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

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Abstract

We examine the effects of the two most common slum policy interventions —*in-situ* upgrading and population relocation— on (i) the physical characteristics of intervened slum areas, (ii) the socioeconomic profiles of slum residents, and (iii) spillover effects on nearby formal neighborhoods. Our analysis uses a unique slum-level panel dataset spanning over 20 years, which covers the universe of slums in Chile and incorporates satellite imagery, census data, administrative records, construction permits, crime reports, and property tax data. We first document that slums tend to form in the periphery of cities, close to low-skilled labor centers, and that city-level slum expansion correlates with improved labor market prospects for low-skilled workers and higher housing rental rates. Then, using Synthetic Difference-in-Difference for causal identification, we find that, on average, both *in-situ* upgrading and population relocation reduce the share of land used for housing. However, only *in-situ* upgrading leads to long-lasting increases in housing quality and socioeconomic status of residents. *In-situ* upgrading also generates large positive spillovers in adjacent neighborhoods, reducing criminal activity and increasing formal housing investment.

Keywords: Slum Policy, Informal Housing, Development, Chile
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1 Introduction

Slums are an important part of the urban landscape in many developing countries, providing an affordable housing option for low income households. With rapid urbanization, a substantial share of individuals now live in slums to be closer to labor market opportunities in spite of substandard housing. In fact, it is estimated that over one billion people live in slums worldwide, of which 110 million are in Latin America (UN-Habitat, 2020).

Faced with this challenge, the two most important policies governments have historically implemented to enhance housing conditions in slums are *in-situ* upgrading and population relocation. The *in-situ* upgrading program provides essential services in slums such as piped water, electricity, and sanitation, as well as, in some cases, constructing new improved houses. In contrast, the population relocation program moves households out of slums into formal neighborhoods outside of the slum perimeter and sometimes demolishes existing slum housing. This paper evaluates the impact of both policies on slum areas as well as spatial spillovers to surrounding neighborhoods in Chile, a country that has implemented those strategies simultaneously since 2011.

Both strategies are voluntary and executed through both subsidies and direct investment. Housing subsidies are offered to both finance new construction or purchase of existing houses. This new construction can happen inside or outside the slums, and that decision will determine whether the slum is under an *in-situ* upgrading or population relocation strategy. Direct investment budgets are used for infrastructure improvements including sewage connection, and water access, as well as for slum removal, debris management and temporary relocation. In spite of their importance, there is limited knowledge about the relative effectiveness of these two policies both in terms of direct impacts within slum areas as well as their spillovers to adjacent neighborhoods. Chile provides a unique context for our study for multiple reasons: First the national implementation of both policies allows for a study beyond a single city. Second, the availability of rich geocoded microdata over a sufficient time span allowing for a long-term evaluation of impacts.

Our analysis relies on a dataset of the universe of georeferenced polygons that were ever-designated as slums at any point in time between 2011 and 2021. The designation process is done yearly by the Chilean Ministry of Housing and Urban Development (MINVU), sometimes in collaboration with TECHO NGO. Each year, active slums are identified based on three conditions: (i) an area contains at least 8 inhabited structures, (ii) households do not hold property rights, and (iii) houses are substandard quality and lack access to at least one of the basic services — water, sanitation, and electricity. Since boundaries of slums change over time, we define each slum's area as the union of areas across all years that a slum is observed. We use historical Google Earth satellite images to track the evolution of land use within these polygons since 2000, ten years before any of these areas are formally designated as slums for the first time. Using state-of-the-art image processing mask-RCNN algorithms, we identify built structures (as well as their size and shape) inside and outside of slums. The panel covers slums' physical characteristics like building area, building density, similarities in orientation angle, and proximity between buildings.

We next merge in socio-economic variables from two spatially disaggregated population censuses for years 2002 and 2017. To identify development of formal housing, we also match the location of slums with the georeferenced location of new building permits as well as information on property tax records for all formal housing in surrounding neighborhoods. Finally, we add geocoded crime records to analyze spillovers in areas surrounding slum areas.

The data provide a rich and nuanced description of the formation and evolution of slums. Our findings confirm some of the basic hypotheses in the theoretical slums literature.[1] When they start, slums overwhelmingly form at the edge of city boundaries. As time goes by, slums are 'absorbed' inside city boundaries as cities grow and urban borders expand. A second finding is that, while located at the edge of cities, slums are more likely to form on whichever edge of the city is closer to concentrations of firms that hire unskilled labor, confirming the importance of access to work. We also confirm in our data that slum residents have on average worse access to public amenities such as transport, schools, supermarkets, and public safety services. Housing quality inside slums is generally worse than in adjacent areas. And while slums are initially populated primarily by adult males, we observe a gradual movement of women and households into slums over time.

Taking a broader perspective of slums in urban areas, we conduct an analysis at the city (municipal) level and find that total slum populations grow as the local cost of rental housing rises and local labor market opportunities improve. This is consistent with previous models of slum formation in which major drivers are labor market opportunities (attracting workers), high formal housing costs (making formal housing unaffordable) and low income (also making formal housing unaffordable). More specifically, using a first-differences model we study how changes in local economic factors are related to the growth of total slum population in a municipality. We find that (i) doubling quality-adjusted housing rents is associated with up to 14% higher slum population, (ii) employment growth and average salary growth for low-skilled workers also fosters slum growth, and (iii) municipalities with significant improvements in extreme poverty do experience increments in slum population.

[1] For a review of the slum literature, see Marx et al. (2013). For models of slum formation, see Jimenez (1984, 1985); Duranton (2008); Brueckner and Selod (2009); Brueckner (2013); Duranton and Puga (2015); Cavalcanti et al. (2016, 2019); Henderson et al. (2021); Duranton and Puga (2023).

Together with the slum level descriptive analysis, it is clear that proximity to more labor opportunities that can provide a higher return is an attractive factor for low-skill workers who, due to budget constraints and housing market frictions, end up populating slums.

For our main analysis on the causal effect of both policies, we rely on a Synthetic Difference-in-Difference (SDiD) approach (Arkhangelsky et al., 2021; Clarke et al., 2023) using the annual panel data of slums. The SDiD estimator combines the usual Difference-in-Difference model with Synthetic Controls and accounts for differential timing of treatment. In this approach, the control group for each treatment cohort is chosen from never treated slums. For each of the non-treated slums, SDiD assigns an optimal weight such that the control group looks alike treated observations before the treatment (similar pretreatment outcome trends). For the causal effect on socio-demographic variables, we use the standard two-way fixed effects regression since we only observe two waves of the population census.

We first explore direct impacts of both policies on the slum areas. We find that population relocation reduces the amount of land used for residential purposes at six years after the onset of the intervention by 12%. We find a concomitant significant decline in population for the population relocation strategy with a point estimate of -16%. As expected, no significant changes in the share of residential land and population are found for the *in-situ* upgraded slums. This is consistent with the intent of the relocation policy that families targeted by the relocation strategy leave the slum area.

In contrast, while population relocation has no impact on housing quality in the slum polygon, in situ upgrading has large and meaningful positive effects on housing quality. First, upgrading sites attract 5% more new formal housing starts. *In-situ* upgrading also generates larger and more regularly oriented structures that are spaced further apart. They are also 4.5% more likely to have two or more bedrooms. Slums that benefited from *in-situ* upgrading also attract a higher SES population than those areas offered relocation in terms of education of inhabitants.

We next turn to an analysis of spillovers of both programs on surrounding neighborhoods using the same methodology. We find that *In-situ* upgrading has strong positive spillover effect in adjacent neighborhoods compared to population relocation policies. Housing quality measures are better in *in-situ* upgrading adjacent areas. We find an 10% increase in the probability of new housing starts expanding all the way up to 500 mt from the *in-situ* upgraded slums. In contrast, we find no effects in the surrounding areas of population relocation slums. The results on building permits are complemented by the spillover effects from the land registry data. Buildings within 200 mt of *in-situ* updated slums are 11% younger and more likely to undergo renovations after six years from the treatment assignment. Also pointing to the creation of more desirable neighborhoods, areas surrounding *in-situ* upgrading slums attract higher SES residents in terms of education and employment.

Our data on crime reports also points to neighborhoods surrounding *in-situ* upgraded slums experiencing a sizable reduction in both violent and property crimes up to 200 meters away. These adjacent neighborhoods have 5 less property crimes and almost 3 less violent crimes per km^2 after 5 years of the policy assignment. Lower crime levels together with the effect on housing permits and high SES residents are consistent with neighborhood desirability.

Overall, both the direct impacts and spillover results strongly support the view that *in-situ* upgrading is preferable to population relocation as competing strategies for the creation of more desirable neighborhoods.

Finally, we obtained data on fiscal costs of both strategies from the government and find that the average fiscal cost per slum household of *in-situ* upgrading is only two-thirds the cost of population relocation, making the case for slum upgrading even stronger when both strategies are feasible. Of course, there are cases in which *in-situ* upgrading will not be preferred to population relocation. For example, when the slum area is located in a high risk areas from natural hazards like flooding and landslide.

Our research contributes to a limited body of research on slums, their dynamics, and how they interact with their surrounding environment. There have been significant developments in both computer science and economics research to find new approaches to identify and delineate slum areas (Angeles et al., 2009; Kohli et al., 2016; Montana et al., 2016; Friesen et al., 2018; Abascal et al., 2022). That work has provided strong bases for this research. Another set of studies has focused on the determinants of slum formation and growth, and how their location and economic conditions are key factors in explaining slum changes (Barnhardt et al., 2017; Henderson et al., 2021; Celhay and Undurraga, 2022). In addition to that, other authors have documented how local labor and housing markets can affect the formation and evolution of slums (Glaeser, 2011; Marx et al., 2013; Wong, 2019; Henderson et al., 2021; Alves, 2023; Gechter and Tsivanidis, 2023). In fact, Celhay and Undurraga (2022) show that slum households are willing to sacrifice housing quality for better labor opportunities. Alves (2021) finds a positive correlation between slum growth and economic growth in Brazilian cities, which is explained partly by the attraction of a large number of low-income households to cities with higher wages. The author finds that rents in non-slum housing have a higher elasticity with respect to housing demand. This implies that economic growth in cities leads to slum growth because it results in higher rent growth for non-slum housing, making slum housing more affordable for low-income households.

Another relevant contribution of this research is to compare two mainstream policies that aim to overcome the challenges of slum growth. There is also some work that studies each of these policies individually in other context, such as Dasgupta and Lall (2009); Collins and Shester (2013); Gonzalez-Navarro and Quintana-Domeque (2016); Barnhardt et al. (2017); Galiani et al. (2017); Bazzi et al. (2019); Picarelli (2019); Harari and Wong (2024). [2]. There are other policies that although not widely implemented in Chile, they are still available for policy makers, some examples are changes in sites and services (Michaels et al., 2021); and land titling (Field, 2005, 2007; Galiani and Schargrodsky, 2010; Franklin, 2020).

Our work is closely related to that of Harari and Wong (2024) and Rojas-Ampuero and Carrera (2023). Harari and Wong (2024) use data from the most extensive slum upgrading program worldwide, the Kampung Improvement Program (KIP) in Jakarta, Indonesia. They suggest that slum upgrading may be more cost-effective for cities in the early stages of urban development. The authors find that areas that underwent KIP upgrades have, on average, 15% lower land values and 50% fewer high-rises compared to historical slums, indicating delayed formalization. However, KIP areas deliver sizable positive effects in other locations, suggesting the trade-offs between upgrading and preserving slums as cities expand. Rojas-Ampuero and Carrera (2023) study a slum clearance program in Santiago, Chile in the 80s that move some slum households to formal neighborhoods while others were given housing *in-situ*. Rojas-Ampuero and Carrera (2023)) find that displaced children who were moved to high-poverty neighborhoods experienced negative long-term effects on their earnings and education compared to non-displaced children. Displaced children were also more likely to work in informal jobs.

This paper is divided into seven sections. Section 2 discusses the different Chilean slum policies. Section 3 describes the main datasets used in this study, while Section 4 focuses on the link between slum growth and local economic conditions. Section 5 presents the different estimation strategies. Results are provided in Section 6, and the last section concludes.

2 Chilean Slum Renewal Policies

Improving slum conditions requires significant investment. In 2020, the Global Steering Group (GSG) estimated that the investment required to sufficiently improve slum conditions worldwide surpasses US$6 trillion. In Chile, the Ministry of Housing and Urban Development (MINVU) has invested more than $400 million dollars since the "Villages and Slums Program" was established in 2011. The primary objectives of the program are to close slums, improve housing quality, and revitalize affected areas. The program focuses on two main comprehensive interventions at the slum level: *in-situ* upgrading and population relocation.

[2]For a thorough review on relocation policies, see Belsky et al. (2013). For specific relocation policies in the European context, see Hall (1997).

2.1 In-situ upgrading

In-situ upgrading is a slum renewal policy that focuses on improving the living conditions within existing informal settlements without displacing the residents. This strategy involves direct investment in infrastructure enhancements such as paving streets, installing basic services like water and electricity, and supporting the construction of better housing. In addition to direct investment, MINVU also allocates housing vouchers (officially named DS49) for the construction of new public housing within the slum territory.[3]

In-situ housing construction is financed mainly through DS49 subsidies. This housing voucher targets the lowest 40% income bracket in the country, which includes slum residents. Typically, groups of eligible families from informal settlements collectively apply for subsidies to fund housing projects. These collective subsidies average around $15,000 dollars per household, with an additional approximate contribution of $800 required from beneficiaries. The terms of the subsidy prohibit the rental or sale of the properties, though they can be passed down to offspring. Housing projects within the informal settlements involve the demolition of existing structures and the construction of new units on the site. This is feasible when the land is owned by a public entity capable of donating it, such as a municipality, or when situated in a low-value area compatible with DS49 funding.

Table 1 shows that the average cost per household in an *in-situ* upgrading slum is $20,177 dollars. Cost estimates confirm that *in-situ* upgrading uses both direct investment and housing subsidies for its implementation. Over half of slum households received a housing voucher, while the slum itself received, on average, $230,000 in direct investments.

2.2 Population relocation

Population relocation involves moving residents from informal settlements to formal housing in different locations. This strategy typically requires the government to find suitable land for public housing projects and cover the construction costs of these developments, while potentially clearing the original slum area. MINVU also uses direct investment and DS49 subsidies to implement this policy. Direct investment targets expenditures such as slum clearance, debris removal, and temporary housing, while subsidies follow a similar pattern

[3]The DS49 program, which originated in the early 2000s, is part of a long history of housing policies dating back to 1906, beginning with the Workers Housing Law. Notable developments in this arena include the establishment of the Dwelling Corporation (CORVI) in 1953 and the foundation of MINVU in 1965, which formalized housing policy and added urban planning to its goals. The involvement of the private sector increased significantly during Pinochet's regime, and this trend continued after the restoration of democracy in 1990. Since the early 2000s, the provision of public housing to the poorest sectors has become more prevalent, with over 70% of housing projects initiated after 2000 being almost entirely developed by private companies and supported by subsidies like DS49.

as in *in-situ* upgrading, except that they are redirected to public housing outside the slum boundaries.

Slum dwellers are offered the opportunity to participate in a DS49 housing project in a different location to which they can voluntarily relocate. Post-relocation, the area is cleared of slum dwellings and debris to make way for public infrastructure such as parks, markets, and commercial zones, or to return the properties to their owners if privately owned. This strategy requires careful coordination to prevent the reformation of slums in the cleared areas. Some slums might have a prolonged existence due to repopulation dynamics. Vacated areas may attract new settlers, while family splits can lead to the perpetuation of certain households, as older generations move out but younger ones stay behind.[4]

Regarding cost per household, population relocation is one-third more expensive than *in-situ* upgrading. Table 1 shows that a household received around $29,969 dollars associated with the population relocation program. Subsidies are the main method used in population relocation slums, with an average of 4 out of 5 households receiving housing vouchers.

2.3 Slum program implementation

The government begins by identifying potential slums, which are then visited to confirm that the area qualifies as a slum: (i) it has at least eight families in close proximity, (ii) lacks property rights, and (iii) lacks at least one basic service. Once slum status is determined, the national and municipal governments establish an agreement to implement the slums program. After a slum has been deemed eligible, program representatives engage the slum community to secure their collaboration. The community must agree to participate in the program before the specific strategy is determined. Once there is commitment from both the government and the affected households, the national government assesses the feasibility of both intervention strategies and determines which strategy to implement. See the program's flowchart in Figure A1.

Although the program has a well-defined implementation process, there are no clear guidelines on how the government decides which slum to intervene in first, nor how to choose between *in-situ* upgrading and population relocation (Budget Division—DIPRES—report, Marcelo et al. (2019)). MINVU records only show the relevant factors considered when deciding on the treatment strategy. These factors include: social and cultural attachment, spatial dispersion, housing materials, public transit access, green and public space, city location,

[4] This is not the first time that Chile has implemented slum relocation interventions. During 1979–1985, the Pinochet dictatorship executed a massive slum clearance of 340 slums with more than 40,000 residents. That program focused on land tenure, providing ownership rights of newly developed public housing to slum dwellers. Some of the new public housing projects were built in the areas where the slum was located, while others were relocated to the outskirts of cities (Rojas-Ampuero and Carrera (2023)).

natural hazards, propensity to public disturbances, household eligibility for subsidies, slum social structure, political concerns, feasibility for new construction, piped water, sewage, and electrical grid.

Given the lack of information on how exactly the government decides which intervention to carry out, we conducted two logistic regressions to identify the observable factors that predict the probability of any treatment and those that predict the conditional probability of *in-situ* upgrading strategy. We considered the following variables for each of the logistic models: inclusion in the 2011 slum census, slum size, number of families, elevation, distance to the nearest river, terrain roughness, slum located in the periphery, distance to the city center, proximity to amenities, and building density in areas within 200 meters of the slum.[5]

Table 2 shows that inclusion in the 2011 slums census affects only the probability of receiving any treatment but does not favor any particular treatment. This aligns with the government program's directives: slums must be on the 2011 census to be eligible for any intervention. Slums with limited access and connectivity with the city are less likely to receive any treatment; being located on the periphery and having lower proximity to amenities reduces the probability of being treated. Slums with more households, located at higher elevations, and farther away from rivers are more likely to undergo *in-situ* upgrading. The positive effect of the number of households is present when controlling for slum size, suggesting that population density is driving the higher probability of receiving *in-situ* upgrading. Flooding risk, as measured by proximity to rivers, is also an important factor that determines if a slum should be relocated. Finally, many aspects included in the program guidelines, such as distance to the city center and amenities, did not influence the probability of receiving *in-situ* upgrading over population relocation.

