Slums

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STEG Theme 4

Workshop on Trade and Spatial Frictions

November 24, 2025

Motivation

By 2024, $\approx$ 1.1 bi people (25% of urban pop.) resided in slums or informal settlements; 2 billion more expected in 30 years. (UN, 2024)

Huge policy concern. Substantial resources have already been devoted to policies (titling, upgrading,...).

Yet, we have little systematic, large-scale evidence on slums' characteristics and residents' livelihoods.

- Are slums "just" poor neighborhoods?
- What are their defining characteristics and the associated trade-offs?

Filling these gaps is key for a better understanding of the individual- and city-level consequences of slums and the policies targeted at them.

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This Project

Questions:

1. What are the defining characteristics of slums? What are the trade-offs individuals face when choosing whether to live in a slum?
2. What are the aggregate (city-level) consequences of slums?
3. Are slums intergenerational stepping stones or poverty traps? (Glaeser, 2011; Marx et al. 2013)

What we do:

1. Leverage unique, granular data sources from Brazil to characterize slums and their population, including intergenerational mobility (IGM).
2. Establish new facts about slums covering nearly 80,000 census blocks and over a wide range of income p.c. ($40\times$ or Niger to Luxembourg)
3. Develop a spatial model of slums w/OLG: rationalizes main facts + impacts of prototypical slum policies in equilibrium
   (e.g. Ahlfeldt et al., 2015; Tsivanidis, 2024; Eckert & Kleineberg, 2024)

Outline

Outline

Definition

Typically: slums defined based on a range of characteristics: tenure insecurity, inadequate housing, infrastructure and services (e.g. UN-Habitat, 2023).

This Paper:

Territorial Informality: Non-marketable land → no legal ownership, hard to formalize.

Operational definition (used by Brazilian Bureau of Statistics):

- **Necessary condition**: Illegal land occupation

  +

- **One of**: irregular urban form or limited access to services and infrastructure.

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Data

Unit of analysis: Census' block $\rightarrow$ more granular than the US census tract (avg. 449 vs. $\approx$4,000 dwellers).

Dummy for all blocks that constitute slums in the 2000 and 2010 censuses.

We focus on Brazil's 19 largest Metropolitan areas (MAs), totalizing 76,967 blocks, of which 7,054 are slums.

Data Sources

1. National HH Survey: individual labor market outcomes for slum vs. formal.
2. Decennial Population Census: geo-locate individuals at the census block level; demographics, infrastructure, public goods.
3. Education: School-level Index (IDEB) w/graduation rates and test scores for all public schools $\rightarrow$ Tract level, distance-weighted school quality.
4. Victimization: mortality by cause, geocoded to residence.
   $\Rightarrow$ Tract level assault hospitalizations and mortality.
5. RAIS: geocoded formal establishment-level job counts.
   $\Rightarrow$ Commuter Market Access (CMA).
6. CadUnico: Welfare Registry, $\approx 2/3$ of population.
7. Google Open Buildings: finely-gridded building height and coverage.
8. Brazilian Person Registry: name, DoB, ID #, mother's name for *entire pop.*

Measuring Intergenerational Mobility

Challenges: (i) Linking children to parents (from Britto et al., 2022); (ii) Georeferencing households, especially slums; (iii) measuring outcomes

Family Links:

1. Brazilian Person Registry: mother-children links.
2. CadUnico to link children to fathers (and mothers).
3. Dependent claims in tax returns data, 2006-2020 ($\approx 1/3$ pop.).
4. Additional links using addresses-names + School Census.

Cohort: 7.3 million individuals born 1983-90 linked to their parents. Childhood block based on parents' address in 2000.

Children's outcomes as adults measured in 2015-2019: (i)completed schooling; (ii) Bolsa Familia beneficiary; (iii) living in slum.

▶ Blocks in our sample

Outline

1 Territorial Informality

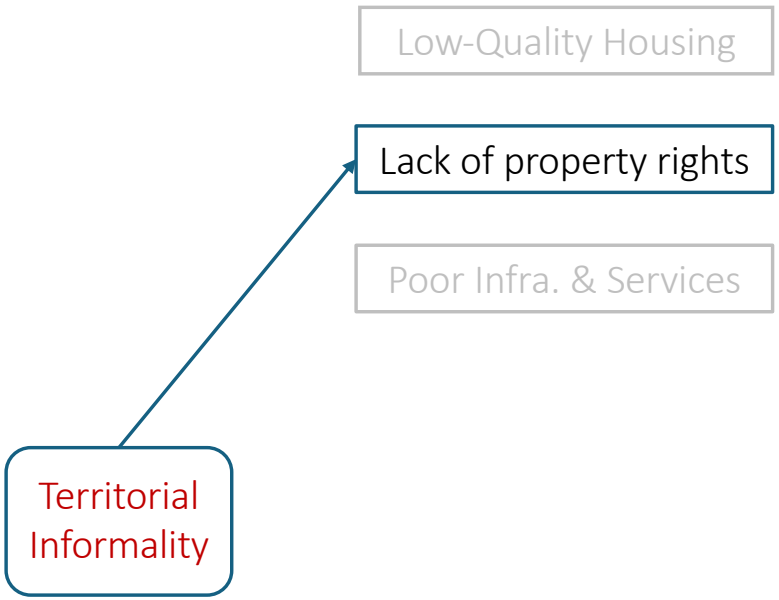
Slums typically defined as areas with:

(e.g. UN-Habitat, 2023; Cavalcanti et al., 2019)

- Low-Quality Housing
- Lack of property rights
- Poor Infra. & Services

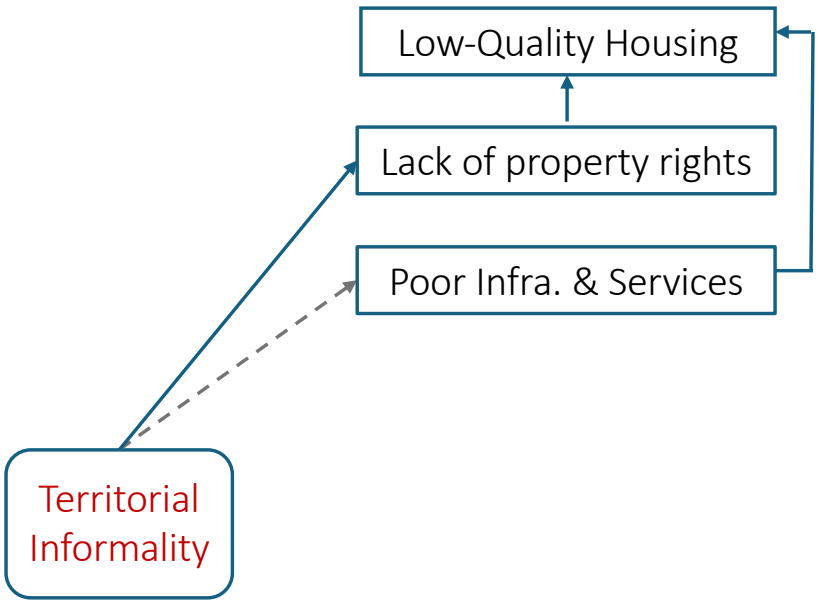
1 Territorial Informality

We emphasize territorial informality as the defining characteristic of slums → extreme form of informality, hard to formalize. (e.g. Nairobi – Henderson et al., 2021)



2 Infrastructure and services

Territorial informality doesn't necessarily imply lack of state-provided infrastructure and services (e.g. Blattman et al., 2025).



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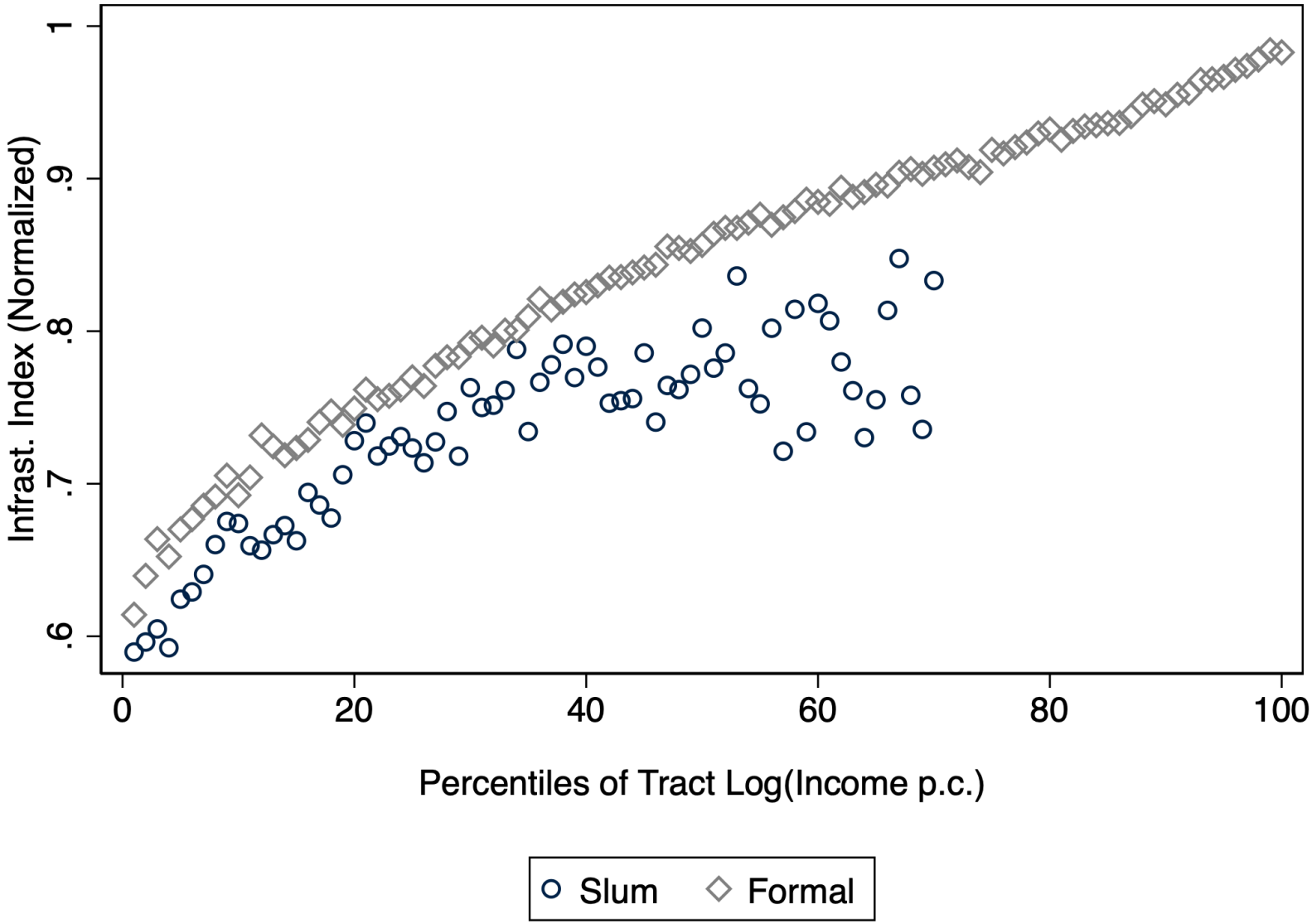
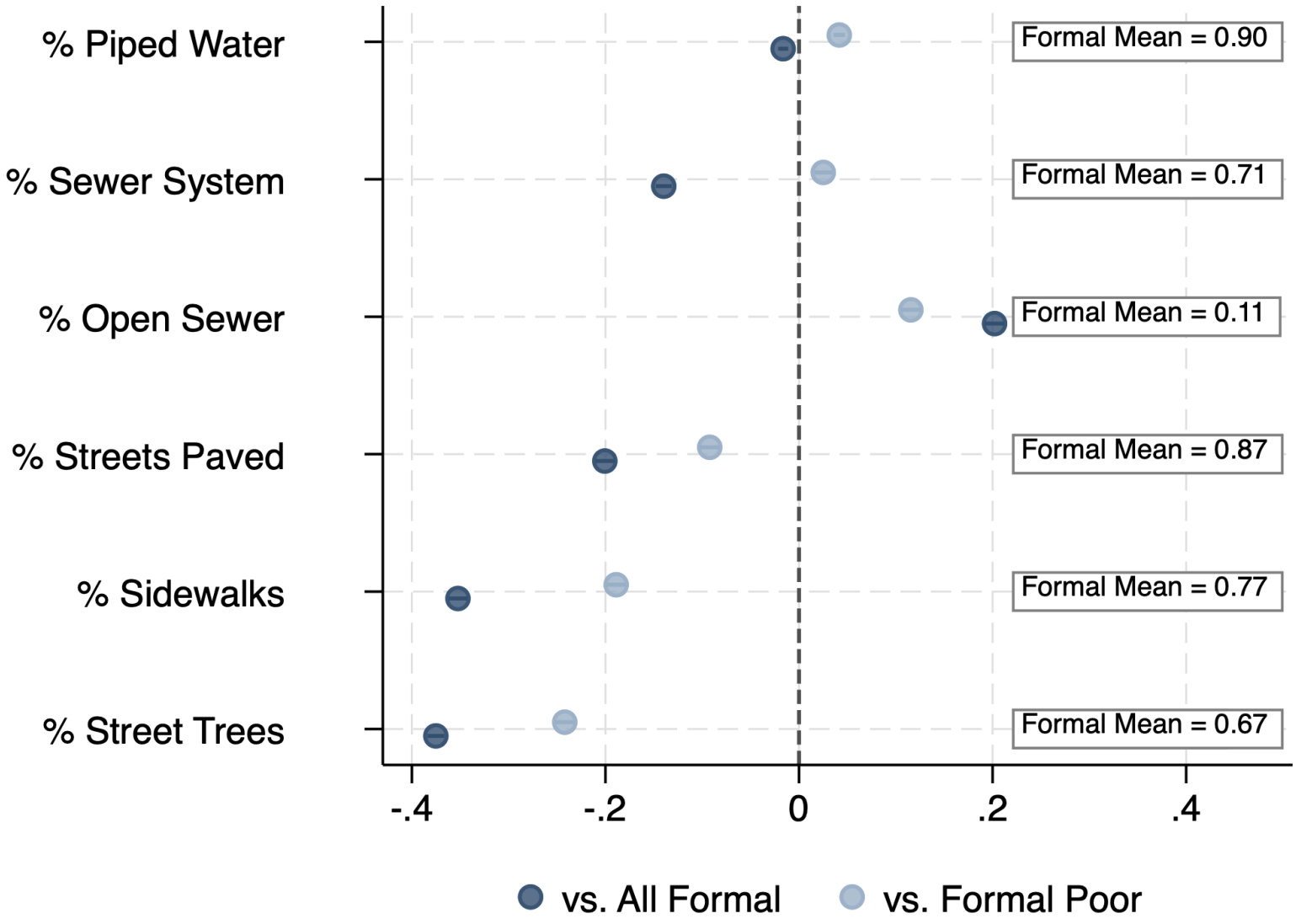


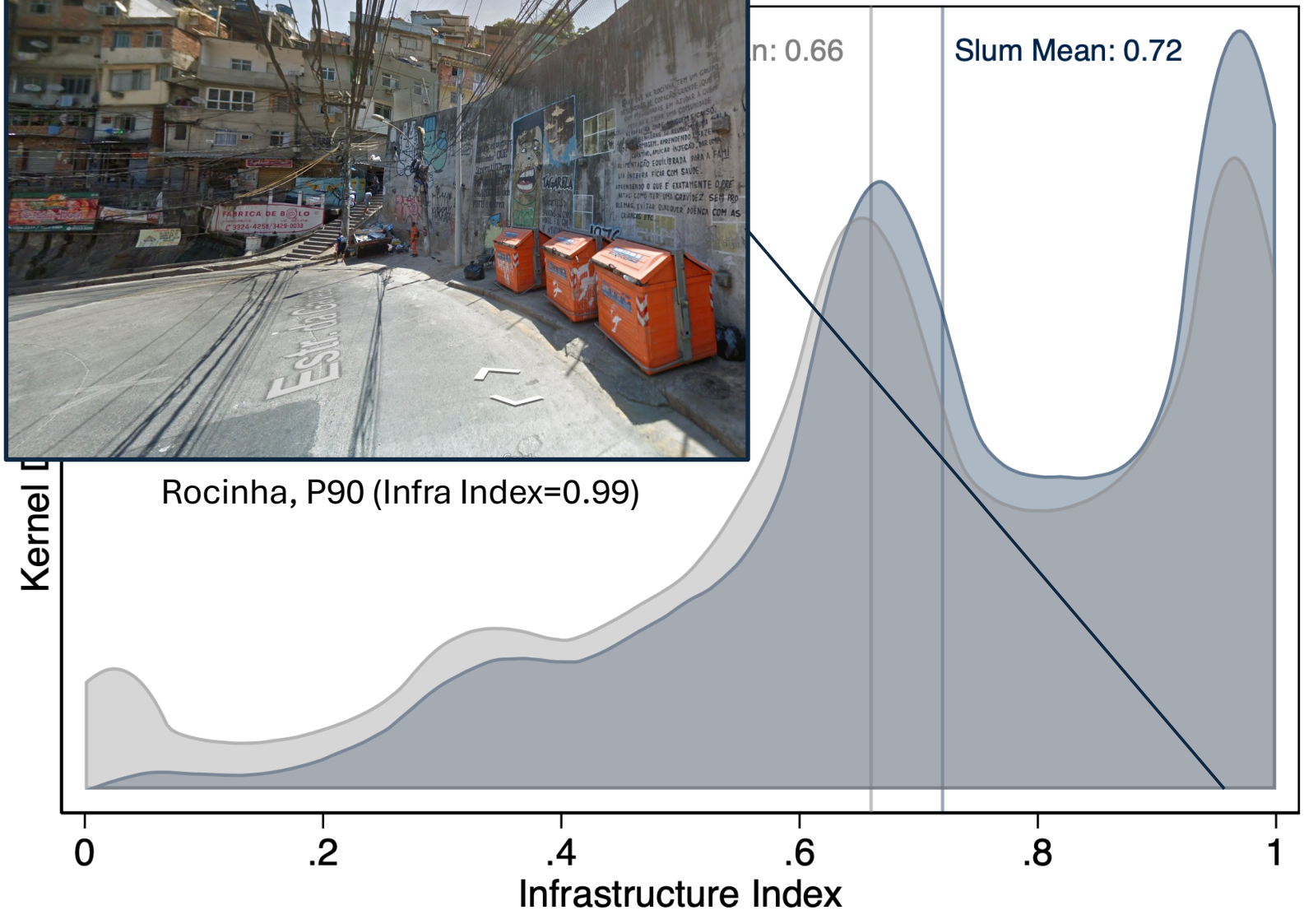
Index = average of: access to water and sewer, trash collection, street lighting and pavement, sidewalks, open sewer, and trash in the streets

It's a combination of high access to infrastructure and poor quality



There is huge heterogeneity in infrastructure within slums...

