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

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Abstract

Urban planners often face two main options for slum policy: remedying slum infrastructure and housing needs (*in-situ* upgrading) or offering affordable housing outside slums (population relocation). We examine and compare the effects of these interventions on (i) the physical characteristics of targeted 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, covering the universe of slums in Chile. The panel incorporates satellite imagery, census data, administrative records, construction permits, crime reports, and property tax data. First, we document that slums tend to form on city peripheries and are later absorbed within city boundaries as urban areas expand. They typically emerge near low-skilled labor centers, with their growth correlating with improved labor market prospects for low-skilled workers and rising housing rents. Second, using Synthetic Difference-in-Difference for causal identification, we find that, on average, both policies reduce the share of land used for housing within the original slum perimeter —*in-situ* upgrading repurposes land for neighborhood infrastructure while population relocation reduces slum households and housing footprints. However, only *in-situ* upgrading leads to long-lasting increases in housing quality and socioeconomic status of residents. Moreover, *in-situ* upgrading generates significant positive spillovers in adjacent neighborhoods, reducing criminal activity and increasing formal housing investment.

Keywords: Slum Policy, Spatial Spillovers, Urban Planning
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1 Introduction

Slums are an important part of the urban landscape in many low and middle income countries (LIMC), 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 (Glaeser, 2011, 2014). In fact, over one billion people live in slums worldwide, of which 110 million are in Latin America (UN-Habitat, 2020). Two popular slum policies that governments have historically implemented to enhance slum housing are *in-situ* upgrading and population relocation. The *in-situ* upgrading programs provide essential services in slums such as piped water, electricity, and sanitation, as well as, in some cases, constructing new improved houses along with land titling. In contrast, the population relocation program moves slum dwellers out of slums (sometimes demolishing existing slum housing) and offers them improved housing in formal neighborhoods located outside of the slum perimeter.

This paper evaluates the impact of both policies on slum areas as well as spatial spillovers to surrounding neighborhoods in Chile, whose government has simultaneously implemented both slum policies since 2011. Chilean slum policies are voluntary, i.e., slum dwellers are not forced to participate, and both are executed through subsidies and direct investment. Housing subsidies are offered to finance new construction, either inside or outside the slum, and that decision will determine whether the slum is under an *in-situ* upgrading or population relocation policy. 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 popular slum 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 allows 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 spatially close, (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 image processing mask-RCNN algorithms, we identify built structures (as well as their size and shape) inside and outside of slums. We measure 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 in 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.

Our slum data are unique in terms of the large number of dimensions of slum development that can be analyzed, as well as for its large time horizon spanning more than 20 years, which allows us to provide a nuanced description of the formation and evolution of slums. We start confirming 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 on, cities grow and urban borders expand, and slums are 'absorbed' inside city boundaries. Second, 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 relevant labor markets. Third, our data show that slum residents have on average worse access to public amenities such as transport, schools, supermarkets, and public safety services, and housing quality inside slums is generally worse than in adjacent areas.

Taking a broader perspective of slums in urban areas, we then 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) combined with high formal housing costs and low income (which makes 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, and find that (i) doubling quality-adjusted housing rents is associated with up to 14% more slum population, (ii) employment growth and average salary growth for low-skilled workers also fosters slum growth, and (iii) municipalities with significant

[1]For a founding review of the slum literature, see Field and Kremer (2008). For complementary reviews, see Brueckner and Lall, 2015 and 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).

improvements in extreme poverty do experience increments in slum population.

Next, we take the 20-years panel of slums to evaluate the impact of *in-situ* upgrading and population relocation policies on the evolution of slum sites over time. Choosing between the two slum policies typically depends on a combination of demand and supply side factors including land conditions, housing costs, and eviction costs, to name a few, and these are generally endogenous to slum location. For our main analysis, we take advantage of treatment variations across space and over time and rely on a Synthetic Difference-in-Difference (SDiD) approach (Arkhangelsky et al., 2021; Clarke et al., 2023) to recover quasi-experimental estimates of the policy effects. 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 recovering quasi-experimental effects on socio-demographic variables, we use the standard Two-Way Fixed Effects regression since we only observe two waves of the population census.

After six years of treatment exposure, we find that, on average, population relocation generates a population decline of 16% in intervened slum areas, which in turn reduces the amount of land used for residential purposes by 12%. This is consistent with relocating slum dwellers to non-slum areas. In contrast, no significant changes in population are found for the *in-situ* upgraded slums, which allows slum dwellers to remain in the same area after intervention.

Second, we find population relocation has no impact on housing quality in the slum polygon. In contrast, *in-situ* upgrading has large and meaningful positive effects on housing quality. First, upgrading sites are 5 *pp.* more likely to attract new formal housing starts along with the *in-situ* upgrading implemented six years before, and the share of paved streets doubles relative to the non-intervened areas. *In-situ* upgrading also generates larger and more regularly oriented structures that are spaced further apart, suggesting coordinated formalization. They are also 4.5% more likely to have two or more bedrooms. Finally, slums that benefited from *in-situ* upgrading also attract a higher SES population in terms of education of inhabitants. None of these welfare effects are observed in slum sites intervened through the population relocation program.

We next turn to an analysis of spillovers in surrounding neighborhoods using the same methodology, i.e., we evaluate changes in adjacent areas six years after the implementation of the programs. We find that *In-situ* upgrading has strong positive spillover effect in adjacent neighborhoods. We find a 10% average increase in the probability of new housing starts

expanding all the way up to 200 mt from the *in-situ* upgraded slums. In contrast, we find no effects in the surrounding areas of population relocation slums. Second, buildings within 200 mt of *in-situ* updated slums are 11% younger and more likely to undergo renovations. As a result, areas surrounding *in-situ* upgrading slums also attract higher SES residents in terms of education and employment.

Given the prevalence of informal roads, the Chilean Ministry of Security cannot geocode crimes inside slums with precision, which limit our ability to estimate crime effects within the intervened areas. However, geolocated crime records are available for non-slum areas surrounding the slum sites (where formal street network exists), allowing us to estimate the spillover effects on criminal activity. Specifically, we calculate the number of property and violent crimes per km^2, and find that, after five years of exposure to intervention, neighborhoods located within up to 200 meters away from *in-situ* upgraded slums experienced a sizable reduction in both violent and property crimes. On average, we find 5 fewer property crimes and 3 fewer violent crimes, which represent between 15% and 25% crime reduction relative to the criminal activity observed in surrounding areas of non-intervened slums. Moreover, we find negative and statistically significant spillover effects on the number of homicides within 200 meters of the slum boundaries, for an effect size greater than 100%. None of these crime reduction effects are observed in neighboring areas surrounding slum sites intervened through the population relocation program.

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. Moreover, we calculate the fiscal costs of both strategies 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. Still, there are cases in which *in-situ* upgrading will not be preferred to population relocation, e.g., when the slum area is located in a high risk area from natural hazards like flooding and landslide. More generally, cost-effectiveness analysis across these two policies may be limited by feasibility conditions in their implementation, which may lead the urban planner to evaluate case by case.

Our study 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; Gechter and Tsivanidis, 2023). That work has provided strong basis 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). 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 main 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 contexts, 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, 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), who use data from the most extensive slum upgrading program worldwide, the Kampung Improvement Program (KIP) in Jakarta, Indonesia, to estimate the long-run effects of slum upgrading. More than 40 years after the intervention, 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. Importantly, while the KIP program upgraded the slum areas by providing slum dwellers with access to basic services like water and sanitation as well as to public services like schools and health services, the program did not guaranteed the formalization of the intervened slums. Thus, the authors hypothesize that slum upgrading delayed the process of formalization of intervened areas in comparison to non-intervened areas that developed along the formal urbanization process derived from city growth. Still, KIP areas deliver sizable positive effects in near locations, suggesting a trade-off between upgrading and preserving slums as cities expand. Our results differ from the KIP program, and this is in part due to the *in-situ* upgrading program in Chile works as a *de facto* formalization program, as it provides slum dwellers with land titles and formal housing from the very beginning of the intervention. In other words, Chile's *in-situ* upgrading program does not allows for "delayed formalization" but it formalizes the slum instantaneously: slum dwellers are no longer slum dwellers, they have now formal housing and live in a formal neighborhood with all the legal

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

services and land property rights of households residing in formal neighborhoods.

Also related, Rojas-Ampuero and Carrera (2023) study a slum clearance program in Santiago, Chile in the 80s that moved 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. We see our results as complementary in that these are derived from *in-situ* upgrading and relocation programs where slum dwellers are not forced to participate, but voluntarily enroll.

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

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 establishment of the "Villages and Slums Program" 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.