3 Data and Measurement

In this study, we construct a longitudinal panel dataset that tracks all ever recorded slums in Chile over time by combining administrative data, georeferenced information, and satellite imagery. Rather than relying on algorithms to identify and delineate slum areas, we base our analysis on data from slum censuses conducted by the Chilean government and the non-governmental organization TECHO between 2011 and 2020.[6] These censuses provide

[5]We consider all hydrological sources when calculating the distance to the nearest river. We use an index similar to that of Anderson (2008) for terrain roughness and distance to amenities. The first combines slope and Terrain Ruggedness Index (TRI), and the second uses distance to clusters of firms in low- and high-skill industries, bus stops, supermarkets, libraries, fire stations, police stations, schools, health centers, and financial institutions.

[6]TECHO is a Latin American NGO with the mission to improve the region's housing quality.

precise locations of slums, allowing us to map their distribution and assess their proximity to various urban amenities such as distance to the city center, transportation networks, and public services.

Moving beyond a static mapping of slum locations, our study aims to understand the dynamic characteristics that define these areas. By examining their physical and socioeconomic attributes, we provide a comprehensive characterization of slum regions. To this end, we incorporate additional datasets—including building footprints—that offer detailed information on the physical structures within slums and their surrounding neighborhoods. This section details the main datasets gathered to construct our panel, highlighting the extensive information needed to better capture the physical and socioeconomic characteristics of slum areas.

3.1 Slum Locations and Boundaries

The Chilean government defines slums based on three criteria: (i) having at least eight households living in close proximity, (ii) irregular land property rights, and (iii) lack of access to water, electricity, or sanitation. Using this definition, the Ministry of Housing and Urban Development (MINVU) published slum censuses in 2011 and 2019. These censuses identify the precise locations and boundaries of all active slums in those years. They also provide information on the number of households. Between 2011 and 2019, TECHO published similar data, making it possible to construct an initial panel of active slums between 2011 and 2020. Figure 1 shows the number of active slums and slum households reported in this preliminary panel data. Notably, the number of slums has increased by 36%, while the number of slum households more than doubled, from approximately 31,000 to more than 80,000.

Slums are predominantly located on the periphery of cities, in areas that do not enjoy the full benefits of urban agglomeration. Figure 2 illustrates where slums are situated in the Valparaiso/Viña del Mar area, alongside the urban footprint in 1993 and 2020. Slums are primarily positioned at the city's borders. Moreover, new slums—those established in the last 10 years—are mostly found in the expansion areas of the urban footprint. This suggests a dynamic relationship between slum locations and city boundaries: as the city expands, peripheral slums get absorbed into the urban area. Therefore, relying on a static picture of slum locations can be misleading, as it fails to capture the ongoing urbanization process.

These patterns are not unique to the Valparaíso/Viña del Mar area. For every slum in our sample, we calculate its distance to the city center and identify its nearest city border. We then normalize the slum's distance to the city center by the distance between the city center and the respective city border. This normalization provides an easy spatial interpretation of the slum's location: values below one indicate slums inside the city borders, while values greater than one correspond to informal settlements outside the city. More importantly, normalized distances close to zero correspond to slums at the city center, while values closer to one refer to locations on the city's periphery. Figure 3 shows the distribution of slums along this normalized distance. Panel (a) focuses on slums founded before 1993, while Panel (b) displays the distribution for slums created between 1993 and 2020. At any given time, more than 60% of slums developed on the periphery of the city.[7] Older slums were once on the city's outskirts, and as cities grew, they were absorbed into the urban footprint. By 2020, more than 20% of the slums that were at the city border in 1993 were already inside the city.

This dynamic underscores the importance of considering temporal changes when analyzing slum locations. A static snapshot does not capture how urban expansion affects the integration of slums into the city over time. As cities continue to grow, understanding the shifting geography of slums is crucial for effective urban planning and policy-making.

3.1.1 Proximity to Labor Markets and Other Amenities

While slums are typically located on the outskirts of cities, an important question arises: Do they sacrifice proximity to city amenities when settling in these peripheral areas? To investigate this, we examined whether slums strategically position themselves near certain economic opportunities, particularly local labor markets. Using the 2017 national firm census, we identified clusters of low- and high-skilled firms. Low-skilled industries include agriculture, mining, low-tech manufacturing (e.g., food, wood, plastic), construction, retail, and transportation, while high-skilled industries encompass sectors like chemicals, pharmaceuticals, electronics, and professional services. Figure 4 illustrates the location of these clusters in the Coquimbo-La Serena region, where the distinction between these industries is clear. All slums, in this case, are situated closer to low-skilled firm clusters, suggesting that even when located on the periphery, slum households prioritize proximity to labor markets capable of absorbing their labor supply.

Table 3 replicates this pattern at the national level, comparing slums with a random sample of non-slum census blocks in a simple regression framework. The results suggest that new slums (created after 2010) do not sacrifice proximity to low-skilled labor markets and health centers. However, they are approximately 200 meters farther from schools and 100 meters farther from bus stops.

Moreover, the distinction between newer and older slums reveals additional insights.

[7] Samper et al. (2024) find almost the same percentage of slums located on the periphery among 30 cities worldwide.

Newer slums tend to be closer to low-skilled labor markets, whereas older slums are approximately half a kilometer farther away. Although we cannot fully interpret the location decisions of low-skill-intensive firms and slum areas independently, it is important to consider that many new slums appeared after the 2017 firm census. Together, these findings indicate that households in informal settlements may prioritize proximity to employment opportunities over access to certain public services when choosing their locations.

3.2 Physical Characteristics of Slums

We use the slum censuses to identify all areas ever considered as slums by the Chilean government or TECHO. So far, we have only explored the location of slums, but administrative records also provide slum boundaries. These boundaries are not constant over time; they expand and contract, and these changes are captured from one slum census to another. We define the unit of analysis as the area ever covered by a slum, which is calculated as the spatial union of all the slum boundaries observed over time. Figure 5 provides an empirical example of how the "ever slum area" is constructed. In this manner, we guarantee a constant area across time in which changes in outcome variables are not driven by variations in the slum area.

Focusing on ever-slum areas, we obtained satellite images for these locations for the period 2000 to 2022 and constructed a panel of slum physical characteristics. This is one of the few exercises that build a panel of slum characteristics and probably the one associated with the longest time (Kraff et al., 2020). We downloaded approximately 90,000 satellite images using Huang et al.'s (2021) procedure to download images from Google Earth.[8] Each picture covers approximately 1 km^2 and captures the exact area where a slum is located, as well as the formal neighborhoods in the vicinity (see Figure 5 Panel b).

We trained a machine learning (ML) algorithm that leverages recent advancements in the field of remote sensing and computer vision to identify building structures. The procedure uses U-Net architectures, a convolutional neural network that performs well when classifying spatial data and images with limited color bands (Ronneberger et al., 2015; Abascal et al., 2022; Alsabhan et al., 2022; Fisher et al., 2022). This architecture allows for precise extraction of building footprints, achieving high levels of accuracy. Our approach was inspired by algorithms developed in programming challenges like the AI Crowd Mapping Challenge, which have demonstrated significant success in building footprint detection. The algorithm achieved a precision level of 0.94. Further details about the processing of images and the calibration of the models are included in Appendix B.

[8] We thank Luna Yue Huang for her excellent guidance in this process. The baseline code to download images from Google Earth is available on her GitHub website.

Our ML strategy involved a four-stage process tailored to the Chilean context and the specific characteristics of informal settlements. First, we pre-processed high-resolution Google Earth images by fragmenting each $4,800 \times 4,800$-pixel image into 256 tiles of 300×300 pixels to optimize the model's performance and manage computational resources efficiently. Second, the the U-Net base model was adapted to work with RGB images instead of multispectral images and incorporated Test Time Augmentation (TTA) by making predictions on various transformations of each image to enhance accuracy. Third, we calibrated the model by allowing for greater geometric irregularity to account for the non-uniform shapes of informal constructions and adjusted the masking cutoff to balance precision and recall, minimizing false positives by processing each image twice with shifted grids. Fourth, we computed metrics such as total building area, building density, and measures of building regularity from the predicted footprints to analyze building activity within and around slums over time. This comprehensive approach enabled us to effectively identify and assess the built environment in informal settlements.

We complemented the machine learning techniques with human observational data (HOD). Six undergraduate students were tasked with observing all images for a given slum and selecting, for each year, the first image with sufficient quality to clearly identify building structures. For each of those images, they reported the number of recreational facilities, the presence of roads, and the coverage of residential and vacant land using four categories: none (<5%), some (5–49%), most (50–95%), and all (>95%). Figure 6 Panel A shows the evolution of residential coverage inside slums over the last 20 years. To calculate the average residential coverage, we used the mid-percentage value of each category. In the 2000s, most areas were vacant, with limited urban development. There are two periods during which the share of residential coverage inside slums increased rapidly: from 2005 to 2009 and from 2015 to 2020. The first expansion leading up to 2011 could have motivated the government's agenda on slum intervention. The period between 2015 and 2020 represents a time of civil unrest and culminates with the start of the COVID-19 pandemic, which affected both formal and informal housing.

Figure 6 Panel B shows the evolution of building density inside slums and in areas near the slums' borders using the building structures identified by the ML algorithm. The building footprint data allow us to look inside slums, but since all images cover around 1 km2, we are also able to observe nearby formal neighborhoods. This figure presents the first documented description of how built-up patterns evolve near slums. We constructed rings outside the slum to capture building density in neighborhoods within 100 m, 100 to 200 m, and 200 to 500 m of the slum's border. Note that the building density in the ring beyond 200 m remains mostly flat over time, whereas the density in the first ring more than doubles compared to the density inside the slums. This suggests (i) slums develop near highly urbanized locations and (ii) these locations are in neighborhoods likely on the outskirts of the city.[9]

3.3 Sociodemographics of Slums

In addition to building density, it is important to consider changes in sociodemographic characteristics and housing quality. We obtained the 2002 and 2017 population censuses at the block level (called "manzanas" in Spanish) and matched census blocks with ever-slum areas. On average, each block has 100 people and 33 households, and 99% of blocks have fewer than 700 people. We matched blocks to slum areas by using the block centroid to determine if it falls inside the slum boundaries. If the block's centroid is inside a slum, we label that block as representing slum population. We also complement the assignment process with the reverse geographic matching to account for slum areas in big census blocks, i.e. confirming that the slum's centroid falls inside a given census block. [10] [11]

Table 4 presents descriptive statistics from the 2002 and 2017 geocoded population censuses, comparing census blocks in slum areas with blocks located between 200 and 500 meters from the slums' borders. The average population living in slums increased by 11% between 2002 and 2017, more than twice the population expansion in nearby blocks. In 2002, slums were populated mainly by adult males. The adult male-to-female ratio in 2002 was 1.3 and decreased to 0.97 by 2017. In the nearby census blocks, the male-to-female ratio has remained stable around 0.96. We also observed an increase of more than 30% in the number of households within slums. Together, these statistics suggest a change in family structure, where males initially populated slums and families followed afterward.

Using the population census, we also examined changes in housing quality, measured by the percentage of houses considered inadequate, those without piped water, and those with good floor materials. Although we observe improvements in most of these variables in nearby blocks, this is not the pattern in slum blocks. In fact, the percentage of houses without piped water in slum areas increased between 2002 and 2017 from 6.84% to 10.5%, likely due to the creation and expansion of slums during this period. Regarding the number of houses

[9] We also compared the building activity inside slums between small and large informal settlements. Both groups had similar levels of residential coverage and building density up until 2011. However, Smaller slums experienced a rapid decline in building density; by 2015, they had reached densities similar to those 20 years ago. On the contrary, bigger faced high building densities for the last ten years.

[10] The 2017 Census data are available directly from the National Institute of Statistics (INE), while the 2002 Census was obtained from a private company named East View Information Services through the University of California Berkeley Library.

[11] Wurm and Taubenböck (2018) attempt a similar exercise in Rio de Janeiro. The authors combine a systematic mapping of morphological slum areas using satellite images with official census data. The advantage is that the Brazilian census also identifies slum blocks, which allows the author to calculate accuracy. Remote sensing-based mapping yields accuracies above 90%.

considered inadequate, we observed only a 20% decline in slum areas, while nearby blocks saw a more than 60% reduction. These findings suggest that while adjacent neighborhoods experienced significant improvements in housing quality, slum areas did not see comparable progress and, in some aspects, conditions worsened.

By integrating these results, we provide a comprehensive view of the demographic and housing quality changes within slum areas and their surroundings over time. This highlights the persistent challenges faced by slum communities, even as nearby areas show signs of improvement.

3.4 Other datasets

Building footprints and population censuses offer an initial glimpse into all slums observed in Chile over the past 20 years. While these datasets reveal the effects of slum renewal policies on certain physical and socio-demographic characteristics, they have limitations. Population censuses provide data on long-term changes but fail to capture short-term dynamics. Crucial factors like housing developers' expectations—which are important for assessing investment potential—cannot be derived from satellite images alone. Additionally, other neighborhood dynamics can be influenced by *in-situ* upgrading and population relocation. For example, property owners might alter their investment strategies in housing quality in response to changes in local amenities. Criminal activity could also be affected directly by increased institutional presence and indirectly by shifts in the area's physical and socio-demographic makeup.

A substantial amount of data is required to thoroughly explore these complex relationships. We address this need by merging detailed local geographic information, including population estimates, building permits, land tax records, and crime reports. This comprehensive dataset allows us to analyze the multifaceted impacts of slum policies on both informal settlements and the surrounding formal neighborhoods, providing deeper insights into the dynamics at play.

3.4.1 LandScan Population Estimates

We use the yearly LandScan Global dataset to approximate the population living in an area of roughly one kilometer squared between 2001-2021. The LandScan Program is a project of the Oak Ridge National Laboratory (ORNL) with a spatial resolution of 30 arc-seconds (approximately 1 km in the equator). It is one of the finest resolution global population distribution data available. LandScan uses an algorithm that combines high-resolution imagery and advanced computer science methods to disaggregate census counts within an administrative boundary. To calculate the estimated population in a slum area, we match LandScan grids to slums based on the grids that overlap the slum. In most cases, one grid completely contains the slum (due to their difference in area). For the rest of the cases, we average the population in all LandScan grids within 500 mt of the slum centroid. LandScan is a smoothing approximation of population distribution, the average population is less affected by random errors than the sum. Note that this approach is likely to underestimate the population contained within one squared kilometer since most official population records in informal settlements tend to be a lower bound (Breuer et al., 2024).

3.4.2 Building Permits

The National Statistics Institute (INE for its acronym in Spanish) provides a dataset of geocoded building permits containing information about future constructions of commercial or residential buildings and the amount of square meters they would represent. We used data from 2010 until 2022. The way this data is populated depends on developers and architects submitting building permits to the corresponding local department of planning. Each municipality shares the data with the INE to construct a countrywide dataset. 90% of local municipalities shared this information.

3.4.3 Land Registry

We also incorporate land registry data from the Chilean Internal Revenue Service, which provides detailed information about building constructions on each of the country's parcel tax lots. This dataset includes variables such as building size, primary construction material, year of construction, year of last renovation, and assessed property value. Although it contains data on building size, it does not offer insights into the internal configuration of buildings—such as the number of bedrooms, bathrooms, or floors. A particularly relevant aspect of this dataset is the "year of last renovation," which we use to identify buildings that underwent renovation in a specific year. Additionally, the data records all building permits submitted for each property, allowing us to track construction activity over time. Although assessed value is included in the dataset, it follows an appreciation formula that does not fully capture changes in the real estate market.[12]

[12] This data was obtained though a partnership between the University of California - Berkeley and the ESE School of Business of Universidad de los Andes, Santiago de Chile.

3.4.4 Household surveys and subnational government finance

We complement all the data gathered until now with information about the local economic conditions in the municipalities where the slums are located. We use household surveys representative at the municipality level to characterize local labor markets and formal housing. We also have information on local public finance to calculate government expenditure by different categories. Chile has a a total of 346 municipalities, which they refer to as "comunas."

We use the National Employment Survey (ENE for its Spanish acronym) to calculate labor market outcomes such as employment rate, average salary by educational level, unemployment rate, and distribution of employment across industries. We combine this dataset with the household survey CASEN to gather data on housing rental prices. Data from the National Municipality Informational System (SINIM for its Spanish acronym) provide local government expenditures in health, social programs, and education, among others.

3.4.5 Crime Records

The Sub-secretary for Crime Prevention (SPD for its Spanish acronym) collects all crime reports and arrests made by the national police and geocodes this information at the national level. We use geocoded crime reports between 2013 and 2021 that happened within 500 mt of all slum areas. Using this information we can estimate the spillovers effect of each one of the policies in criminal activity. One would probably be interested in calculating crime effect inside slums. However, geocoding is only possible in areas containing roads and addresses which is not usually the case for slum areas,

4 Local Economic Conditions and Slum Growth

We assess how local economic conditions contribute to slum growth by estimating a First-Difference model in which slum population growth at the municipality level is a function of different socioeconomic variables. We focus on the following equation,

$$\Delta y_i = \alpha + \beta \Delta X_i + \gamma \mathbb{B}_i + \varepsilon_i \tag{1}$$

where Δy_i is the change in total slum population in the municipality between 2002 and 2017 (slum growth). ΔX_i refers to changes in different municipality characteristics over time. $\mathbb{B}_i$ is a vector of baseline variables, such as the initial population in the municipality.

Using equation (1), we can test different economic theories regarding slum growth. Informal settlements are usually associated with limited access to the formal housing market and proximity to jobs. First, we focus on the link between slums and the housing market by constructing a quality-adjusted rent measure using the National Household Survey of Socioeconomic Characterization (CASEN, for its Spanish acronym). The municipality-specific quality-adjusted rent corresponds to the fixed effects associated with a hedonic regression of rental prices on different housing characteristics (e.g., square meters, water access, roof materials, and roof conditions). In this fashion, the variable captures municipality-specific rental prices uncorrelated with the particularities of the houses in the sample.

Second, we use the National Employment Survey (ENE, for its Spanish acronym) to study the link between slum growth and job opportunities. We calculate the number of workers in the municipality as a proxy for labor market size and obtain their average salaries by education level. Therefore, we can estimate equation (1) using three specific variables of interest related to the labor market: the number of employees, the average salary across all education levels, and the average salary of people with only secondary education (51% of the population in slums have only secondary education; see Table 4).