Rocinha, P90 (Infra Index=0.99)



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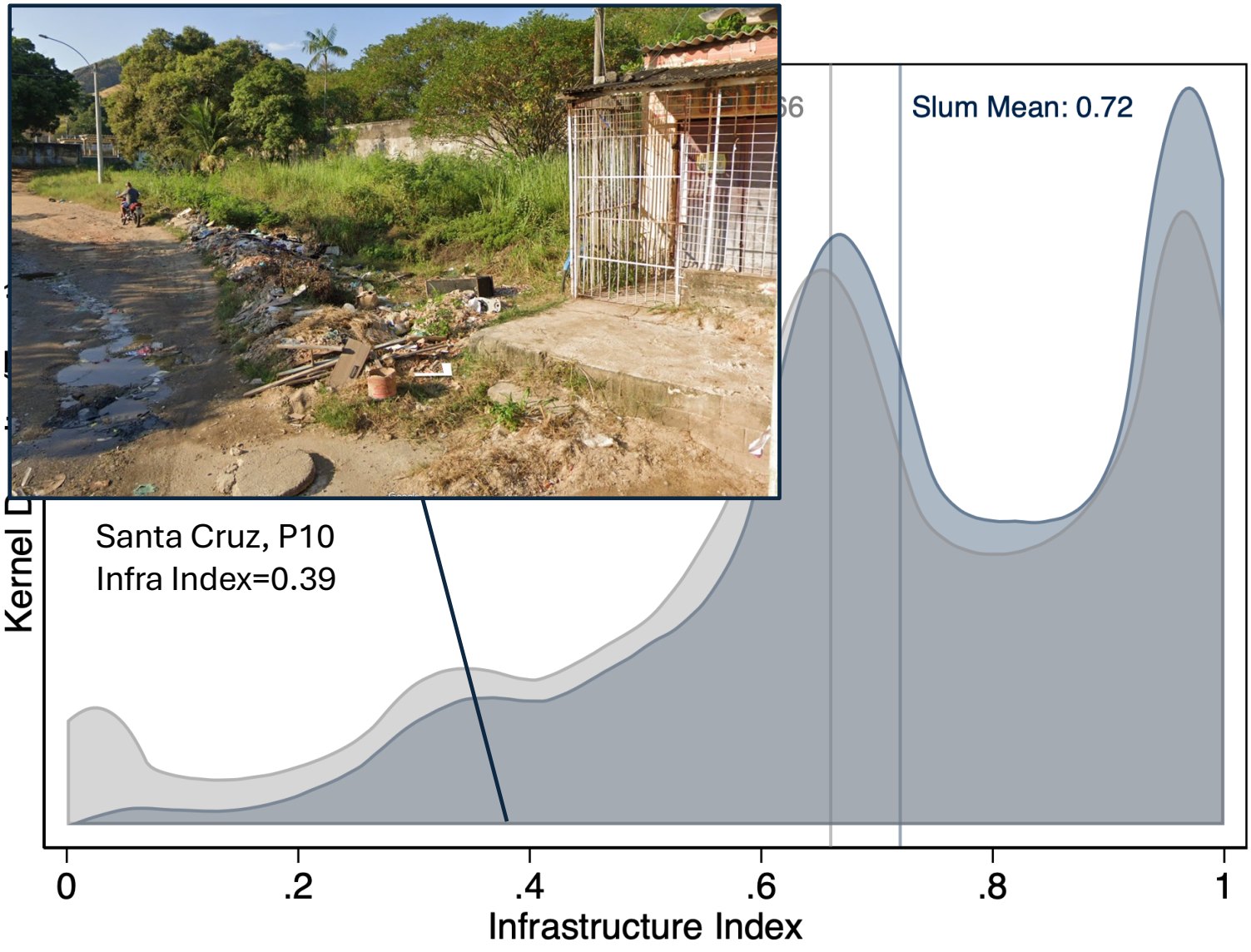


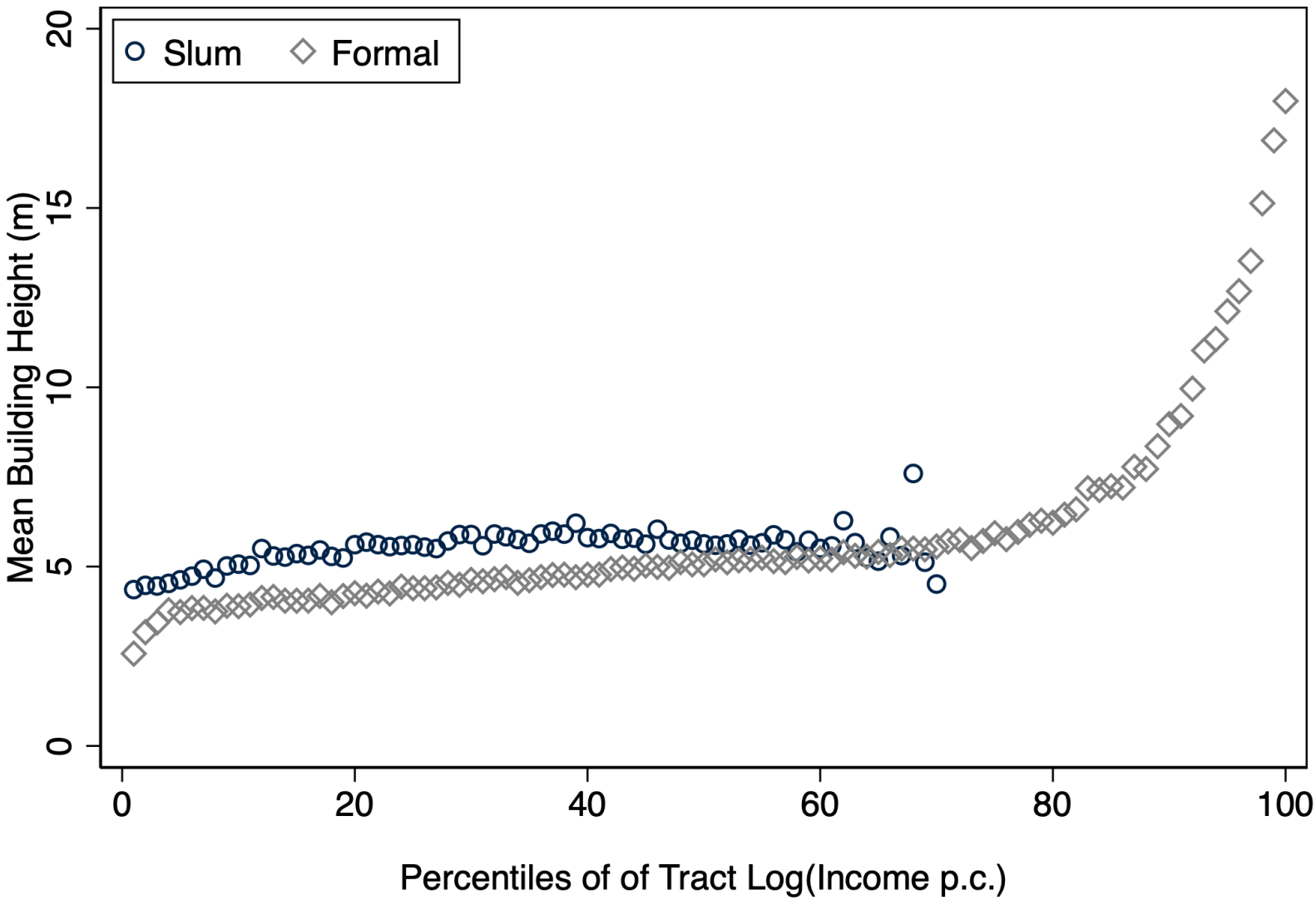
3 Housing: quality

Slums are not defined by poor housing conditions when compared to poor formal areas...

	% Cement/Dirt Floor		% Uncoated Brick Wall	
	(1)	(2)	(3)	(4)
Slum dummy	0.052***	-0.050***	0.055***	0.018***
	(0.003)	(0.003)	(0.002)	(0.002)
Constant	0.356***	0.459***	0.148***	0.184***
	(0.001)	(0.002)	(0.001)	(0.001)
Observations	69,836	31,512	69,836	31,512
Poor formal	No	Yes	No	Yes
Source	CadUnico	CadUnico	CadUnico	CadUnico

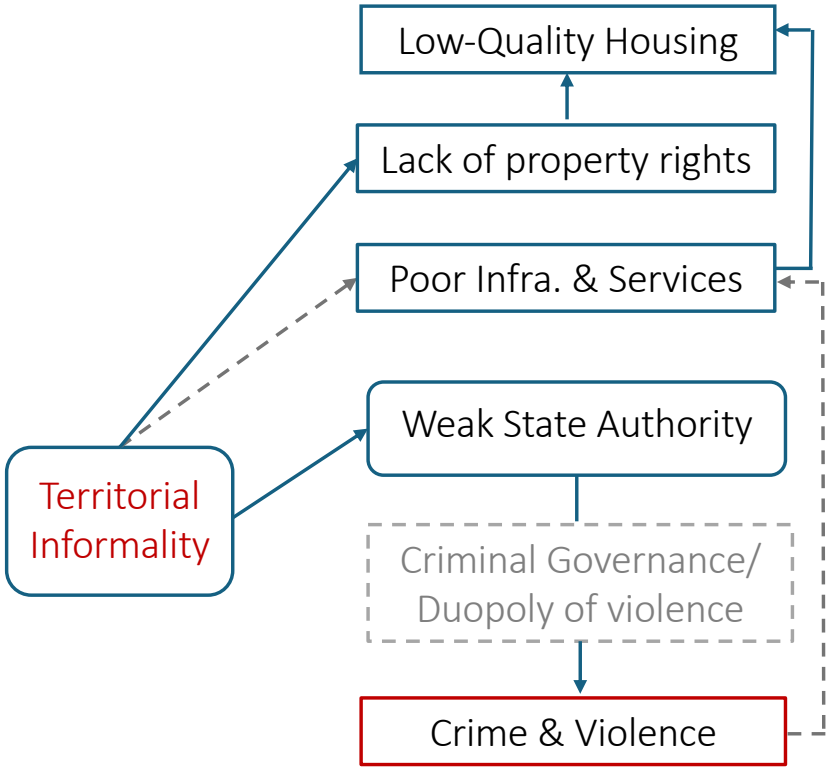
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3 Housing: Low building height



4 Crime and violence

Areas of weak state authority and duopoly of force → can be stable or turbulent (e.g. Lessing, 2020) → possibility of violent confrontations (e.g. Monteiro and Rocha, 2017).



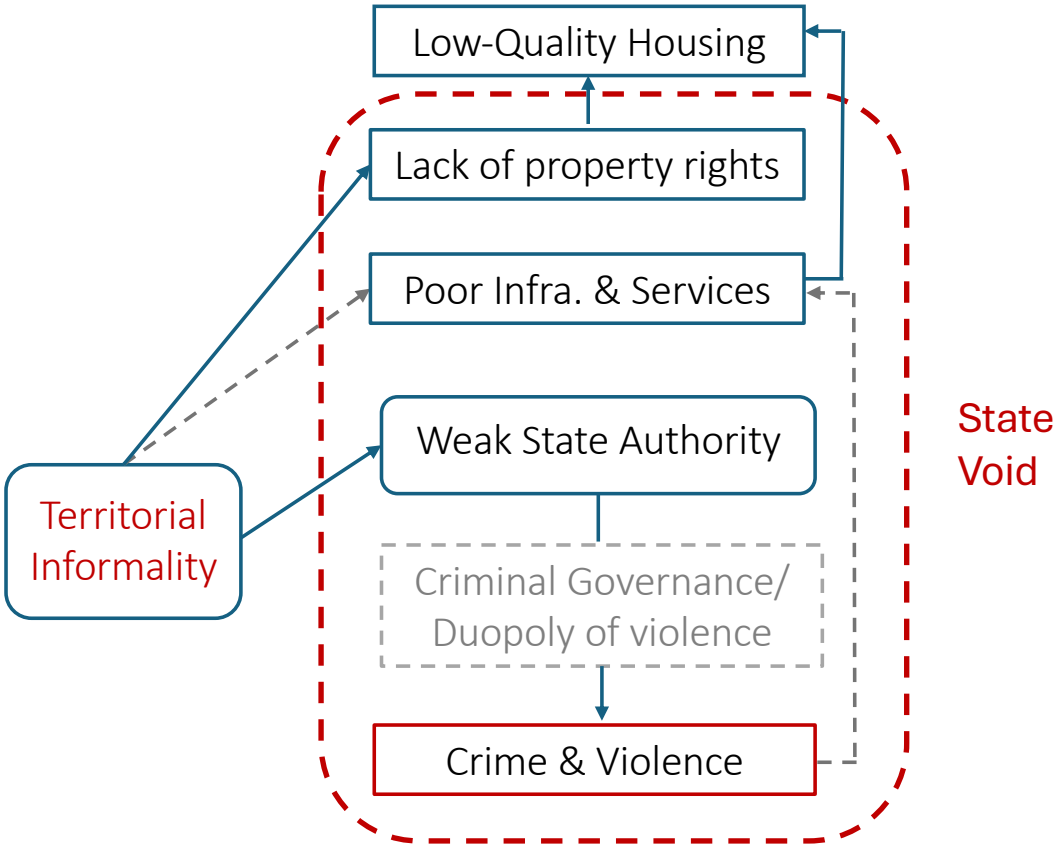
4 Crime and violence: higher in slums, even vs. poor formal areas

	Log(Victimization) (1)	Log(Victimization) (2)	Log(Victimization) (3)
Slum dummy	0.772***	0.466***	0.876***
	(0.036)	(0.023)	(0.029)
Observations	67,399	67,399	28,216
R-squared	0.005	0.395	0.442
Sample	All	All	Slums+Formal Poor
MA FE	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

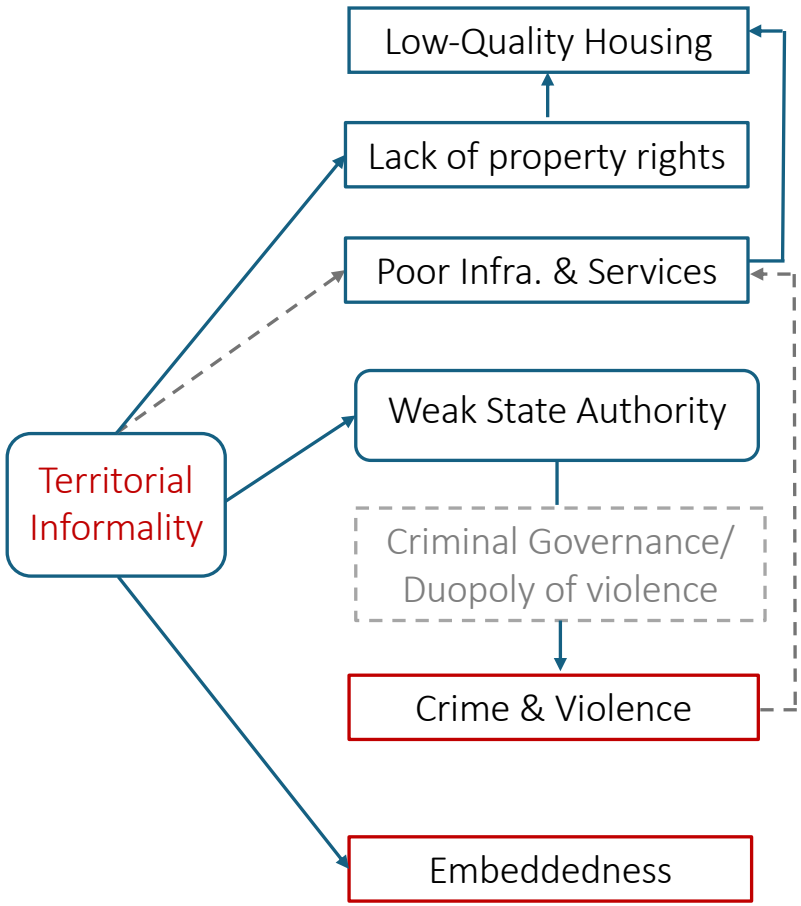
Slums in Brazil: "State Voids"

There can be great variation in observed characteristics across slums and over time. We propose state void as the unifying concept.



Slums in Brazil: "State Voids"

Key: slums are pockets of state void **embedded** in the city → next to areas with full state presence, often very affluent.

