In-situ Upgrading or Population Relocation? Direct Impacts and Spatial Spillovers of Slum Renewal Policies

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NBER Summer Institute 2025

July 25th, 2025

Motivation

- In low- and middle-income countries, one in four urban residents lives in slum conditions - more than 1 billion people (UN-Habitat, 2020)
- 110 million people in Latin America alone ($\sim$ 17%)

Motivation

- Slums are characterized by substandard housing and inadequate access to essential services (water, sanitation, electricity and property rights)
- Perceived as sources of negative externalities for nearby neighborhoods

Motivation

- Faced with extensive slum populations, governments invest heavily in renewal policies that can be classified into two types:

1. In-situ upgrading: improvement of slum area with missing public infrastructure (safe water, sanitation, electricity, street paving and land titles as well as housing structures if needed)

2. Population relocation: moving households out of slum areas and into formal housing elsewhere

This Paper

- Assemble panel of the universe of slum areas for Chile spanning more than two decades merged with administrative slum-level renewal data, satellite data, housing investment data, geocoded population censuses and crime data

- What are the effects of in-situ upgrading & population relocation

  (i) Slum Areas (Direct effects)
    - Population
    - Housing investment and quality
    - Sociodemographics

  (ii) Adjacent Neighborhoods (Spatial Spillovers)
    - Population
    - Housing investment and quality
    - Sociodemographics
    - Criminal activity

Preview of Results - Direct Effects

- We implement Synthetic Difference-in-Differences (Arkhangelsky et al 2021) to evaluate and compare:

In-situ upgrading

- Total population unchanged after treatment
- Improved housing quality inside slums (larger, more regular buildings) and infrastructure
- Higher SES among inhabitants
- Lower cost per treated slum household

Population relocation

- Failed at moving all population out of the slum (Net -16%): voluntary take-up & repopulation
- No significant changes in housing quality inside slums or infrastructure
- No significant changes in SES of inhabitants
- Higher cost per treated slum household ($\approx$50% more)

Preview of Results - Spatial Spillovers to Surrounding Non-Slum Areas

In-situ upgrading

- Strong positive spillover effects on housing investment, new housing starts
- Adjacent areas have 15% less property crime and 25% less violent crime
- Higher-SES households in terms of education and employment

Population relocation

- No significant spillover effects on adjacent neighborhoods across a range of outcomes

- Overall, data point to in-situ upgrading being a more effective strategy than population relocation at developing more desirable neighborhoods - though not feasible everywhere

Contribution & Relevant Literature

Effects of Slum Renewal policies

- Population Relocation: Barnhardt et al. (2016): impact of housing lottery in India on location, socioeconomic wellbeing, and the network cost of relocation.

- In-situ Upgrading: Harari & Wong (2024): long-term impacts of the Kampung Improvement Program in Jakarta. Gonzalez-Navarro & Domeque, (2016): capitalization effects of paving streets.

- Forced Population Relocation & In-situ Upgrading: Rojas-Ampuero & Carrera (2024) effect of historical slum interventions in Chile on people (earnings, schooling).

Contribution & Relevant Literature

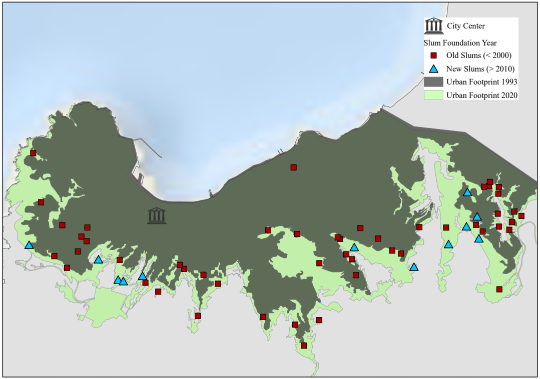
- First high-frequency panel of slums – universe of slums for more than 20 years. Delineating slums (Kohli et al., 2012), static (Marx et al., 2013), long-difference (Harari & Wong, 2024), and households (Rojas-Ampuero & Carrera, 2024)
- Economics of Slums & Households Living in Slums (Glaeser, 2011; Marx et al., 2013; Galiani et al., 2017; Gechter & Tsivanidis, 2023; Rojas-Ampuero & Carrera, 2024)
- Slum growth influenced by economic growth, institutional frictions & location preferences (Henderson et al., 2020; Alves, 2021; Celhay & Undurraga, 2022)

