treat)

	OLS	OLS censored at 1%	OLS censored at 10%	Tobit censored at 1%	Tobit censored at 10%
	(1)	(2)	(3)	(4)	(5)
"Won" in 1st lottery	0.025	0.128***	0.092***	0.279***	0.220***
	(0.028)	(0.031)	(0.024)	(0.058)	(0.050)
Control mean	-0.36	-1.16	-0.88	-1.16	-0.88
N	15,026	15,026	15,026	15,026	15,026

Figure on estimates across all possible censoring points using: OLS Tobit

Main Findings

- Receiving free public housing for 4 years *on average*:
  - Years of schooling: $\uparrow$ 0.5 yrs (5.7%)
  - HS graduation: $\uparrow$ 7pp (15.9%)
  - Prob(taking the ICFES): $\uparrow$ 7pp (13.8%)
  - Prob(enrollment in tertiary educ): $\uparrow$ 1pp (10.0%)
  - ICFES: $\uparrow$0.09 SD (post selection-correction)

Outline

Types of Mechanisms

1. School-level mechanisms
   - School quality
2. Neighborhood-level mechanism
   - Poverty, pollution, crime
3. Household-level mechanism
   - Family assets, amenities, income, and expenditures

- We combine admin and survey data to analyze these pathways...

School-level mechanisms

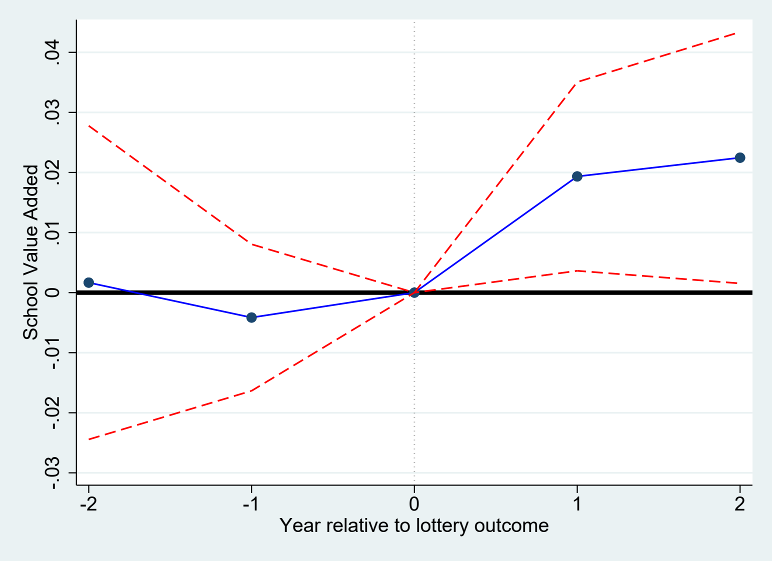
- Use “Census of the Poor” matched to *pre-lottery* education data to construct school *value-added*
- VA Data: 2006-2008 entering sixth grade cohorts
  - schools usually span K-5 or 6-11
- VA Model:

$$Y_{ist} = \beta X_{ist} + \mu_s + \epsilon_{ist} \ ,$$

- where:
  - i =student, s=school, t=year
  - Y_{ist}: HS graduation indicator
  - X_{ist}: vector of individual controls (e.g., parental and housing characteristics)
  - μ_s: school fixed effect (parameter of interest)
- Use empirical Bayes to estimate μ_s Details

VAHS VAicfes VAhsColombia VAicfesColombia

Event-time of School Value-Added on High School Graduation



Neighborhood-level Mechanisms

Post-Lottery Household Perceptions on Neighborhood Attributes

	Low-quality neighborhood index	Air Pollution	Presence of insects, rats	Trash on streets	Bad street odors
Won lottery	-0.088***	-0.049**	-0.120***	-0.008	-0.041*
	(0.029)	(0.019)	(0.014)	(0.027)	(0.021)
N	2,563	2,563	2,563	2,563	2,563
Mean	0.03	0.25	0.34	0.25	0.25

Neighborhood-level Mechanisms

Post-Lottery Crime and Poverty at the Neighborhood Level

	Crime Index	Assaults	Robberies	Homicides	Poverty Index
Won Lottery	-0.049** (0.021)	-1.184* (0.691)	-2.620*** (0.894)	-0.103 (0.071)	-0.037*** (0.003)
Control Mean	0.03	29.77	38.09	2.87	0.01
# Observations	100,520	100,520	100,520	100,520	10,912

Note: the unit of observation in (1)-(4) is the cuadrante*year level for years 2018-2020.