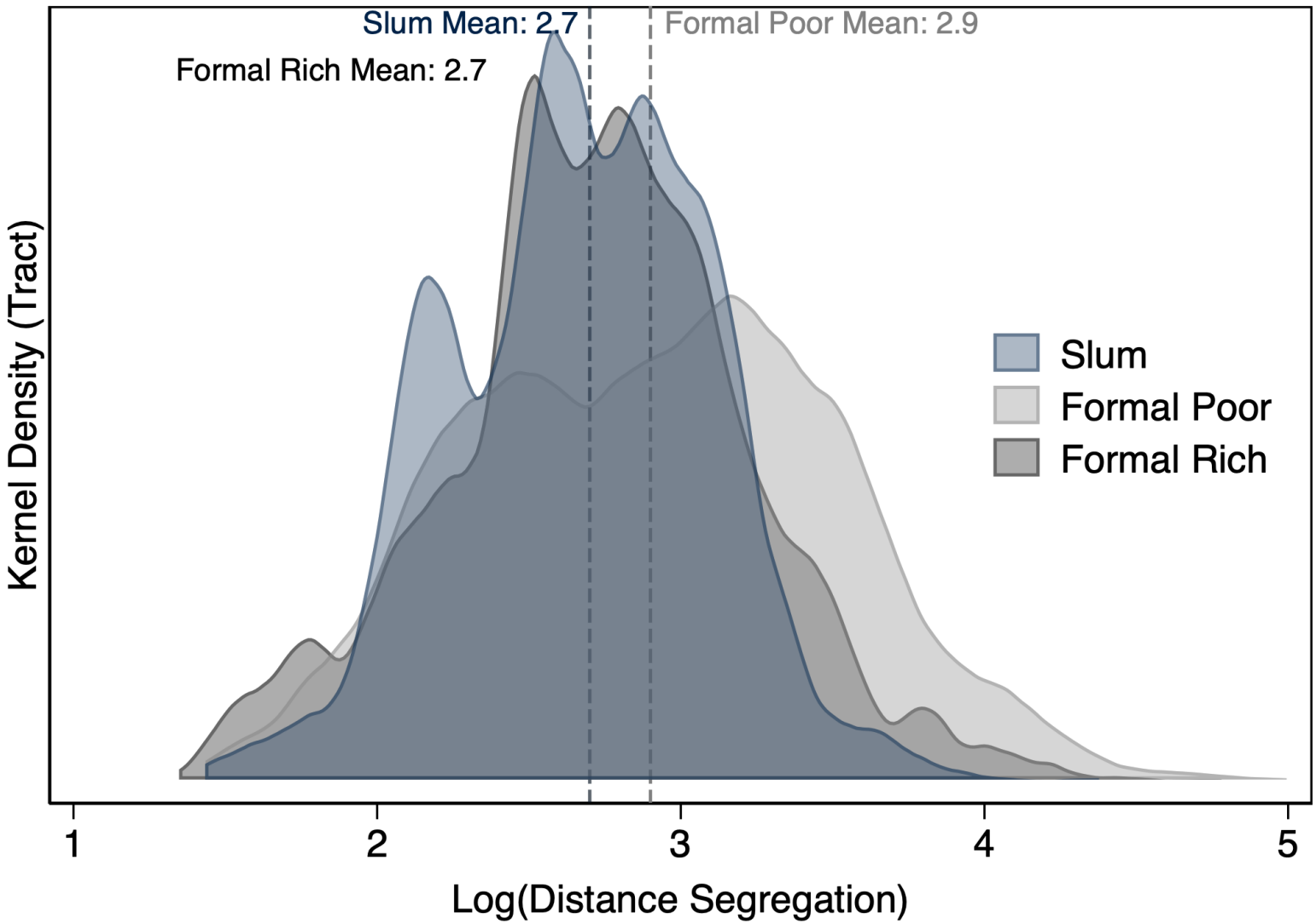


Rio

Mumbai

Nairobi

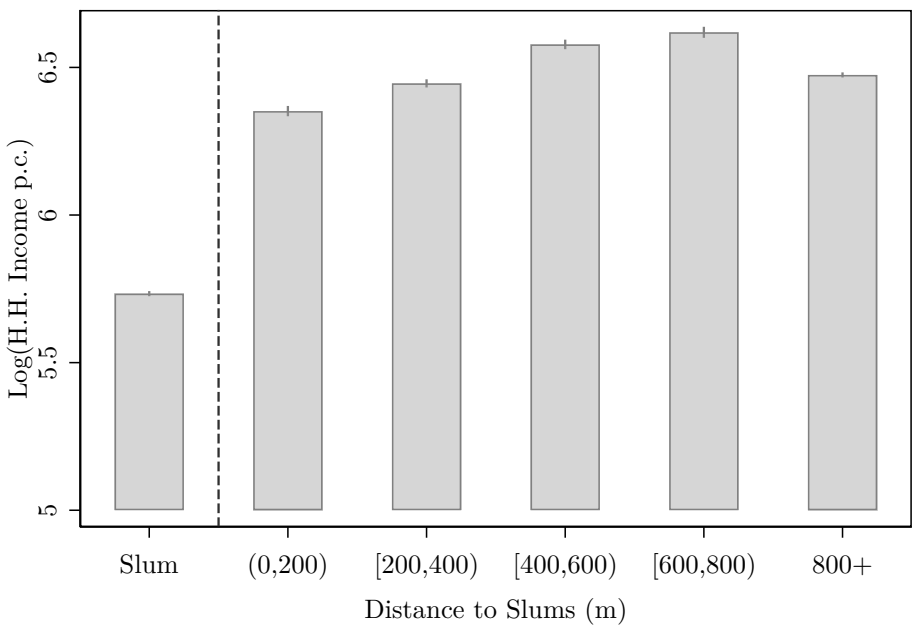
5 Location-wise, slums look like rich formal areas...



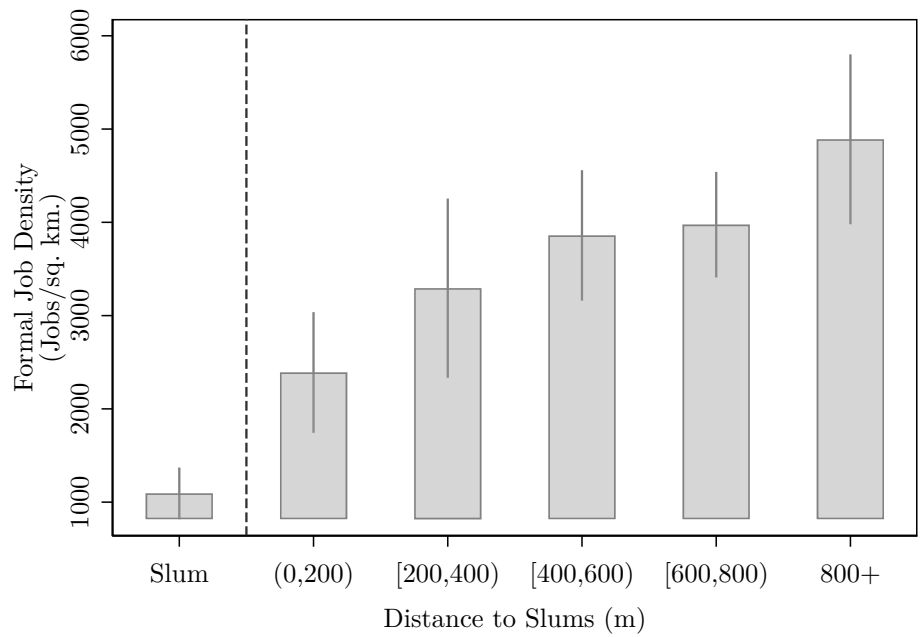
Distance Segregation (Harari 2024) = avg. distance to top-quartile-income nhbds.