Choosing between *in-situ* upgrading and population relocation is a policy decision that typically depends on a combination of factors including land conditions (e.g., slums could be located in hazardous areas that are not recommended for *in-situ* upgrading); land tenure (e.g., legal order that mandate relocating slum inhabitants under illegal occupation); housing costs (e.g., *in-situ* upgrading may be costlier if the government has to pay private owners for the well-located, expensive land inhabited by slum dwellers); eviction costs (e.g., slum dwellers are not willing to abandon the occupied land and evicting them is too costly for the State); and demand-side considerations (providing *in-situ* upgrading allows slum dwellers to keep their networks and geography of opportunities).

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 such as paving streets, installing basic services like piped 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 the 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.

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.

Although the intervention is at the slum level, household move voluntarily to these new housing projects. Once they relocate, 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, on average, $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

Now that we have described the two types of slum renewal policies, we focus on how the program was implemented. The process starts 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 interventions 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 treat in first, nor how to choose between *in-situ* upgrading and population relocation (Budget Division—DIPRES—report by Marcelo et al. (2019)). Official documents and reports from MINVU only list the relevant

[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)).

factors considered when deciding on the specific treatment strategy. These factors include: social and cultural attachment, spatial dispersion, housing materials, public transit access, green and public space, city location, natural hazards, propensity to public disturbances, household eligibility for subsidies, slum social structure, political concerns, feasibility for new construction and basic service connectivity (piped water, sewage, and electrical grid).

Given the lack of information on how exactly the government decides which intervention to implement, 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 the *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 city border, 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 in 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

One important contribution of this study is the construction of a high frequency panel of slums that combines information from satellite images with administrative records. Additionally, we do not need to rely 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-

[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.

governmental organization TECHO between 2011 and 2020.[6] These censuses provide the precise locations of slums, allowing us to assess their proximity to various urban amenities such as distance to the city center, transportation networks, and public services.

Our data efforts allow us to go beyond a static picture or cross-sectional analysis of informal settlements. We start by documenting the slum censuses from MINVU and TECHO, and providing a descriptive analysis of the location of slums. To include information on physical characteristics, we present the methodology used to identify building footprints. Our analysis continues with the results from population censuses, showing how sociodemographics have changed inside slums. Finally, this section describes all other datasets gathered and processed to study the causal effects of the two slum renewal policies considered in the paper.

3.1 Slum locations and boundaries

MINVU slum censuses in 2011 and 2019 identify the precise locations and boundaries of all active slums, as well as the number of households residing in them. Between 2011 and 2019, TECHO published similar data, making it possible to construct an initial panel of active slums between 2011 and 2020. This initial panel accounts for repopulation of slums and guarantees only unique areas are considered. 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 (see Figure B1).

Slums are predominantly located on the periphery of cities, in areas that have limited access to urban amenities. Figure 1 illustrates where slums are located in Valparaiso, 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 Valparaíso. 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 dis-

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

tances close to zero correspond to slums at the city center, while values closer to one refer to locations on the city's periphery. Figure B2 shows the distribution of slums along this normalized distance. 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 integrate slums into the city over time. 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 actually sacrifice proximity to city amenities when settling in these peripheral areas? And if so, which are the amenities that they care the most? 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 firms in low- and high-skilled industries. 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 2 illustrates the location of these clusters in the Coquimbo-La Serena region, where the distinction between these industries' location 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 (those created after 2010) do not sacrifice proximity to low-skilled labor markets and health centers. However, they are approximately 200 meters farther from the nearest schools and 100 meters farther from the nearest bus stop compare to non-slum census blocks.

Moreover, the distinction between newer and older slums reveals that the former 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

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

appeared after the 2017 firm census. Together, these findings indicate that households in informal settlements prioritize proximity to employment opportunities over access to certain public services when selecting their residential 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. However, the reported boundaries of each slum 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 3 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 the slum sample of constant boundaries, we obtained satellite images for these locations for the period 2000 to 2022 and construct a panel of slum physical characteristics. This is one of the few exercises that build a high frequency 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 3 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 C.

Our ML strategy involves 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

[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.

to optimize the model's performance and manage computational resources efficiently. Second, 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 complement 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 B3 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 motivated the government's agenda on slum intervention. The period between 2015 and 2020 represents a time of civil unrest and covers the COVID-19 pandemic, which affected both formal and informal housing.

Figure B3 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 km^2, we are 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 mt, 100 to 200 mt, and 200 to 500 mt 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 the residential density observed inside 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]

[9]We also compared the building activity inside slums between small and large informal settlements. Both

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 considered inadequate, we observed only a 20% decline in slum areas, while nearby blocks experienced more than 60% reduction. These findings suggest that while adjacent neighborhoods underwent significant improvements in housing quality, slum areas did not

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 slums 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%.

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. This highlights the persistent challenges faced by slum communities, even as nearby areas show signs of improvement.

3.4 Other datasets

Satellite images and population censuses offer an initial description of the dynamics of slums. However, these dataset have their own limitations. For instance, relevant factors like housing developers' expectations—which are important for assessing investment potential—cannot be derived from satellite images alone. Population censuses provide data on long-term changes but fail to capture short-term dynamics. To provide a more comprehensive analysis of slum dynamics beyond descriptive results, we now focus on estimating causal effects for the two different slum renewal policies. For that, we add other neighborhood dynamics that 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 approach 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 since the average is less

affected by random errors from the LandScan smoothing approximation 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 will 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]

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

[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.

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, and distribution of employment across industries. We combine this dataset with the National Household Survey of Socioeconomic Characterization (CASEN, for its Spanish acronym) 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 on 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. Measuring crime inside slums will lead to a biased positive effect on crime for *in-situ* upgrading slums since the intervention involves the construction of roads. The difference in the ability of geocoding crime before and after the intervention will drive any results estimated inside the informal settlement.

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 mar-

ket by constructing a quality-adjusted rent measure using the CASEN household survey. The municipality-specific quality-adjusted rent corresponds to the municipality fixed effects associated with a hedonic regression of rental prices controlling for 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 ENE survey 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 settlements. 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).

For our municipality-level analysis, we also include variables capturing social assistance.

[13]For most of the control variables, the baseline year depends 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.

We find that slum growth occurs in areas experiencing a decline in extreme poverty, suggesting that low-income household tend to avoid locations with high poverty levels. The expected benefits from 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 and their resident need to be included in the slum census to be eligible, and the program did not consider updating the records until 2018.[15] That motivates our focus on treated slums between 2011 and 2017. Third, the number of slums intervened

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

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) methodology to identify causal effects (Arkhangelsky et al., 2021; Clarke et al., 2023). 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 took 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 or 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

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

and the never-treated slums.

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. This assumption requires that, in the absence of treatment, the trends in the outcomes would have been similar 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

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

traditional Synthetic Control methods.

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 E for the CSDiD results).

5.2 Slum sociodemographic characteristics

Unlike slums' physical characteristics, we only observe sociodemographic variables for the two population censuses in 2002 and 2017. Data restrictions limit our ability to estimate equation (2) for sociodemographic measures using 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 directly 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 present the direct effects and spillovers 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 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 selecting a synthetic control group from the pool of never treated slums that match the pretreatment trends of treated slums. Due to the staggered nature of the treatment, a synthetic control 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 4 shows the full dynamic effects of each policy intervention on the log of population. The confidence intervals are obtained using bootstrapping. Table 6 provides a summary of the estimated causal effects after six years of treatment assignment.

We complement the measures from the slum panel with variables from the 2002 and 2017

population censuses. These censuses not only provide sociodemographic information on slum areas but also include variables of housing quality such as the number of bedrooms and the quality of the walls. The effects on these variables are obtained using Two-Way Fixed Effects (TWFE) models following Equation (4), since we only observe two periods. The results are presented in Table 7.

Table 6 confirms that the population relocation policy reduces the share of residential land by 12% and the population by almost 16% six years after the intervention. For *in situ* upgrading slums, we did not find a significant effect on residential land and population in general. Slums under the *in-situ* upgrading strategy doubled the share of streets paved within 6 years of treatment.

Focusing solely on the effects on population, recall that our measure in Table 6 also captures the population in the immediate vicinity. This implies that the findings should be interpreted as reflecting a local neighborhood trend. However, data from the census variables in Table 7 show an almost identical effect on population for the relocation strategy —a decline of 15.4% compared to 15.6% from the slums panel. Together, these observations provide strong evidence of a decline in residents in population relocation slums. Nonetheless, the magnitude of the population decline is small for these types of policies, likely due to the high risk of slum repopulation, particularly in areas where not all households can move out. New settlers or family splits can perpetuate the existence of informal settlements.

We now examine different measures of housing quality from both the slum panel and the population censuses. We focus on three specific outcomes from the slum panel and two from the population censuses. In Table 6, we present the effects on the following outcomes: 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 consistent measurement between buildings inside and outside slums. The orientation angle serves as a proxy for building regularity. In formal neighborhoods, 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 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 significant changes. Table 6 shows a 14.5% 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 orientation angles. Buildings are also further apart by almost 9 meters.