Household-level Mechanisms

Impact of Winning the Lottery on Family Wealth and Expenditures

	Family Wealth	Family Income		Family Expenditures	
	Assets (percentile)	Household Head Employed	Log Income	Log Education	Log Food
Won lottery	9.37***	0.019*	0.341**	0.220*	0.114*
	(1.31)	(0.012)	(0.163)	(0.127)	(0.059)
Observations	10,084	10,084	10,084	10,084	10,084
Control Mean	33.55	0.43	6.44	1.46	11.70

Horse race

Conclusion

- Examine effects of public housing on children's education
  - Leverage lottery assignment for highly-generous public housing
    - Free units were located in desirable areas of the city
- Findings:
  - Free public housing increases HS graduation, years of schooling, enrollment in terciary educ, test scores
  - Gains largely driven by higher quality of schools attended by lottery winners and higher family wealth
- Results contribute to literature on effects of public housing, focusing on children in developing countries

Thank you!

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Quantifying the Role of Diff. Mechanisms: "Horse Race" ▸ Back

Outcome: HS grad.	Main Result		All Mechanisms
Won lottery	0.067***	0.061***	0.030
	(0.017)	(0.017)	(0.020)
Family Wealth and Expenditures			
Household Asset Index			0.06***
			(0.02)
Household Amenities Index			0.08***
			(0.03)
Household Head Employed			0.16
			(0.16)
Log Household Income			0.02
			(0.14)
Household Expenditure on Education			0.40***
			(0.14)
Household Expenditure on Food			-0.24
			(0.20)
Neighborhood Quality			
Neighborhood Poverty Index			0.04
			(0.03)
Neighborhood Crime Index			-0.01
			(0.04)
School Quality			
School Value-Added (percentile)			0.28***
			(0.05)
# Observations	15,026	10,084	10,084

Quantifying the Role of Different Mechanisms: Mediation

Outcome: HS grad.	First-Stage (γ^j)	Second-Stage (θ^j) (p.p.)	% Explained by Mechanism
Won lottery (κ^{Res})	0.067*** (0.017)	2.00 (1.99)	30.3%
Family Wealth			
Household Asset Index	9.08*** (1.32)	0.121*** (0.029)	16.7%
Household Amenities Index	13.06*** (1.11)	0.099** (0.040)	19.6%
Family Income and Expenditures			
Household Head Employed	0.015 (0.013)	0.179 (2.339)	0.0%
Log Household Income	0.330* (0.168)	0.033 (0.245)	0.2%
Expenditure on Education	0.178 (0.119)	0.526*** (0.189)	1.4%
Expenditure on Food	0.093* (0.058)	-0.305 (0.243)	-0.4%
Neighborhood Quality			
Neighborhood Poverty Index	-0.037*** (0.003)	0.750 (0.551)	-0.4%
Neighborhood Crime Index	-0.049*** (0.021)	-0.712 (2.779)	0.5%
School Quality			
School Value-Added	0.021*** (0.008)	100.75*** (16.74)	32.1%

Public Housing in Developing Countries (I)

- Few studies on relocation policies
- Focused on adults
- Minimal benefits of expensive public programs
  - Franklin (2019): using housing lottery to purchase gov't built apartments in the outskirts of an Ethiopian city, moving into public housing does not impact earnings, reduces social interactions; N=1,600 participants
  - Picarelli (2019): uses RD on allocation of publicly-built homes in South Africa; finds reductions in labor earnings and female labor supply; N=1,960 participants
  - Barnhardt et al. (2017): 14 years after public housing lotteries in India, no improvements in income or human capital, declines in social connectedness; N=497 participants
- Location (long distance to economic opportunities) plays an important factor

Public Housing in Developing Countries (II)