5 ...but with sharp differences at the border

(a) H.H. Income

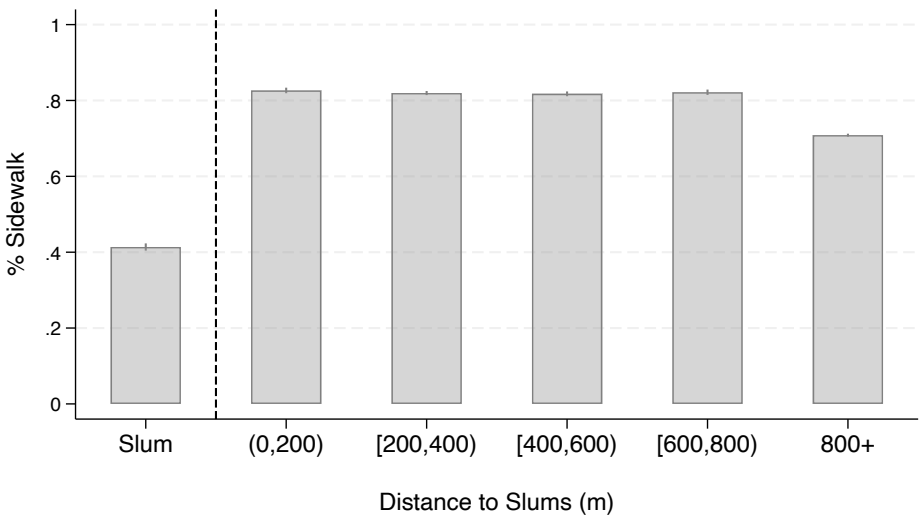


(b) Formal Job Density

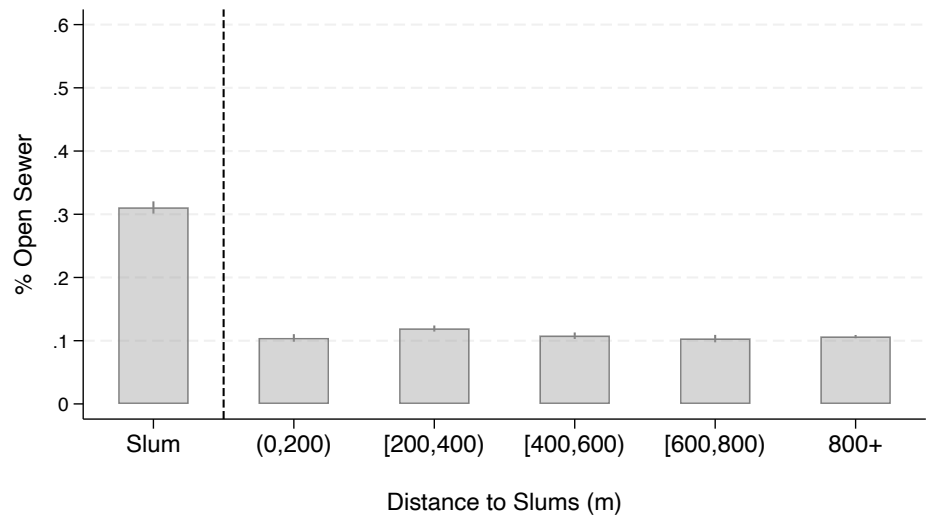


5 ...but with sharp differences at the border

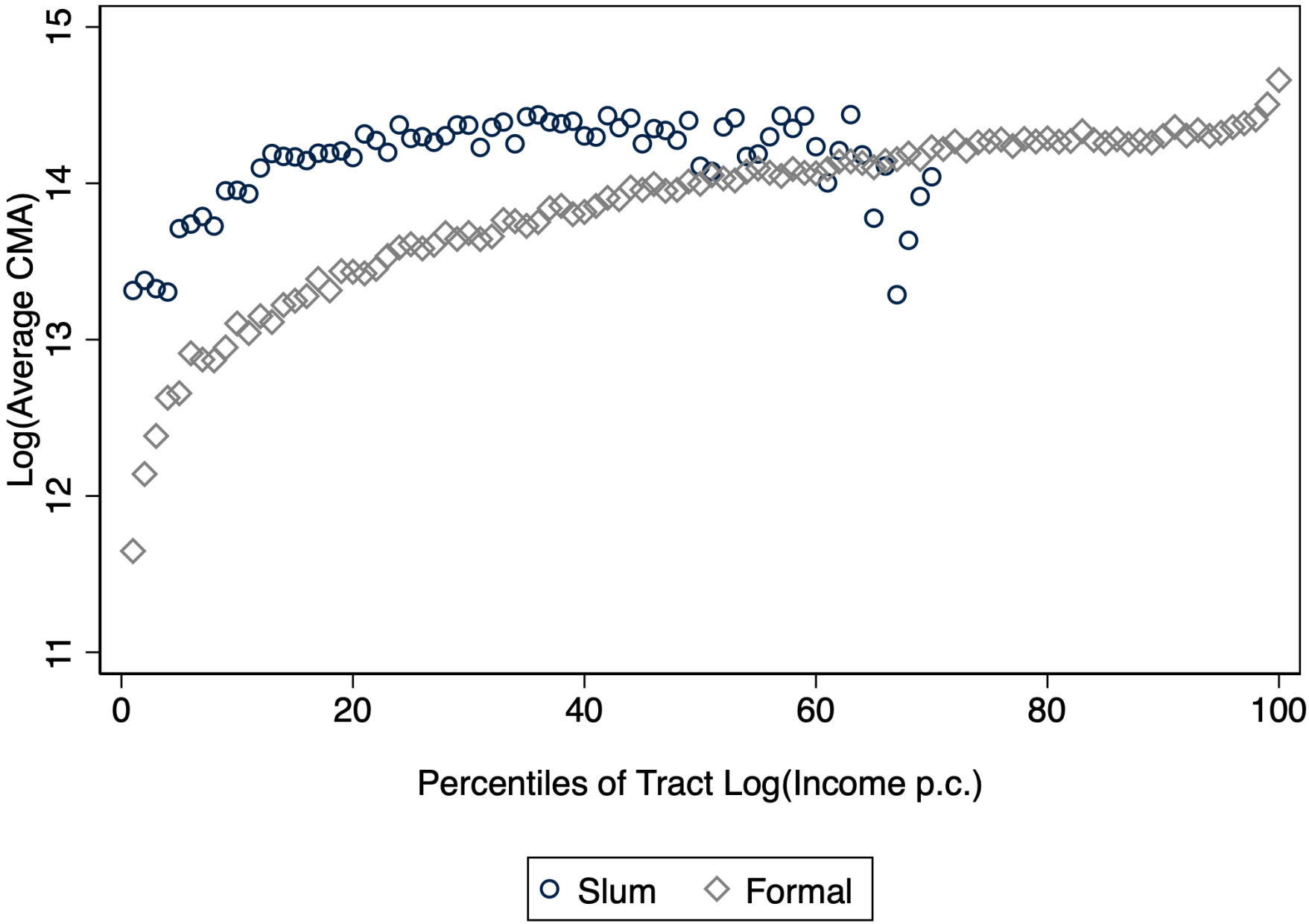
(a) % HHs w/sidewalks



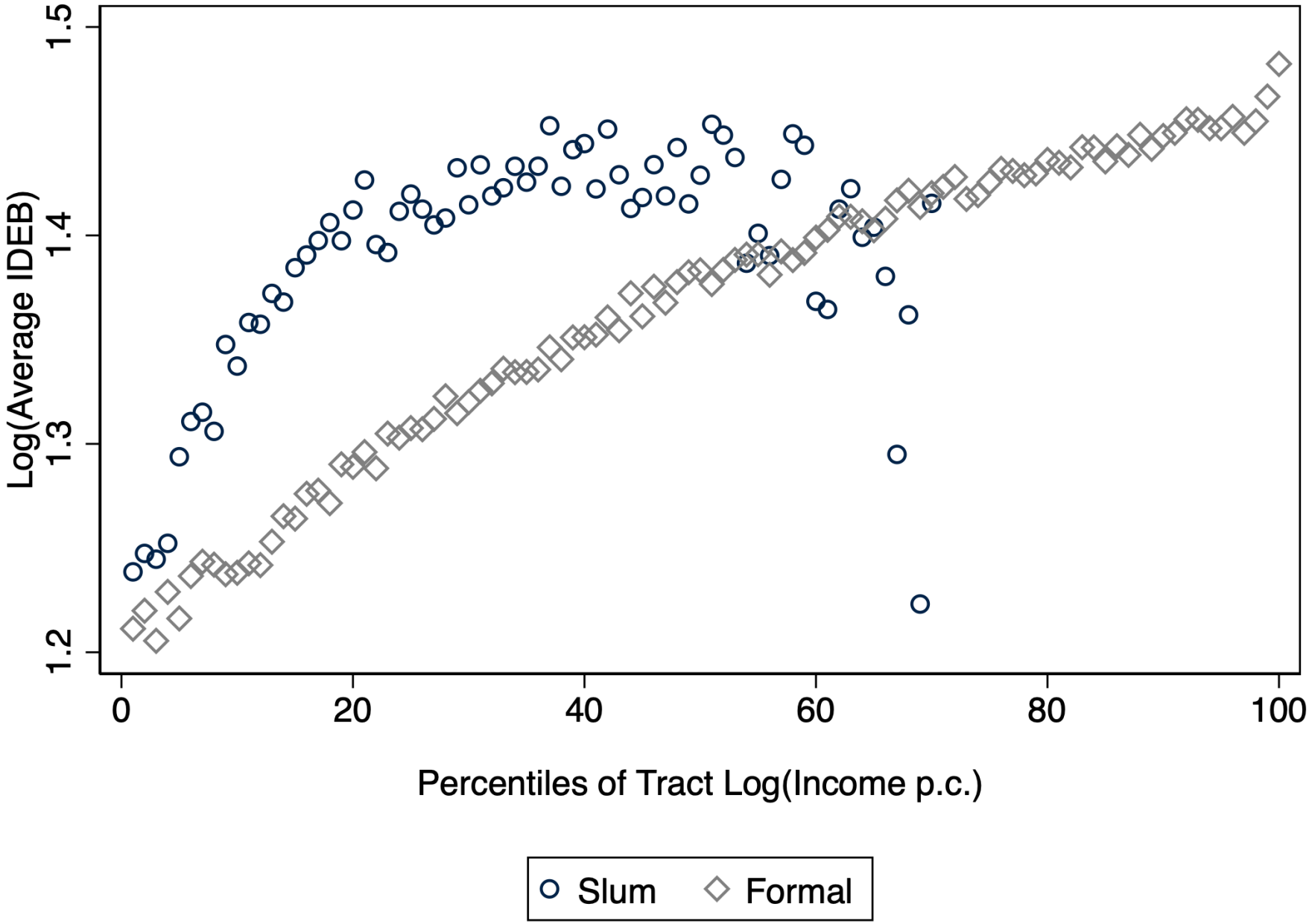
(b) % HHs w/open sewer



6 Slums allow low-income residents to access **formal jobs**...

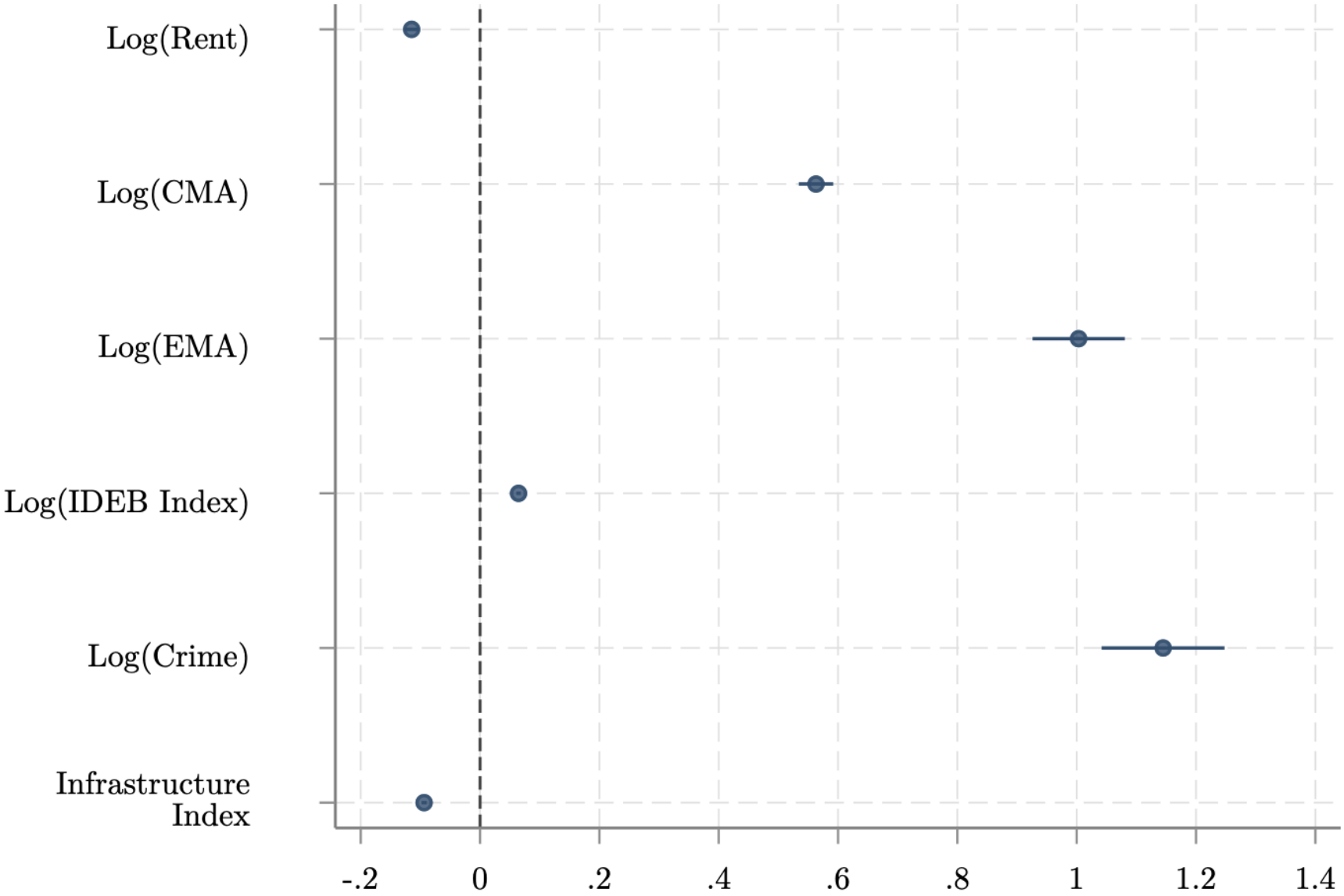


. . . and **good schools.**



7 The unique tradeoff slum residents face

Slums vs Formal Poor Tracts



8 On average, slums display similar labor market outcomes...

▸ Resident Characteristics

8 ... but slightly lower Intergenerational Mobility

	$\Pr$[HS|Parents $<$ HS]			E[Yrs Schooling|Parents $<$ HS]		
	(1)	(2)	(3)	(4)	(5)	(6)
Slum	-0.050***	-0.022***	-0.026***	-0.325***	-0.106***	-0.133***
	(0.003)	(0.003)	(0.002)	(0.016)	(0.016)	(0.013)
Constant	0.650***	0.622***	0.553***	10.916***	10.697***	10.323***
	(0.002)	(0.002)	(0.012)	(0.009)	(0.010)	(0.081)
Obs.	65,249	27,532	27,532	65,249	27,532	27,532
R^2	0.008	0.003	0.233	0.010	0.003	0.223
Metro Area FE			✓			✓
Sample	All	Slums & Formal Poor	Slums & Formal Poor	All	Slums & Formal Poor	Slums & Formal Poor

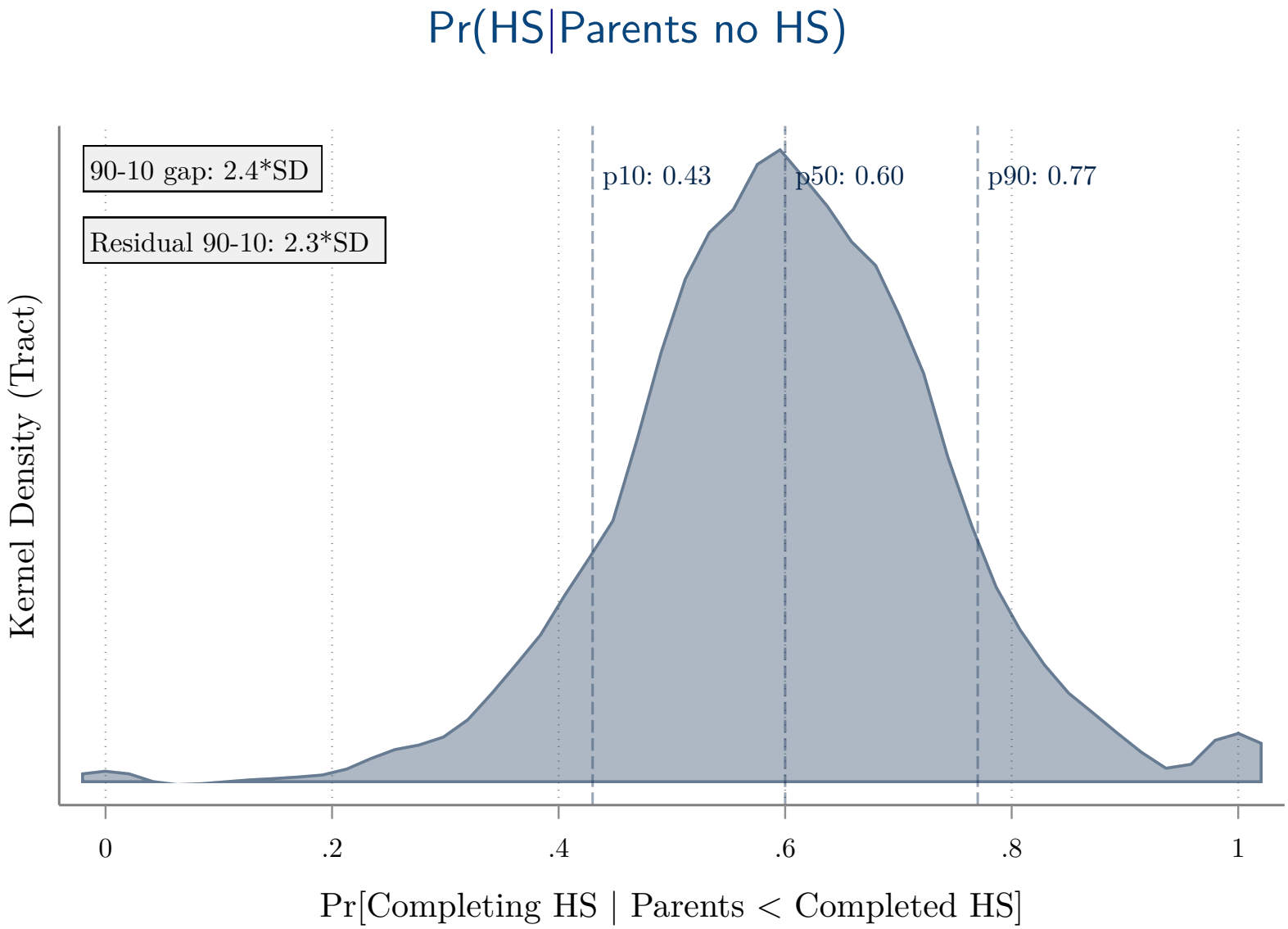
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

8 ... but slightly lower Intergenerational Mobility

	Pr[Slum Dweller]			Pr[Bolsa Familia]		
	(1)	(2)	(3)	(4)	(5)	(6)
Slum	0.236***	0.214***	0.189***	0.084***	0.029***	0.018***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Constant	0.058***	0.081***	0.051***	0.200***	0.256***	0.258***
	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.007)
Obs.	60,292	23,768	23,768	60,292	23,768	23,768
R^2	0.231	0.244	0.428	0.031	0.010	0.228
Metro Area FE			✓			✓
Sample	All	Slums & Formal Poor	Slums & Formal Poor	All	Slums & Formal Poor	Slums & Formal Poor

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

9 There is huge variation in IGM across slums



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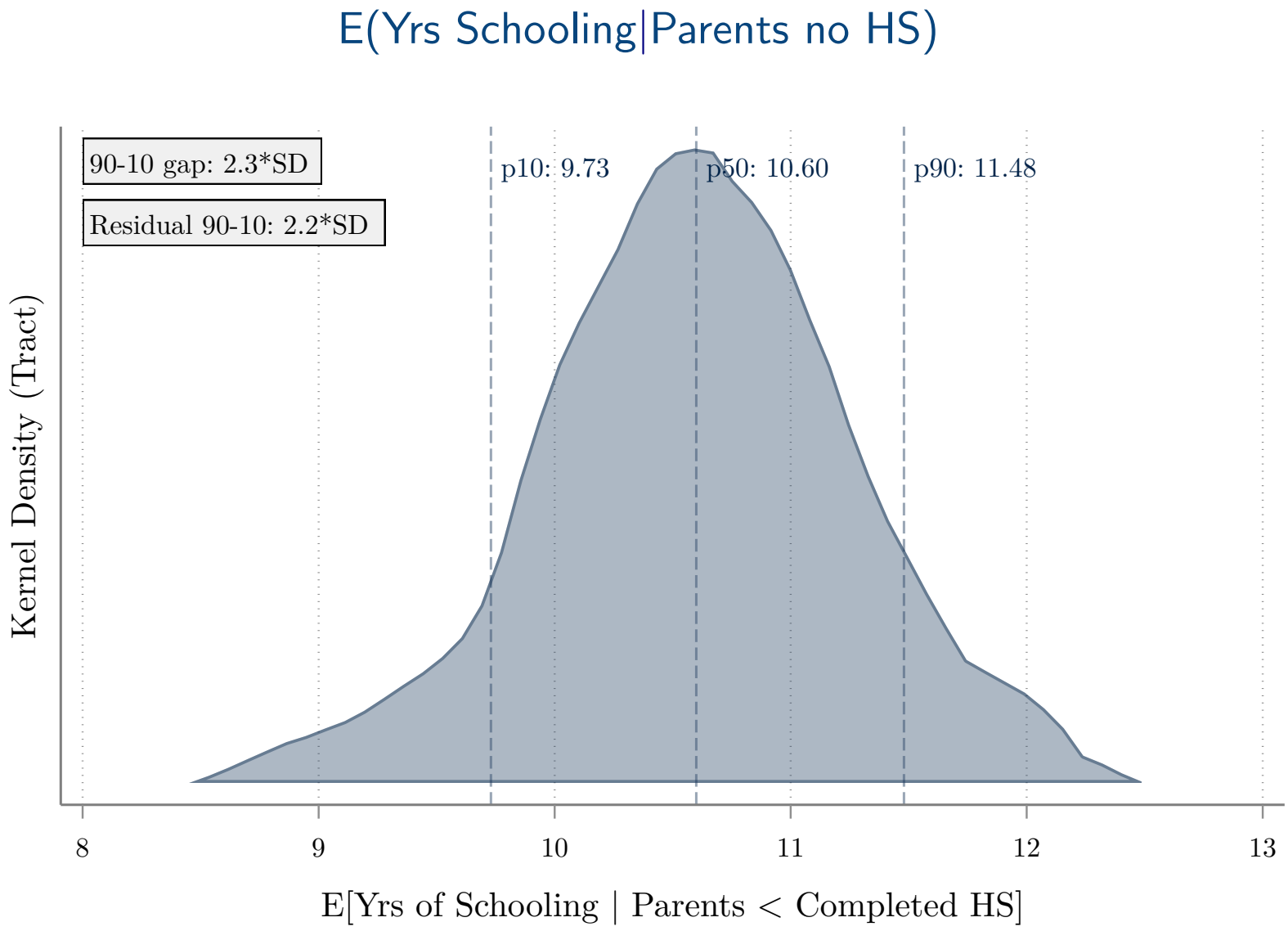

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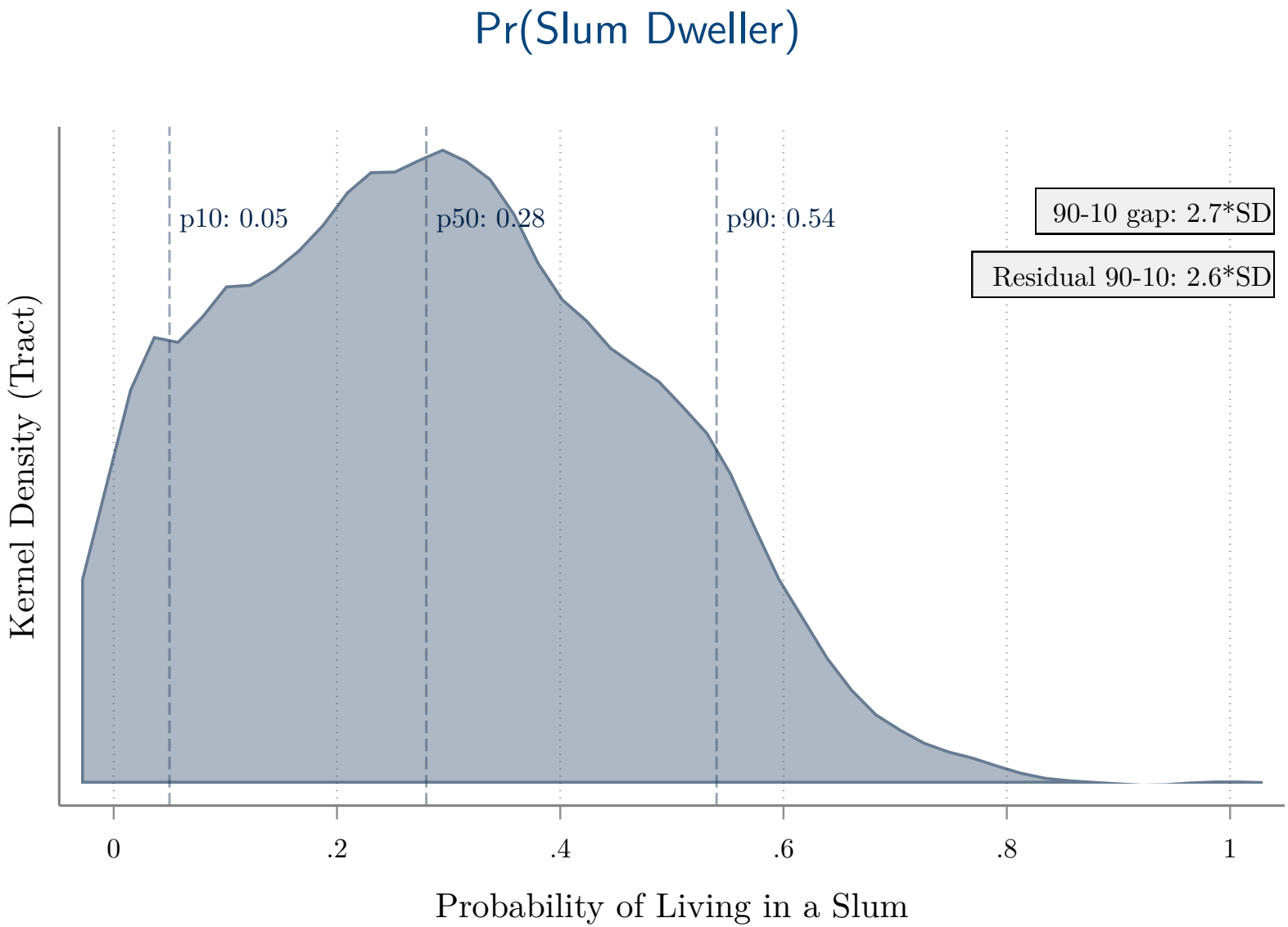