The two variables from the population censuses related to housing quality are the share of houses with two or more bedrooms and the share of houses with high-quality wall materials (concrete, stone, brick, and prefabricated blocks). Results are presented in Table 7, and further support the results from the slums panel. We find evidence of better housing quality in *in-situ* upgraded slums, as the share of houses with two or more bedrooms increases by almost 4.5 percentage points. For population relocation, we do not find positive effects on housing quality and observe a slight decline in the share of houses with good wall materials.

Improvements in slum physical characteristics and housing quality influence developers' perspectives on neighborhood transformation. We measure changes in housing investment using building permits. Housing starts represent future development and are the closest measure to formal construction observable 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% 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 of the treatment assignment. *In-situ* upgrading not only increases housing quality but also initiates a neighborhood transformation that attracts formal housing investment.

Table 7 shows the direct effects of each policy on a selected set of census outcomes. All models control for log of slum population and slum fixed effects. In terms of sociodemographics, we observe more individuals over 25 years old with secondary or higher education.[18] The point estimates associated with population and employment rate inside *in-situ* upgrading slums are also positive, although not statistically significant. These results suggest a population composition change in *in-situ* upgrading slums that attract higher socioeconomic status (SES) individuals to the previously slum area. Regarding population relocation slums, we find no significant effect on the sociodemographic characteristics of the residents.

It is important to mention some caveats regarding the results from the population census in Table 7. The 2002 census might not provide a comprehensive picture of every slum before treatment, since most slums had not yet developed by 2002. Government interventions started after 2011, implying that actual activities in slums did not begin 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; specifically, the time between receiving a housing voucher and moving to the new house is usually 24 to 48 months. This applies to both *in-situ* construction and relocation.

Our analysis demonstrates that *in-situ* upgrading is more effective than population reloca-

[18] We estimate the same models restricting individuals to ages 30, 35, and 40. The point estimates did not change.

tion 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 material quality.

6.2 Spillovers on nearby formal neighborhoods

There is limited evidence on the effects of slum renewal policies on the physical and sociodemographic characteristics of slums, and even less is known about their spillover effects on nearby formal neighborhoods. In this analysis, we focus on two buffer zones around slums: 0–200 meters and 200–500 meters from the slum border, ensuring that only formal locations are included in each ring. We are interested in spillovers related to housing quality, housing investment, sociodemographic changes, and crime rates.

Table 9 presents the effects of each slum policy on various outcomes, grouped into two categories: housing investment and housing quality. Regarding housing quality, we find that the average building age decreases by about 11% in areas within 200 meters of *in-situ* upgraded slums, indicating newer buildings in these neighborhoods. Although we also find positive spillovers in building age for population relocation areas, the effect is about 60% of that near *in-situ* upgraded slums. We do not find significant effects on building orientation angle and distance between buildings, which is expected in established neighborhoods where changes in building regularity and distribution are unlikely.

We observe weak evidence of an increase in the building's reported size on land tax records. This suggests internal housing modifications and vertical expansions—indicating housing renovations. It is likely that additional floors have been added to some units, while others have repurposed certain areas within their building footprints. Further evidence of improvements in housing quality comes from Table 10, which shows increases in the share of houses with high-quality wall materials only near *in-situ* upgraded slums.

Regarding housing investment, we find significant positive spillovers in areas close to *in-situ* upgraded slums. Specifically, there is a 4 percentage point increase in new buildings (with less than five years from construction) and a 30% increase in yearly renovations in formal areas within 200 meters of *in-situ* upgrading slums (Table 9). For neighborhoods near population relocation slums, we find a smaller effect on new buildings and no signifi-

cant effect on building renovations. Nearby communities are more willing to invest in and maintain their properties. Changes in neighborhood amenities affect expected returns from housing investment, motivating further improvements in housing quality and fostering a more connected community.

The effects on building permits indicate neighborhood transformation resulting from *in-situ* upgrading strategies. The probability that at least one building permit is approved in a formal neighborhood within 200 meters of the slum increases by 10%. Similarly, there is a 13% increase in the number of building permits, an effect that persists up to 500 meters from the slum. Formal neighborhoods near population relocation slums do not exhibit similar gains in developers' confidence.

We now examine how policy interventions affect the population in formal neighborhoods beyond physical characteristics. Table 10 shows the effects of each intervention on socioeconomic outcomes in neighborhoods within 200 meters and 200–500 meters of the treated slums, respectively. Areas near 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 contrast, near *in-situ* upgrading slums, the population within 500 meters is more educated and more likely to be employed, although there are no significant changes in population size. This suggests socioeconomic compositional changes, with higher SES individuals being attracted to these areas. Note that these effects occur within six years from treatment assignment, implying 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 8 summarizes the effect of each policy on each ring after five years using the SDiD methodology. We focus on five years post-intervention due to data availability (crime records cover 2013 to 2023). Again, neighborhoods near *in-situ* upgraded slums perform 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 or areas beyond 200 meters.

One might be concerned about changes in reporting behavior that could bias the results. To address this, we also present the effect on homicides in Table 8. Although homicides are rare events, they are less susceptible to 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 activity; in particular, attachment to the formal labor market reduces the probability of participating in the illegal market.

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 given the decrease in population.

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. Housing development and renovations also likely increase neighborhood safety. New constructions have better security standards, and landowners may install safer doors and windows during renovations. Additionally, vertical expansions result in taller buildings, which have a lower probability of trespassing. Although we cannot distinguish between the effects of population compositional changes and improved security mechanisms, the observed crime reductions clearly indicate improvements in neighborhood amenities.