Slums Data

- Georeferenced MIINVU & TECHO Slum Censuses (2011-2019) - defined as 8 or more proximate inhabited structures lacking basic services and property rights

Slum Locations

- Valparaiso urban footprints 1992, 2020
- New slums tend to locate in periphery, and get absorbed as cities grow

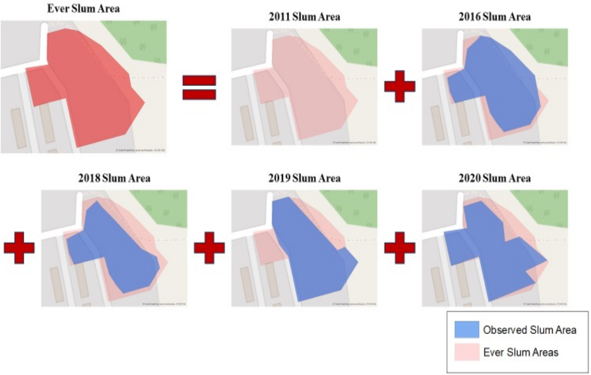


Slum Characteristics

- Compared to all non-slum census blocks, slum blocks are on average:
  - Further away amenities (school, fire station, supermarket, bank branch, bus stop, police station)
  - On terrain that is higher sloped, more rugged, and closer to a river

Unit of Analysis

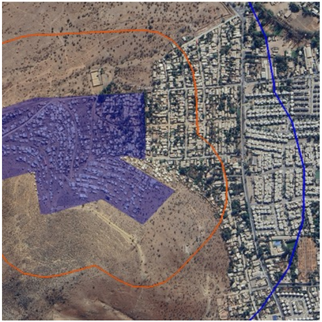
- Define the spatial union of all observed boundaries associated with each slum ('ever slum area') as our unit of analysis



Satellite Images

- More than 90,000 Google Earth images ($\sim$750 GB) from 2000 – 2022
- Each image covers around 1 km^2
  - Analyze data within the slum + adjacent areas including in years before a polygon was identified as a slum
- We measure both inside and outside slums:
  - Building area and density
  - Residential area coverage
  - Orientation angle - regularity
  - Distance to nearest neighboring buildings
  - Paved road presence (HOD)
  - Residential land (includes housing and private space) (HOD)

Identifying Building Footprints



(a) Blue shaded area is the slum, orange line is a 200 m buffer, and blue line is a 500 m buffer

Building Footprints Prediction

Matching Other Geocoded Datasets

- 2 waves of population censuses at the block level (on average, 100 people / 33 HH)
- WorldPop 100mX100m dataset 2011-2017
- Housing starts – INE Building permits dataset
- Renovations, year of construction - Formal housing database (cadaster)
- Government expenditures on slums
- Geocoded crime reports since 2013 in areas surrounding slums

Government Interventions

- In-situ Upgrading
  - Objective: transform a slum into a formal neighborhood
  - Investment in public infrastructure: electricity, piped water, roads
  - Investment in rebuilding housing structures on site

- Population Relocation
  - Objective: Move slum households to formal neighborhoods & clean up slum area

-Slum residents decide whether to participate in the program before the specific type of intervention (in-situ upgrading or relocation) is determined

-Once treatment is assigned, implementation takes 2-4 years

Cost per Household (HH) is lower in Slums under In-situ Upgrading (2011 – 2020)