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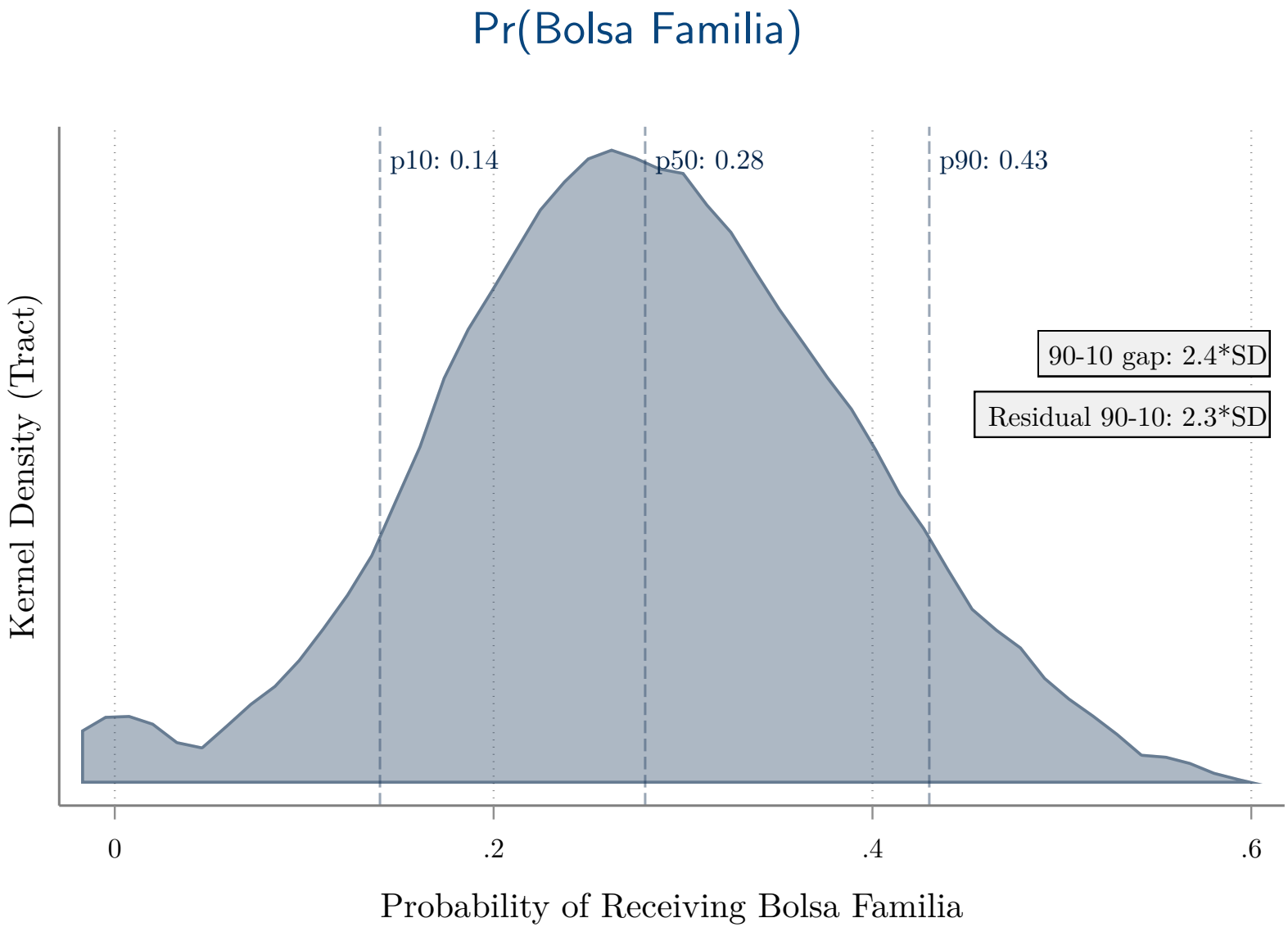


Outline

Main Ingredients

Closed city with N nhbds., type $g \in \{\text{formal}, \text{slum}\}$.

Individuals choose where to live, work, and to invest in their child's education.
details

Preferences: non-homothetic in housing, goods + intergenerational altruism.
details

Place of Residence:

- Amenity B_i
- Pr. λ_i of receiving *formal job* offer; else, work informally locally
- School quality $\varsigma_i \rightarrow$ determines cost of HK investment
- Victimization risk $\kappa_{g(i)} \implies$ lose income. details

Housing Developers details

- Formal: perfectly competitive, choose building height v_i at cost $\Xi_0 v_i^{\Xi_1}$.
- Slum: same cost, but height cap $\bar{v}$, factor σ additional floorspace.

Calibration $\Rightarrow$ Rio de Janeiro

External: victimization rates, school quality, location choice elasticities, formal job offer probability.

Internal

- Housing preferences: housing share vs. income $\Longrightarrow$ share γ, subsistence requirement $\bar{l}$.
- Intergenerational altruism: education expenditure share $\Longrightarrow$ weight β.
- Housing Supply:
  - Height vs. rents $\Longrightarrow$ cost elasticity Ξ_1.
  - Relative slum p95/5 height ratio $\Longrightarrow$ slum height cap $\bar{v}$.
  - Relative slum rents $\Longrightarrow$ extra floorspace factor σ.
- Education...
  - Skill premia $\Longrightarrow$ productivities $\overline{h}_e$.
  - IGM vs. school quality $\Longrightarrow$ costs ψ_e + school quality effect ξ.

Model Inversion: Amenities B_i + wages w_j.

▸ details

Model Matches Non-Targeted Facts

- Lower income and amenities, *even at the border* ▸ Figure
- Constrained height (▸ Figure) despite being embedded in desirable locations (▸ Figure)
- Unique tradeoff: low-income, high-crime but high-CMA ▸ Figure
- Similar IGM to formal, but huge variation across slums ▸ Figure

Outline

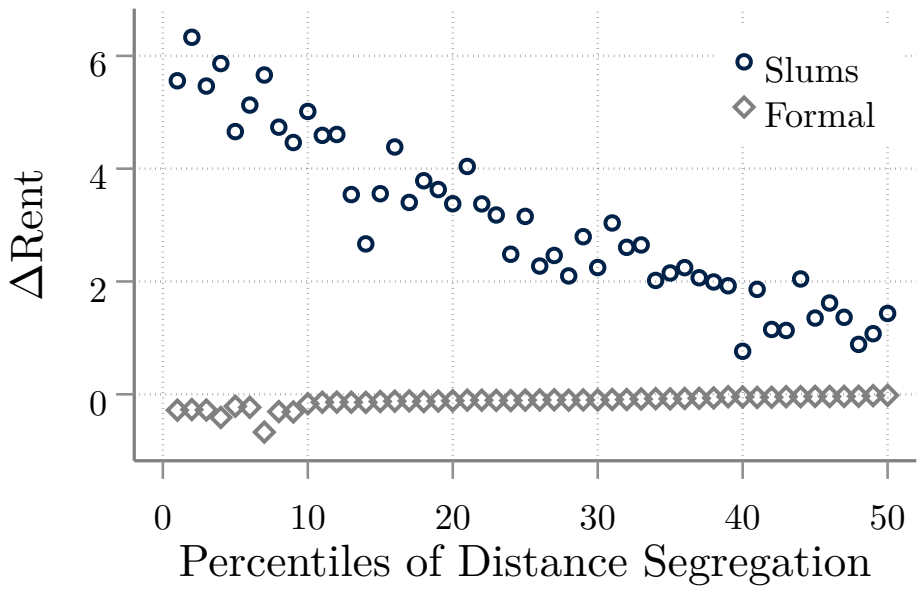
Eliminating the differences between slums and formal areas

Slums receive:

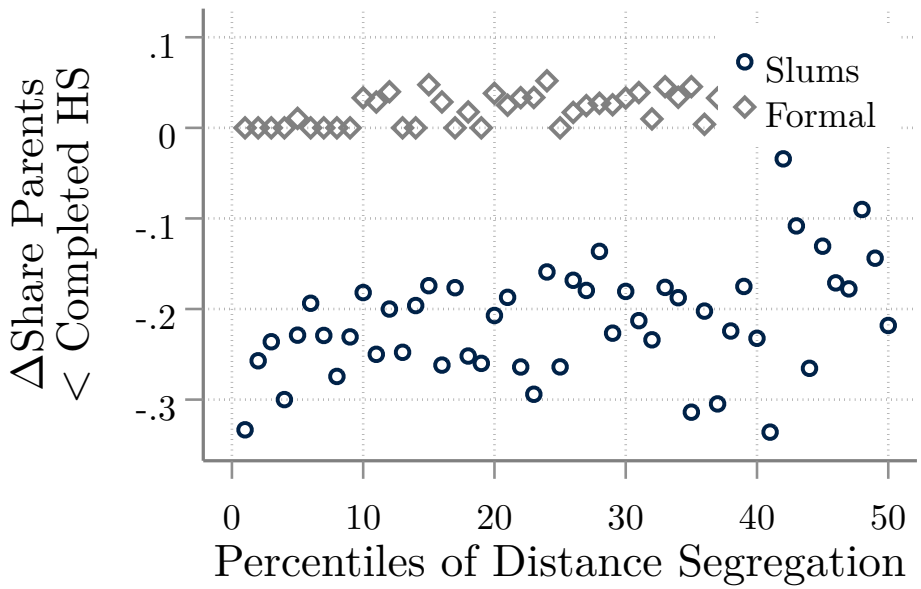
1. Formal amenities B_i, on average.
2. Formal housing technology: $\bar{v} \to \infty$, $\sigma = 1$.
3. Formal-neighborhood victimization rate: $\kappa_{\text{Slum}} = \kappa_{\text{Formal}}$.

Gentrification

(a) Rents

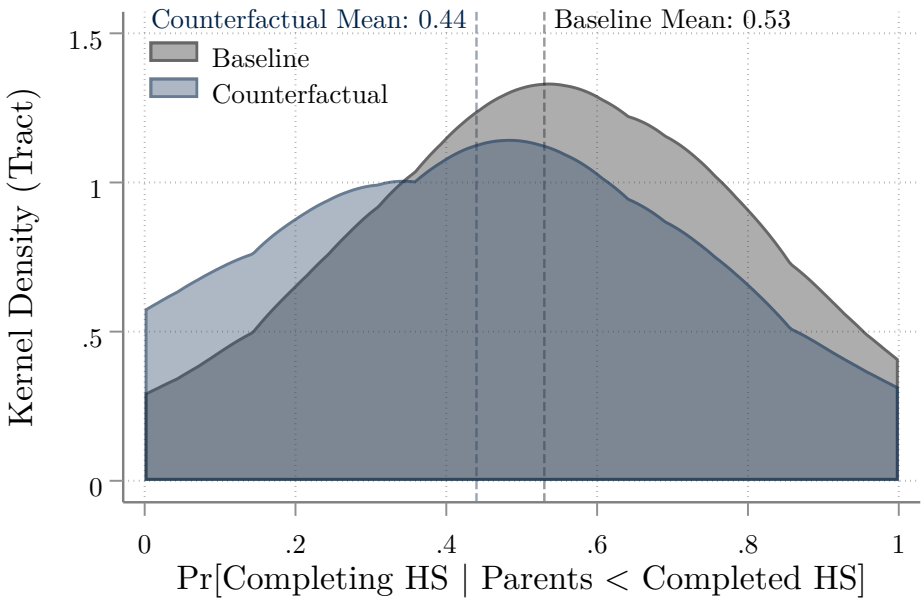


(b) Low-Skill Population

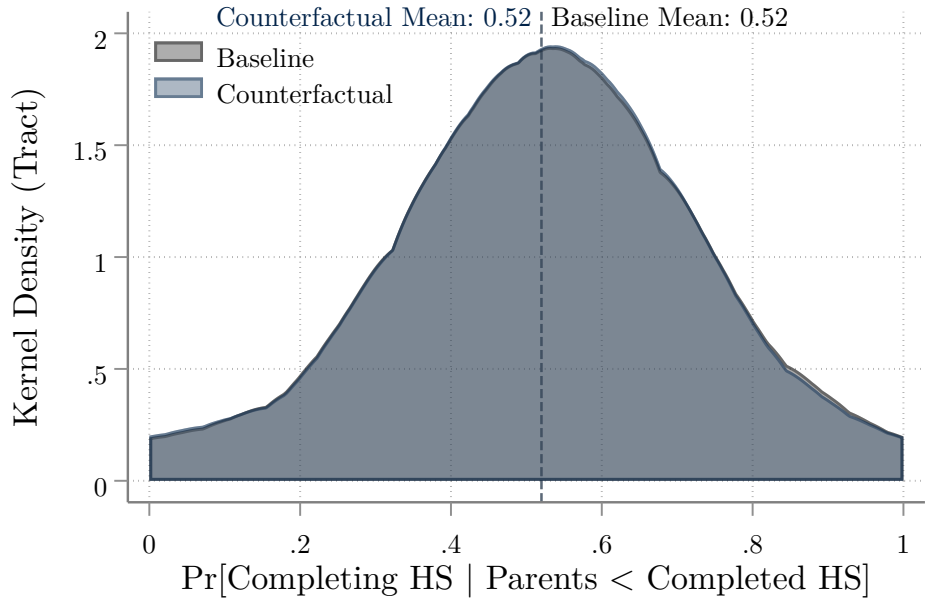


↑ Rents ⟹ ↓ Human Capital Investment ⟹ ↓ Former Slum IGM

(a) Former Slums (Unweighted)

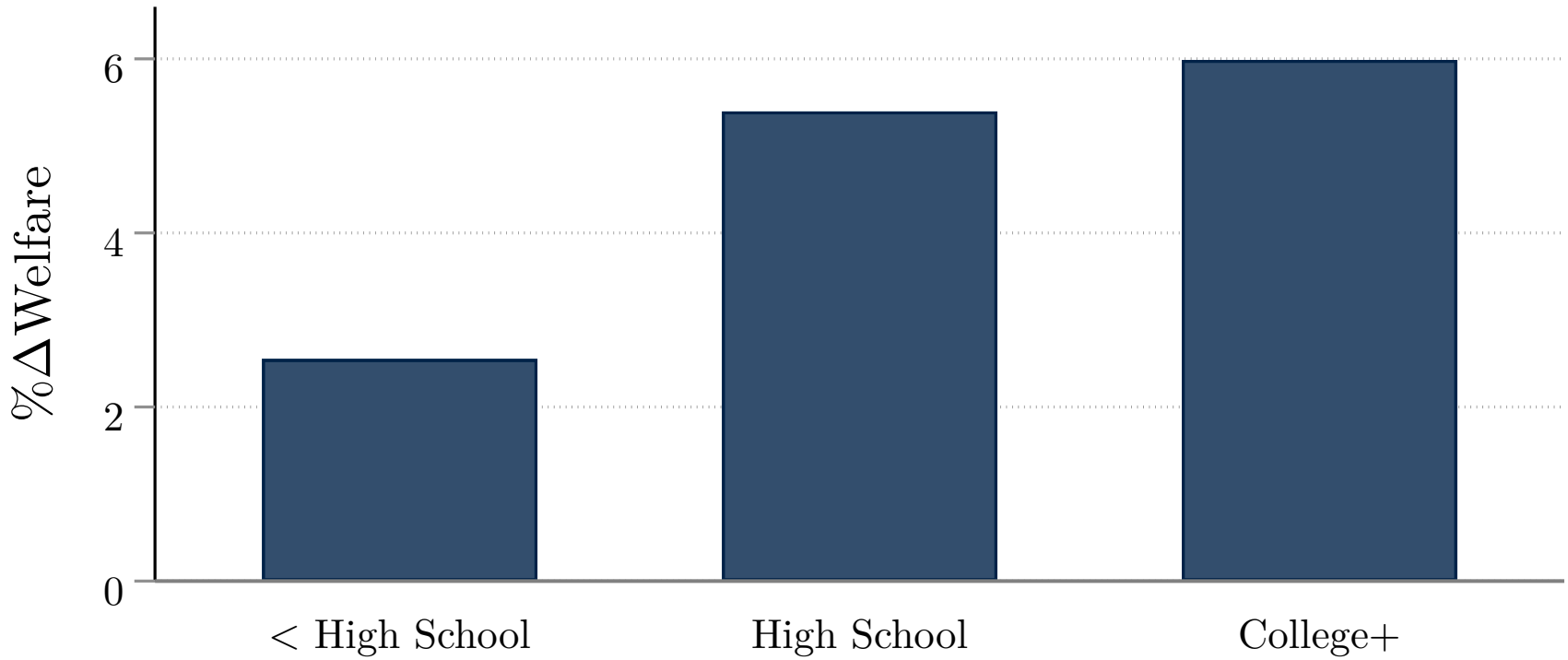


(b) All Neighborhoods (Weighted)



Welfare

Aggregate Welfare Inequality Increases:



Outline

Final Remarks

- We show that, contrary to what has previously emphasized, slums are not characterized by poor housing conditions, nor lack of infrastructure.
- Instead, slums constitute state voids embedded in the city proper, which gives rise to a unique trade-off:
  - Access to formal jobs and schools **X** higher exposure to crime
- There is huge heterogeneity across slums in all dimensions considered. Critically, there are high- and low- IGM slums.
- Eliminating these state voids leads to gentrification, lower IGM in previous slums, higher aggregate welfare, but also higher welfare inequality.