- Most studies focus on titling and slum upgrading
  - Field (2007): uses DD on gov't program that issued property rights to informal slum residents; increases adult and child labor supply; N=2,465 households
  - Galiani et al. (2007): uses DD on upgrading slum dwellings in Mexico, El Salvador, and Uruguay; increases wellbeing, child's health; N=2,373 households
  - Cattaneo et al. (2009): uses DD on Mexican program replacing dirt floors with cement; improvements in child's health and adult wellbeing; N=3,000 households

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Effects of public housing on HS and potential mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
"Won" housing unit in first lottery	**0.067*** **	**0.061*** **	**0.053*** **	**0.051*** **	**0.063*** **	**0.061*** **	**0.060*** **	**0.062*** **	**0.062*** **	**0.054*** **	**0.049*** **	0.030
	(0.017)	**(0.017)**	**(0.016)**	**(0.017)**	**(0.018)**	**(0.017)**	**(0.017)**	**(0.018)**	**(0.017)**	**(0.017)**	**(0.016)**	(0.020)
Family mechanisms												
Household asset index			**0.001*** **									**0.001*** **
			(0.000)									**(0.000)**
House ammenities index				**0.001*** **								**0.001*** **
				(0.000)								**(0.000)**
Household head employed					0.012							0.002
					(0.008)							(0.016)
Log household income						0.001						0.000
						(0.001)						(0.001)
Household expenditure on education							**0.006*** **					**0.004*** **
							(0.001)					**(0.001)**
Household expenditure on food								0.002				-0.002
								(0.002)				(0.002)
Neighbourhood mechanisms												
Neighbourhood poverty index									0.0003			0.0004
									(0.0002)			(0.0003)
Neighbourhood crime index										-0.00001		-0.00001
										(0.0003)		(0.0004)
School mechanisms												
School VA - percentile											**0.003*** **	**0.003*** **
											(0.000)	**(0.000)**
Observations	15,026	10,084	10,084	10,084	10,084	10,084	10,084	10,084	10,084	10,084	10,084	10,084

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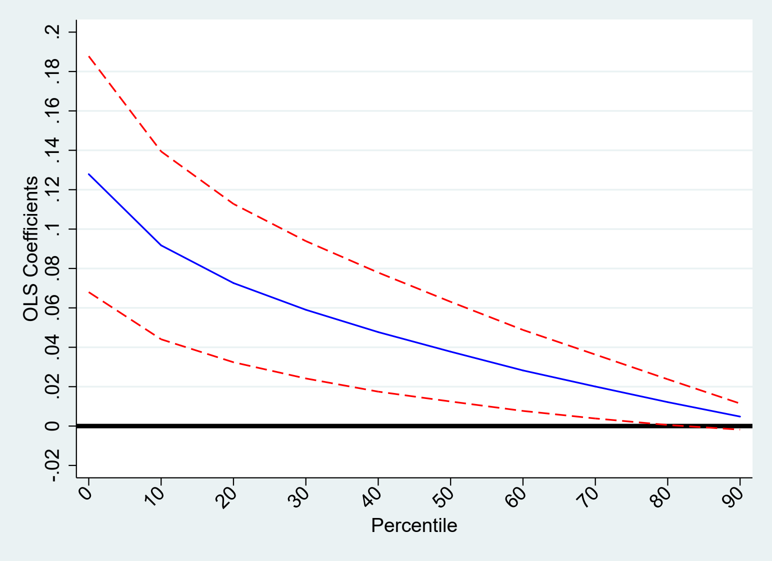
OLS Coefficients by Censoring Percentile in Score Distribution