Table 5 shows the results of the long difference model for slum population growth. Column (1) only includes controls for municipality population, quality-adjusted rent, and employment. Columns (2) to (5) add additional controls such as average salaries for low educated workers, extreme poverty and social expenditures directed to slums.[13]

Slums tend to expand when rental prices are higher. Our results suggest that a one standard deviation increase in quality-adjusted rent is associated with up to a 14% increase in the slum population. Low-income households have limited ability to cover housing expenses, so when formal housing becomes more expensive, they turn to informal settlements as an alternative to reduce their housing cost burden. Qualitative research in Chile also supports this argument. López-Morales et al. (2018) find that, on average, households spent 40% of their income on housing before moving to a slum. After moving, the rent-to-income ratio decreases to 19%, even accounting for the possible decline in income.

Table 5 also provides evidence of the positive link between slum growth and local labor markets. We find that larger labor markets and higher wages are associated with slum expansion. Municipalities offering more and better employment opportunities attract low-income households, who are at a higher risk of residing in informal housing. Notably, it is not the average market salary that influences slum growth but rather the wages of workers with only a high school education. These findings align with previous research by Glaeser et al. (1995); Glaeser (2014); Alves (2021).

[13]For most of the control variables, the baseline year depended on the availability of data. The first year we were able to estimate hedonic models to construct the housing rental price index was 2009. For labor market outcomes and municipal expenditures, the first observed year is 2010.

For our municipality-level analysis, we also include variables capturing social assistance. We find that slum growth occurs in areas experiencing a decline in extreme poverty, suggesting that vulnerable populations tend to avoid locations with high poverty levels. The expected benefits for households moving to an informal settlement decrease when the population already living in the municipality exhibits higher poverty rates. Additionally, in the last column of Table 5, we include municipal expenditures related to slum areas, specifically direct investments and subsidies. Although these variables might be endogenous, the results indicate that direct investment in slums, unlike subsidies, is negatively associated with slum growth.[14]

Although the analysis conducted in this section is not specifically designed for causal inference, it allows us to identify factors associated with slum growth. Since the slum population represents less than 2% of the total municipal population, concerns about reverse causality affecting the formal housing and labor markets should be minimal. Additionally, the first-difference model accounts for time-invariant unobserved factors, enhancing the robustness of our findings.

5 Empirical Methods

This section describes the methods used to estimate the effect of the two policy interventions —*in-situ* upgrading and population relocation— on slum characteristics and spillovers. There are several challenges to consider when estimating the causal effects of these policies. First, the specific policy assignment is not random. Therefore, a direct comparison between slums under *in-situ* upgrading and those under population relocation is infeasible due to the idiosyncratic characteristics of each slum. Our identification approach involves estimating causal effects for each strategy using the pool of never-treated slums as potential controls.

There are three characteristics of the program's implementation that support our identification strategy. First, the slum community decides to participate in the program before the specific treatment is determined. Unobserved characteristics influencing community preference for one treatment or another are unlikely to have an effect on the chosen strategy. Second, the policy did not take into account the creation of new slums and the expansion of the existing ones. Slums need to be included in the slum census to be eligible, and the intervention did not consider updating the records until 2018.[15] That motivates our focus

[14]Concerns about the endogeneity of these measures refer to the possibility that households move to slums seeking social assistance. However, the nature of the program significantly reduces this risk, as discussed in Section 2. SUR (2017) and López-Morales et al. (2018) document some of the reasons why households move to slums, and direct investment and subsidies are not significant drivers.

[15]Marcelo et al. (2019) reports that 50% of the slum population growth and 25% of the growth in the

on treated slums between 2011 and 2017. Third, the number of slums intervened each year was capped by MINVU's budget, which contributed to more than 98% of the program costs. MINVU allocated around 2% of its yearly budget to the program.[16] These factors suggest a high degree of substitutability between *in-situ* upgrading and population relocation policies and a certain degree of randomness between the ones treated first versus later.

Motivated by the staggered nature of the treatment assignment, we rely on a Synthetic Difference-in-Differences (SDiD) model to identify causal effects. This approach constructs a "synthetic control" group for each treatment cohort using the pool of never-treated slums between 2011 and 2018. We also focus on the treatment assignment itself and not necessarily on when all the direct investment and relocation take place. Technically, results should be considered as Intent to Treatment (ITT) causal effects. Once a slum receives the treatment assignment, there is a lag of approximately two to four years until the treatment is completed. Although we have information on direct investments related to *in-situ* upgrading and the number of subsidies allocated to each slum, we have limited knowledge of when the investments are completed and when the households cash out their subsidies.

5.1 Slum Physical Characteristics

Our panel of slums provides an optimal scenario to estimate the effects of each policy on the physical characteristics of slums and the nearby environment. In this section, we present the methodological approach used to estimate the causal effects of each policy on annually observed outcomes. The outcome variables are not limited to those obtained from satellite images; we also estimate effects on outcomes derived from land tax records and criminal reports using the strategy outlined here. We start with the following general equation,

$$y_{it} = \alpha_i + \alpha_t + \beta \mathbb{D}_{it} + \gamma X_{it} + \varepsilon_{it} \tag{2}$$

where y_{it} is the outcome of interest, such as residential land coverage, building area, population, distance between building footprints, number of building permits, and violent crime rates within 200 mt of the slum. α_i and α_t represent the slum- and time-fixed effects, respectively. X_{it} represents time variant slum characteristics used as controls (in most models, we control for the lag of LandScan population). $\mathbb{D}_{it}$ is the variable that identifies the treated slums. It is equal to one if slum i is treated in year t or before. This model can be estimated for each one of the policies restricting the sample to those treated under the policy of interest and the never-treated slums.

number of slums were not even considered for intervention between 2011-2018.

[16]The total budget assigned to MINVU is approved annually by the National Congress.

One common method to estimate equation (2) is the Two-Way Fixed Effects (TWFE) estimator. However, estimated coefficients from TWFE represent a weighted average of treatment effects from three types of comparison groups, one of which does not represent a proper control group in our setting. Specifically, TWFE uses already-treated units as the comparison group for later-treated units (Goodman-Bacon, 2021). This implies that slums intervened as early as 2011 could serve as the control group for those treated in 2016, which may not be appropriate.

To address this issue, Callaway and Sant'Anna (2021) developed a Difference-in-Differences estimator that avoids this problem by restricting comparison groups to never-treated and no-yet-treated units. Although this model—denoted as CSDiD —improves upon some limitations of the usual TWFE, the parallel trends assumption remains unchanged.

The parallel trends assumption requires that, in the absence of treatment, the average change in the outcome would have been the same for never-treated and treated slums. However, since treatment assignment was not random, a naïve comparison using all never-treated slums would lead to biased estimates. Recall that intervened slums had to be included in the 2011 slum census, implying that a significant portion of never-treated slums are slightly younger than those in the treatment group. There is also the potential for unobserved characteristics that influence the probability of treatment.

To overcome these challenges, we use the SDiD estimator developed by Arkhangelsky et al. (2021) as our main estimation method.[17] The SDiD estimator combines the usual DiD with Synthetic Controls, optimally choosing the control group to match the pre-treatment trends of the treated slums. Specifically, SDiD focuses on the following optimization model:

$$(\hat{\beta^{sdid}}, \hat{\alpha}, \hat{\gamma}) = \arg\min_{\beta,\alpha,\gamma} \left\{ \sum_{i=1} \sum_{t=1} (Y_{it} - \alpha_i - \alpha_t - \beta \mathbb{D}_{it} - \gamma X_{it})^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{3}$$

$\hat{\omega}_i^{sdid}$ captures the individual slum weights while $\hat{\lambda}_t^{sdid}$ corresponds to time weights. If $\hat{\omega}_i^{sdid} = 1$ and $\hat{\lambda}_t^{sdid} = 1$, we are back to the canonical optimization equation for the Difference-in-Difference model. Also, if the time weights are all set to one, $\hat{\lambda}_t^{sdid} = 1$, we have the usual Synthetic Controls.

SDiD integrates the strengths of DiD and Synthetic Controls to estimate causal effects more reliably, especially when the standard DiD assumptions may not hold. By constructing a synthetic control group that closely matches the treated group's pre-treatment trends, SDiD improves the choice of counterfactual and reduces reliance on the parallel trends assumption. Additionally, SDiD can handle multiple treated units and staggered treatment timing, unlike traditional Synthetic Control methods.

[17] See Clarke et al. (2023) for a more empirical approach on how to estimate SDiD.

This model is particularly well-suited for studying the slum renewal policies. For each treated slum cohort, we use data from untreated slums to build a synthetic slum that mirrors the treated slums' pre-treatment characteristics and trends. Table 2 shows that the two most relevant variables explaining the probability of any treatment are being included in the 2011 slum census and the number of slum households. Therefore, we focus only on slums treated between 2011 and 2017 and consider lagged LandScan population data when selecting the synthetic control group and determining its weights.

Finally, we compare the post-treatment outcomes (e.g., building density, building regularity, crime rates) between the treated slums and their synthetic counterparts. The difference in these outcomes is attributed to the specific intervention. We also test the robustness of our estimates using the CSDiD estimator. For almost all of our outcomes of interest we get the same sign but larger and more significant effects. Given the discussion presented above and to be on the conservative side, SDiD remains as our main specification (see Appendix C for the CSDiD results).

5.2 Slum Sociodemographic Characteristics

Unlike slums' physical characteristics, we only observe sociodemographic variables for two years: 2002 and 2017. Those years correspond to the national population censuses. Data restrictions limit our ability to estimate equation (2) for sociodemographic measures using the methods described above, such as CSDiD or SDiD. Based on these limitations, we estimate a standard Two-Way Fixed Effects (TWFE) model for the population census outcomes. However, we implement a slight variation of the TWFE model in which we consider both treatment strategies simultaneously. We include two binary treatment variables, one for each intervention. Using the TWFE in a pooled model increases statistical power and allows us to test the equality of the two treatment effects. We rewrite equation (2) as follows,

$$y_{it} = \alpha_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \alpha_i + \alpha_t + \gamma X_{it} + \varepsilon_{it} \tag{4}$$

where y_{it} is the outcome of interest measured from the population census, with $t = 2002, 2017$. D_{1i} is a dummy variable that equals one if the slum received the *in-situ* upgrading treatment and D_{2i} is for the population relocation strategy. X_{it} is a set of baseline covariates. Empirically, we use the lagged population from LandScan, given the limited availability of exogenous regressors.

If never-treated slums are a good comparison group for those intervened by the government before 2017, then the estimated β's coefficients capture the effects of the interventions on the outcomes of interest. We restrict our sample in two ways to improve the comparison group: first, we include only slums observed up to 2017; second, we include only treated slums that have been under the assigned treatment for at least three years. These restrictions reduce concerns related to differences in the treatment probability, as discussed previously. Additionally, table 2 shows that the probability of any treatment also depends on slum size and time-invariant characteristics such as location on the periphery and distance to amenities. The proposed TWFE model controls for population estimates and slum fixed effects, which should capture most of that variation.

Population censuses are our only option to understand sociodemographic changes motivated by the different intervention strategies. One would expect that improving housing quality will significantly affect educational choices and employment within the slum and in nearby areas. If there are changes in formal neighborhoods close to slums attributable to any of these slum renewal policies, it is likely that they are transmitted through changes in the sociodemographic composition of the neighborhood.

6 Results

In this section, we discuss the direct and spillover effects of both policies, *in-situ* upgrading and population relocation. Although the focus is on the benefits of the policies, their costs are also noteworthy. Table 1 provides summary statistics of the cost of each strategy, broken down by the amount of subsidies and investment per household and per slum. The average cost per household of *in-situ* upgrading is two-thirds of the average cost of population relocation. *In-situ* upgrading is, on average, less expensive to implement.

6.1 Direct Effects of the Policies

We can estimate the direct effects of *in-situ* upgrading and population relocation on slums' physical characteristics using our panel of slums. Our preferred methodology, Synthetic Difference-in-Differences (SDiD), relies on the selection of a synthetic control group from the pool of never-treated slums that match the pre-treatment trends of treated slums. We have a staggered treatment, which implies that a synthetic control group is created for each treated cohort. We aggregate the cohort estimates to create an event-study-type figure for each dependent variable and treatment arm. Figure 7 shows the full dynamic effects of each policy intervention (columns) for a selected group of outcome variables (rows). Confidence intervals are obtained using bootstrapping. We also report in Table 6 a summary of the estimated causal effect after six years from the treatment assignment.

We confirm that the population relocation policy reduces the share of residential land by 12% and the population by almost 16% after six years from the intervention. For *in-situ* upgrading slums, we find no significant effect on residential land and population overall. However, the dynamics presented in Figure 7 suggest an initial 9% decline in residential land that rebounds after five years. This pattern is consistent with urban renewal processes and the increases in building permits discussed later.

Regarding population, recall that our measure captures not only the slum population but also includes part of the immediate vicinity. This implies that the results should be interpreted as reflecting a local neighborhood trend, which we will confirm using population census data. Even when taking the results at face value, the changes in population are relatively small for a strategy that targets slum closures. There is a high risk of slum repopulation, particularly in areas where not all households are able to move out. Households taking the place of relocated families may be new settlers joining the slum or may result from family divisions.

Housing quality is one of the main objectives of slum renewal policies. We have observed that slums face poor housing conditions in terms of space, regularity, and basic services. We focus on five specific outcomes: paved streets, average building size, number of large buildings (larger than 64 m^2), the standard deviation of the buildings' orientation angles, and the distance between building footprints. For the last two variables, we compare each building to its nearest eight neighbors. This approach limits drastic changes in the outcomes due to adjustments in the number of buildings and ensures a consistent measure between inside and outside slums. The orientation angle is a proxy for building regularity. In formal neighborhoods, for example, most houses tend to face the same direction, resulting in a standard deviation of orientation angles close to zero. Slum dwellings are typically built very close to each other; thus, increases in the distance between a building footprint and its neighbors are likely associated with improved housing quality.

In-situ upgraded slums exhibit a general improvement in housing quality, while structures remaining in population relocation slums show no improvement over their pre-intervention quality. We find an 11% increase in the share of paved streets and an almost 15% increase in the number of large buildings for *in-situ* upgrading areas. Additionally, building footprints appear more regular, with a decline of about 1 degree in the standard deviation of the orientation angles. Buildings are also further apart by almost 9 meters. No significant housing quality effects are found within the population relocation areas. In fact, we observe a slight reduction in the average building size by almost 10%, which is particularly relevant considering slum houses are already much smaller than formal structures.

Improvements in housing quality and slum clearance are indicators of community investment and could change developers' perspectives on future neighborhood changes. We measure changes in neighborhood transformation and desirability using building permits. Housing starts represent future development and are the closest measure to formal construction that we can observe from administrative records. Focusing on the extensive and intensive margins, we find an increase of 5% in the probability of at least one new building permit and an increase of 2.3% in the number of permits in *in-situ* upgrading areas. There is no evidence of changes in building permits within population relocation slums after six years from the treatment assignment. *In-situ* upgrading not only increases housing quality but also initiates a neighborhood transformation that attracts formal housing investment.

For the panel data outcomes, we also estimate the same models using the Difference-in-Differences estimator developed by Callaway and Sant'Anna (2021) (CSDiD). This model is closer to the canonical Two-Way Fixed Effects approach. The appendix C presents the results using CSDiD for both policies. Estimated effects for most of the outcomes are either of similar magnitude or display a similar comparison between the two strategies as those obtained from the SDiD models.

Now we turn our focus to outcomes measured using the 2002 and 2017 population censuses. Here we study the effect of the different government interventions on slums' sociodemographic characteristics. There are some caveats that are important to mention. The 2002 census might not provide a comprehensive picture of every slum before treatment; recall that most slums had not yet developed by 2002. Government interventions started after 2011, which implies that actual activities in slums did not start until 2012. The 2017 census will only capture short-term effects for slum cohorts that started intervention in 2013 and 2014. Both treatments take time to complete; in particular, the time between receiving a housing voucher and moving to the new house is usually 24 to 36 months. That applies to construction *in-situ* as well as to relocation. Nevertheless, census variables can provide additional insights related to housing quality beyond the five measures mentioned above and changes in the population structure.

Table 7 Panel A shows the direct effects of each policy on a selected set of census outcomes. All models control for LandScan population and slum fixed effects. Houses in slums under the *in-situ* upgrading strategy are larger; we find positive effects on houses with two or more bedrooms. In terms of sociodemographics, we observe more individuals over 25 years old with secondary or higher education. The point estimates associated with population and employment rate inside *in-situ* upgrading slums are also positive, although not statistically significant. However, the coefficient on employment rate is comparable to those estimated for formal neighborhoods near slum areas in Panels B and C. All these results suggest a population composition change in *in-situ* upgrading slums that attracts higher socioeconomic status (SES) individuals to the previously slum area. Regarding population relocation slums, we observe only a significant decline in the quality of building materials and some weak evidence of a 15% population decline. Although the latter figure is not statistically significant, it echoes the result from the slum panel.

Our analysis demonstrates that *in-situ* upgrading is more effective than population relocation in improving slum conditions. The *in-situ* upgrading strategy not only enhances housing quality within slums—through increased paved streets, larger and more regular buildings, and greater distances between dwellings—but also stimulates neighborhood transformation by attracting formal housing investment, as evidenced by the rise in building permits. Additionally, *in-situ* upgrading appears to attract higher SES residents, contributing to positive changes in the sociodemographic composition of the area. In contrast, population relocation does not yield significant improvements in housing quality within the slums and may even lead to a decline in building size and material quality.

6.2 Spillovers on nearby formal neighborhoods

There is limited evidence on the effect of slum renewal policies on the physical and sociodemographic characteristics of slums, and the knowledge gap is even larger regarding spillover effects on nearby formal neighborhoods. In this analysis, we focus on two buffer zones around the slums: 0 to 200 meters and 200 to 500 meters. We measure the distance from the slum border and ensure that only formal locations are included in each ring (Figure 6 illustrates the different patterns for these two groups). Our interest lies in spillovers related to building activity, housing investment, sociodemographic changes, and crime rates.