Our analysis reveals that *in-situ* upgrading 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, attracting more 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 Synthetic Difference-in-Differences (SDiD) methodology. we 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. 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 (Gonzalez-Navarro and Undurraga, 2023). 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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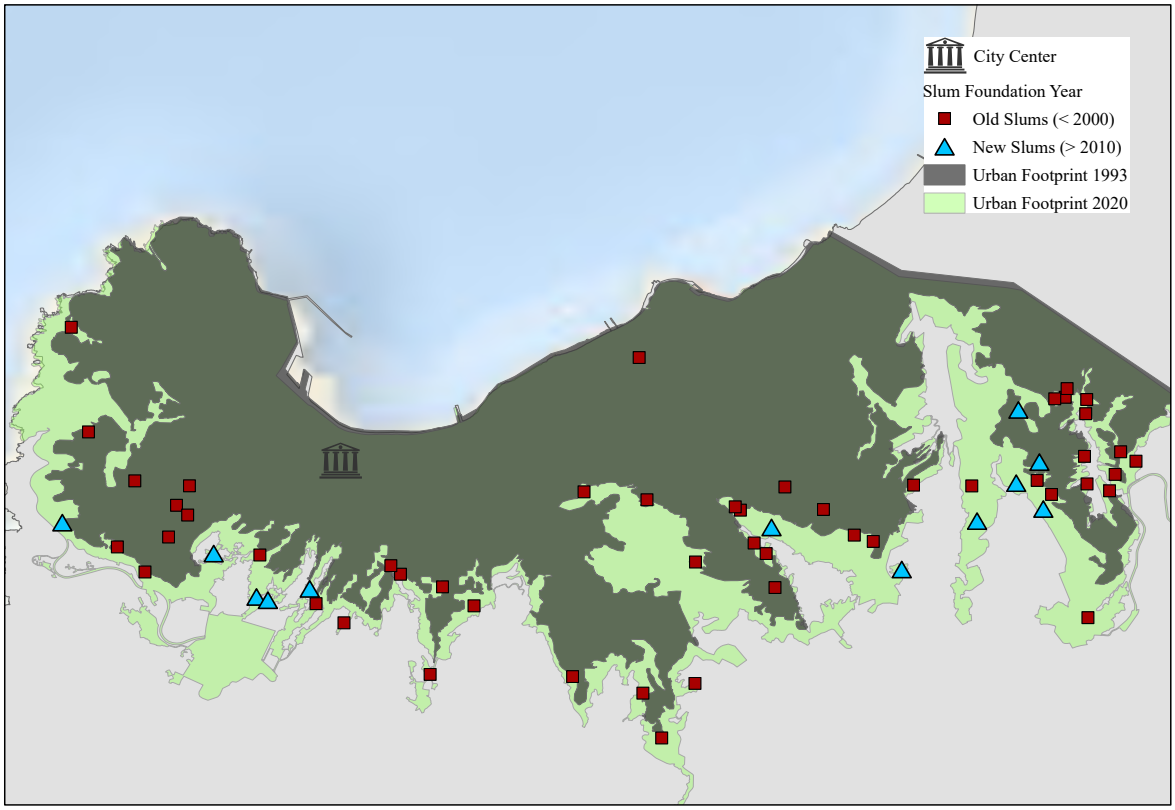
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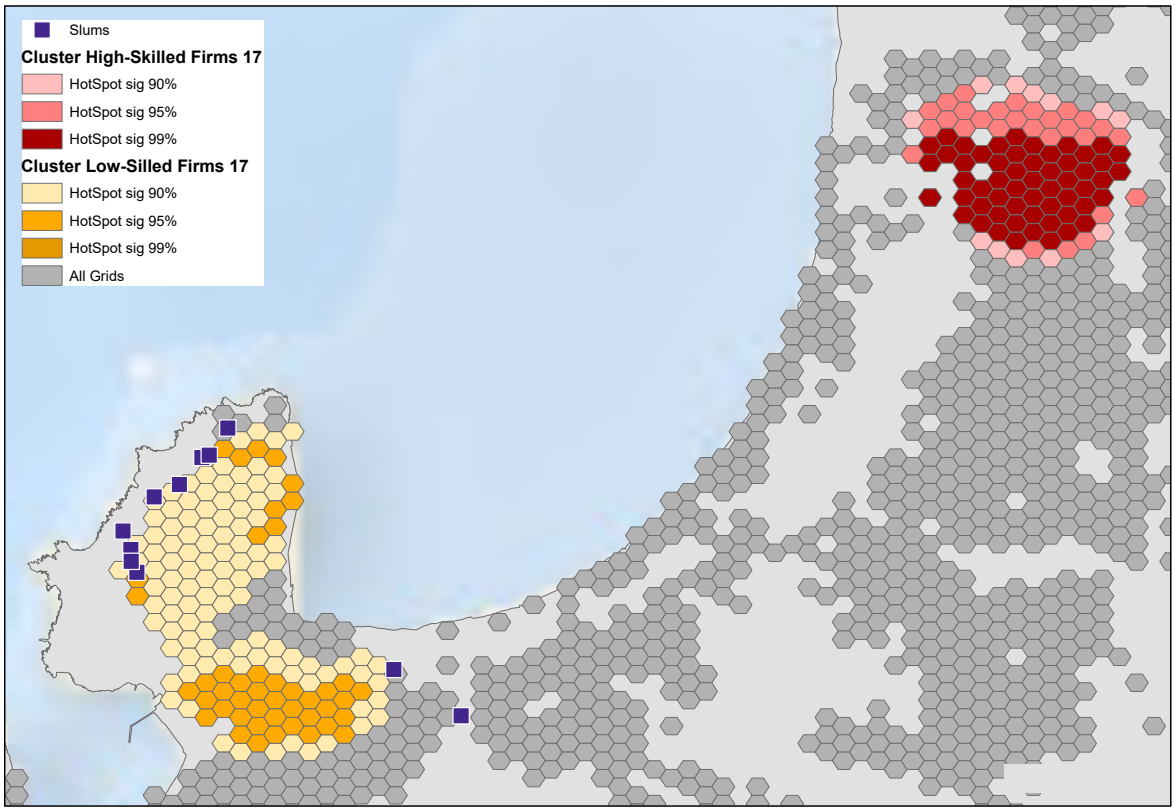
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Figure 1: Location of Slums in Valparaiso, 1993 & 2020



City boundaries for 1993 and 2020 refer to the city continued urban construction (CUC). City centers are obtained from the Urban Functional Areas project (AUF for its Spanish acronym) by INE, MINVU, SECTRA and SUBDERE. City centers take into account residential and labor locations, and mobility patterns.

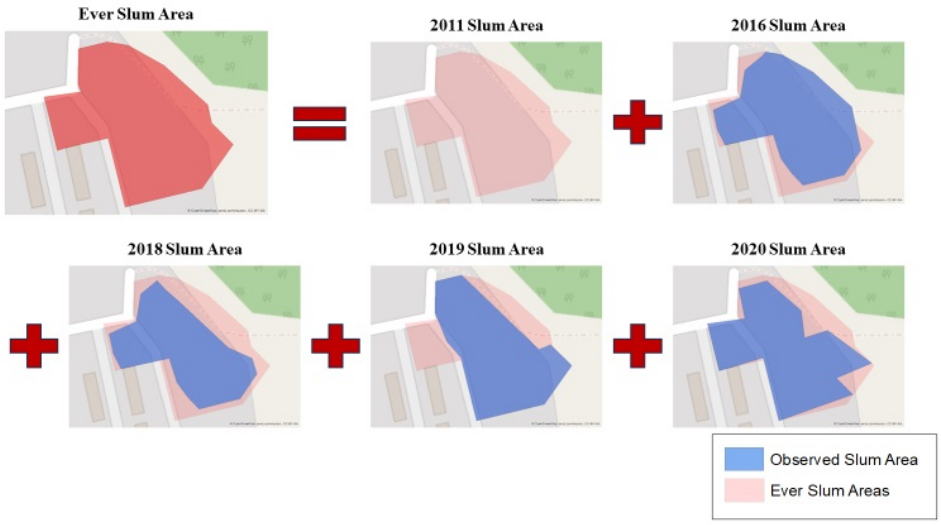
Figure 2: Proximity of Slums to Centers of Low- and High-Skilled Employment, Coquimbo



Clusters are calculated using the 2017 National Firms Census. We divide the country into hexagons with sides of approximately 125 meters and count the number of firms within each hexagon. Low-Skilled industries are agriculture, mining, manufacture (food, beverages, leather, wood, paper, plastic, minerals and furniture), construction, retail and transportation. High-skilled industries are other manufacture (chemicals, pharmaceuticals, electronics, machinery, automobiles), services, teaching, professional and scientific activities.

Figure 3: Unit of Analysis - Fixed Slum Areas

(a) Geographical Union of Observed Slum Areas over Time



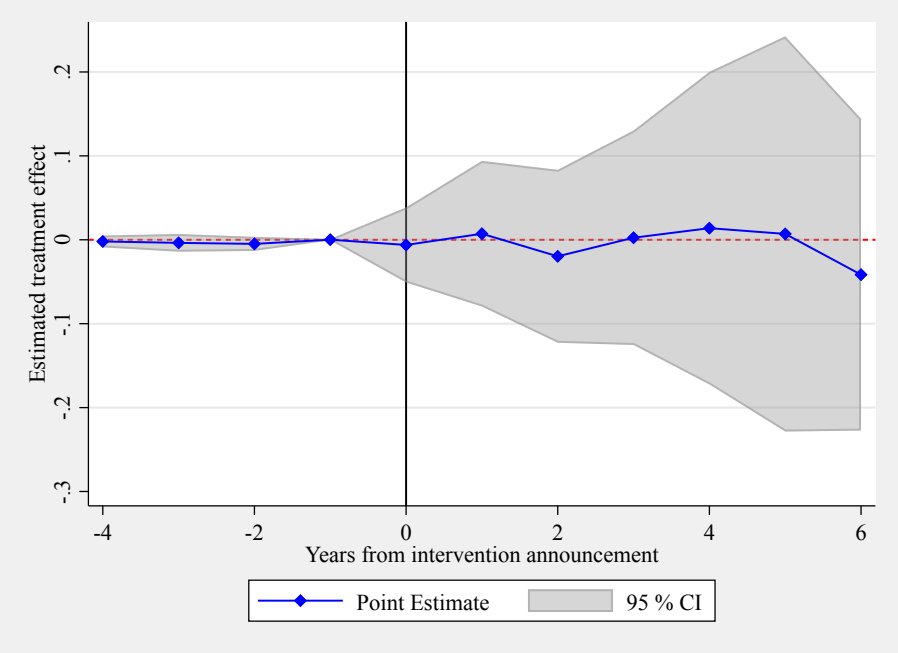
(b) Satellite Images of the Fixed Slum Area



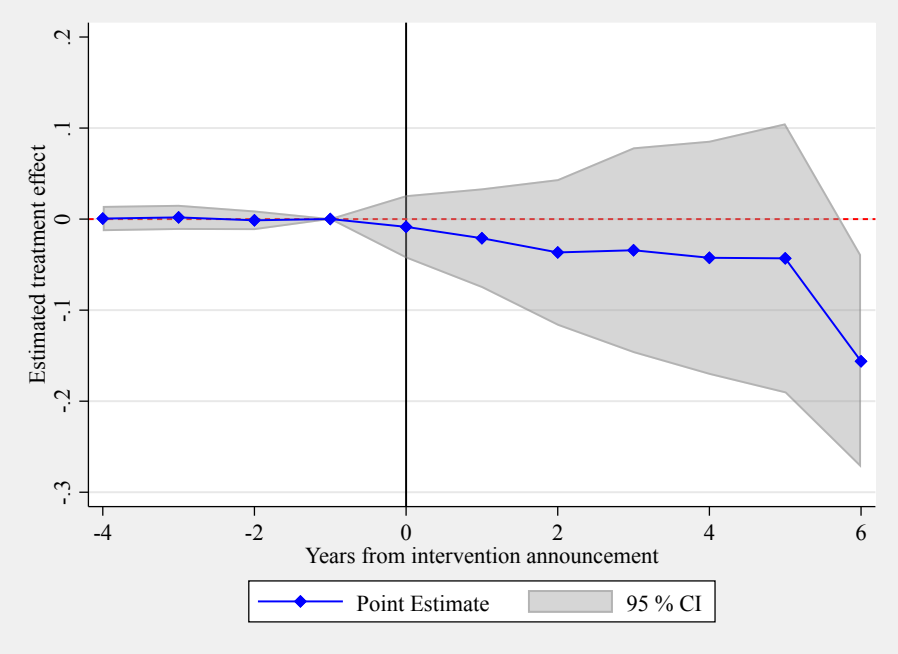
Representation of the slum La Iglesia in the municipality of Tome. Satellite images from Google Earth.