Additional Slides

Census vs. IGM sample, individual level

	Slum Areas			Non-Slum Areas		
	Census MA	Parents MA	IGM Sample	Census MA	Parents MA	IGM Samp
age	32.13	39.72	40.66	34.41	40.04	41.73
white	0.38	0.39	0.30	0.55	0.57	0.41
literate	0.89	0.87		0.94	0.94	
male	0.49	0.48		0.48	0.47	
Obs.	384316	104785	122784	4203474	1216998	2505937

Universe of blocks vs. IGM sample

	Census		IGM Sample	
	Non-Slums	Slums	Non-Slums	Slums
HH income per capita	1009.57	333.72	1011.12	333.72
% illiterate (age 5+)	90.36	82.95	90.39	82.96
Avg. years of schooling (HH head)	7.25	4.73	7.25	4.73
Share male	166.19	123.15	166.40	123.15
Share aged 0–18	100.00	100.00	100.00	100.00
Average age (years)	30.11	24.57	30.15	24.57
Avg. people per household	3.57	3.94	3.57	3.94
% HHs w/water network	87.46	88.50	87.50	88.51
% HHs w/piped water	87.17	88.41	87.50	88.51
% HHs w/o bathroom	2.39	4.01	2.36	3.99
% HHs w/sewer network	61.89	47.75	62.12	47.75
% HHs w/garbage collection	91.72	91.53	91.82	91.54
Obs.	70,482	7,066	69,913	7,054

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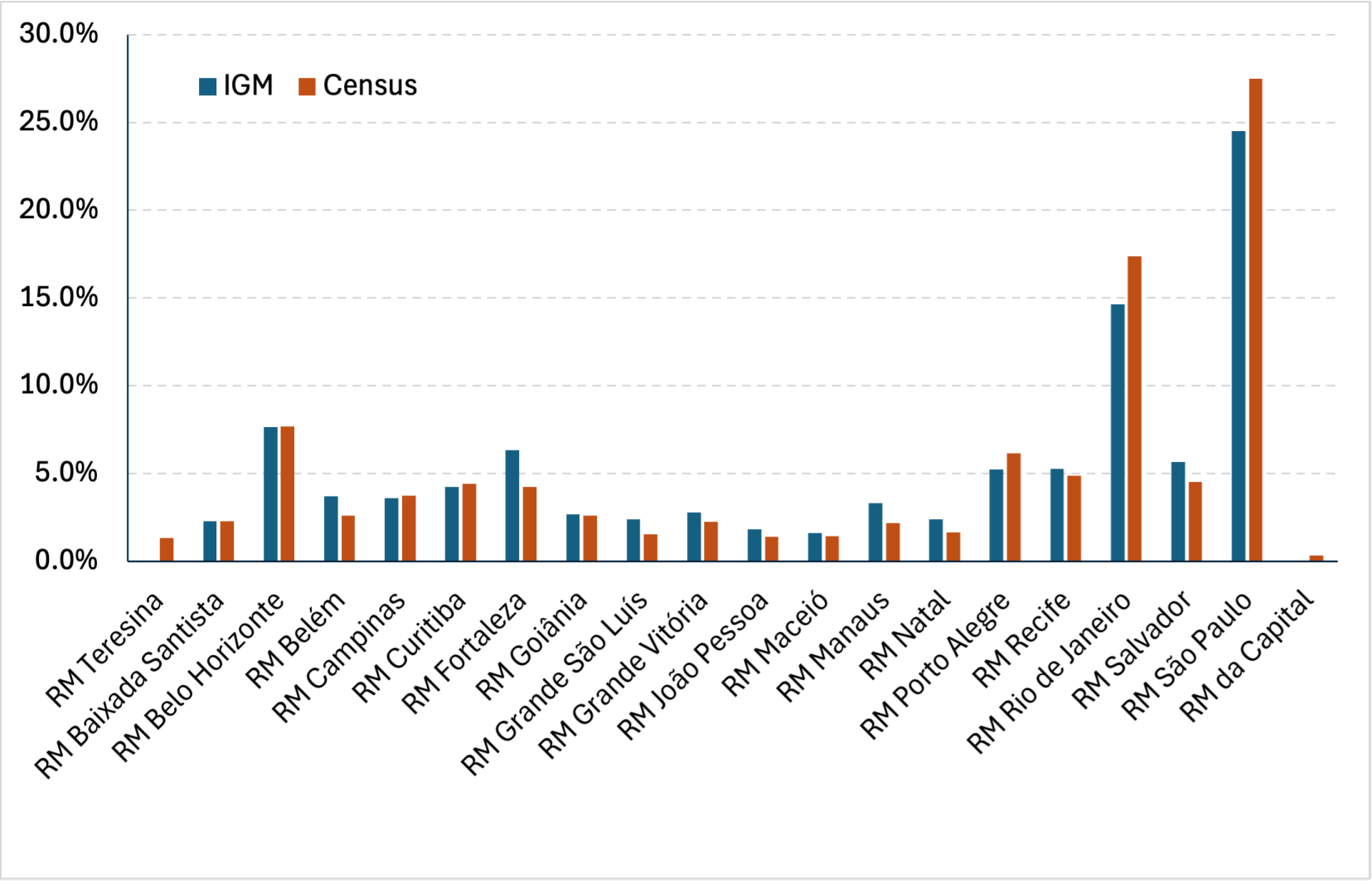
Population coverage: Census vs. IGM sample



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Slum dwellers are more disadvantaged,...

...with a higher share of non-whites, lower education, higher illiteracy rate, and much lower household income per capita:

	Non-Slums	Slums
Age	37.3	35.4
% Male	0.47	0.47
% White	0.55	0.38
Schooling (years)	8.8	6.5
% Illiterate	0.04	0.08
Log(HH Income p.c.)	6.39	5.74

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On average, slums display similar labor market outcomes

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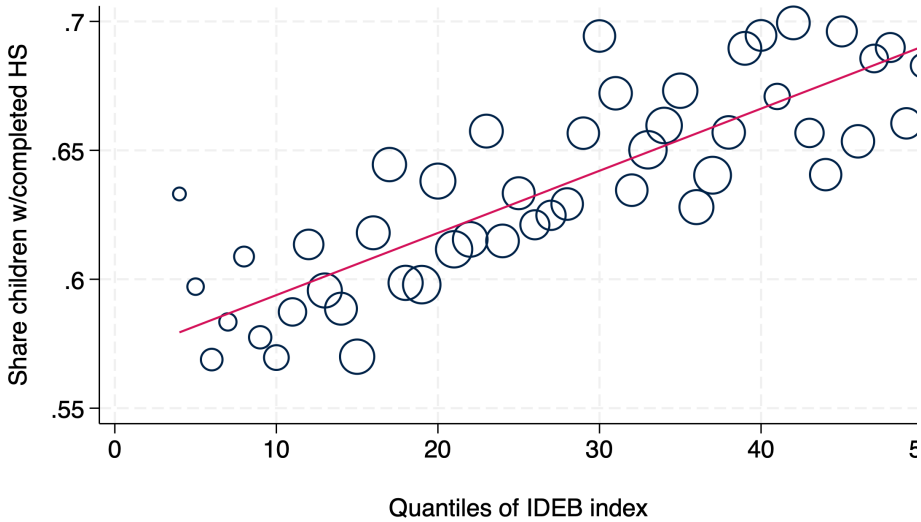
(a) Access Pub. Schools



(b) Access Quality Pub. Schools

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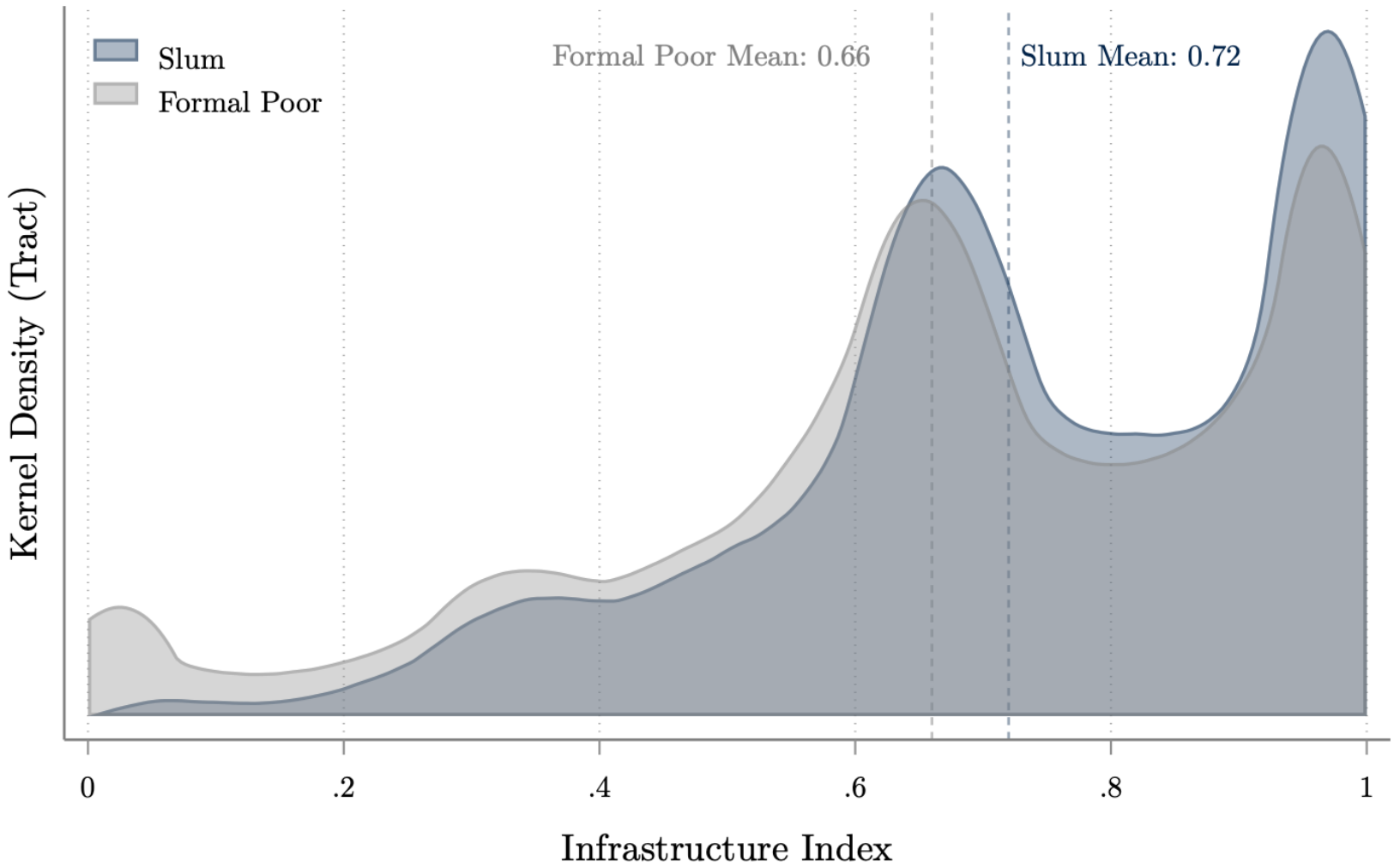
Heterogeneity in Infrastructure in Both Slums and Formal



Infrastructure Index = (Access Sewer + Piped Water + Trash Collection) /3

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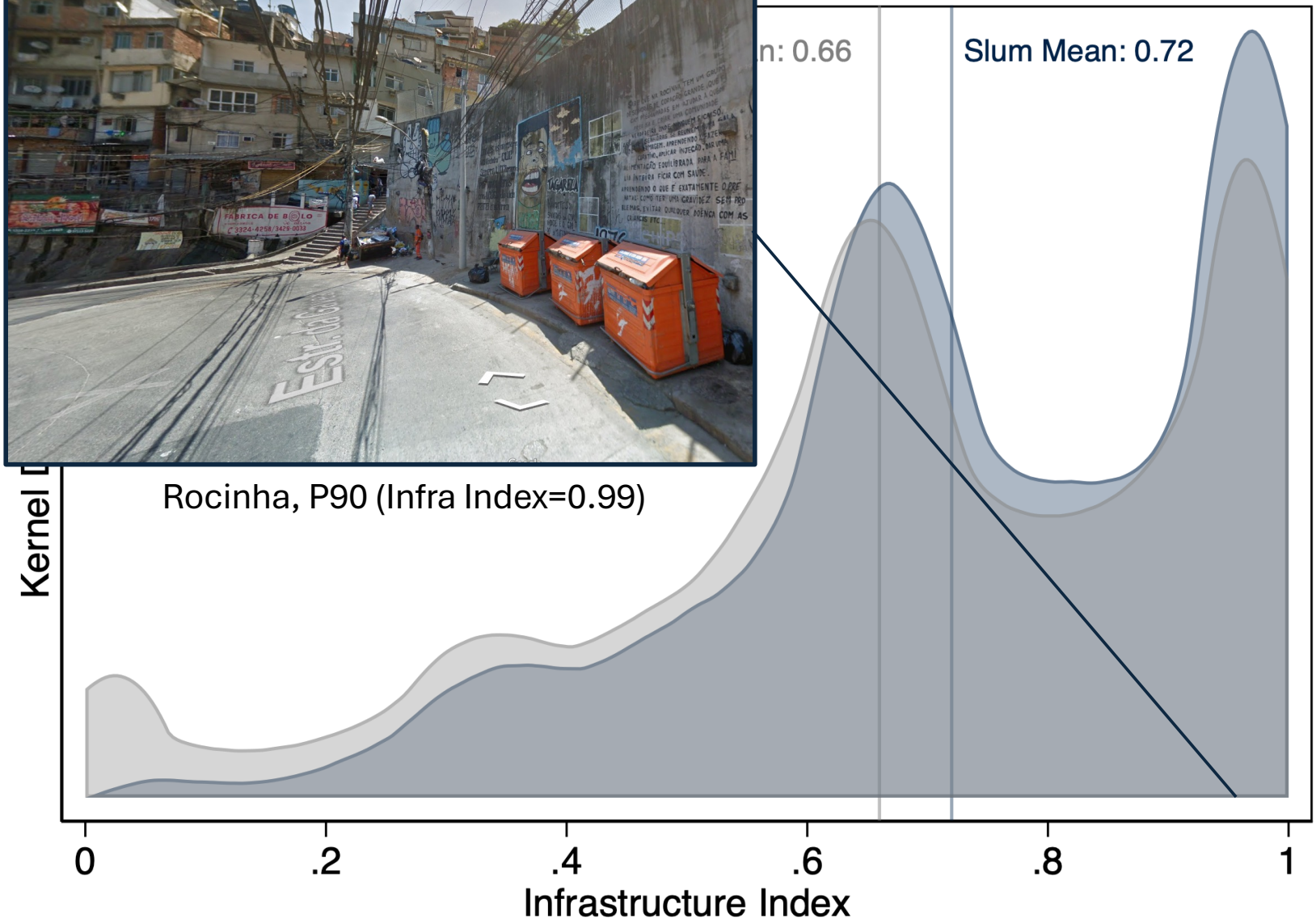
Heterogeneity in Infrastructure in Both Slums and Formal

Rocinha, P90 (Infra Index=0.99)



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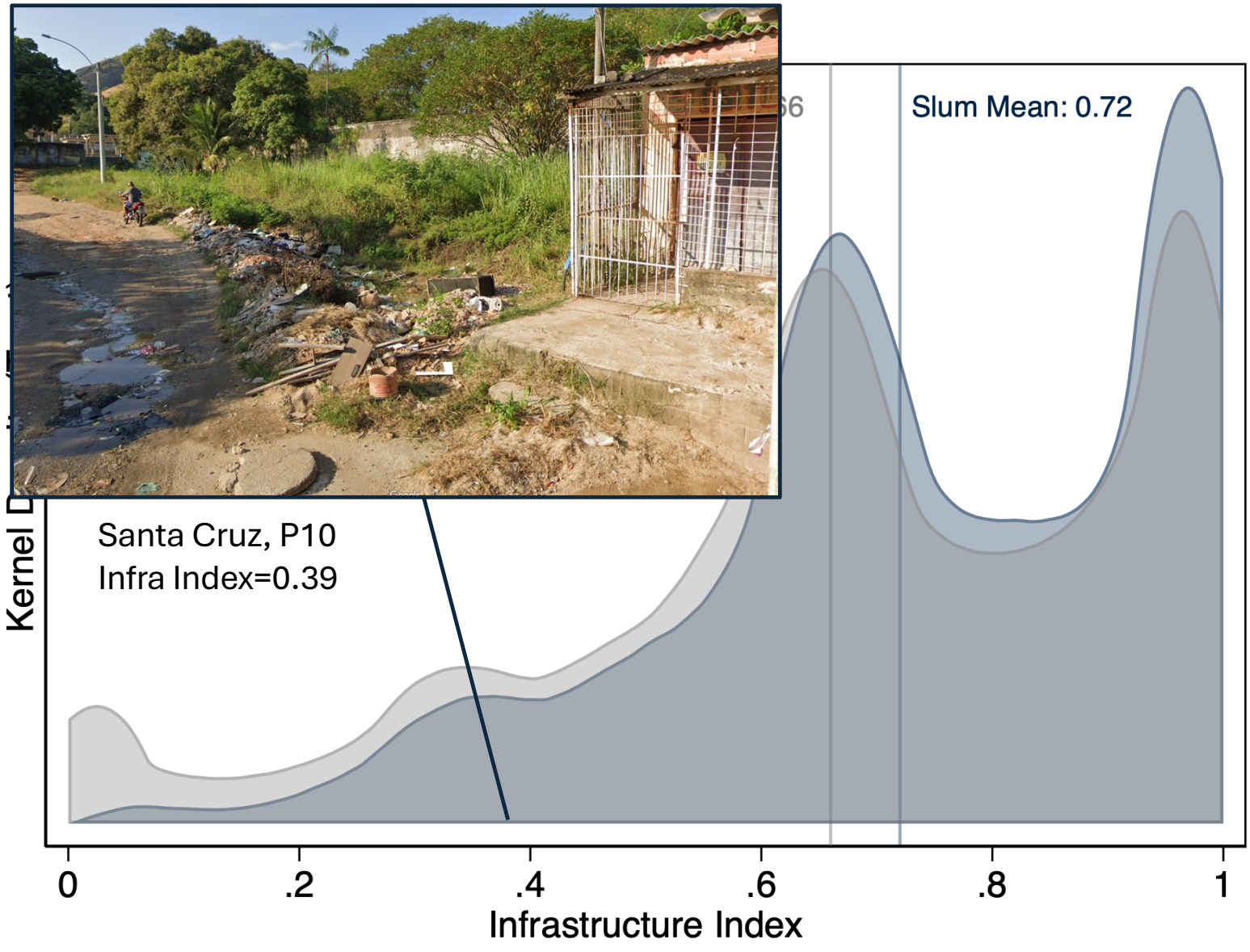
Heterogeneity in Infrastructure in Both Slums and Formal