Table 8 presents the effects of each slum policy on various outcomes of interest. The outcomes included in the table come from three data sources: building permits, land registry, and building footprints. In terms of building activity and housing investment, we find large positive spillovers for areas close to *in-situ* upgrading slums. Specifically, the probability that at least one building permit is approved in a formal neighborhood within 200 meters of the slum increases by 10%. The effect on the intensive margin is similar, with a 13% increase in the number of building permits that persists up to 500 meters from the slum. Formal neighborhoods close to population relocation slums do not exhibit similar gains in developers' confidence.

The effects on building permits suggest a neighborhood transformation as a result of *in-situ* upgrading strategies. This is also evident when we examine spillovers on housing investment, particularly indicators of building renewal. Table 8 presents spillover effects for the following outcomes: age of buildings, share of buildings younger than five years, buildings undergoing renovations, and reported building size. We find a 4 percentage point increase in young buildings and a 30% increase in yearly renovations in formal areas within 200 meters of *in-situ* upgrading slums. For neighborhoods close to population relocation slums, we find a smaller effect on young buildings and no significant effect on building renovations. Nearby communities are more willing to invest in and maintain their properties. Changes in neighborhood amenities affect the expected returns from housing investment, motivating further improvements in housing quality and fostering a more connected community.

We do not find changes in outcomes from the building footprints data for any of the slum renewal policies. These are formal neighborhoods where changes in building regularity and distance between buildings are unlikely. However, while we find no effect on the building footprint size, we do observe weak evidence of an increase in the reported size on land tax records. This is consistent with internal housing modifications and vertical expansion. Considering the significant effects on building renovations, it is highly likely that additional floors are added to some units, while others repurpose certain areas of their building footprint.

We now focus on the population undertaking these housing investments and how policy interventions could affect formal neighborhoods beyond physical characteristics. Table 7 panels B and C show the effect of each intervention on socioeconomic outcomes measured from the population census in neighborhoods within 200 meters and 200 to 500 meters of the intervened slum, respectively. Areas close to population relocation slums show no signs of changes in socioeconomic composition. In fact, we find a decline in population of at least 17% up to 500 meters from the slum. In the case of *in-situ* upgrading slums, we find that the population within 500 meters of the slum is more educated and more likely to be employed. However, there are no significant changes in population size near *in-situ* upgrading slums. There is evidence of socioeconomic compositional changes in the neighborhood, with higher SES individuals being attracted to these locations. Note also that the effects documented here correspond to less than six years from treatment assignment, which implies that changes in population structure happen concurrently with housing investment.

Finally, we estimate spillovers on criminal activity from the two interventions in nearby formal neighborhoods. Table 9 summarizes the effect of each policy on each of the rings after five years of the intervention using the SDiD methodology. We focus on only five years from the intervention assignment due to data availability; crime records only cover 2013 to 2023. Once again, neighborhoods near *in-situ* upgraded slums are performing better. We find a decline in property and violent crimes per km^2 of 5.1 and 2.6 within 200 meters of *in-situ* locations, respectively. We find no effect for neighborhoods near population relocation slums, as well as areas beyond 200 meters. One might be concerned about changes in reporting behavior that could bias the results. To mitigate those concerns, we present in column (4) the effects on homicides. Although homicides are rare events, they are less affected by misreporting. We find the same pattern as with property and violent crimes.

One potential mechanism through which *in-situ* upgrading, rather than population relocation, reduces criminal activity is the population composition change discussed above. Higher SES individuals are less likely to engage in criminal behavior; in particular, attachment to the formal labor market reduces the probability of participating in illegal activities. This argument does not rely on the assumption that offenders prefer living in slum areas. In fact, if that were the case, the population relocation strategy should also lead to a decline in criminal activity.

Changes in the provision of public and private security could also contribute to the decline in criminal activity near *in-situ* upgraded slums. There is high institutional participation around informal settlements undergoing urbanization. Specific investments such as street pavement and connection to basic services increase state presence and reduce the cost for police to actively patrol these areas. There are other documented effects that likely increase neighborhood safety, such as housing development and renovations. New building constructions have better security standards. Landowners could incorporate strategies to mitigate the probability of victimization during renovations, such as installing safer doors and windows. Additionally, in the case of vertical expansion, taller buildings have a lower probability of trespassing. Although we cannot distinguish between the effects of population compositional changes and improved security mechanisms, positive crime spillovers are clear indicators of improvements in neighborhood amenities.

Our analysis reveals that *in-situ* upgrading of slums generates significant positive spillover effects on nearby formal neighborhoods, whereas population relocation strategies do not produce similar benefits. Areas within 200 meters of *in-situ* upgraded slums experience increased building activity and housing investment, as evidenced by higher probabilities of approved building permits and a surge in building renovations. These neighborhoods also witness improvements in sociodemographic characteristics, with more presence of high SES residents. Importantly, we observe a substantial decline in property and violent crimes in these areas, suggesting enhanced neighborhood safety. Our findings highlight the effectiveness of *in-situ* upgrading policies in not only improving conditions within slums but also fostering beneficial transformations in surrounding formal neighborhoods.

7 Conclusion

In this study, we have undertaken an extensive data collection and analysis effort to examine slums and to estimate the direct and spillover effects of two widely implemented policies: *in-situ* upgrading and population relocation. We obtain satellite images and implement machine learning strategies to extract building footprints and monitor changes over time. We geocode administrative records—including land registry data and population censuses—and match household surveys to enrich our analysis. All of this highlights the substantial amount of data required to better understand informal settlements. Our descriptive findings reveal that slums are dynamic places that evolve over time and experience changes in family composition. Although slums are located on the outskirts of the city, their specific locations are not random; they are situated near low-skilled job opportunities. We also find that slum growth is particularly responsive to increases in housing rental prices and to the availability of more and better jobs for low-skilled workers.

We examine the effects of the two slum renewal policies in the Chilean context, a country that has implemented both strategies simultaneously since 2011. Recognizing the challenges posed by non-random policy assignment, we address identification issues by estimating causal effects for each strategy using never-treated slums as potential controls. Leveraging the staggered nature of treatment assignment and employing the Synthetic Difference-in-Differences (SDiD) method, we construct synthetic control groups that closely match the pre-treatment trends of treated slums. This approach enables us to isolate the impact of each intervention on observed outcomes derived from satellite images, land registry, and crime reports.

Our findings indicate that *in-situ* upgrading is more effective than population relocation in improving slum conditions and generating positive spillovers in nearby formal neighborhoods. *In-situ* upgrading leads to significant enhancements in housing quality within slums, including increased paved streets, larger and more regular buildings, and greater distances between dwellings. It also stimulates neighborhood transformation by attracting formal housing investment, as evidenced by a rise in building permits. Moreover, we observe improvements in the sociodemographic composition of adjacent formal areas and reductions in property and violent crimes. In contrast, population relocation shows limited effects on housing quality and sociodemographic changes beyond the expected effect on population. The relative benefits of *in-situ* upgrading over population relocation become more relevant when considering that the former costs one-third less than the latter, making *in-situ* upgrading a more efficient strategy when both are possible to implement. However, these results should be interpreted with caution, as both strategies are not always available for a given slum, particularly those located in riskier areas that should be relocated for safety concerns.

This paper highlights significant implications for public policy, especially in addressing the challenges of informal housing. Low-income households are the most vulnerable to moving into informal settlements due to high living costs in cities. This situation raises concerns for policymakers aiming to provide equitable opportunities. Additionally, the issue is compounded by migration patterns, as cities grapple with rural-to-urban migration and international migrants seeking better prospects. Some of these migrants end up in slums, further straining resources and infrastructure. Policymakers must therefore consider comprehensive strategies that not only mitigate the adverse effects of existing slums but also limit the creation of new ones. This could involve expanding affordable housing options, implementing inclusive urban planning, and improving access to low-cost formal housing.

Despite our extensive data collection and analysis, the study has limitations that point to areas needing further research. Notably, we lack detailed information on the post-relocation outcomes of individuals moved from population relocation areas. Understanding whether these individuals resettle in better neighborhoods and improve their well-being, or if the disruption of their community ties adversely affects them, is crucial (Rojas-Ampuero and Carrera, 2023). Future research should also focus on the relationship between local labor markets and slums, particularly how the availability of low-skilled jobs influences slum formation and growth. Gaining insights into these dynamics could inform more effective policies that address both housing and employment challenges faced by low-income populations.

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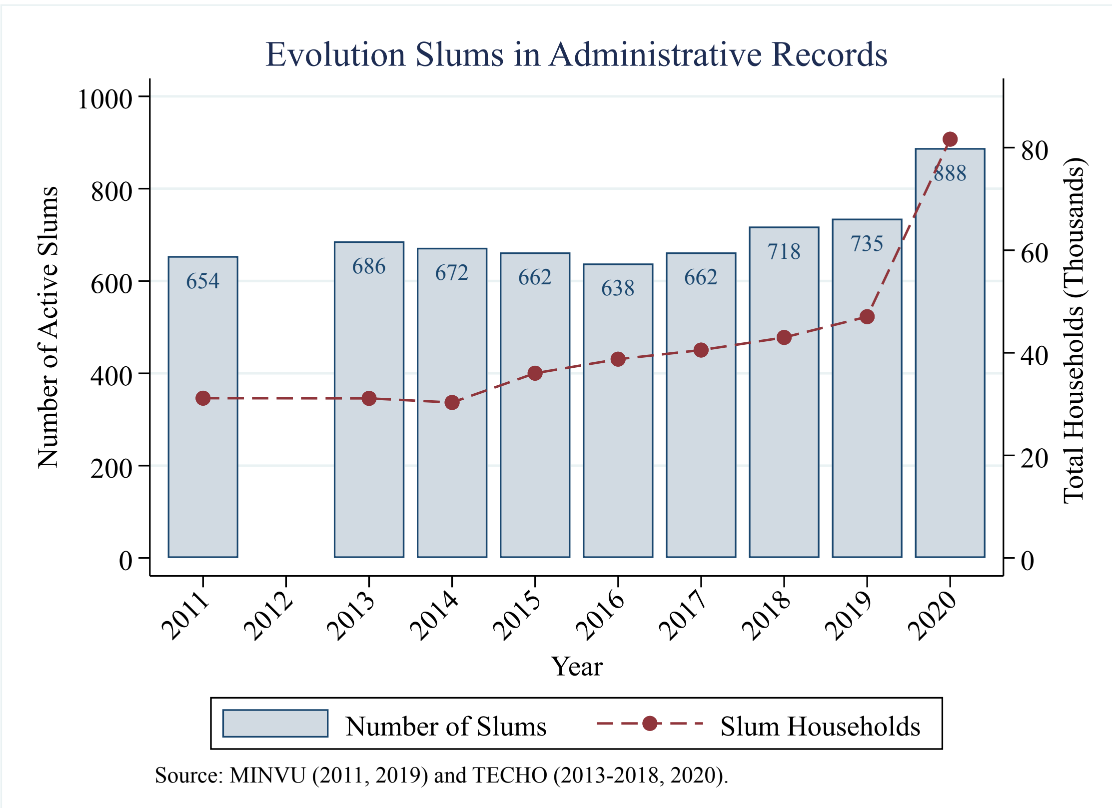
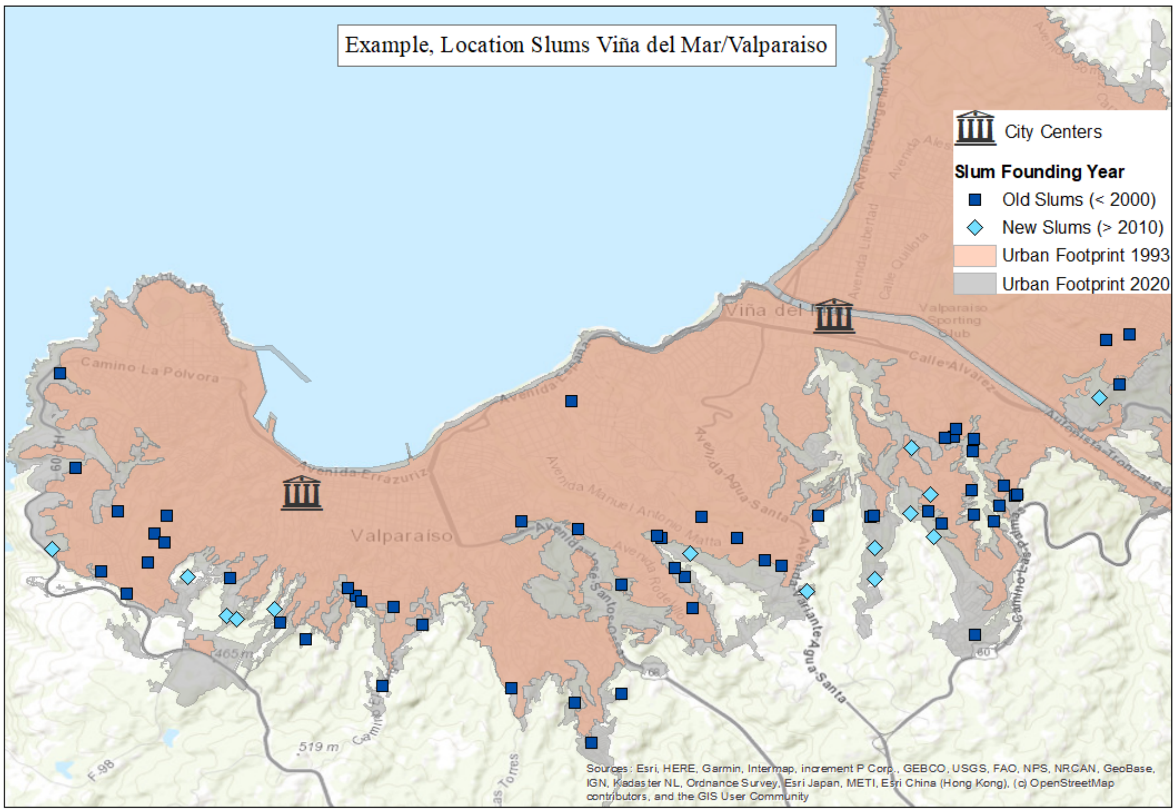
Figure 1: Number of Active Slums and Slum Households in Administrative Records [a]



[a]Active slums refers to informal settlements that are included in administrative record (either MINVU or TECHO censuses) in a given year. Chile has a well-established definition of slums, it requires that an informal settlement complies with the following conditions: (i) has eight or more households spatially closed, (ii) lacks property rights, and (iii) has no access to one or more of the basic needs services: electricity, sanitation and water.

Figure 2: Location of Slums in Valparaiso Area & City Limits [a]

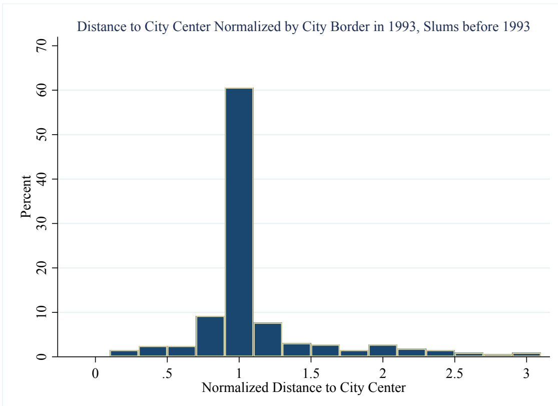


[a] 1993 and 2020 city limits come from the continued urban construction (CUC) of the city of Valparaiso and its neighboring municipalities in 1993 and 2020, respectively. City centers are provided as a result of the Urban Functional Areas project (AFU for its Spanish acronym) by INE, MINVU, SECTRA and SUBDERE. City centers take into account residential and labor locations, and mobility patterns.

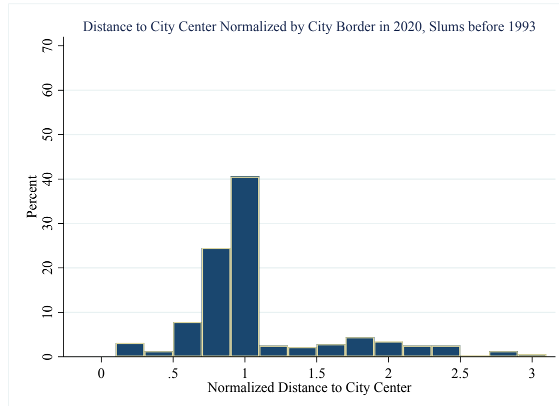
Figure 3: Slums Distance to the City Center Normalized by Distance to the City Border[a]

(a) Slums created before 1993

1993 City Limits

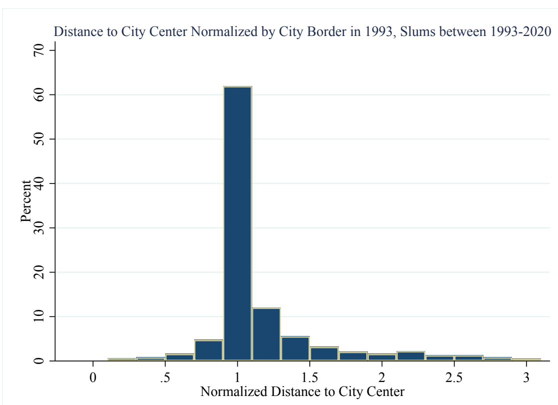


2020 City Limits

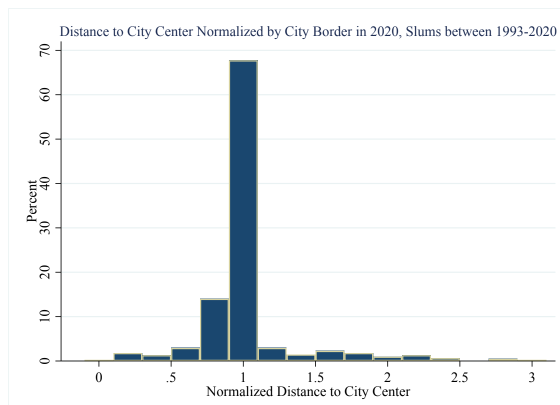


(b) Slums created after 1993

1993 City Limits



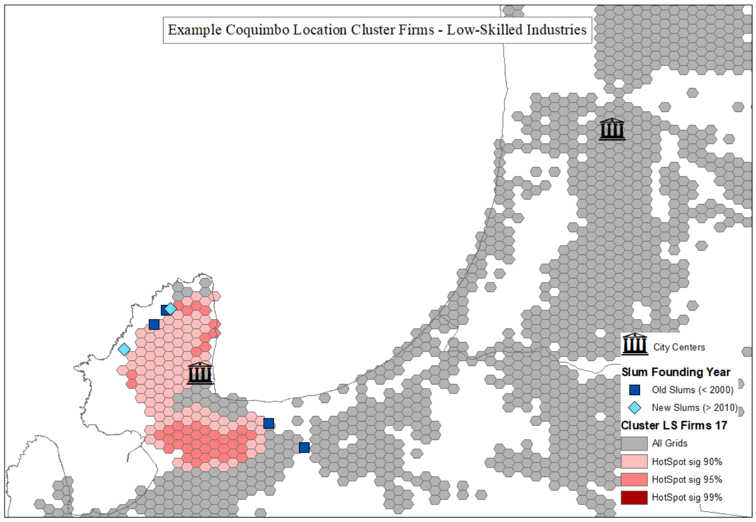
2020 City Limits



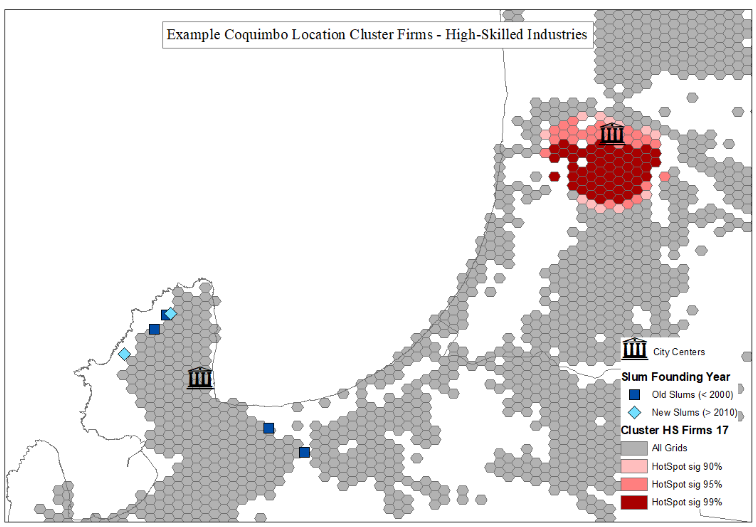
[a] 1993 and 2020 city limits come from the continued urban construction (CUC) of each city in 1993 and 2020, respectively. City centers are provided as a result of the Urban Functional Areas project (AFU for its Spanish acronym) by INE, MINVU, SECTRA and SUBDERE. City centers take into account residential and labor locations, and mobility patterns. "Normalized distance" refers to the distance to the city center divided by the short path between the city center-slum-city border. Values close to one represents slums located near the city border.