Figure 4: Effects of Slum Renewal Policies on Log Slum Population (SDiD)

(a) *In-situ* Upgrading



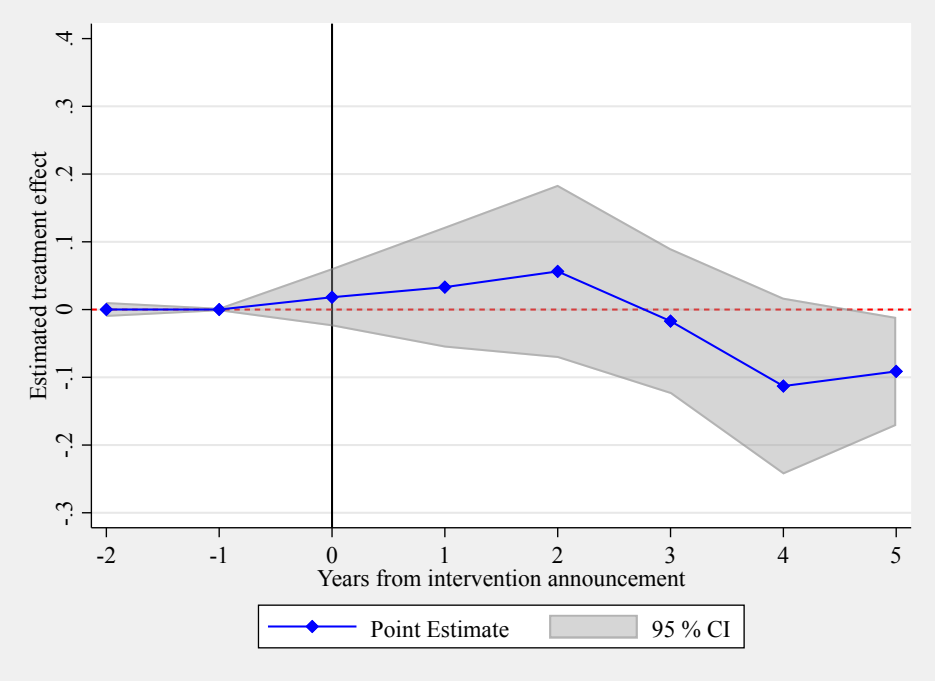
(b) Population Relocation



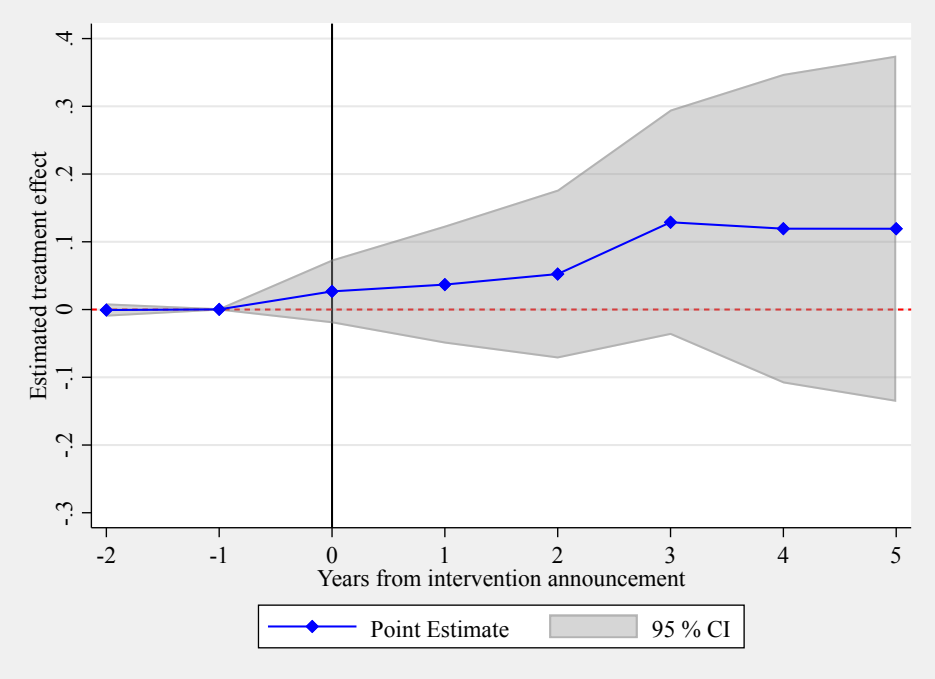
SDiD - Synthetic Difference-in-Difference methodology developed by Arkhangelsky et al. (2021). Confidence intervals are obtained using bootstrapping. We focus on slums treated between 2011 and 2017. These are the dynamics for the log of population, the results for the complete list of outcomes are presented in table 6.

Figure 5: Effect of Slum Renewal Policies on Crime Index (sd) in Adjacent Formal Areas

(a) *In-situ* Upgrading



(b) Population Relocation



SDiD - Synthetic Difference-in-Difference (Arkhangelsky et al., 2021). Confidence intervals are obtained using bootstrapping. Crime data comes from the Subsecretaria de Prevencion del Delito, and data covers the sample of slums treated between 2015-2018. Additional outcomes are presented in Table 9.

Table 1: *In-situ* Upgrading and Population Relocation Program Expenditures

	Mean	SD	Median
In-situ Upgrading (N Slums = 209)			
# Households (HH) per Slum	56.22	63.57	38
Share HH Receiving Housing Voucher	0.54	0.48	0.43
Voucher Value per Beneficiary HH	$25,839	$11,650	$24,300
Voucher Value per Slum HH	$13,796	$12,772	$11,215
Infrastructure Investment per Slum HH	$6,381	$10,138	$1,831
Total Expenditure per Beneficiary HH	$31,994	$16,967	$26,401
Total Expenditure per Slum HH	$20,177	$19,241	$16,221
Population Relocation (N Slums = 440)			
# Households (HH) per Slum	34.43	46.92	23
Share HH Receiving Housing Voucher	0.82	0.63	0.79
Voucher Value per Beneficiary HH	$32,912	$2,020	$32,000
Voucher Value per Slum HH	$26,998	$20,495	$25,792
Infrastructure Investment per Slum HH	$2,970	$6,421	$545
Total Expenditure per Beneficiary HH	$35,851	$7,068	$33,264
Total Expenditure per Slum HH	$29,969	$22,984	$28,282

Data source: MINVU. Data covers the period 2011-2020. Monetary values are in 2007 US dollars. Households (HH) residing in slums correspond to the first slum census in which the slum appears.