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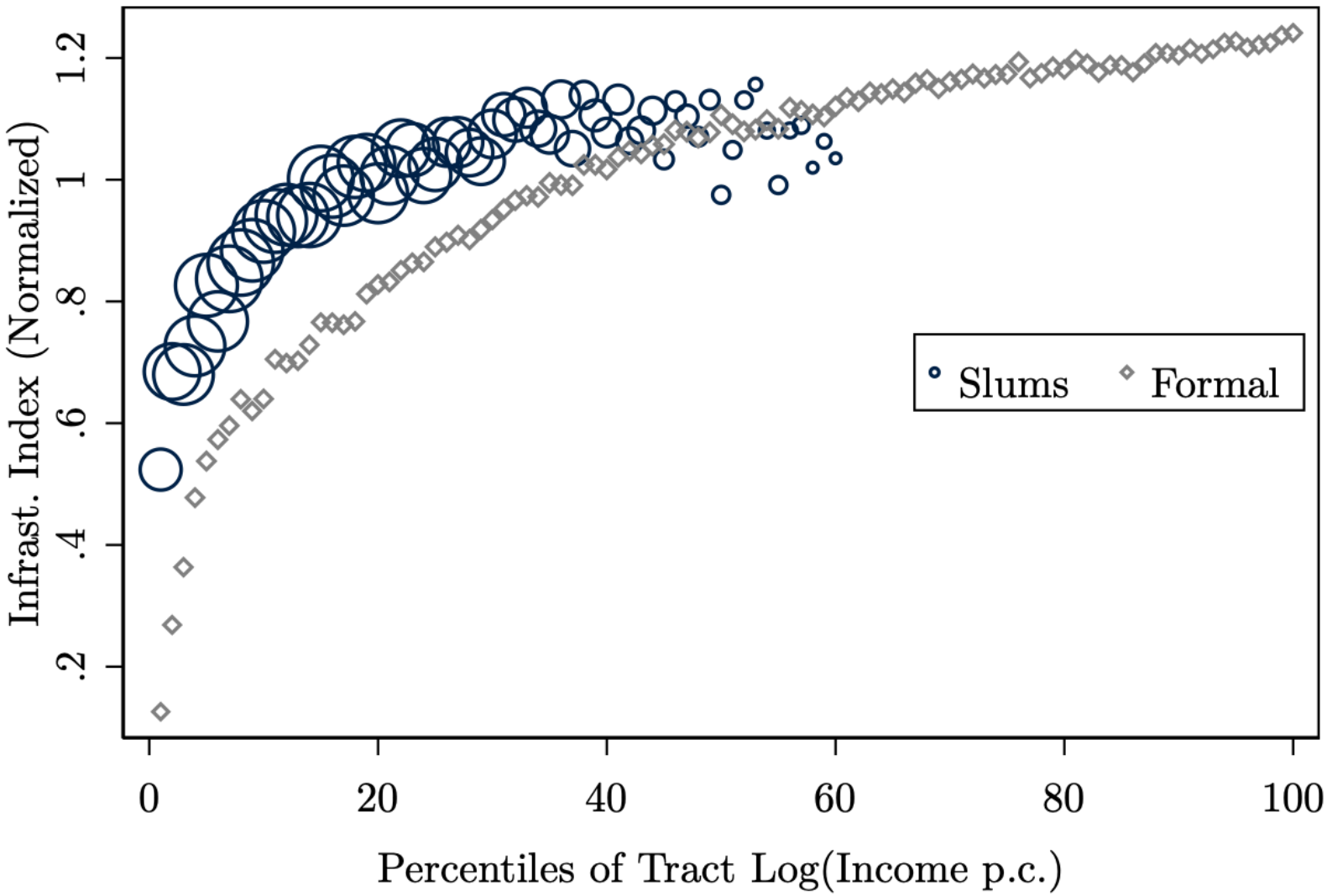
Infrastructure in Slums and Formal Nbhoods by Income



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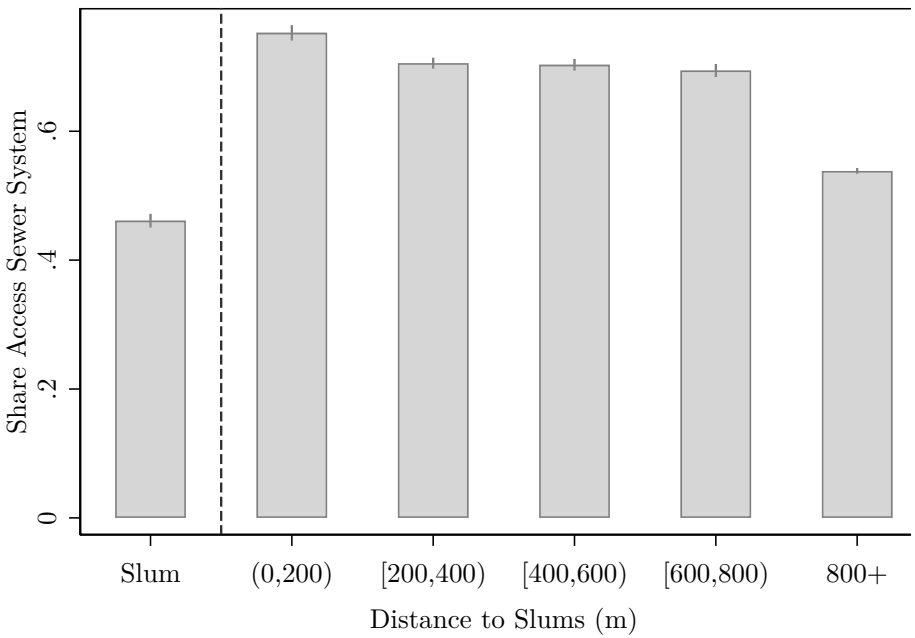
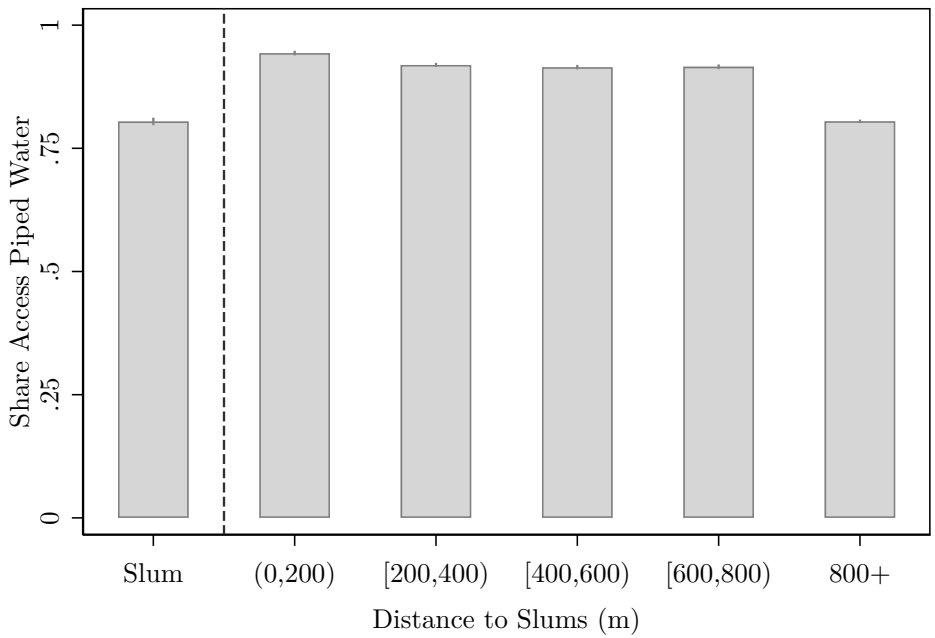
Infrastructure border analysis

Slum Border Effects

(a) Acces to Sewer System



(b) Access to Piped Water



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$$U_{ijs\omega}(c,l,e') \equiv B_i u\left(c,l\right)^{1-\beta} \overline{U}_{e'}^{\beta} \varepsilon_{i\omega} \zeta_{j\omega}^{1\{s=F\}} \sigma_{e'\omega}$$

1. Idiosyncratic pref. over home location i: $\varepsilon_{i\omega}$
2. *If* $s = F$*:* Work location, s.t. idiosyncratic preference $\zeta_{j\omega}$.
3. Education e' of *child* s.t. idiosyncratic pref. $\sigma_{e'\omega} \Rightarrow$ child EU $\overline{U}_{e'}$.
4. S-G preference over consumption c and housing l: $u\left(c,l\right) \equiv c^{1-\gamma}\left(l-\bar{l}\right)^{\gamma}$

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Human Capital

- Discrete education levels $e \in \{\text{No HS}, \text{HS}, \text{College}\}$.
- Fixed cost $M_{ie} \equiv \frac{\psi_e}{\varsigma_i^{\alpha}}$ to parents, where...
  - $\psi_e =$ base cost of education level e.
  - $\varsigma_i =$ local school quality.

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Labour Market and Shocks

- Formal workers $(s = F)$ commute to work, keep income $I_\omega = \frac{w_j h_e}{\tau_{ij}}$.
  - w_j = work location wage.
  - h_e = education productivity.
  - τ_{ij} = commute costs.
- Informal workers $(s = I)$ work at home $\implies$ $I_\omega = \chi w_i h_e$.
  - χ = informal sector wage discount.
- All face risk of negative shocks...
  - Probability $\kappa_{g(i)}$ of crime victimization.
  - *If* $s = I$*:* Probability δ of job loss.
    $\implies$ left with government benefit, $I_\omega = \underline{w}$.

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Housing Supply

- Formal: competitive developers $\uparrow$ height v_i at cost $\Xi_0 v_i^{\Xi_1}$.

$$\Pi_i \equiv \left(r_i - \Xi_0 v_i^{\Xi_1}\right) v_i \overline{T}_i$$

$\Longrightarrow$ Housing supply $H_i \equiv \left[\frac{r_i}{\Xi_0(1+\Xi_1)}\right]^{1/\Xi_1} \overline{T}_i$.

- Slums: same cost, but height cap $\bar{v}$, factor σ additional floorspace.

$\Longrightarrow$ Housing supply $H_i \equiv \left[\frac{r_i}{\Xi_0(1+\Xi_1)}\right]^{1/\Xi_1} \sigma\overline{T}_i \leq \bar{v}\sigma\overline{T}_i$.

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Expected Utilities

- Formally-employed parent, given home i, work j, own education e and child education e':

$$EU_{ijF}(e,e') \equiv \left(\overline{\gamma}\frac{B_i}{r_i^{\gamma}}\right)^{1-\beta}\left[\left(1-\kappa_{g(i)}\right)\left(\frac{w_j h_e}{\tau_{ij}}-\frac{\psi_{e'}}{\varsigma_i^{\alpha}}-r_i\bar{l}\right)^{1-\beta}+\kappa_{g(i)}\underline{w}^{1-\beta}\right]\overline{U}_{e'}^{\beta}.$$

- Informally-employed parent, given home i, work j, own education e and child education e':

$$EU_{iI}(e,e') \equiv \left(\overline{\gamma}\frac{B_i}{r_i^{\gamma}}\right)^{1-\beta}\left[\left(1-\kappa_{g(i)}-\delta+\kappa_{g(i)}\delta\right)\times\left(\chi w_i h_e-\frac{\psi_{e'}}{\varsigma_i^{\alpha}}-r_i\bar{l}\right)^{1-\beta}+\left(\kappa_{g(i)}+\delta-\kappa_{g(i)}\delta\right)\underline{w}^{1-\beta}\right]\overline{U}_{e'}^{\beta}.$$

Choice Probabilities and Expected Utility

- Child education e, given $\sigma_{e'\omega} \sim$ Frechet, shape ν:

$$\pi_{e'|ijs}(e) = \frac{[EU_{ijs}(e,e')]^{\nu}}{\sum_{e''}[EU_{ijs}(e,e'')]^{\nu}}.$$

$$\Longrightarrow \; EU_{ijs}(e) \equiv \Gamma\left(\tfrac{\nu-1}{\nu}\right)\left[\sum_{e''}[EU_{ijs}(e,e'')]^{\nu}\right]^{1/\nu}.$$

- Formal work location j, given $\zeta_{j\omega} \sim$ Frechet, shape ν:

$$\pi_{j|iF}(e) = \frac{[EU_{ijF}(e)]^{\theta}}{\sum_{j'}[EU_{ij'F}(e)]^{\theta}}.$$

$$\Longrightarrow \; \Omega_{iF}(e) \equiv \Gamma\left(\tfrac{\theta-1}{\theta}\right)\left[\sum_{j'}[EU_{ij'F}(e)]^{\theta}\right]^{1/\theta}, \; \Omega_{iI}(e) \equiv EU_{iI}(e)$$

- Home location i, given $\varepsilon_{i\omega} \sim$ Frechet, shape η:

$$\pi_i(e) = \frac{[\lambda_i \Omega_{iF}(e) + (1-\lambda_i)\Omega_{iI}(e)]^{\eta}}{\sum_{i'}[\lambda_{i'}\Omega_{i'F}(e) + (1-\lambda_{i'})\Omega_{i'I}(e)]^{\eta}}.$$

$$\Longrightarrow \; \overline{U}(e) \equiv \Gamma\left(\tfrac{\eta-1}{\eta}\right)\left\{\sum_{i'}[\lambda_{i'}\Omega_{i'F}(e) + (1-\lambda_{i'})\Omega_{i'I}(e)]^{\eta}\right\}^{1/\eta}.$$

Calibration: Labour Market, Crime, and Human Capital

Parameter	Description	Method	Data/Source
Labour Market + Crime			
η	Home Frechet Shape	External	Tsivanidis (2023)
θ	Formal Work Frechet Shape	External	Tsivanidis (2023)
ρ	Commute Distance Disutility	Internal: commute gravity	Chaves et al. (2023)
χ	Informal Wage Factor	Internal: ratio of mean informal to formal income	Census (2000)
δ	Informal Pr(Job Loss)	External	Ulyssea (2010)
κ_g	Pr(Victimization)	External	SUS
Human Capital			
ν	Education Frechet Shape	Internal: HS share given HS vs. given non-HS parents	Individual-level
$\boldsymbol{\Psi}$	Base Education Cost	Internal: aggregate IGM	Individual-level
α	School Quality Elasticity	Internal: neighborhood high-school share on school quality	Individual-level + IDEB
$\boldsymbol{h}$	Productivities	Internal: relative incomes by education	Census (2000)

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Calibration: Preferences and Housing Supply

Parameter	Description	Method	Data/Source
Preferences			
γ	Housing Share	Internal: regression of housing expenditure share on income	POF
$\bar{l}$	Housing Subsistence Requirement	Internal: regression of housing expenditure share on income	POF
β	Intergenerational Altruism	Internal: mean educational expenditure share of income	POF
Housing Supply			
Ξ_0	Height Cost Intercept	Internal: median height	Open Buildings
Ξ_1	Height Cost Elasticity	Internal: neighborhood building height on rent	Open Buildings + Cadunico
ϕ	Coverage	External	Open Buildings
σ	Slum Floorspace Factor	Internal: mean slum rent, relative to formal	PNAD
$\overline{v}$	Slum Height Cap	Internal: p95/p5 of height in slum relative to formal	Open Buildings

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Calibration: Geography and Miscellaneous

Parameter	Description	Method	Data/Source
Geography			
$\boldsymbol{B}$	Amenities	Model Inversion: population	Census (2000)
$\boldsymbol{w}$	Formal Wages	Model Inversion: formal employment by workplace	RAIS
$\boldsymbol{\Delta}$	Commute Distances	External	geobr
$\overline{\boldsymbol{T}}$	Land Supply	External	geobr
$\boldsymbol{\lambda}$	Pr.(Formal Job Offer)	External	Census (2000)
$\boldsymbol{\varsigma}$	School Quality	External	IDEB
Miscellaneous			
$\frac{w}{\overline{L}}$	Government benefit	External	POF
	City Population	External	Census (2000)

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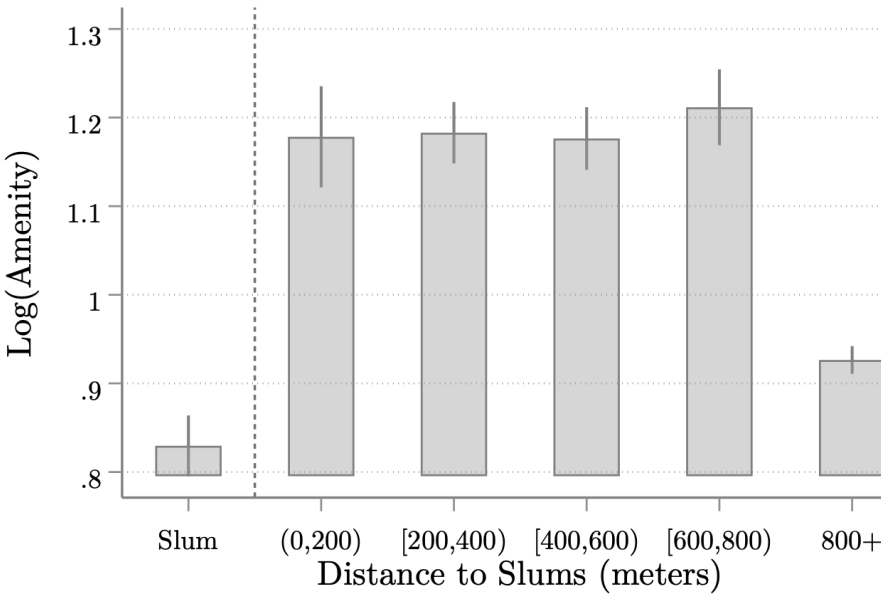
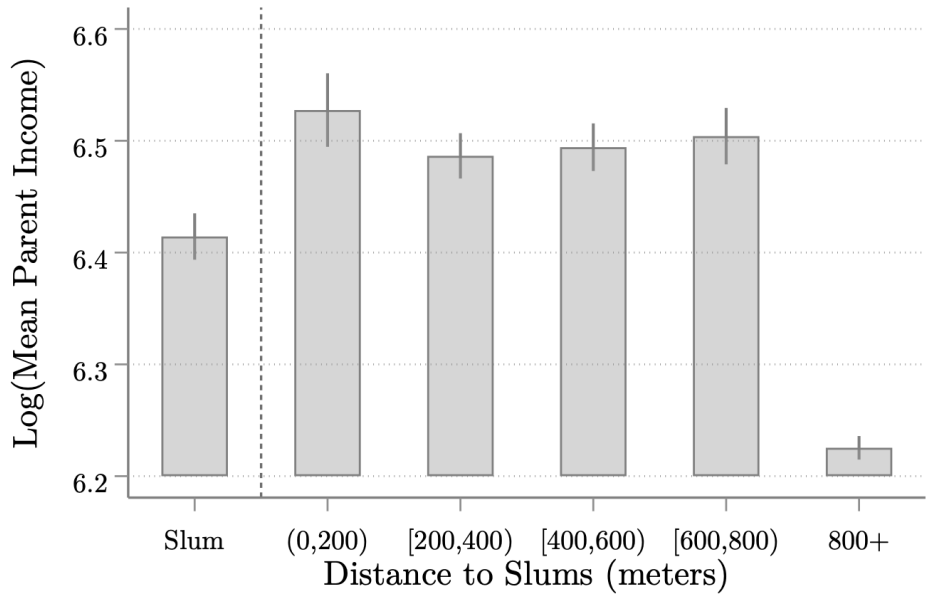
Model-Implied Slum Border Effects on...