	Mean	SD	Median
In-situ Upgrading (N slums = 209)			
# Households (HH) per Slum	56.22	63.57	38
Share HH Receiving Housing Voucher	0.54	0.48	0.43
Voucher Value per Beneficiary HH	\$36,672	\$16,534	\$34,487
Infrastructure Investment per Slum HH	\$9,057	\$14,389	\$2,599
Total Expenditure per Slum HH	\$28,636	\$27,307	\$23,021
Population Relocation (N slums = 440)			
# Households (HH) per Slum	34.43	46.92	23
Share HH Receiving Housing Voucher	0.82	0.63	0.79
Voucher Value per Beneficiary HH	\$46,710	\$2,867	\$45,415
Infrastructure Investment per Slum HH	\$4,215	\$9,112	\$773
Total Expenditure per Slum HH	\$42,532	\$32,620	\$40,138

U\$ dollars (2017)

Determinants of Treatment

	Pr(Any Treatment)		
	Marginal Effect (at the mean)		Covariates Mean
Slum Characteristics			
Identified as Slum in 2011	0.89***	0.97***	0.50
Log Slum Area	0.00	0.03	9.23
Log Slum Households	-0.12***	-0.15***	3.45
Terrain Characteristics			
Not Suitable for Construction	-0.27**	-0.30**	0.04
Within 250m of a River	-0.02	-0.02	0.35
Location & Muni Characteristics			
City Border or Beyond	-0.10*	-0.07	0.78
Region FE	No	Yes	
Mean dependent var	0.5	0.5	

Determinants of Slum Upgrading Given Any Treatment

	Pr(In-situ Upgrading | Any Treatment)		
	Marginal Effect (at the mean)		Covariates Mean
Slum Characteristics			
Identified as Slum in 2011	0.04	0.11	0.84
Log Slum Area	0.08***	0.07***	9.08
Log Slum Households	0.06	0.07**	3.37
Terrain Characteristics			
Not Suitable for Construction	-0.31**	-0.14	0.03
Within 250m of a River	-0.09*	-0.12**	0.35
Location & Muni Characteristics			
City Border or Beyond	0.11**	0.13***	0.73
Region FE	No	Yes	
Mean dependent var	0.33	0.33	

Synthetic Difference-in-Differences

- As shown, we have a case of non-random assignment of treatment, but our long panel has many pre-treatment observations for the majority of our main outcomes
- Good setting for Arkhangelsky, Athey, Hirshberg, Imbens and Wager (2021 AER)
- Well-suited for settings where standard DiD assumptions, such as parallel trends, are likely to be violated
- Constructs a weighted counterfactual for the treated units by assigning both unit and time weights to untreated slums, ensuring that the synthetic control group closely replicates the pre-treatment trends of the treated group
- Accommodates staggered treatment timing by constructing a separate synthetic control for each treated cohort using weighted combinations of untreated slums observed over the same period

Synthetic Difference-in-Differences

Consider the following equation of interest:

$$y_{it} = \alpha_0 + \alpha_i + \alpha_t + \beta \mathbb{D}_{it} + \gamma X_{it} + \varepsilon_{it} \qquad (1)$$

- where α_0, α_i and α_t represent the constant term, and the slum- and time-fixed effects, respectively. X_{it} represents time-variant slum characteristics used as controls. $\mathbb{D}_{it}$ is a treatment indicator equal to one in the year slum i is first treated and thereafter

Synthetic Difference-in-Differences

- The objective optimization function for the SDiD model is:

$$(\hat{\beta^{sdid}}, \hat{\alpha}, \hat{\gamma}) = \arg \min_{\beta,\alpha,\gamma} \left\{ \sum_{i=1} \sum_{t=1} (Y_{it} - \alpha_0 - \alpha_i - \alpha_t - \beta \mathbb{D}_{it} - \gamma X_{it})^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{2}$$

- $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ represent the individual slum and time weights
- The weights $\hat{\omega}_i^{sdid}$ are chosen to minimize the average squared difference in pre-treatment trends between slums exposed to a given treatment strategy and non-treated slums
- Time weights $\hat{\lambda}_t^{sdid}$ are selected to minimize the sum of squared differences between the time-weighted pre-treatment outcomes of the control slums and the simple average of their post-treatment outcomes
- SDiD nests other well-known estimators: standard DiD (when $\hat{\omega}_i^{sdid} = 1$ and $\hat{\lambda}_t^{sdid} = 1$) and SC (when only $\hat{\lambda}_t^{sdid} = 1$)