Table 2: Determinants of Treatment Assignment

	Pr(Any Treatment)			Pr(In-situ Upgrading | Any Treatment)		
	Marginal Effect (at the mean)		Covariate Mean (sd)	Marginal Effect (at the mean)		Covariate Mean (sd)
	(1)	(2)	(3)	(4)	(5)	(6)
Slum Characteristics						
Identified as Slum in 2011	0.89***	0.97***	0.50	0.04	0.11	0.84
	(0.05)	(0.05)	(-)	(0.06)	(0.11)	(-)
Log Slum Area	0.00	0.03	9.23	0.08***	0.07***	9.08
	(0.02)	(0.03)	(1.27)	(0.02)	(0.02)	(1.21)
Log Slum Households	-0.12***	-0.15***	3.45	0.06	0.07**	3.37
	(0.03)	(0.04)	(0.96)	(0.04)	(0.03)	(0.80)
Terrain Characteristics						
Not Suitable for Construction	-0.27**	-0.30**	0.04	-0.31**	-0.14	0.03
	(0.12)	(0.13)	(-)	(0.15)	(0.15)	(-)
Within 250m of a River	-0.02	-0.02	0.35	-0.09*	-0.12**	0.35
	(0.05)	(0.03)	(-)	(0.05)	(0.05)	(-)
Elevation (km)	0.10	0.20***	0.28	-0.04	0.19	0.28
	(0.09)	(0.07)	(0.27)	(0.09)	(0.16)	(0.27)
Elevation Slope, percentage rise	0.00	0.00	4.90	0.01	0.00	4.71
	(0.01)	(0.01)	(5.30)	(0.01)	(0.01)	(4.88)
Terrain Ruggedness Index (km)	0.01	0.00	0.12	0.62**	0.54***	0.11
	(0.24)	(0.18)	(0.13)	(0.27)	(0.19)	(0.13)
Location & Muni Characteristics						
Located at City Border or Beyond	-0.10*	-0.07	0.78	0.11**	0.13***	0.73
	(0.05)	(0.05)	(-)	(0.05)	(0.05)	(-)
Distance to City Center (km)	0.002***	0.003**	18.51	-0.002***	0.00	20.25
	(0.00)	(0.00)	(30.13)	(0.00)	(0.00)	(32.34)
Amenities Distance Index	0.00	0.01	0.00	0.01	-0.03	0.03
	(0.02)	(0.02)	(0.95)	(0.02)	(0.04)	(0.98)
Building Density within 200m	0.60*	0.59	0.10	-0.04	-0.25	0.11
	(0.36)	(0.36)	(0.07)	(0.36)	(0.24)	(0.08)
Log Municipality Expenditures	0.00	0.10***	16.57	-0.07***	-0.01	16.54
	(0.01)	(0.03)	(1.06)	(0.01)	(0.02)	(1.07)
Obs.	1,102	1,102	1,102	546	546	546
Region FE	No	Yes		No	Yes	
Mean dependent var	0.50	0.50		0.33	0.33	

Significance: * p<0.1, ** p<0.05, *** p<0.01. Models estimated using Logit. Robust standard errors. Only standard deviations for continuous covariates are reported in columns 3 and 6. Terrain not suitable for construction corresponds to areas with a slope above 20% or ruggedness greater than 0.497 km. The Amenities Distance index follows Anderson (2008) combining distance to bus stops, supermarkets, libraries, fire stations, police stations, schools, health centers, and finance institutions. The Pr(Population Relocation|Any Treatment) is the converse of the Pr(In-situ Upgrading|Any Treatment).

Table 3: Distance to Amenities & Differences in Terrain, Slum vs Non-Slum Census Areas

Dependent Variable:	Mean Control	Slum Indicator	Romano-Wolf (p-value)
Amenities Distance index (sd)	0.00	0.06***	-
		(0.02)	
Individual Amenities			
Distance Nearest Fire Station (m)	1,994	213.63**	0.03
		(89.67)	
Distance Nearest Police Station (m)	2,047	210.08***	0.01
		(61.86)	
Distance Nearest School (m)	637	200.99***	0.00
		(32.54)	
Distance Nearest Health Center (m)	1,438	50.42	0.27
		(42.88)	
Distance Nearest Bus Stop (m)	810	64.77**	0.14
		(28.75)	
Distance Nearest Supermarket (m)	2,900	225.41**	0.05
		(99.05)	
Distance Nearest Finance Institution (m)	2,777	524.13***	0.00
		(109.06)	
Terrain Characteristics			
Slope (%)	2.68	1.19***	0.00
		(0.14)	
Elevation (m)	329	14.10***	0.00
		(1.98)	
Terrain Ruggedness Index (m)	74	13.55***	0.00
		(2.68)	
Distance Nearest River (m)	2,006	-339.37***	0.00
		(34.05)	

Significance based on individual p-values: * p<0.1, ** p<0.05, *** p<0.01. Romano-Wolf p-values correcting for multiple hypotheses reported in column 3. Each row corresponds to a different OLS regression of the distance to the nearest amenity as a function of a slum indicator, the number of households, and Municipality FE. The Amenities Distance index follows Anderson (2008) combining all reported individual amenities in the table. Sample size = 156,654 (slums plus non-slum areas).

Table 4: Sociodemographic Changes - Population Censuses 2002 and 2017

	Census Year		$\%\Delta_t$	$\%\Delta_t$Slums $-$ $\%\Delta_t$NonSlum	
	2002	2017	(2017-2002)	Diff-in-Diff	Romano-Wolf (p-value)
Population					
Slums	277	308	24.2%		
Nearby Non-Slum Blocks	6,870	7,206	11.5%	12.7%	0.002
Ratio Adult Males/Females					
Slums	1.30	0.97	-33.0%		
Nearby Non-Slum Blocks	0.96	0.95	-0.6%	-32.4%	0.585
% Pop w Secondary Educ					
Slums	39.58%	51.03%	30.5%		
Nearby Non-Slum Blocks	43.21%	50.65%	16.6%	13.8%	0.585
% Pop w some Tertiary Educ					
Slums	10.20%	18.45%	64.7%		
Nearby Non-Slum Blocks	14.45%	20.24%	39.2%	25.5%	0.002
Employment rate					
Slums	80.63%	90.19%	12.2%		
Nearby Non-Slum Blocks	82.41%	90.31%	9.3%	2.9%	0.585

Nearby non-slum census blocks are within 200 to 500 m of the slum border. % change and Romano-Wolf adjusted p-values for multiple hypotheses come from the standard Diff-in-Diff regression. We geocoded census blocks to slums based on the blocks' centroid. Adult males and females refer to males and females between 25 - 64 years old.

Table 5: Correlates of Municipal Slum Population Growth, 2002-2017

	Δ Log Municipal Slum Population			
	(1)	(2)	(3)	(4)
Log Municipality Pop. 2005	-0.10**	-0.09**	-0.08	-0.09
	(0.05)	(0.05)	(0.05)	(0.06)
Δ Log Municipality Pop.	0.57	0.73*	0.63	0.59
	(0.38)	(0.39)	(0.43)	(0.44)
Δ Log Quality Adj. Rent		0.38**	0.40**	0.43**
		(0.17)	(0.20)	(0.20)
Δ Log Employees			0.22*	0.27**
			(0.13)	(0.13)
Δ Log Labor Salary			-0.16	-0.09
			(0.18)	(0.18)
Δ Log Labor Salary - High School			0.12*	0.12**
			(0.06)	(0.06)
Δ Log Municipality Expenditures				-0.05
				(0.25)
Δ Log Municipal Social Expenditures				-0.02
				(0.02)
Log Investments in Slum				-0.05**
				(0.02)
Log Housing Subsidies for Slum				0.07
				(0.04)
Constant	1.25**	0.81	0.61	0.7
	(0.49)	(0.54)	(0.65)	(0.67)
Obs.	230	226	197	197
R2	0.04	0.06	0.10	0.13
Mean Dependent variable	0.15	0.15	0.14	0.14

Significance: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parenthesis. Slum population growth is calculated using the log difference between the slum population in 2017 and 2002. Changes in quality-adjusted rent cover the period 2009-2017, while changes in employment and salary cover 2010-2017. Changes in municipality expenditures correspond to differences between 2011 and 2017. Specifications control for whether a municipality has ever had slums.

Table 6: Direct Effect of Slum Renewal Policies —SDiD

Dependent variable:	Mean Control (Level)	*In-situ* Upgrading β_1	Population Relocation β_2	p-value $\beta_1 = \beta_2$
Slum Characteristics				
Log Population	2,063	-0.04	-0.16***	0.00
		(0.10)	(0.06)	
Share Residential Land	0.26	-0.03	-0.12**	0.00
		(0.06)	(0.05)	
Share Streets paved	0.09	0.11**	0.04	0.00
		(0.05)	(0.03)	
Housing Investment				
Pr(Building Permits > 0)	0.01	0.05**	0.01	0.00
		(0.02)	(0.01)	
Log # Building Permits	0.01	0.02**	0.01	0.00
		(0.01)	(0.01)	
Housing Quality				
Log # Buildings, size > 64m^2	4.6	0.15*	0.03	0.00
		(0.08)	(0.08)	
SD Bldg. Main Angle Across Neighbors	5.27	-0.82**	-0.09	0.00
		(0.41)	(0.38)	
Avg. Distance to Neighbors (m)	60.05	8.67**	4.74	0.00
		(4.26)	(5.74)	

Significance: * p<0.1, ** p<0.05, *** p<0.01. Each coefficient is from a different SDiD regression for the dependent variable (row) six years after the indicated treatment (column). We control for lag population. Equality of coefficients is tested with a paired t-test using the bootstrapped distributions. *Slum Characteristics* and *Housing Quality* variables come from satellite images. *Housing Investment* variables are from building permits. Baseline mean for building permits is for 2010 and for the rest of the variables is for 2009.