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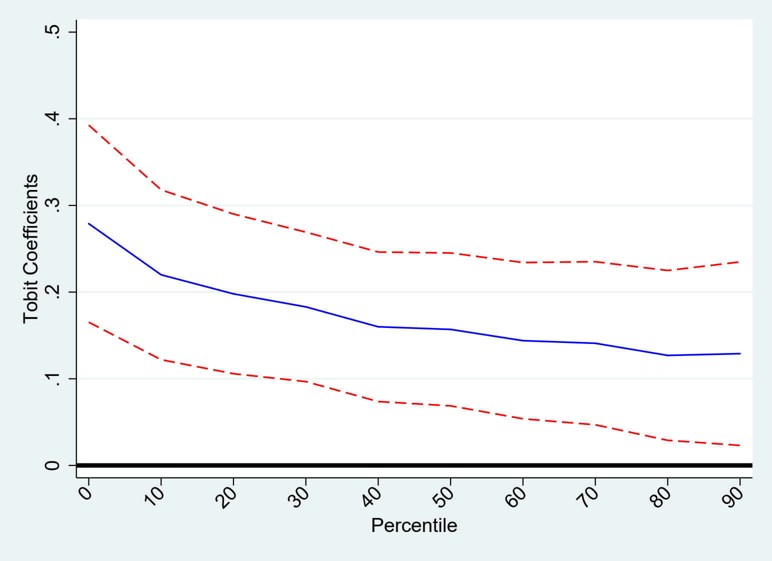
Tobit Coefficients by Censoring Percentile in Score Distribution



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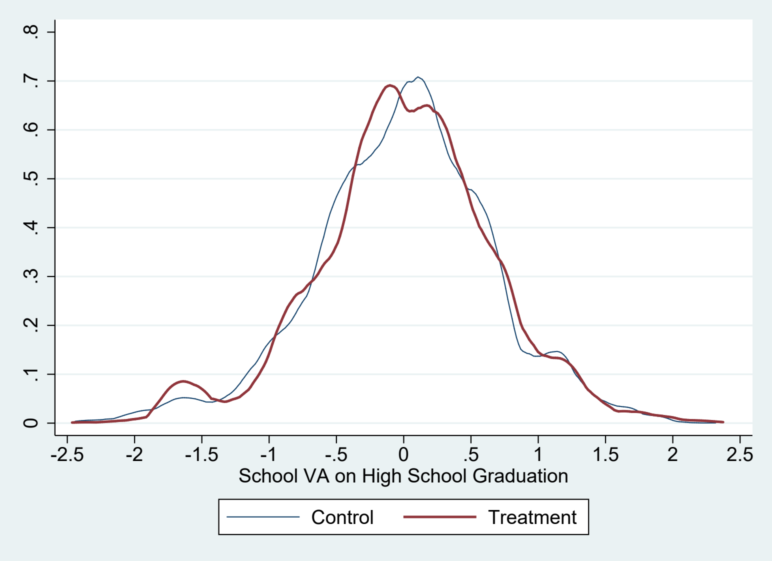
Distribution of School Value-Added on High School Graduation



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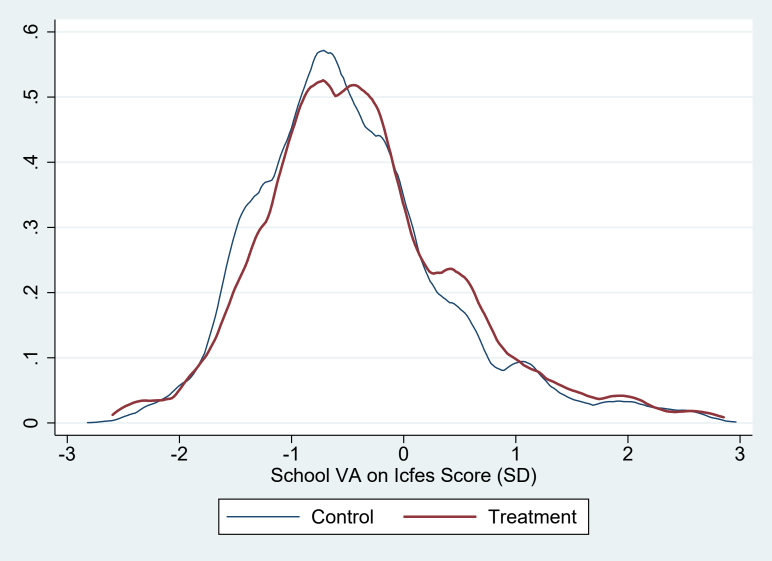
Distribution of School Value-Added on Icfes Score