Figure 4: Proximity of Slum Areas to Cluster of Low- and High-Skilled Labor Markets [a]

(a) Cluster Firms Low-Skilled



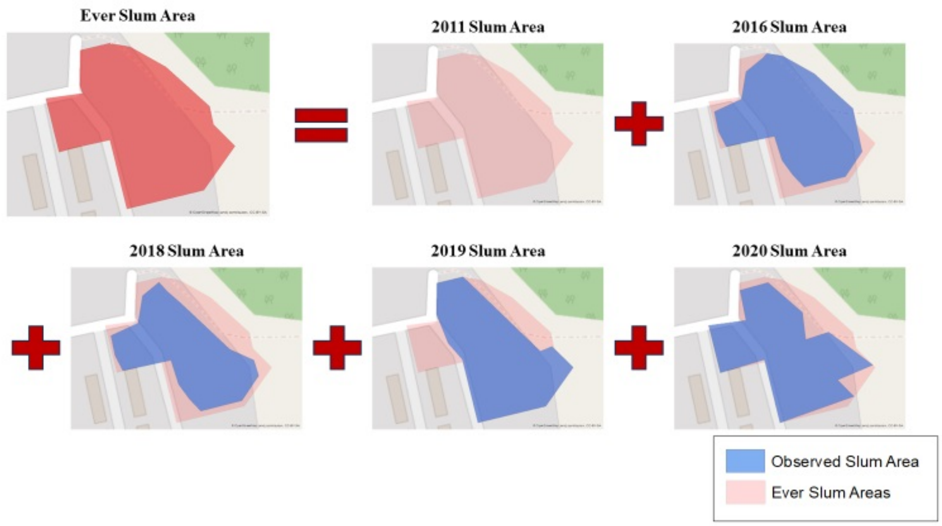
(b) Cluster Firms High-Skilled



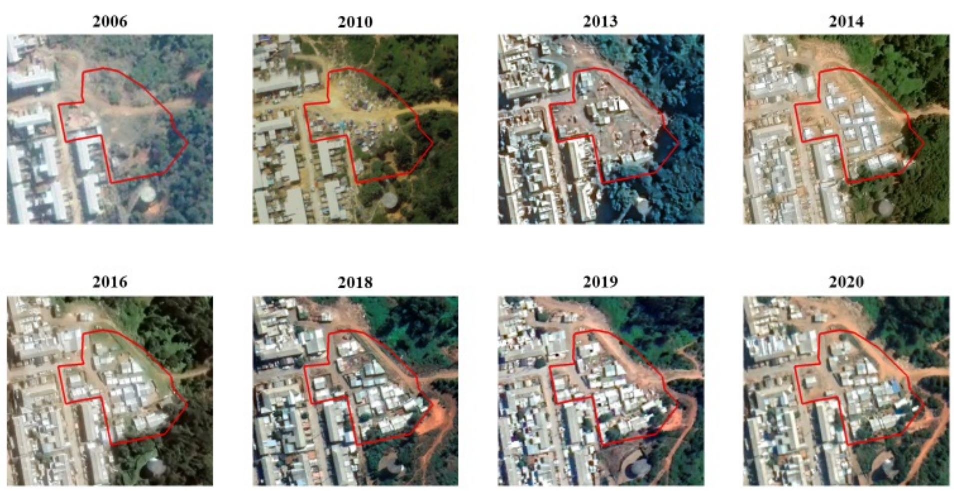
[a] Firms' location obtained from the Firms National Census of 2017. Hexagons with high concentration of firms given the number of firms in the nearby area are defined as clusters. The high of the hexagons is approximately 250 mt. Low-Skilled industries refer to agriculture and mining, manufacture (food, beverages, leather, wood, paper, plastic, minerals and furniture), construction, retail and transportation. High-skilled industries refer to other manufacture (chemicals, pharmaceuticals, electronics, machinery, automobiles), services, teaching, professional and scientific activities.

Figure 5: Construction of Slum Areas – Reference Sample[a]

(a) Creating the Ever-Slum Area from MINVU and TECHO Observed Area



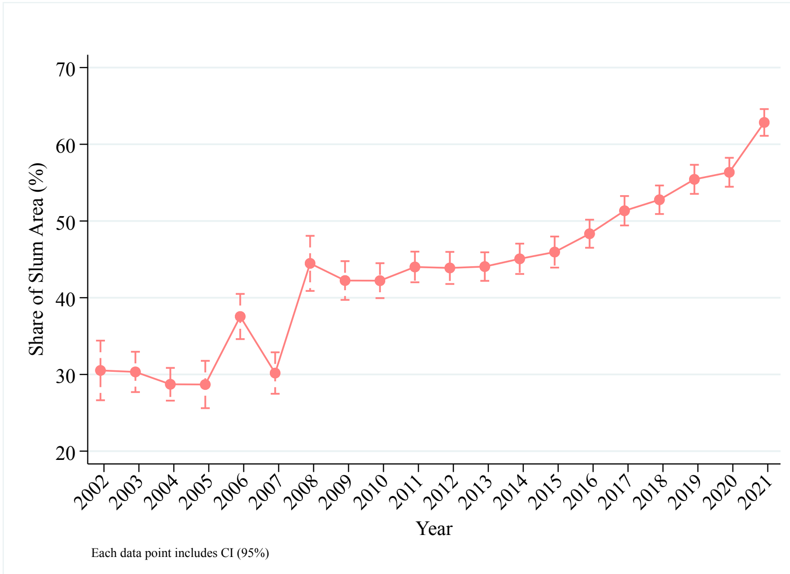
(b) Satellite Slum Images Delineating Ever-Slum Area



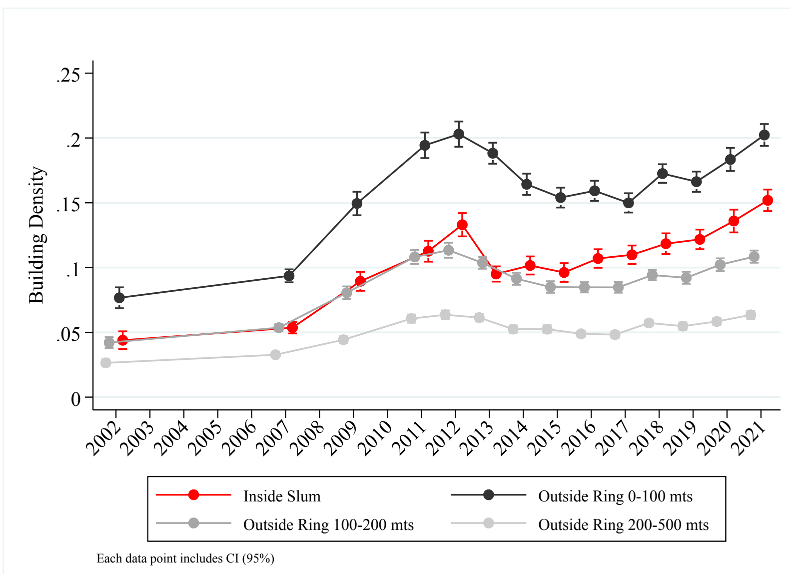
[a]MINVU and TECHO provide the slum boundaries for 2011, 2016, 2017, 2018, 2019, and 2020. We define an area as "ever slum" as the geographic union of all observed covered areas across the different samples. Panel A presents the observed slum areas for a given slum in each year. Notice, that the example slum was not included in the 2011 sample. Slum area for 2017 is omitted since it has the same georeferenced as 2016. Panel B shows different satellite images for the same slum.

Figure 6: Evolution Residential and Building Density in Slums [a]

(a) Share of Land Devoted to Residential Housing



(b) Building Density Inside and Outside Slums



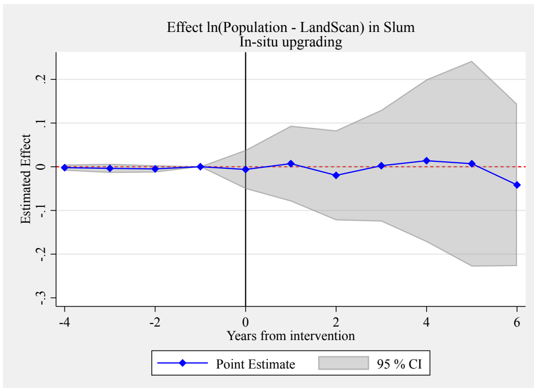
[a]Panel A plots the share of slum area occupied by residential structures. This is derived from the Human Observational Data and refers to an estimate of what is the coverage of residential areas rather than the exact area occupied by buildings.

[b]Panel B shows the building density inside and outside slum areas using the ML algorithm. In this case, we use the exact area occupied by identified buildings.

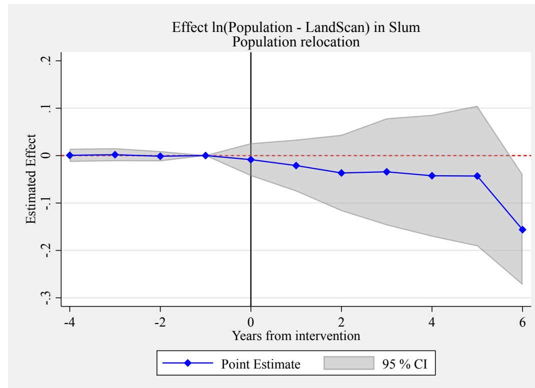
Figure 7: Event Study for Selected Direct Effect on Slums - SDiD[a]

(a) ln(Population - LandScan)

in-situ Upgrading

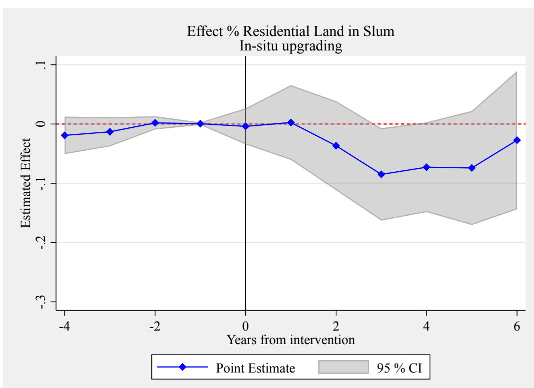


Population Relocation

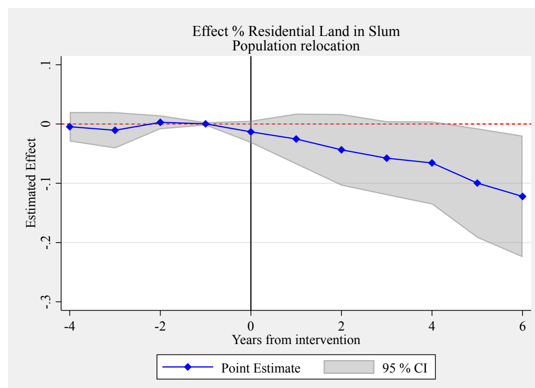


(b) Share of Residential Land in the Polygon

in-situ Upgrading

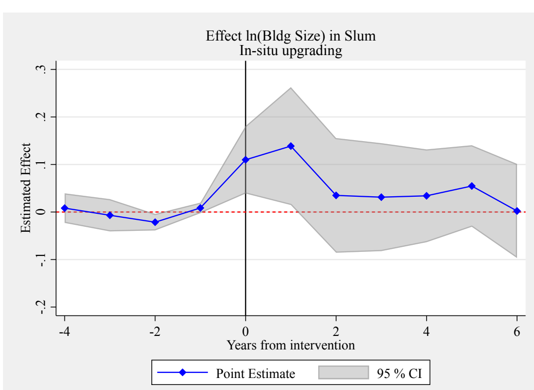


Population Relocation

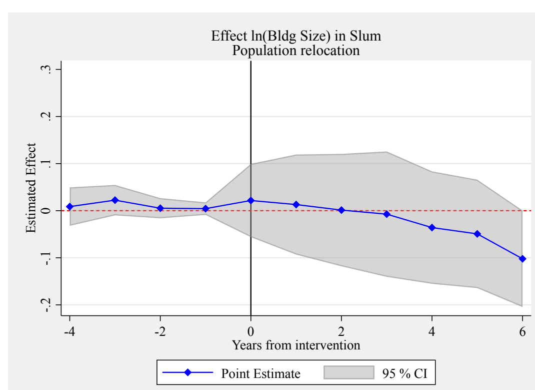


(c) ln(Building Size)

in-situ Upgrading



Population Relocation

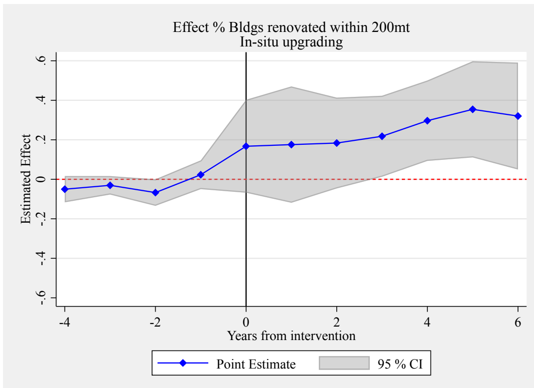


[a] Synthetic Difference-in-Difference (SDiD) developed by Arkhangelsky et al. (2021). Confidence intervals are obtained using bootstrapping. Figures are from a selected set of outcomes and show the dynamics beyond the coefficients reported in table 6.

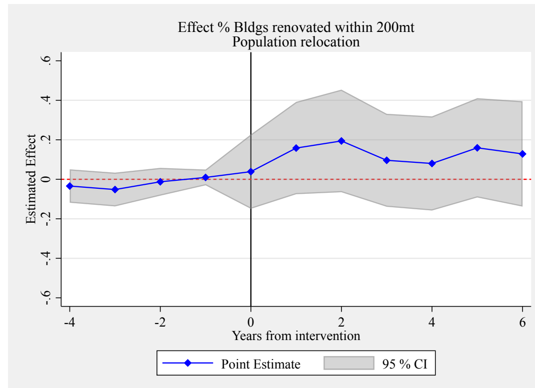
Figure 8: Event Study for Selected Spillover Outcomes - SDiD [a]

(a) Share Buildings Undergoing Renovations within 200mt

in-situ Upgrading

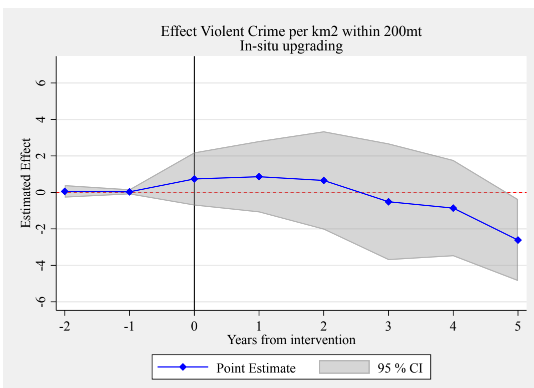


Population Relocation

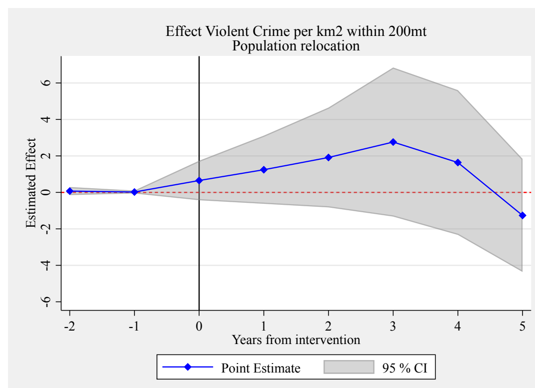


(b) Violent Crime per Km2 within 200mt

in-situ Upgrading

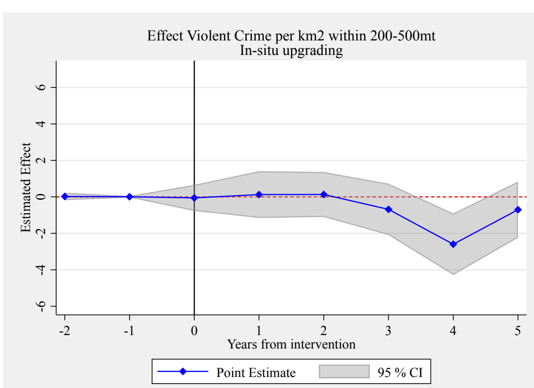


Population Relocation

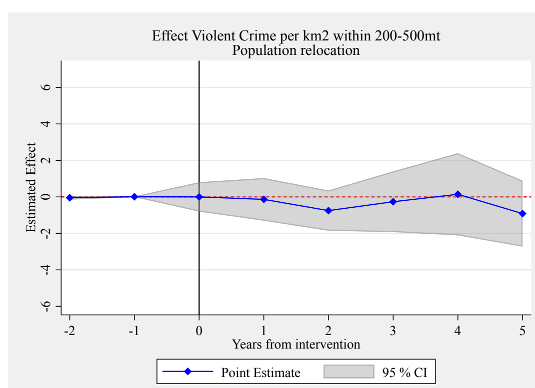


(c) Violent Crime per Km2 between 200 to 500mt

in-situ Upgrading



Population Relocation



[a] Synthetic Difference-in-Difference (SDiD) developed by Arkhangelsky et al. (2021). Confidence intervals are obtained using bootstrapping. Figures are from a selected set of outcomes and show the dynamics beyond the coefficients reported in Table 8.