Synthetic Difference-in-Difference

- We restrict the sample to slums created before 2017, ensuring never-treated slums were either listed in the 2011 census or excluded only because they formed a few years later
- We include one-year lagged LandScan population data to account for differences in outcome trends related to slum size
- Inference based on non-parametric bootstrap procedure (250 reps) using Stata code following Clarke, Pailañir, Athey, and Imbens (2023)
- We do not have precise data on the completion dates of infrastructure works or the timing of subsidy disbursement and uptake by beneficiary households $\rightarrow$ our SDiD estimates capture Intent-to-Treat (ITT) effects

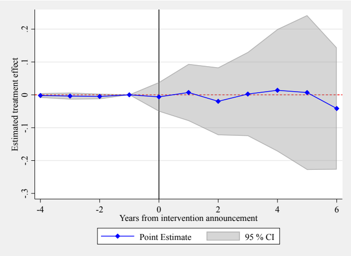
Results

i. Direct Effects on Slum Polygons

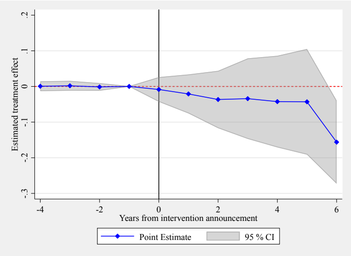
ii. Spillover Effects on Nearby Formal Neighborhoods

Direct Effects: Slum Population

In-situ Upgrading



Population Relocation



- In-situ upgrading objective: Improve conditions without displacing residents → no change in population
- Population relocation objective: Depopulate slum area → achieves only a 17 percent reduction at year 6

Direct Effects at Year 6

Dependent variable:	Mean Control	In-situ Upgrading β_1	Population Relocation β_2	Equal. Test p-value $\beta_1 = \beta_2$
Slum Characteristics				
Log Population	5.92	-0.04	-0.16***	0.00
Share Residential Land	0.26	-0.03	-0.12**	0.00
Share Streets paved	0.09	0.11**	0.04	0.00
Housing Investment				
Pr(Building Permits $>$ 0)	0.00	0.05**	0.01	0.00
Log # Building Permits	0.003	0.02**	0.01	0.00
Housing Quality				
Log # Buildings, size $>$ 64 m^2	0.97	0.15*	0.03	0.00
SD Bldg. Main Angle-Neighbors	5.27	-0.82**	-0.09	0.00
Avg. Distance to Neighbors	60.05	8.67**	4.74	0.00

-In-situ upgrading is associated with significant improvements in urban quality, while population relocation effects are limited to a reduction in population and a decline in the share of residential use of land

TWFE – Census Variables

We only observe two periods for population census variables: 2002 & 2017. Treated units are those that received government aid at any point between 2011-2014
So we estimate a standard TWFE specification

$$Y_{it} = \alpha_0 + \alpha_i + \alpha_t + \delta \, Treated_{it} + \varepsilon_{it}$$

where δ is the estimated effect of the intervention

TWFE - Sociodemographics

Dependent variable:	Mean Control	In-situ Upgrading β_1	Population Relocation β_2	Equal. Test p-value $\beta_1 = \beta_2$
Sociodemographics				
% Pop. with High Educ	55.87	**3.05***	1.24	0.32
		(1.62)	(1.58)	
Employment Rate	83.32	1.28	0.43	0.57
		(1.24)	(1.03)	

Results

i. Direct Effects on Slum Polygons

ii. Spillover Effects on Nearby Formal Neighborhoods

Spillovers Adjacent Formal Neighborhoods

- How do these interventions differ in their effects on nearby neighborhoods?
  - Crime outcomes
  - Housing investment
  - Sociodemographics

Crime within 200m of slums

Dependent variable:	Mean Control	In-situ Upgrading β_1	Population Relocation β_2	Equal. Test p-value $\beta_1 = \beta_2$
Crime Index	0.13	**-0.09**** (0.04)	0.12 (0.13)	0.00
Property Crime per km^2	35.92	**-5.07*** (2.61)	15.35 (12.91)	0.00
Violent Crime per km^2	9.70	**-2.62**** (1.15)	-1.26 (1.58)	0.00
Homicide per km^2	0.05	**-0.07***** (0.03)	0.06 (0.13)	0.00