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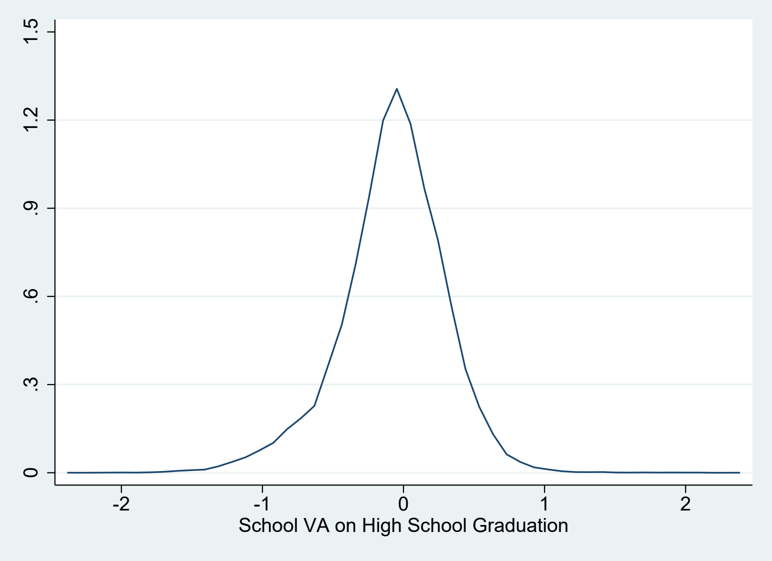
Distribution of School Value-Added on Icfes Score - Colombia



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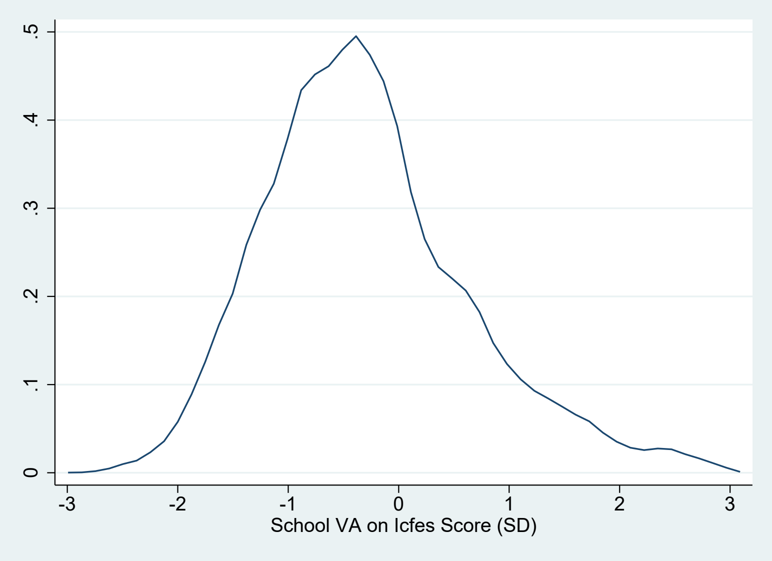
Distribution of School Value-Added on Icfes Score - Colombia



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Empirical Bayes

- VA model $Y_{ist} = \beta X_{ist} + \mu_s + \varepsilon_{ist}$
- Assume $\varepsilon_{ist} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, $\mu_s \sim \mathcal{N}(0, \sigma_\mu^2)$
- Mean squared error $\left(\frac{1}{N}\sum_j(\hat{\mu}_s - \mu_s))^2\right)$ is minimized by

$$\hat{\mu}_s = \overline{Y}_s \left(\frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2 / \sum_t n_{st}} \right)$$

where: n_{st}: number of students, $\overline{Y}_s = \frac{1}{n_{st}} \sum_{i=1}^{n_{st}} (Y_{ist} - \beta X_{ist})$

Intuitively: as $\sum_t n_{st} \to \infty$ obtain fixed effect estimator

- Implemented with MLE

back detailsdata

Computing School VA using Colombian Admin Data

1. Select three 6th-grade cohorts (years 2007-2009) (in R-166)
   - These cohorts will graduate before the lotteries, ensuring that lotteries do not impact our school VA measures
2. Follow them until they graduate from HS (in R-166), take the Icfes exam (link R-166 to Icfes records)
3. Link information on family and housing characteristics (in Sisben 2005)
   - This allows to control for all observable characteristics, X_{ist}
4. Estimate School VA model using MLE VAmodel
   - VA model $Y_{ist} = \beta X_{ist} + \mu_s + \varepsilon_{ist}$