Table 1: In-situ Upgrading and Population Relocation Cost per Slum and Household (HH)[a]

	N	Mean	SD	p50
In-situ Upgrading				
#Subsidies per Slum	209	29.56	47.68	15
Value Subsidies per Slum (USD)	209	$718,187	$1,158,580	$364,500
Investment per Slum (USD)	209	$229,327	$320,112	$97,856
Total Expenditure per Slum (USD)	209	$947,514	$1,246,133	$562,986
#Subsidies per HH	209	0.54	0.48	0.43
Value Subsidies per HH (USD)	209	$13,139	$11,559	$10,452
Investment per HH (USD)	209	$7,038	$11,825	$2,047
Total Expenditure per HH (USD)	209	$20,177	$19,241	$16,221
Population Relocation				
#Subsidies per Slum	442	25.23	30.03	17
Value Subsidies per Slum (USD)	442	$807,312	$961,083	$544,000
Investment per Slum (USD)	442	$81,865	$155,815	$26,375
Total Expenditure per Slum (USD)	442	$889,178	$1,016,605	$599,879
#Subsidies per HH	440	0.82	0.63	0.79
Value Subsidies per HH (USD)	440	$26,297	$20,124	$25,273
Investment per HH (USD)	440	$3,671	$6,926	$1,166
Total Expenditure per HH (USD)	440	$29,969	$22,984	$28,282

[a]Subsidies and investments covered the period 2011-2020. We observe the value of investment, however, for subsidies we only observe the number of subsidies allocated in each slum. To calculate the value of subsidies, we use $32,000 for subsidies in locations under population relocation, and $24,000 for slums in in-situ upgrading. These figures are conservative and focus on the price of building a new house vs. acquiring a house from the housing market. The government estimates that the cost of each subsidy ranges from $20,000 to $40,000.

Table 2: Logit Models Pr(Any Treatment) and Pr(In-situ)[a]

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Logit Model for the Prob. Any Treatment vs No Treatment						
Included 2011 Census	4.179***					4.218***
	(0.310)					(0.345)
ln(Slum Households)		-0.045				-0.579***
		(0.084)				(0.181)
Elevation (mt)			-0.001			0.000
			(0.001)			(0.001)
Dist. Nearest River (km)			0.011			0.048
			(0.070)			(0.085)
Periphery				-0.069		-0.577*
				(0.210)		(0.337)
Index Dist. Amenities					-0.693***	-0.563**
					(0.239)	(0.284)
Obs.	1,139	1,139	1,086	1,139	1,087	991
Muni FE	115	115	110	115	110	102
Dist. CBD & Near Bldg Density	No	No	No	No	No	Yes

Panel B: Logit Model for the Prob. In-situ upgrading vs Population relocation						
Included 2011 Census	0.430					0.628
	(0.518)					(0.649)
ln(Slum Households)		0.420*				0.579*
		(0.225)				(0.340)
Elevation (mt)			0.005*			0.004**
			(0.003)			(0.002)
Dist. Nearest River (km)			0.242			0.289*
			(0.167)			(0.165)
Periphery				0.439*		0.411
				(0.256)		(0.341)
Index Dist. Amenities					-0.526	-1.085
					(0.751)	(0.960)
Obs.	406	406	402	406	402	363
Muni FE	55	55	54	55	54	51
Dist. CBD & Near Bldg Density	No	No	No	No	No	Yes

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered at the municipality level. All specifications include municipality FE, an index for the roughness of the terrain and log of slum area. Index terrain follows Anderson (2008) combining slope (degrees) and terrain roughness (TRI). Similarly, Index Dist. Amenities combines distance to low-skill firms cluster, high-skill firms cluster, bus stops, supermarket, library, fire station, police station, school, health center, and finance institutions.

Table 3: Proximity to City Amenities for New & Old Slums vs Random Sample of Non-Slum Areas [a]

	Local Labor Markets		**Neighborhood Amenities**				
	Dist. Firm High-Skill (mt) (1)	**Dist. Firm Low-Skill (mt)** (2)	**Index Dist. Amenities** (3)	**Dist. Police Station (mt)** (4)	**Dist. School (mt)** (5)	**Dist. Health Center (mt)** (6)	**Dist. Bus Stop (mt)** (7)
Old Slum (< 2010)	122.89	470.18***	0.02**	250.10***	185.61***	52.03	48.53
	(186.48)	(174.39)	(0.01)	(88.82)	(47.70)	(64.90)	(40.55)
New Slum (> 2010)	458.37**	269.26	0.03***	260.80***	199.71***	54.13	113.26***
	(191.36)	(178.43)	(0.01)	(85.95)	(45.61)	(58.20)	(41.03)
Obs.	24,452	24,452	24,452	24,452	24,383	24,452	24,452
R2	1.00	0.99	0.55	0.21	0.20	0.55	0.30
Test equal (p val)	0.20	0.41	0.37	0.93	0.83	0.98	0.235
Control mean	72,944	33,344	-0.12	2,064	641	1,447	811

[a] Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. All distances are measured in meters. These are standard OLS regressions for a random sample of non-slum census blocks and slum areas. All regressions control for Municipality FE (except distance to cluster of firms that use Region FE because the nearest cluster can be in another municipality) and the slum households.
We select a 15% random sample of non-slum census blocks in each municipality to compare with the slums located in the same area.

Table 4: Summary Statistics Census Variables, Slums and Nearby Non-Slum Blocks [a]

	2002	2017	% Change
Avg. Population			
Slums	277	308	11.2%
Nearby Blocks	5,492	5,752	4.7%
Avg. Househods			
Slums	73	96	32.6%
Nearby Blocks	1,843	2,233	21.2%
Ratio Adult Males/Females			
Slums	1.30	0.97	-25.4%
Nearby Blocks	0.96	0.95	-0.7%
% Pop w Secondary Educ			
Slums	39.58%	51.03%	28.9%
Nearby Blocks	43.21%	50.65%	17.2%
% Pop w some Tertiary Educ			
Slums	10.20%	18.45%	80.9%
Nearby Blocks	14.45%	20.24%	40.1%
Occupation rate			
Slums	80.63%	90.19%	11.9%
Nearby Blocks	82.41%	90.31%	9.6%
% Inadequate houses			
Slums	16.40%	13.24%	-19.3%
Nearby Blocks	5.77%	2.10%	-63.6%
% Houses w/out piped water			
Slums	6.84%	10.50%	53.6%
Nearby Blocks	1.98%	2.03%	2.8%
% Houses w good floor materials			
Slums	71.57%	72.67%	1.5%
Nearby Blocks	65.26%	78.58%	20.4%

[a] Nearby blocks are those within 200 to 500 mt of the slum border. All values reported corresponded to averages. We assign census blocks to slums based on the blocks' centroid.
Inadequate housing refers to mobile houses or prefabricated wood houses.

Table 5: Long Difference Model - Slum Population Growth and Municipality Covariates[a]

Depvar: Slum Pop. growth in Municipality	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
ln(Pop. Municipality, 2005)	-0.081	-0.084	-0.078	-0.098*	-0.139*
	(0.052)	(0.053)	(0.052)	(0.053)	(0.073)
Change in Municipality Pop.	0.061	0.058	0.059	0.057	0.101*
	(0.044)	(0.045)	(0.045)	(0.044)	(0.060)
Change in Log Quality Adj. Rent	0.099**	0.097**	0.096**	0.093**	0.139**
	(0.045)	(0.045)	(0.045)	(0.045)	(0.063)
Change in Log Employees	0.084**	0.091**	0.081*	0.076*	0.131*
	(0.041)	(0.044)	(0.044)	(0.044)	(0.072)
Change in Log Labor Salary		-0.022	-0.056	-0.056	-0.027
		(0.042)	(0.044)	(0.044)	(0.067)
Change in Log Labor Salary - Sec Complete			0.103**	0.100**	0.098*
			(0.043)	(0.043)	(0.050)
Change Extreme Poverty				-0.088*	-0.138*
				(0.050)	(0.075)
Change in Log Comuna Expenditures					-0.014
					(0.057)
Change in Log Social Expenditures					-0.048
					(0.061)
Investment Slum per HH					-0.124**
					(0.049)
Subsidies Slum per HH					0.093*
					(0.051)
Constant	0.230***	0.232***	0.224***	0.226***	0.236***
	(0.061)	(0.062)	(0.061)	(0.061)	(0.072)
Obs.	264	260	260	260	197
R2	0.066	0.067	0.088	0.098	0.166
Control Mean depvar	0.11	0.11	0.11	0.11	0.14

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parenthesis. All specifications control for a dummy of whether a municipality has never had slums. Slum population growth at the municipality level is calculated as the log difference between slum population in 2017 and 2002. "Change" or growth variables are standardized to have mean zero and standard deviation one. Change in quality-adjusted rent covers the period 2009-2017, while changes in employment and salary cover 2010-2017. Changes in municipality expenditures correspond to differences between 2011 and 2017

Table 6: Policies' Direct Effect on Physical Characteristics, 6 Years After Intervention [a]

depvar	Mean	Synthetic DiD In-situ Upgrading	Synthetic DiD Pop. Relocation	Synthetic DiD Test Equal (pval)
Building Permits				
Pr(Building Permit > 0)	0.005	0.045**	0.012	0.00
		(0.022)	(0.010)	
ln(Approved Bldg permits)	0.003	0.023**	0.005	0.00
		(0.010)	(0.005)	
ln(Approved build area m2)	0.036	0.108	0.026	0.00
		(0.067)	(0.030)	
Satellite Images				
ln(Population - LandScan)	5.922	-0.042	-0.156***	0.00
		(0.095)	(0.060)	
% Residential Land	0.257	-0.027	-0.122**	0.00
		(0.060)	(0.052)	
% Streets paved	0.091	0.109**	0.044	0.00
		(0.045)	(0.031)	
ln(Bldg Size)	2.119	0.002	-0.102*	0.00
		(0.051)	(0.052)	
ln(Number Bldgs > 64 m2)	0.975	0.145*	0.025	0.00
		(0.080)	(0.078)	
SD Bldg Main Angle - 8NN	5.265	-0.822**	-0.088	0.00
		(0.406)	(0.382)	
Avg. Distance - 8NN	60.045	8.674**	4.739	0.00
		(4.256)	(5.743)	

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. Each coefficient comes from a SDiD regression for a given dependent variable and for the slums under the policy strategy indicated. This is a comparison between the "event study" type effects after 6 years from the intervention. All specifications control for the lag of the estimated population in the Km2 using LandScan.
Test of equality of coefficients is a paired ttest using the bootstrap distribution of each estimated coefficient. Mean dependent variable corresponds to the mean for the control group at each one of the rings. Baseline for building permits is 2010 and for the rest of the variables is 2009.

Table 7: Policies' Effect on Population Census, Direct Effect and Spillovers[a]

	Sociodemographics			**Housing Quality**	
	ln(Pop.)	**% Pop. Secondary+**	**Employment Rate**	**% Houses 2+ Bedrooms**	**% Good Wall Materials**
	(1)	(2)	(3)	(4)	(5)
Panel A: Direct Effects on Slum Areas					
In-situ Upgrading	0.141	0.031*	0.013	0.045*	0.001
	(0.175)	(0.016)	(0.012)	(0.026)	(0.033)
Population Relocation	-0.154	0.012	0.004	0.01	-0.050*
	(0.150)	(0.016)	(0.010)	(0.018)	(0.027)
Obs.	920	920	920	920	920
R2	0.03	0.58	0.46	0.46	0.44
Test Same Coeff (p-val)	0.071	0.320	0.565	0.150	0.176
Control Mean depvar	5.065	0.559	0.833	0.705	0.817
Panel B: Spillovers on Areas within 200 mt					
In-situ Upgrading	-0.043	0.015*	0.012*	0.005	0.036**
	(0.067)	(0.009)	(0.006)	(0.009)	(0.015)
Population Relocation	-0.209***	0.004	-0.007	0.004	-0.008
	(0.057)	(0.009)	(0.006)	(0.006)	(0.013)
Obs.	1,900	1,900	1,900	1,900	1,900
R2	0.07	0.68	0.62	0.51	0.45
Test Same Coeff (p-val)	0.011	0.302	0.005	0.893	0.027
Control Mean depvar	6.592	0.577	0.848	0.762	0.843
Panel C: Spillovers on Areas 200 to 500 mt					
In-situ Upgrading	-0.067	0.014*	0.009*	0.015**	0.022*
	(0.059)	(0.008)	(0.004)	(0.007)	(0.012)
Population Relocation	-0.176***	-0.002	-0.007*	-0.007	0.012
	(0.054)	(0.006)	(0.004)	(0.005)	(0.011)
Obs.	2,104	2,104	2,104	2,104	2,104
R2	0.15	0.71	0.74	0.55	0.48
Test Same Coeff (p-val)	0.046	0.036	0.003	0.008	0.605
Control Mean depvar	8.175	0.600	0.852	0.774	0.845

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. Erors are clustered at the municipality level. All models are estimated using TWFE for two periods since the data is only available in the population censuses. Each column in a panel corresponds to one TWFE regression, it is a pool model with two dummy treatment variables. Finally, we test whether the estimated effects for each policy are equal. The p-value of the Wald test is provided in each model.

Table 8: Policies' Spillovers on Physical Characteristics, Nearby Formal Neighborhoods[a]

	Spillovers 0 - 200 mt				Spillovers 200 - 500 mt			
depvar	**Mean**	**In-situ Upgr.**	**Pop. Reloc.**	**Test (pval)**	**Mean**	**In-situ Upgr.**	**Pop. Reloc.**	**Test (pval)**
Building Permits								
Pr(Building Permit > 0)	0.21	0.103**	0.074	0.000	0.42	0.033	0.001	0.000
		(0.041)	(0.046)			(0.026)	(0.028)	
ln(Approved Bldg permits)	0.22	0.132**	0.116**	0.975	0.60	0.127**	0.042	0.000
		(0.052)	(0.051)			(0.051)	(0.044)	
ln(Approved build area m2)	1.20	0.500***	0.326	0.000	2.61	0.424**	0.084	0.000
		(0.189)	(0.229)			(0.196)	(0.17)	
Land Registry								
ln(Building Age)	2.66	-0.110**	-0.071**	0.000	2.69	-0.020	-0.054*	0.000
		(0.052)	(0.033)			(0.029)	(0.03)	
% Bldgs Age < 5	12.33	4.042***	2.649**	0.000	12.84	2.502***	2.188**	0.000
		(1.329)	(1.177)			(0.915)	(1.102)	
% Bldgs renovated	0.95	0.320**	0.129	0.000	1.06	0.215***	0.169*	0.002
		(0.138)	(0.136)			(0.08)	(0.098)	
ln(Reported Bldg Size)	3.69	0.112*	0.064	0.000	3.81	0.077	0.065	0.032
		(0.062)	(0.046)			(0.085)	(0.063)	
Footprints Variables								
ln(Bldg Size)	2.49	0.030	0.007	0.000	2.41	-0.017	-0.004	0.015
		(0.028)	(0.025)			(0.042)	(0.029)	
SD Bldg Main Angle - 8NN	9.30	0.349	-0.153	0.000	9.21	-0.103	0.091	0.000
		(0.244)	(0.194)			(0.299)	(0.197)	
Avg. Distance - 8NN	28.18	0.024	-0.180	0.485	29.33	-0.095	-0.201	0.027
		(0.865)	(0.771)			(1.104)	(0.801)	

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. Models are estimated using Synthetic Difference in Difference and represent the effect after 6 years from the intervention. All specifications control for the lag of the estimated population in the Km2 using LandScan.
Test of equality of coefficients is a paired ttest using the bootstrap distribution of each estimated coefficient. Mean dependent variable corresponds to the mean for the control group at each one of the rings. Baseline for building permits is 2010 and for the rest of the variables is 2009.

Table 9: Crime Spillover on Nearby Neighborhoods after 5 Years [a]

	Crime Index (1)	Property Crime per km2 (2)	Violent Crime per km2 (3)	Homicide per km2 (4)
Panel A: Spillovers on Areas within 200 mt				
In-situ upgrading	-0.091**	-5.065*	-2.616**	-0.074***
	(0.041)	(2.611)	(1.148)	(0.026)
Population Relocation	0.119	15.346	-1.262	0.059
	(0.13)	(12.913)	(1.583)	(0.13)
Test Same Coeff (p-val)	0.000	0.000	0.000	0.000
Control Mean depvar	0.133	35.919	9.698	0.054
Panel B: Spillovers on Areas 200 to 500 mt				
In-situ upgrading	-0.029	-0.282	-0.701	-0.025
	(0.034)	(2.53)	(0.786)	(0.027)
Population Relocation	0.053	29.01	-0.916	0.032
	(0.122)	(26.82)	(0.924)	(0.078)
Test Same Coeff (p-val)	0.000	0.000	0.014	0.000
Control Mean depvar	0.123	40.142	9.754	0.055

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. All models are estimated using Synthetic Difference in Difference. Each coefficient comes from a SDiD regression for a given dependent variable and for the slums under the policy strategy indicated. All specifications control for the lag of the estimated population in the Km2 using LandScan. Results for in-situ upgrading strategy are based on 80 slums, while we have a total of 129 treated slums in the population-relocation models.
Crime index is constructed following Anderson (2008). Property crime includes burglary, theft (violent or not), auto theft, theft from auto, theft from no residential areas, and other economic motivated crimes (fraud, identity theft, others). Violent crime includes, homicide and assault. Mean dependent variables correspond to the mean of the control group at baseline.