Table 7: 2002 - 2017 Direct Effect of Slum Renewal Policies —TWFE

Dependent variable:	Mean Control (Level)	*In-situ* Upgrading β_1	Population Relocation β_2	p-value $\beta_1 = \beta_2$
Sociodemographics				
Log Population	298	0.14	-0.15	0.07
		(0.18)	(0.15)	
% Adults with $\geq$ High School	55.87	3.05*	1.24	0.32
		(1.62)	(1.58)	
% Employed	83.32	1.28	0.43	0.57
		(1.24)	(1.03)	
Housing Quality				
% Houses $\geq$ 2 Bedrooms	70.52	4.49*	0.99	0.15
		(2.60)	(1.84)	
% Houses with High Quality Walls	81.72	0.14	-4.50*	0.18
		(3.31)	(2.68)	

Significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors are clustered at the municipality level. Outcome variables are from the 2002 and 2017 population censuses. Each row corresponds to one pooled TWFE regression with two dummy treatment variables. Sample size = 920. The equality p-values are from Wald tests.

Table 8: Effect of Renewal Policies on Crime in Adjacent Formal Neighborhoods —SDiD

	0 - 200 m				200 - 500 m			
Dependent Variable:	Mean Control	*In-situ* Upgra. β_1	Pop. Reloc. β_2	p-value $\beta_1 = \beta_2$	Mean Control	*In-situ* Upgra. γ_1	Pop. Reloc. γ_2	p-value $\gamma_1 = \gamma_2$
Aggregate Crime Index (sd)	0.13	-0.09**	0.12	0.00	0.12	-0.03	0.05	0.00
		(0.04)	(0.13)			(0.03)	(0.12)	
Individual Crimes								
# Property Crime per km^2	35.92	-5.07*	15.35	0.00	40.14	-0.28	29.01	0.00
		(2.61)	(12.91)			(2.53)	(26.82)	
# Violent Crime per km^2	9.70	-2.62**	-1.26	0.00	9.75	-0.70	-0.92	0.01
		(1.15)	(1.58)			(0.79)	(0.92)	
# Homicide per km^2	0.05	-0.07***	0.06	0.00	0.05	-0.03	0.03	0.00
		(0.03)	(0.13)			(0.03)	(0.08)	

Significance: * p<0.1, ** p<0.05, *** p<0.01. Each coefficient comes from a different SDiD regression for the dependent variable (row) five years after the indicated treatment (column). We control for lag population. Equality of coefficients is tested with a paired t-test using the bootstrapped distributions. Only slums treated between 2015 and 2018 are considered since crime data is available from 2013. Slums sample for *in-situ* upgrading and population relocation are 80 and 129, respectively. Crime index follows Anderson (2008). Property crimes include burglary, theft, auto theft, theft from non-residential areas, and other economically motivated crimes. Violent crime refers to homicide and assault. All crime indicators refer to crimes per km^2 per year.

Table 9: Effect of Slum Renewal Policies on Housing in Neighboring Formal Areas —SDiD

	0 - 200 m				200 - 500 m			
Dependent Variable:	Mean Control (Level)	*In-situ* Upgra. β_1	Pop. Reloc. β_2	p-value $\beta_1 = \beta_2$	Mean Control (Level)	*In-situ* Upgra. γ_1	Pop. Reloc. γ_2	p-value $\gamma_1 = \gamma_2$
Housing Investment								
% New Buildings (age<5)	12.33	4.04***	2.65**	0.00	12.84	2.50***	2.19**	0.00
		(1.33)	(1.18)			(0.92)	(1.10)	
% Renovated Buildings	0.95	0.32**	0.13	0.00	1.06	0.22***	0.17*	0.00
		(0.14)	(0.14)			(0.08)	(0.10)	
Pr(Building Permits > 0)	0.21	0.10**	0.07	0.00	0.42	0.03	0.00	0.00
		(0.04)	(0.05)			(0.03)	(0.03)	
Log # Building Permits	0.48	0.13**	0.12**	0.98	1.98	0.13**	0.04	0.00
		(0.05)	(0.05)			(0.05)	(0.04)	
Housing Quality								
Log Building Age	18.59	-0.11**	-0.07**	0.00	19.21	-0.02	-0.05*	0.00
		(0.05)	(0.03)			(0.03)	(0.03)	
Log Building Size	68.93	0.11*	0.06	0.00	89.91	0.08	0.07	0.03
		(0.06)	(0.05)			(0.09)	(0.06)	
Log #Buildings, size > $64m^2$	14,108	-0.09	-0.01	0.00	22,971	-0.12	-0.04	0.00
		(0.08)	(0.08)			(0.10)	(0.07)	
SD Bldg. Main Angle Neighbors	9.30	0.35	-0.15	0.00	9.21	-0.10	0.09	0.00
		(0.24)	(0.19)			(0.30)	(0.20)	
Avg. Distance to Neighbors (m)	28.18	0.02	-0.18	0.49	29.33	-0.10	-0.20	0.03
		(0.87)	(0.77)			(1.10)	(0.80)	

Significance: * p<0.1, ** p<0.05, *** p<0.01. Each coefficient comes from a different SDiD regression for the dependent variable (row) six years after the indicated treatment (column). We control for lag population. Equality of coefficients is tested with a paired t-test using the bootstrapped distributions. Building age, building size, and renovations come from the land registry dataset. Number large buildings, building main angle, and distance between buildings come from building footprints. Outcomes related to building permits are from housing starts. Baseline mean for building permits is 2010 and for the rest of the variables is 2009.

Table 10: Effects of Slum Renewal Policies on Neighboring Formal Areas —TWFE

	0 - 200 m				200 - 500 m			
Dependent Variable:	Mean Control (Level)	*In-situ* Upgra. β_1	Pop. Reloc. β_2	p-value $\beta_1 = \beta_2$	Mean Control (Level)	*In-situ* Upgra. γ_1	Pop. Reloc. γ_2	p-value $\gamma_1 = \gamma_2$
Sociodemographics								
Log Population	1,117	-0.04	-0.21***	0.01	5,624	-0.07	-0.18***	0.05
		(0.07)	(0.06)			(0.06)	(0.05)	
% Adults with $\geq$ High School	57.68	1.47*	0.42	0.30	59.97	1.43*	-0.24	0.04
		(0.87)	(0.92)			(0.76)	(0.63)	
% Employed	84.76	1.18*	-0.67	0.01	85.20	0.86*	-0.68*	0.00
		(0.62)	(0.55)			(0.45)	(0.41)	
Housing Quality								
% Houses $\geq$ 2 Bedrooms	76.17	0.51	0.38	0.89	77.38	1.49**	-0.71	0.01
		(0.86)	(0.61)			(0.70)	(0.50)	
% Houses with High Quality Walls	84.27	3.62**	-0.79	0.03	84.54	2.15*	1.22	0.61
		(1.47)	(1.32)			(1.24)	(1.12)	

Significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered at the municipality level. Outcome variables come from the 2002 and 2017 population censuses. Each row corresponds to one pooled TWFE regression with two dummy treatment variables. Equal coefficient test p-value is a Wald test.