$\Rightarrow$ Neighborhoods adjacent to in-situ upgraded slums become safer

Housing Investment and Quality

Dependent variable:	Mean Control	In-situ Upgrading β_1	Population Relocation β_2	Equal.Test p-value $\beta_1 = \beta_2$
Housing Investment				
% New Bldgs. (age < 5)	12.33	4.04***	2.65**	0.00
% Bldgs. renovated	0.95	0.32**	0.13	0.00
Pr(Building Permits > 0)	0.21	0.10**	0.07	0.00
Log # Building Permits	0.22	0.13**	0.12**	0.98
Housing Quality				
Log Building Age	2.66	-0.11**	-0.07**	0.00
Log Building Size	3.69	0.11*	0.06	0.00

$\Rightarrow$ Areas within 200 m of in-situ upgraded slums have more housing investment from owners and developers

TWFE - Spillovers of Slum Strategies

Dependent variable:	Mean Control	In-situ Upgrading β_1	Population Relocation β_2	Equal.Test p-value $\beta_1 = \beta_2$
Sociodemographics				
% Pop. with High Educ	57.68	**1.47***	0.42	0.30
		(0.87)	(0.92)	
Employment Rate	84.76	**1.18***	-0.67	0.01
		(0.62)	(0.55)	

⇒ In-situ upgrading attracts high SES population to neighborhoods within 200m of an intervened slum

Conclusions

- What are the effects of in-situ upgrading and population relocation on slum areas?
  - In-situ upgrading leads to better housing and infrastructure conditions in slum polygons
  - Population relocation reduces total slum population but has limited effects on housing quality
- What are the effects of in-situ upgrading and population relocation on surrounding formal neighborhoods?
  - We find positive spillovers from in-situ upgrading: Lower crime rates and more construction in adjacent neighborhoods, attracting higher-SES residents
- Population relocation costs about 50% more per household yet in-situ upgrading brings about superior outcomes for surrounding areas (caveat: population relocation is the only adequate strategy in some situations)

Thank you!

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Predicting Building Footprints

- Pre-processing images
  - Each image fragmented in 256 tiles: 300 x 300 pixels
  - Select images using HOD and Image Size
- Deep Neural Networks and U-Net Architecture
- Model calibration
- Computing building footprints metrics

Predicting Building Footprints

- Pre-processing images
- Deep Neural Networks and U-Net Architecture
  - U-Net: usual CNN+ upsampling to the original image resolution
  - Only needs a 3 band images: RGB
  - Use image rotations (90-180-270 degrees) and flips (up-down, left-right)
  - Precision = 94; Recall = 95
- Model calibration
- Computing building footprints metrics

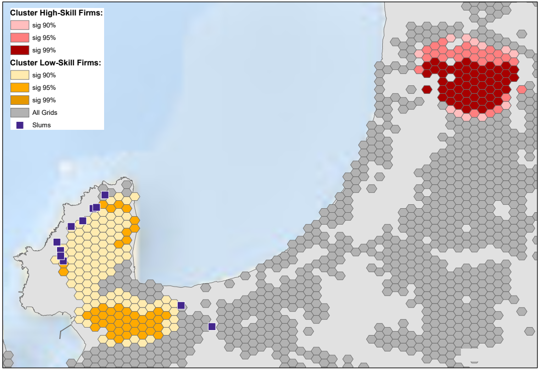
Predicting Building Footprints

- Pre-processing images
- Deep Neural Networks and U-Net Architecture
- Model calibration
    - Geometric regularity
    - Masking cutoff
    - Geographical projections
- Computing building footprints metrics

Predicting Building Footprints

- Pre-processing images
- Deep Neural Networks and U-Net Architecture
- Model calibration
- Computing building footprints metrics
  - Building area
  - Building density
  - SD Building main angle (8 nearest neighbors)
  - Distance between buildings