Appendix

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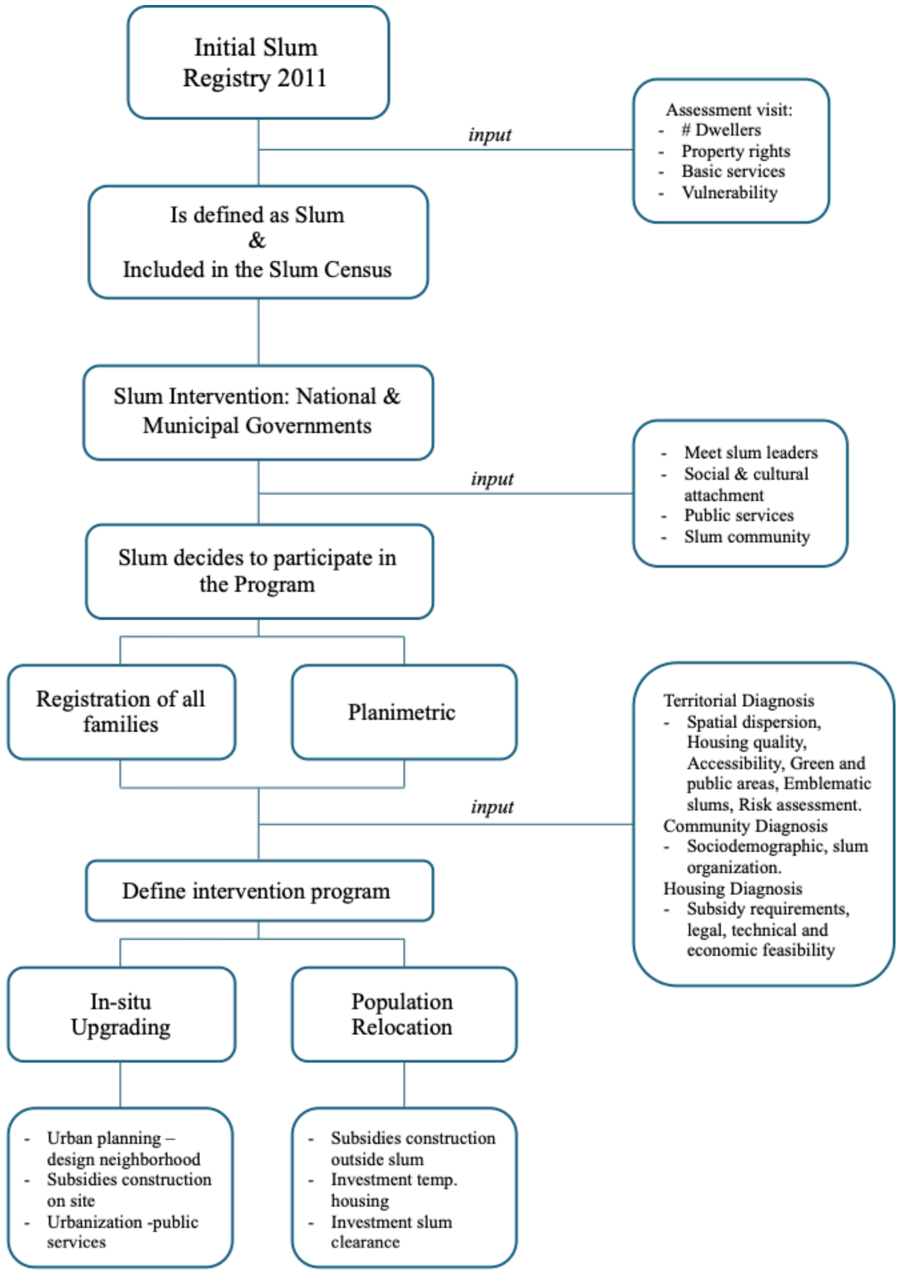
A Flowchart Government Interventions

Figure A1: Flowchart Government Intervention [a]



[a] Source: elaborated by the authors based on the different law regulations and the DIPRES (2019) report.

B Identify Building Footprints

Identifying building structures has become an active area of research due to the increasing availability of high-resolution satellite images. Over the past decade, computer scientists have made significant advancements in structural identification techniques. Kuffer et al. (2016) provide a comprehensive literature review on slum mapping using remote sensing methods from 2000 to 2015, highlighting that machine learning (ML) methods are particularly effective for identifying the physical attributes of slums. Abascal et al. (2022) used deep neural networks (DNNs) to extract building footprints from different areas in Nairobi, achieving a precision level of 92%—meaning that 92% of all positive predictions were indeed true positives. The high level of accuracy demonstrates the advantages of ML algorithms in advancing urban research. Comparisons between satellite images footprints and official data sources further support the accuracy of these methods (Wurm and Taubenböck, 2018). Other relevant studies in the field of computer science and remote sensing include Angeles et al. (2009); Montana et al. (2016); Inostroza (2017); Friesen et al. (2018); Samper et al. (2020).

Another sign of the improvements in the identification of building footprints is that some new research in computer science has started focusing on other attributes of slums beyond those observed through satellite images. Taubenböck et al. (2018) focus on digital inclusion using Twitter data, and they find that slums' households have less access to the digital world than formal areas. In the case of Klotz et al. (2017), they use location-based social networks data in conjunction with satellite images to identify urban neighborhoods and study their socioeconomic characteristics. Closer to the insights from this paper, Wurm et al. (2023) use Convolutional Neural Network (CNN) for the detection of informal buildings to estimate the number of the exposed population to landslides.

One key factor driving advancements in ML techniques is the emergence of programming challenges hosted by online communities such as Kaggle and AI Crowd. These platforms incentivize innovation by encouraging researchers to develop and share cutting-edge algorithms. The baseline code for our ML algorithm originates from the winners of the first Mapping Challenge hosted by AI Crowd. Their algorithm, which achieved an average precision of 94%, employed strategies similar to those documented by Abascal et al. (2022), further illustrating the collaborative progress in this research area.[18] We explain below the four-stage process to identify polygons representing building footprints.

[18]The winning team members are Jakub Czakon, Kamil A. Kaczmarek, Andrzej Pyskir, and Piotr Tarasiewicz. Complete details about the Mapping Challenge can be found here., and replication materials for the winner team are available here.

B.1 Pre-processing images

Our baseline ML algorithm was trained on 300×300 pixel images containing various building structures similar to those depicted in Figure B1. However, Google Earth (GE) images have dimensions of 4800×4800 pixels, covering approximately $1, \text{km}^2$. This is the highest possible resolution in GE and represents approximately 0.21 meters per pixel. To process these images, we fragmented each original GE image into 256 tiles, each measuring 300×300 pixels. We then applied the model to all tiles and, after obtaining the building footprint predictions, reconstructed the full-size image.

We also experimented with fragmenting the original image into tiles of 100, 600, 900, 1,200, and 2,400 pixels, but the model performance was consistently better with 300-pixel tiles. A similar approach is used by Abascal et al. (2022). As an additional robustness check, we adjusted the original zoom level of the image, varying the meters per pixel between 0.16 and 0.3 meters, but the best performance was still achieved using the original dimensions.

Applying the model to all 90,000 images is extremely time-consuming and requires massive computational power. To reduce the time and resource demands, we selected one image per year for each slum using two approaches:

1. *Human Observational Data (HOD):* Analysts selected the first image of a given year with sufficient quality to clearly observe construction details within a slum, reducing the number of images per slum to 20 or fewer.

2. *File Size Selection:* We chose the image with the largest file size within the first three months of each year, under the assumption that a larger file size correlates with higher image quality.

As expected, the results from these two approaches differed only in a few instances. In cases of discrepancy, we retained the older image as long as its file size exceeded a certain threshold (usually 8,000 KB).

By implementing these strategies, we efficiently managed computational resources while maintaining the quality and consistency of our dataset. This approach allowed us to effectively apply the ML algorithm to a manageable number of images, ensuring accurate building footprint predictions across different slum areas over time.

B.2 ML Algorithm: Deep Neural Networks - U-Net Architecture

The U-Net architecture was initially proposed by Ronneberger et al. (2015) and has proven effective in identifying building footprints (Iglovikov et al., 2018; Abascal et al., 2022). This architecture consists of a network with a downsampling-upsampling structure. The first part of the method starts from a given image to which different convolutional functions are applied and is downsampled using max-pooling functions. Each time an image is processed by a set of convolutional and max-pooling functions, the dimensions of the data (or original image size) are reduced. The number of blocks in a U-Net network determines the number of times this process is performed. The second part of the process uses the output from the first part and up-samples it until it reaches the original image resolution. By increasing the dimensions of the output, the network allows propagation of contextual information to higher-dimensional layers. Propagation of contextual information is particularly important for identifying high-resolution features.

Additionally, our baseline model implements the strategies proposed by Iglovikov et al. (2018) that enable identification using only three-band images (such as RGB). Previous satellite image analyses have been restricted to the use of multispectral images. The model also incorporates Test Time Augmentation (TTA), meaning that predictions were made on the original image and several of its transformations, such as rotations (90°, 180°, 270°) and flips (vertical, horizontal). U-Net was implemented in Python using the deep learning libraries TensorFlow and PyTorch. All models were run on a virtual machine with access to an NVIDIA Tesla V100 GPU.

B.3 Model calibration

The training images used for the ML algorithm include building structures in different scenarios and contexts. However, this does not guarantee that the model will perform exceptionally well in the Chilean context, especially considering our focus on informal settlements. To address this issue, we calibrated the baseline algorithm for our research purposes. Two main changes were implemented. First, we allowed for more geometric irregularity. Informal constructions are not regular in shape, and restricting the identification of building footprints to regular geometric shapes omits some of the characteristics we aim to observe. Second, we adjusted the masking cutoff, which refers to the threshold at which an observed feature is labeled as a building footprint. We relaxed this restriction because not all of our images have comparable quality to the training sample.

There is a concern that when lowering the threshold, we will get more false positive building footprints. To minimize this effect, we pass every image twice through our ML algorithm. For the first pass, we divide an image into 256 tiles as shown in Figure B1; for the second pass, we shift the 300-pixel grid layout by 100 pixels. The final prediction is the combination of the two procedures.

Unlike other ML exercises, our purpose extends beyond image analysis. Consequently, we allocated substantial effort to retaining the geographical reference of each image. Maintaining a spatial reference is crucial for building a complete dataset that includes the demographic and socioeconomic variables of the slums. We export each masked image as a shapefile using the 1984 World Geodetic System projection.

B.4 Computing measures using building footprints

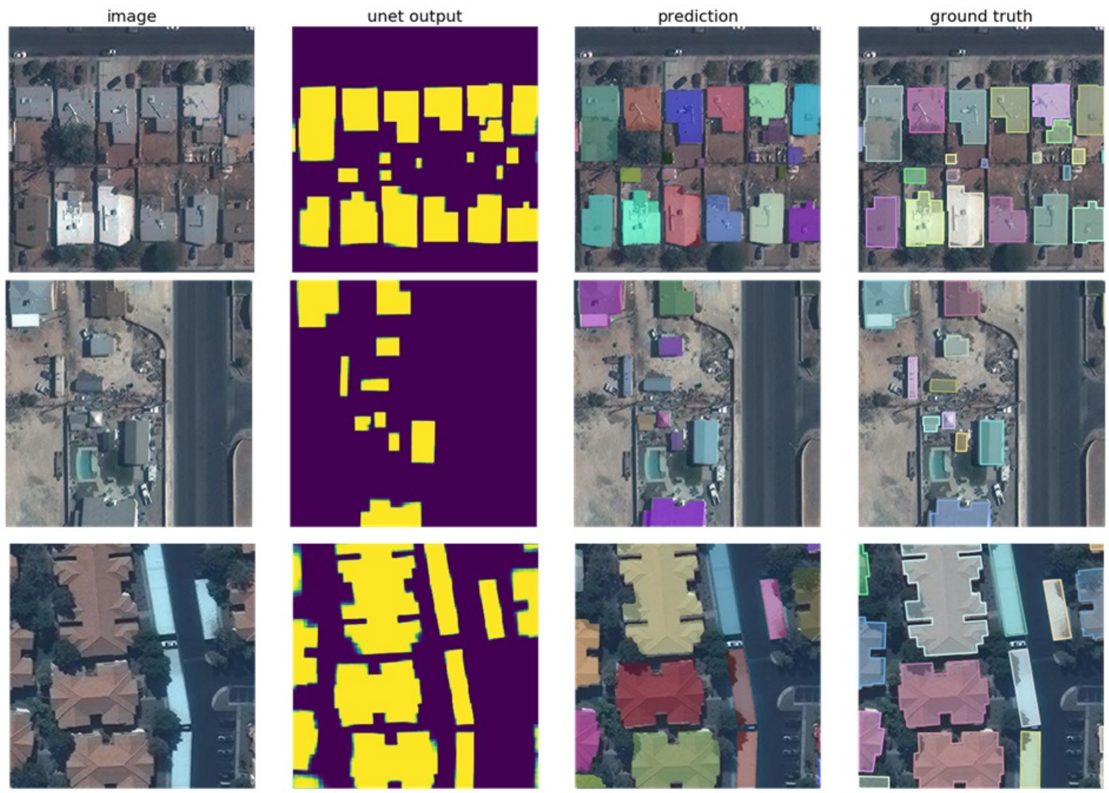
We computed different metrics to measure building activity and regularity inside and outside the slums. We began by calculating the total building area and building density within the slums. We also calculated these measures for areas within a certain distance of the slum border. Additional statistics helped us characterize the built environment inside the slum. The distance to the nearest building footprint provides a proxy for how compact and spatially close the structures are within the slum. We also obtained the orientation angle of each building using the main angle of the minimum bounding rectangle for a given footprint. This measure serves as a proxy for building regularity. In formal neighborhoods, buildings typically face the same direction, which means that the standard deviation of building main angles in that location is close to zero.

B.5 Example building footprints

Figure B2 provides an example of the building footprint prediction for a slum in the Lampa municipality. When processing images using our ML algorithm, we did not differentiate between slum and non-slum locations. By doing so, we ensure that any measurement error due to image quality and other specific image characteristics is homogeneous across slums and nearby neighborhoods. Although Figure B2 demonstrates how accurate the ML algorithm can be, identifying every single building with its exact boundaries is not feasible. There are instances where an existing building is not perfectly delineated or is not identified by the algorithm. Similarly, there are cases where areas are labeled as building footprints when there is actually no building structure in that location. However, these instances do not represent the majority of the identified areas. In fact, the algorithm has a precision level of 94% and a recall rate of 95%.[19] There are about 1,500 slums for which we have geographic references that allow us to obtain satellite images. Processing images of these slums, in addition to calibrating the model, took us over one year.

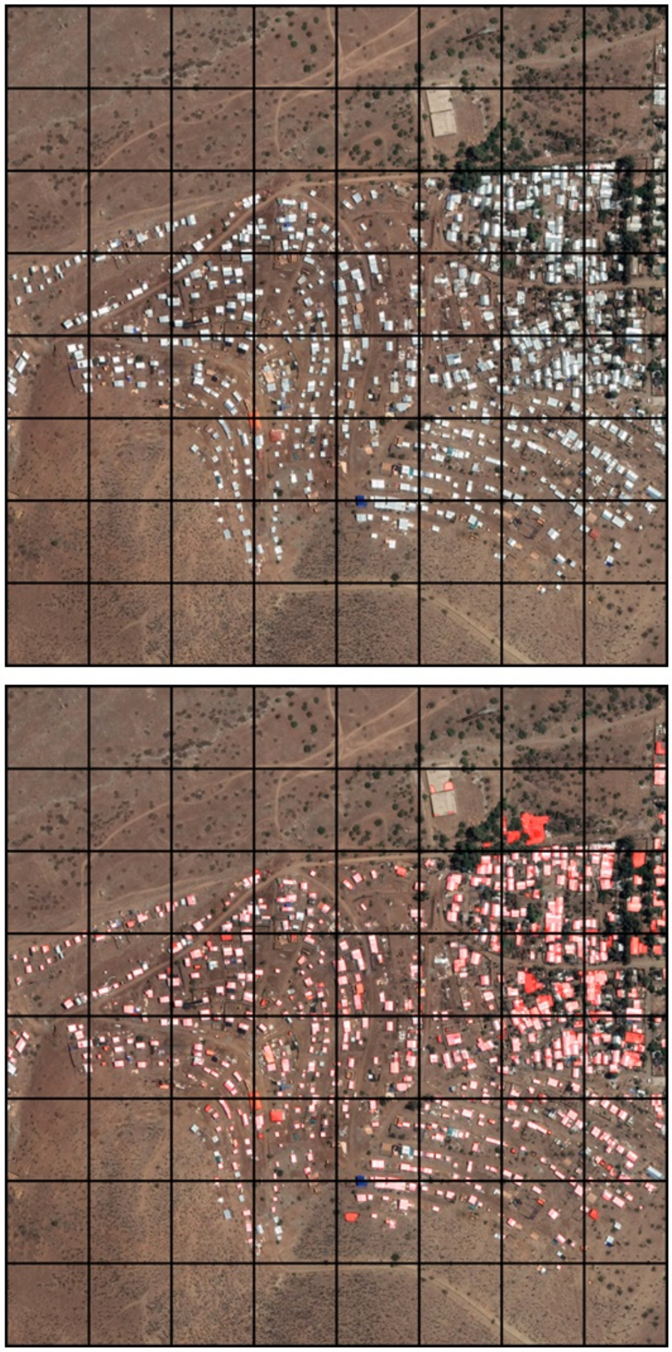
[19] Precision is calculated as the number of true predicted building footprints over the total number of predicted footprints. Recall has the same numerator but uses the actual number of building footprints as the denominator.

Figure B1: Performance ML Algorithm to Identify Building Footprints [a]



[a]Source: Czakon et al. (2021).