(a) Amenities



(b) Income



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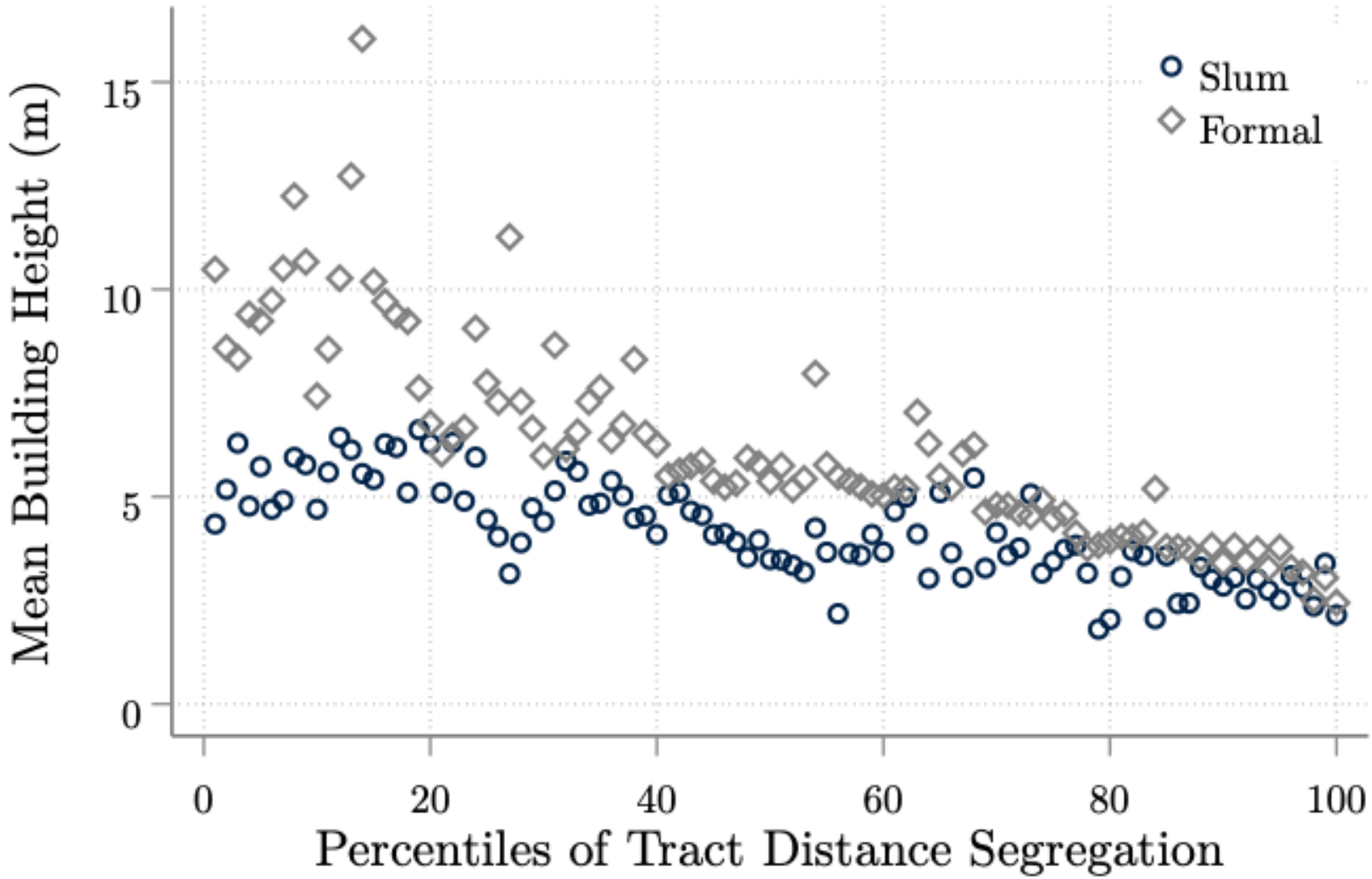
Model-Implied Height vs. Distance Segregation



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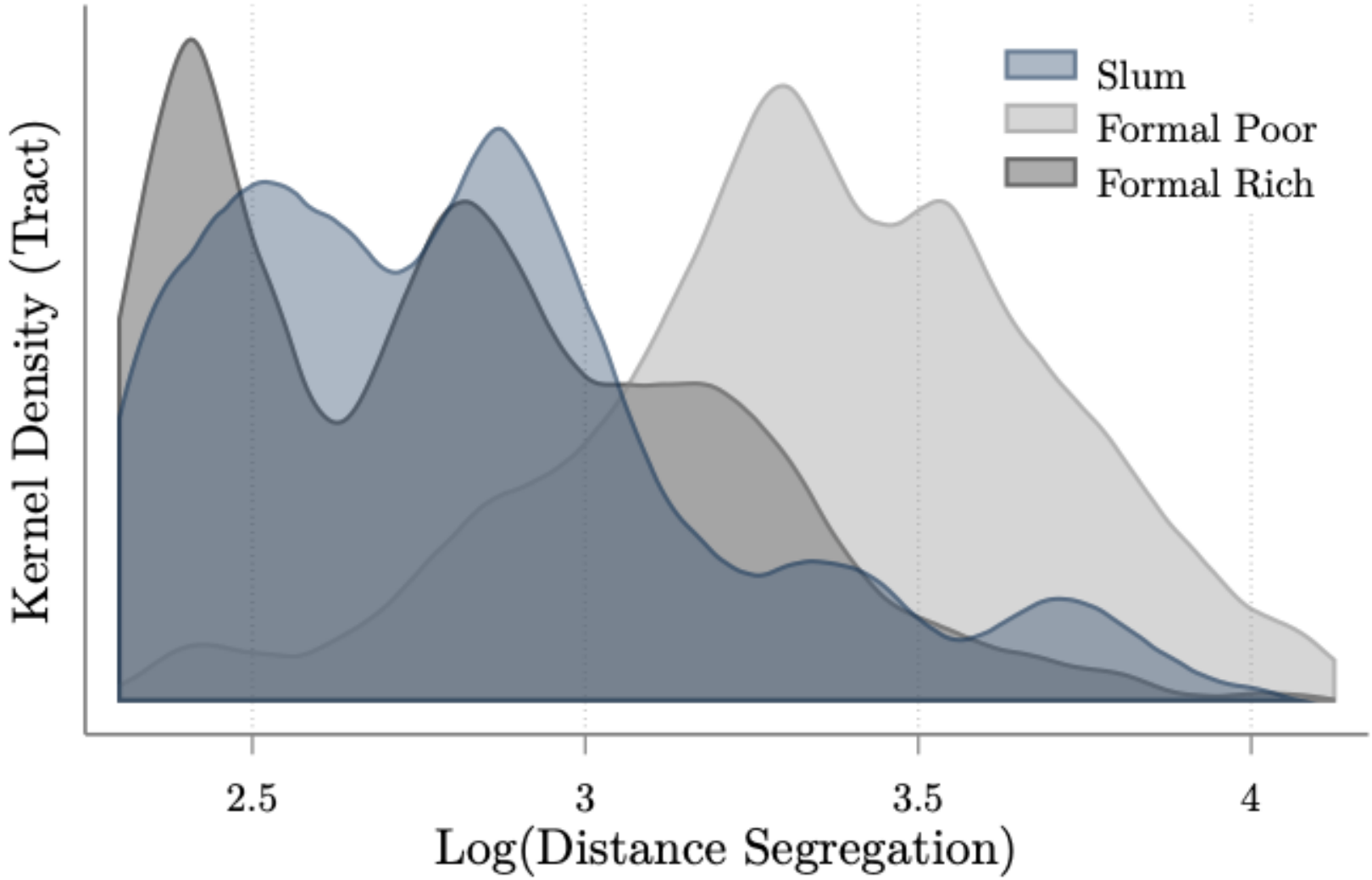
Model-Implied Distance Segregation by Neighborhood Type



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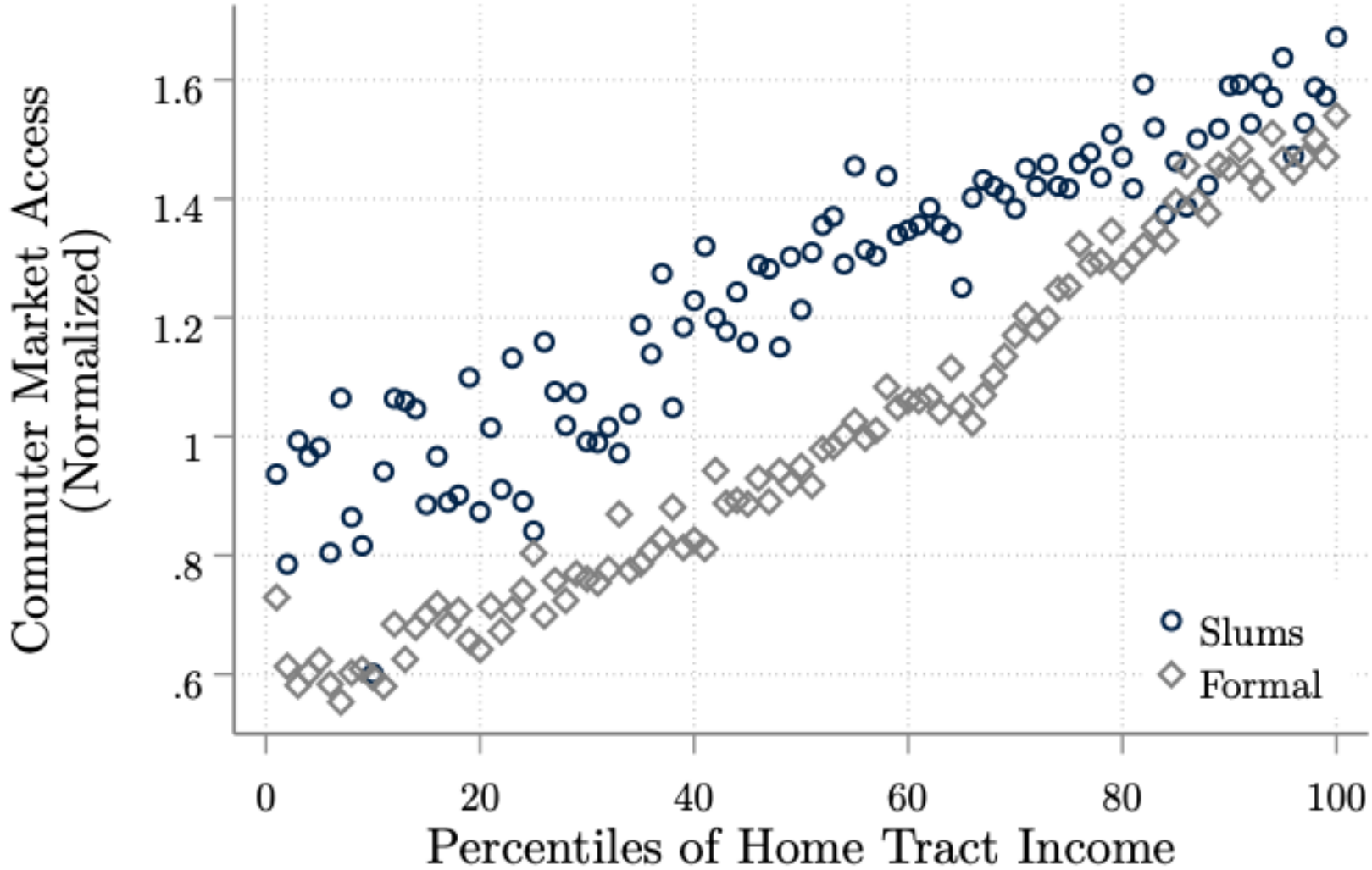
Model-Implied CMA vs. Neighborhood Income



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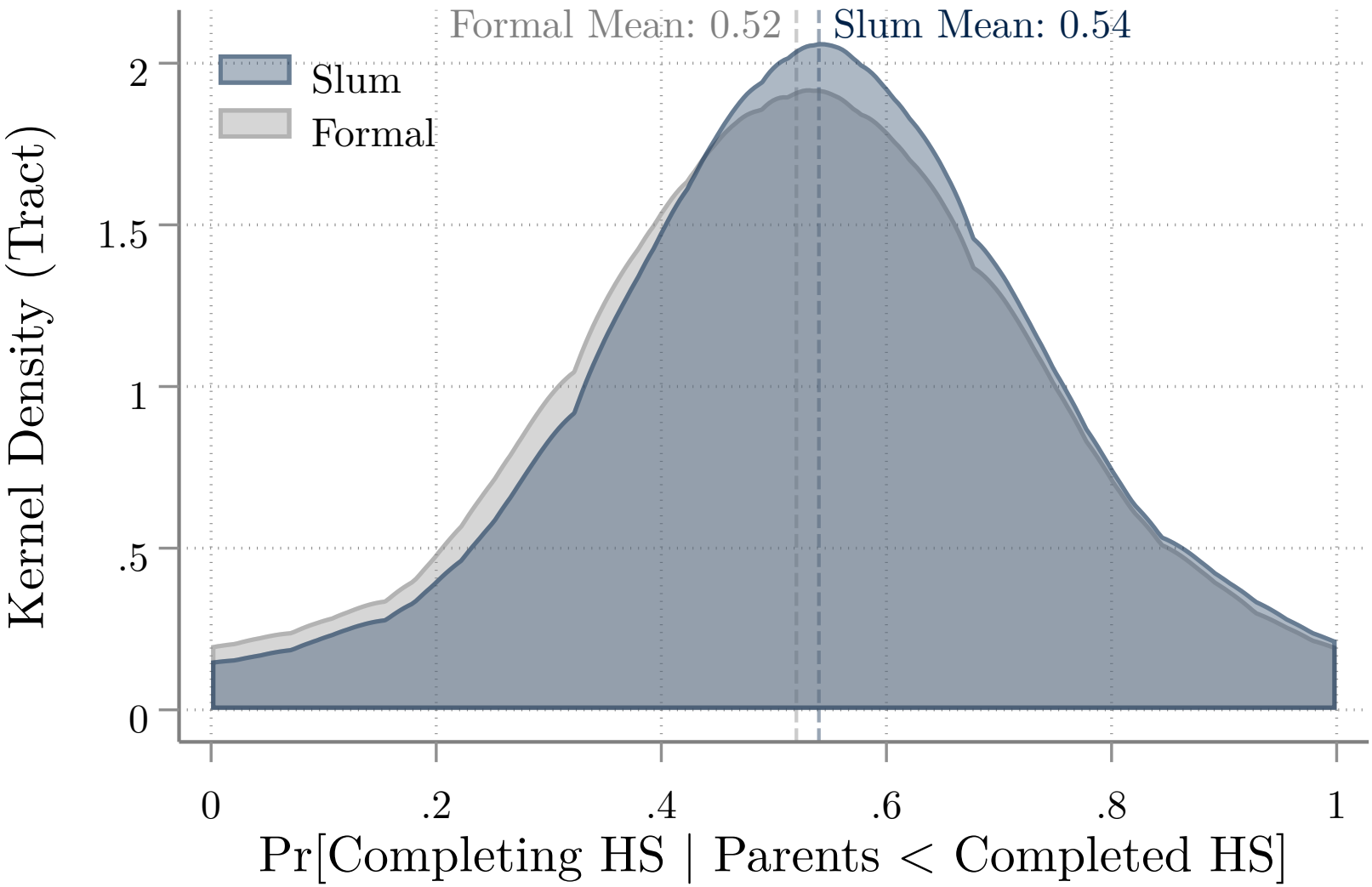
Model-Implied IGM



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