Cluster of Low- and High-Skilled Industries - Coquimbo



Slums are farther away from city amenities

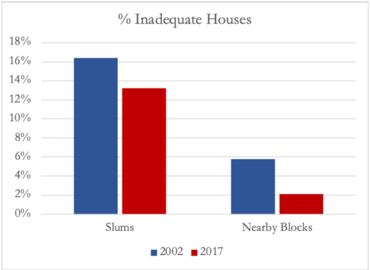
	Mean Control	Slum Indicator	Romano-Wolf (p-value)
Amenities Distance Index (sd)	0.00	0.06***	
Individual Amenities			
Distance Nearest Fire Station (m)	1,994	213.63**	0.01
Distance Nearest Police Station (m)	2,047	210.08***	0.01
Distance Nearest School (m)	637	200.99***	0.00
Distance Nearest Health Center (m)	1,438	50.42	0.25
Distance Nearest Bus Stop (m)	810	64.77	0.11
Distance Nearest Supermarket (m)	2,900	225.41**	0.01
Distance Nearest Finance Institution (m)	2,777	524.13***	0.00
Terrain Characteristics			
Slope (%)	2.68	1.19***	0.00
Elevation (m)	329	14.10***	0.00
Terrain Ruggedness Index (m)	74	13.55***	0.00
Distance Nearest River (m)	2,006	-339.37***	0.00

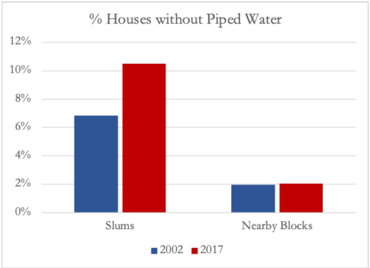
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Slums Converge to Adjacent Non-slum Blocks

	Census Year		$\%\Delta_t$
	2002	2017	(2017-2002)
	(1)	(2)	(3)
Population			
Slums	277	308	31
Adjacent Non-Slum Blocks	6,870	7,206	336
Δ_i (Slums - Non-Slums)	-6,593	-6,898	-305
Ratio Adult Males/Females (25-64 yo)			
Slums	1.30	0.97	-0.33
Adjacent Non-Slum Blocks	0.96	0.95	-0.01
Δ_i (Slums - Non-Slums)	0.34	0.02	-0.32
% Pop w Secondary Education			
Slums	39.58%	51.03%	11.4%
Adjacent Non-Slum Blocks	43.21%	50.65%	7.4%
Δ_i (Slums - Non-Slums)	-3.62%	0.38%	4.0%
% Employed			
Slums	80.63%	90.19%	9.6%
Adjacent Non-Slum Blocks	82.41%	90.31%	7.9%
Δ_i (Slums - Non-Slums)	-1.79%	-0.11%	1.7%

Housing Quality Remarkably Below Nearby Blocks





Nearby blocks correspond to blocks within 200 – 500mt from the slum border

Higher rents & better labor opportunities are tied to municipal level slum population growth

Dependent: Δ Log Municipal Slum Pop.	WorldPop (2011-2017) (1)	Pop. Census (2002-2017) (2)
$\underset{2009-2017}{\Delta}$ Log Quality Adj. Rent	0.24*	0.29**
	(0.13)	(0.14)
$\underset{2010-2017}{\Delta}$ Log Labor Salary	-0.21**	-0.22*
	(0.09)	(0.11)
$\underset{2010-2017}{\Delta}$ Log Labor Salary - High School or more	0.20***	0.17***
	(0.02)	(0.03)
$\underset{2010-2017}{\Delta}$ Log # Employees	-0.12	0.25
	(0.14)	(0.16)
$\underset{2010-2017}{\Delta}$ Log # Employees - High School or more	0.14	-0.09
	(0.11)	(0.12)
$\underset{2011-2017}{\Delta}$ Log Municipality Expenditures	-0.21	-0.06
	(0.20)	(0.19)
Obs.	261	261
R2	0.17	0.11
Mean Dependent variable	0.27	0.11

$$\Delta y_i = \alpha + \beta_1 \Delta X_i + \varepsilon_i$$