Figure B2: Example Predicted Building Footprints - Slum in Santiago Metropolitan Area [a]



[a]These images belong to the Slum Bosque Hermoso in the Lampa municipality in the Metropolitan Area of Santiago. The picture of from February 28, 2021. The original image in the top is 4,800 x 4,800 pixels and to improve prediction we fragmented the picture into tiles of 300 x 300 pixels. We applied the ML algorithm to each tile and reconstructed the original picture as it is shown in the bottom image. For exposition purpose we only considered 64 different tiles.

C Direct Effects - CSDiD

Table C1: Policies' Direct Effect on Physical Characteristics, 6 Years After Intervention [a]

		CSDiD	
depvar	**Mean**	**In-situ Upgrading**	**Pop. Relocation**
Building Permits			
Pr(Building Permit > 0)	0.005	0.061***	0.021**
		(0.017)	(0.009)
ln(Approved Bldg permits)	0.003	0.034***	0.008**
		(0.011)	(0.004)
ln(Approved build area m2)	0.036	0.115**	0.025
		(0.055)	(0.031)
Satellite Images			
ln(Population - LandScan)	5.922	-0.248*	-0.254**
		(0.145)	(0.099)
% Residential Land	0.257	-0.235***	-0.319***
		(0.056)	(0.045)
% Streets paved	0.091	0.015	-0.006
		(0.025)	(0.015)
ln(Bldg Size)	2.119	-0.224*	-0.357***
		(0.116)	(0.101)
ln(Number Bldgs > 64 m2)	0.975	-0.307**	-0.416***
		(0.130)	(0.098)
SD Bldg Main Angle - 8NN	5.265	-2.245**	-1.742**
		(1.098)	(0.708)
Avg. Distance - 8NN	60.045	29.447***	22.547***
		(9.397)	(7.407)

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. CSDiD is the usual DiD using Callaway and Sant'Anna (2021). Each coefficient comes from a CS-DiD regression for a given dependent variable and for the slums under the policy strategy indicated. This is a comparison between the "event study" type effects after 6 years from the intervention. All specifications control for the lag of the estimated population in the Km2 using LandScan.
Mean dependent variable corresponds to the mean for the control group at each one of the rings. Baseline for building permits is 2010 and for the rest of the variables is 2009.

D Proximity to Amenities

We have shown that slums develop on the periphery of cities and are eventually absorbed as the city expands. However, slums are not randomly located along the city borders. Instead, they tend to be close to local labor markets, particularly those specializing in low-skill jobs. Table 3 compares a random sample of non-slum census blocks with both old and new slums. Slums are situated farther from police stations, schools, and bus stops than a random set of non-slum blocks.

Figure D1 illustrates the distribution of distances to various amenities for slum and non-slum areas. These kernel density plots provide a two-dimensional perspective on the accessibility of local labor markets, public transit, schools, supermarkets, and financial institutions. Most non-slum areas are within 500 meters of low-skill firm clusters and within 1 kilometer of high-skill firm clusters. Echoing the results from Table 3, a high concentration of slum areas is just a few hundred meters farther from low-skill labor markets than non-slum areas but more than 1 kilometer farther from high-skill labor markets.

While slums have limited access to certain amenities compared to non-slum areas, there appears to be a preference for attributes such as public transit and schools. Easy access to public transportation is fundamental for low-income households to commute and access other parts of the city.

Focusing exclusively on slums, we examine how access to city amenities changes as slums are located farther from the Central Business District (CBD). By estimating a regression of the distance to different amenities as a function of distance to the city center—controlling for observable characteristics of the slum—we aim to understand the trade-offs between location and proximity to amenities beyond comparisons with non-slum areas. This analysis will help us discern how slums balance the benefits of proximity to labor markets against the drawbacks of reduced access to other amenities as they are situated further from the city center. We estimate the following equation,

$$y_i = \alpha_0 + \alpha' X + \beta_1 DistCC_i + \beta_2 CityBorder_i + \varepsilon_i$$

Where y_i is distance to nearest amenity, $DistCC_i$ distance to the city center, and $CityBorder_i$ dummy for whether the slum is in the periphery or not. X_i is a set of controls at the slum and municipality level, such as original size of the slum and municipality population. Due to the lack of historical data on slums' access to various services at the time of their founding, our measures of proximity to the nearest amenities reflect present-day distances. Consequently, the results from this analysis should be considered suggestive and correlational rather than causal estimates.

Table D1 presents the estimated gradients of proximity to different amenities with respect to distance to the city center in column (1), and the trade-off between being on the periphery and accessibility in column (2). Each row corresponds to a different regression that also controls for slum size and municipality fixed effects. As previously discussed, slums on the periphery are not farther away from local labor markets compared to those inside the city. In fact, the point estimate for proximity to low-skill labor markets is negative, highlighting the importance of job opportunities for populations living in informal settlements.

Our findings indicate that as slums are located farther from the city center, they sacrifice proximity to various public services. Ranking the coefficients for distance to the city center by the steepest gradient, we observe that the largest declines in accessibility are for libraries and financial institutions. An additional kilometer from the city center reduces access to a financial institution by more than 600 meters. The smallest gradients are for bus stops and schools, with one additional kilometer from the CBD associated with only 43 and 84 meters more in distance to each, respectively. This ranking suggests the revealed preferences of slum households; transit, schools, and health centers are services they might consider essential.

Finally, we assess whether slums are located in riskier geographical areas. While there is a general perception that slums are situated on steep hills—true for some—we compare the geographic conditions between non-slum and slum areas. Figure D2 illustrates the distributions of terrain characteristics for these locations by city size, focusing on three geographical features: the Terrain Roughness Index (TRI), elevation, and slope. In small cities (those with fewer than 300,000 inhabitants), non-slum blocks and slums have similar distributions across these characteristics. However, significant differences emerge between formal and informal areas in larger cities. Slums in big cities are found in areas with lower elevation but higher TRI and steeper slopes. In terms of TRI, values below 80 meters represent level terrain, while values between 240 and 497 meters indicate moderately rugged surfaces.[20] Formal areas are mostly located on level terrain, whereas most slums are on rugged surfaces. Regarding elevation, there is a concentration of non-slum blocks around 500 to 700 meters, corresponding to the city of Santiago. Slums, in contrast, are mostly located below these elevations, where they might be at higher risk of natural hazards such as flooding. In terms of slope, our findings follow those of Müller et al. (2020) in which just few slums are located on hills steeper than 10 degrees.

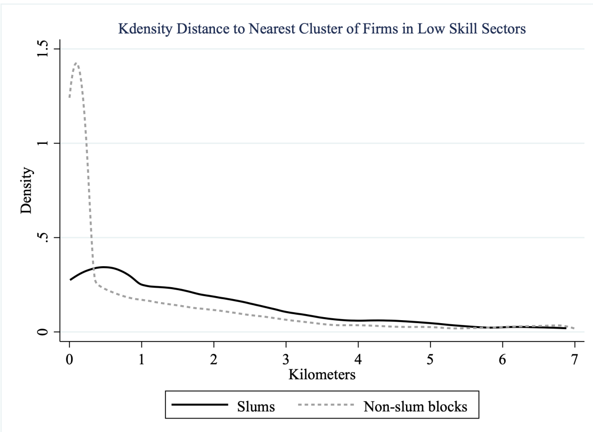
These results raise the question of why slums in big cities face riskier locations compared to those in small cities. The answer may lie in some of the findings documented in this paper. Bigger cities have more competitive formal housing markets, leading to higher rents. Although larger cities offer a wider array of labor opportunities than smaller cities, they also

[20]TRI classification by ESRI is available here.

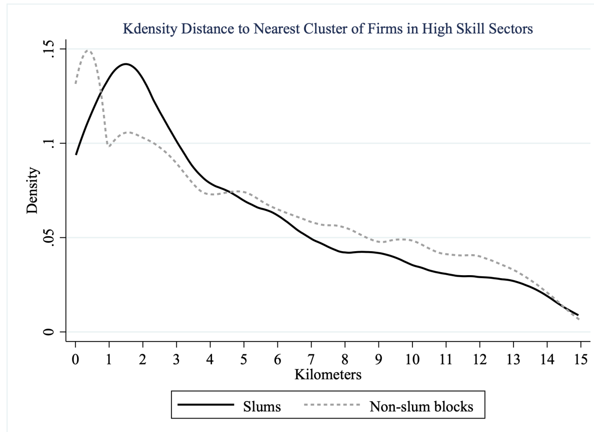
push informal settlers to trade proximity to labor markets for access to amenities. If we consider a slum household indifferent between settling in a small or big city, it could be the case that the small city offers less risky locations as compensation for smaller labor markets and lower low-skill wages.

Figure D1: Slums Proximity to Different City Amenities [a]

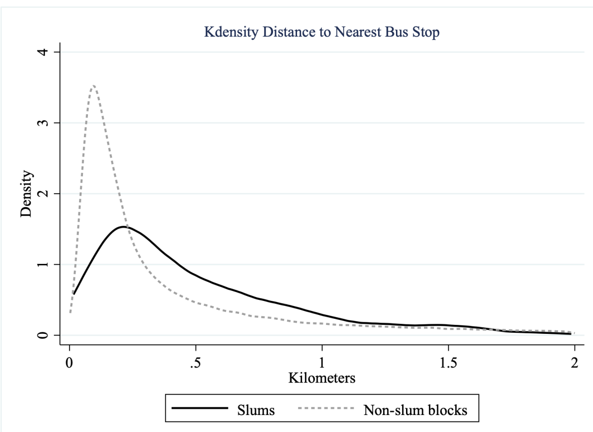
(a) Low-Skill Firms' Cluster



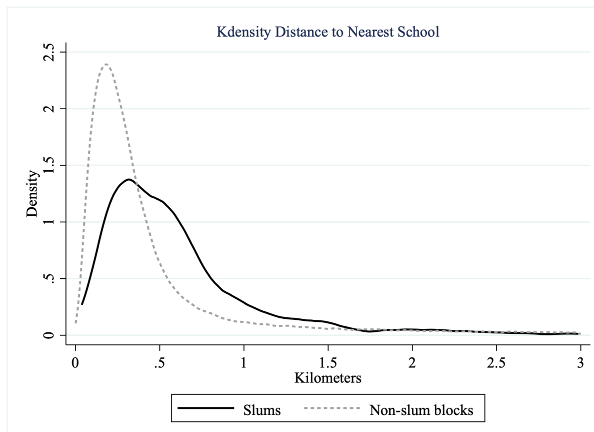
(b) High-Skill Firms' Cluster



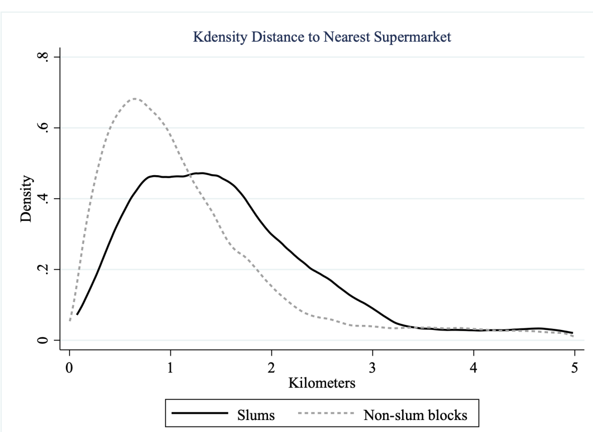
(c) Bus Stop



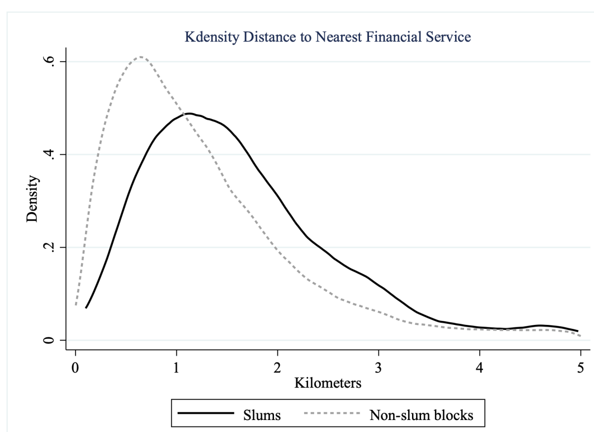
(d) School



(e) Supermarket



(f) Finance Institution

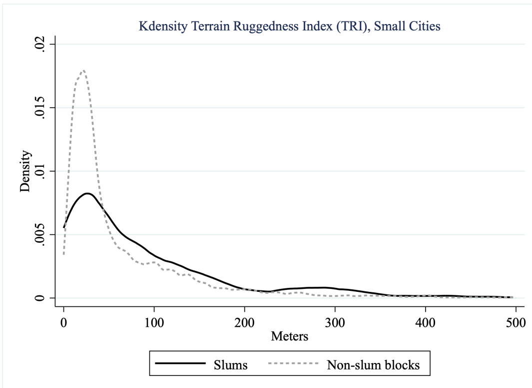


[a] Each figure compares the distribution of distances to the nearest amenity for slum areas and non-slum areas. Non-slum areas refer to municipality census blocks.

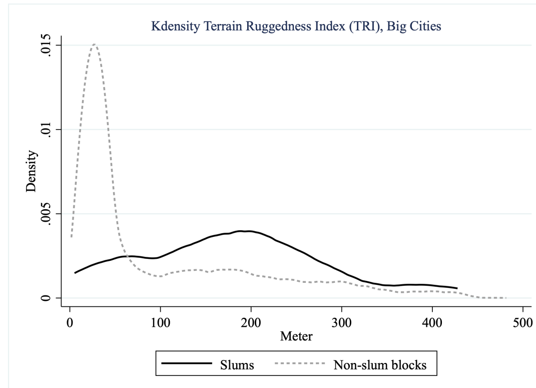
Figure D2: Terrain characteristics of Slums in small and big cities [a]

(a) Terrain Ruggedness Index (TRI)

Small Cities

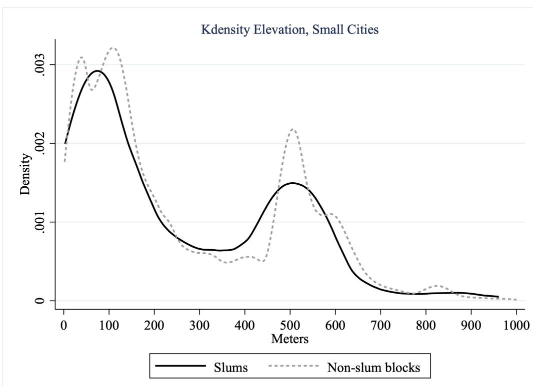


Big Cities

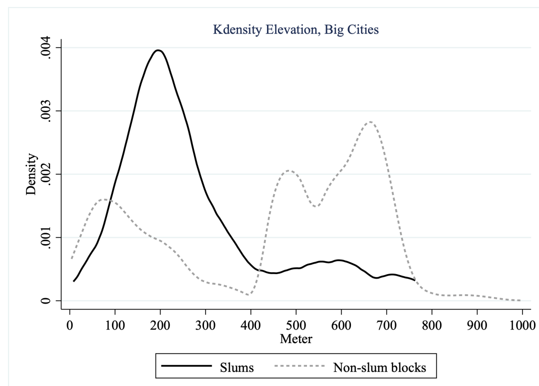


(b) Elevation (mt)

Small Cities

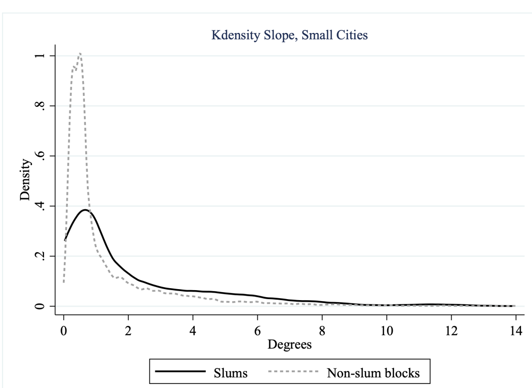


Big Cities

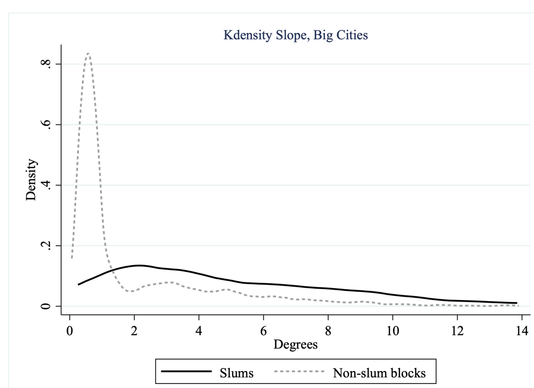


(c) Slope (degrees)

Small Cities



Big Cities



[a] Each figure compares the distribution of different terrain characteristics for slum areas and non-slum areas. Non-slum areas refer to municipality census blocks.

Table D1: Slum's access to amenities moving further from the CBD [a]

	Dist. City Center (km) (1)	Periphery (2)
depvar:		
Dist. Firms' Cluster (mt)	797.67***	-87.98
	(56.68)	(160.07)
Dis. High Skill Firms' Cluster(mt)	531.74***	301.19
	(125.03)	(243.99)
Dis. Low Skill Firms' Cluster(mt)	917.23***	-127.52
	(23.35)	(121.55)
Index Dist. Amenities	0.03***	0.03***
	(0.00)	(0.01)
Dist. Library (mt)	624.15***	333.00**
	(64.20)	(135.18)
Dist. Fire Station (mt)	438.91***	316.76**
	(78.41)	(134.35)
Dist. Police Station (mt)	180.43***	650.91***
	(51.70)	(106.26)
Dist. Schools (mt)	84.34***	236.63***
	(30.71)	(64.67)
Dist. Health Center (mt)	130.76***	317.70***
	(42.29)	(79.38)
Dist. Bus Stop (mt)	43.48***	147.72***
	(15.43)	(40.29)
Dist. Near 5 Restaurants (mt)	568.92***	309.37**
	(65.53)	(122.62)
Dist. Supermarket (mt)	530.15***	101.36
	(74.34)	(138.24)
Dist. Finance Institution (mt)	610.12***	175.62
	(68.68)	(134.82)

[a]Significance is denoted as: p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parenthesis. Each row corresponds to an single regression in which distance is a function of proximity to the city center, being in the periphery, slum size in households, and municipality FE. Dependent variables are all measure in meters (mt) while distance to the city center in in kilometers (km), that is for easy interpretation of the estimated coefficients. Slums on the city border are defined as those with a normalized distance to the city center above 0.9.