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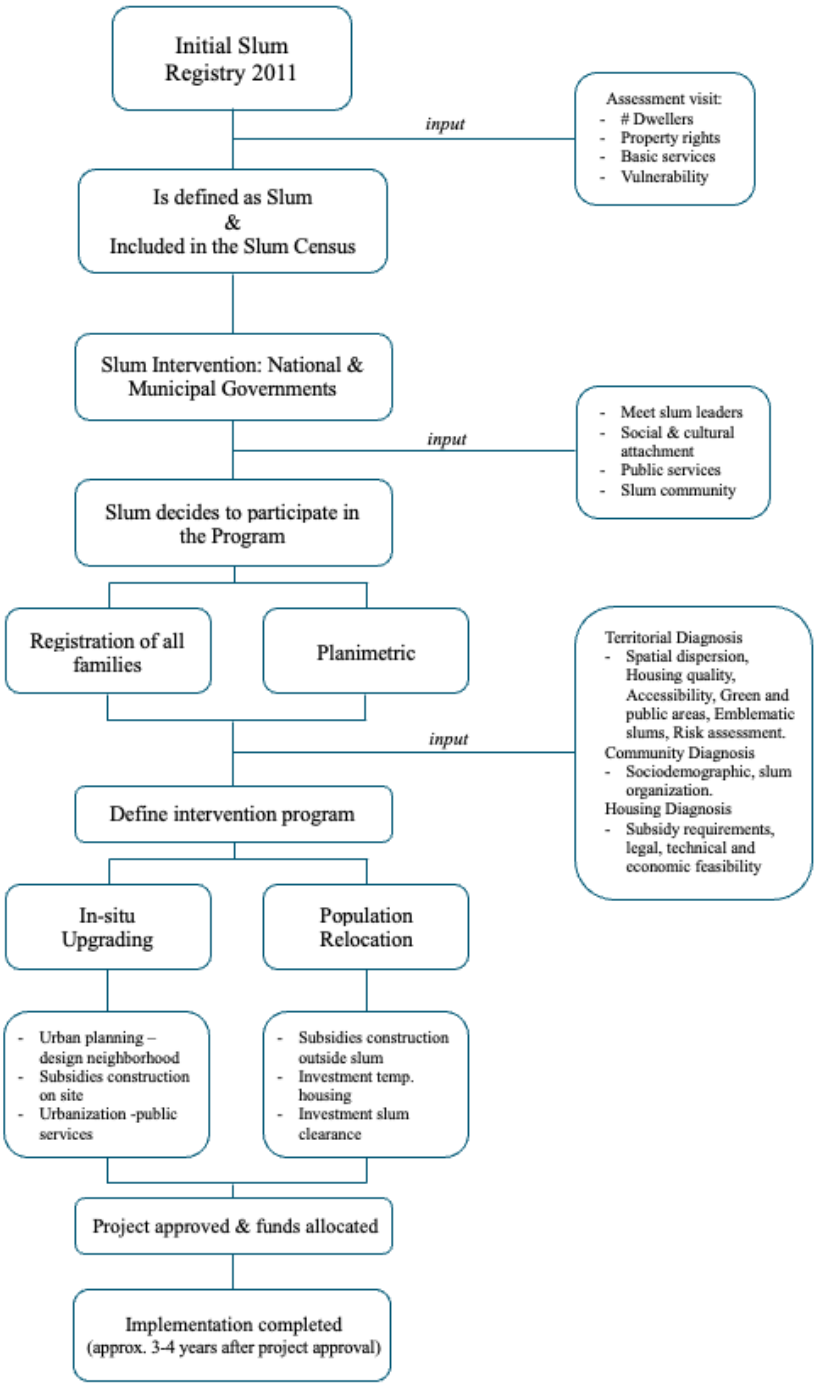
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A Flowchart Government Interventions

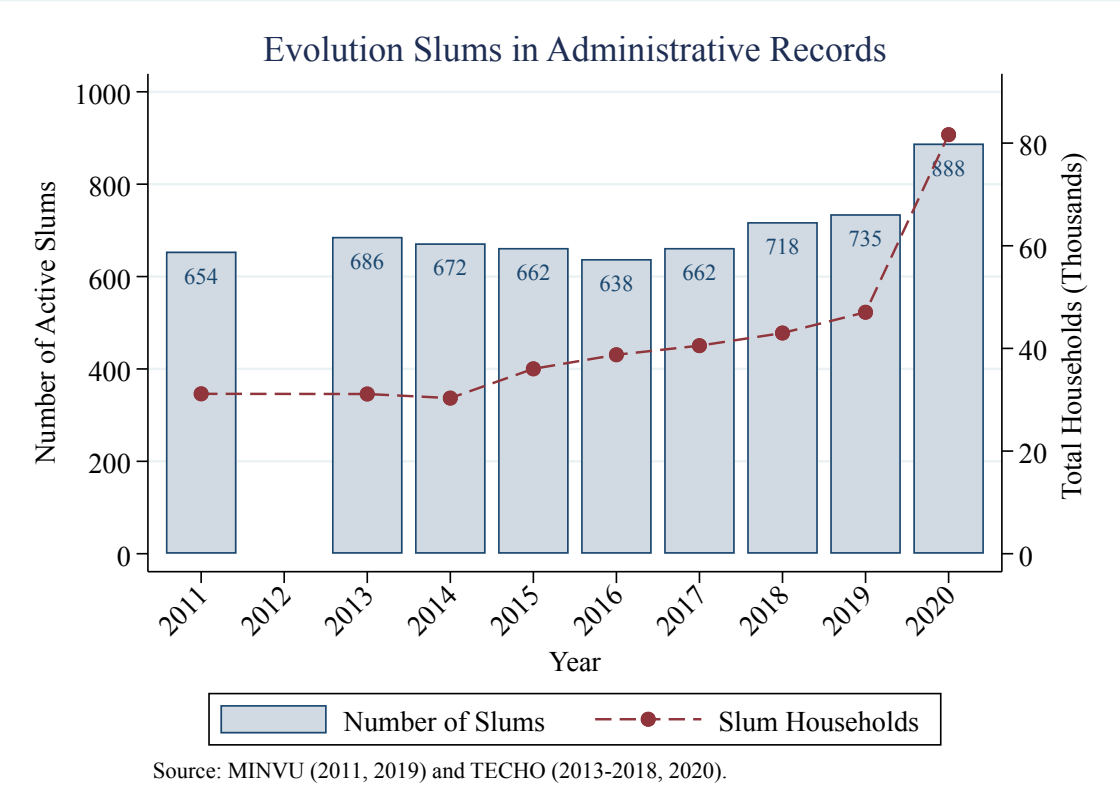
Figure A1: Flowchart Government Intervention



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

B Descriptive Analysis

Figure B1: Number of Active Slums and Slum Households in Administrative Records

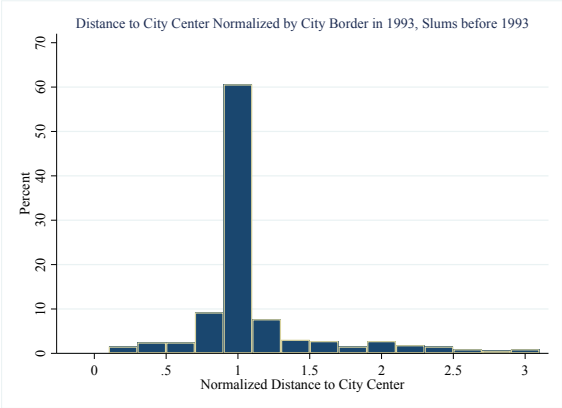


Active slums are to informal settlements included in administrative records. An area is considered a slum if it (i) has eight or more households spatially close, (ii) lacks property rights, and (iii) has no access to one or more of the basic needs services: electricity, sanitation and water.

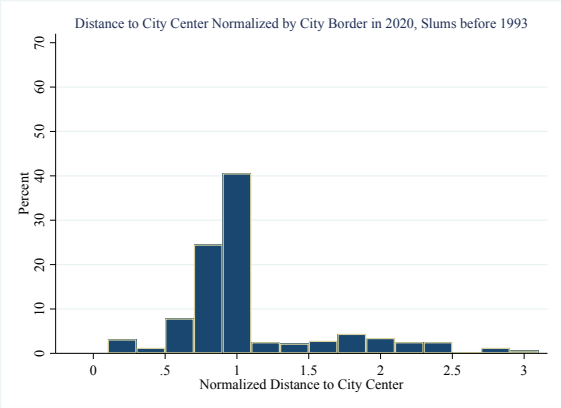
Figure B2: Location of Slums by Normalized Distance to the City Center

(a) Slums founded before 1993

1993 City Boundaries

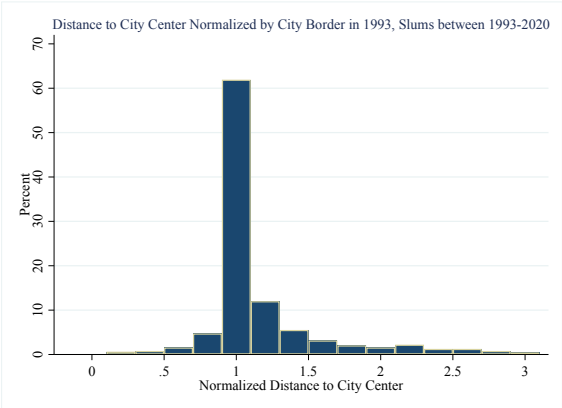


2020 City Boundaries

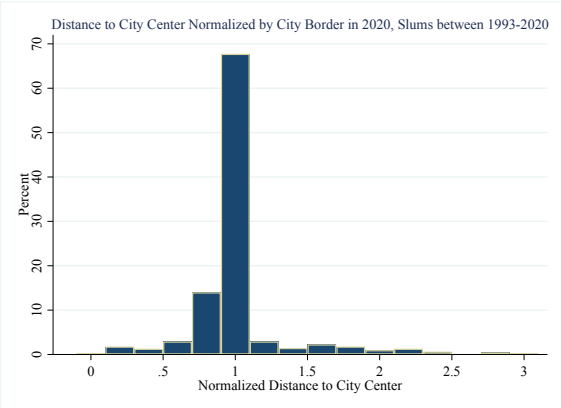


(b) Slums founded after 1993

1993 City Boundaries

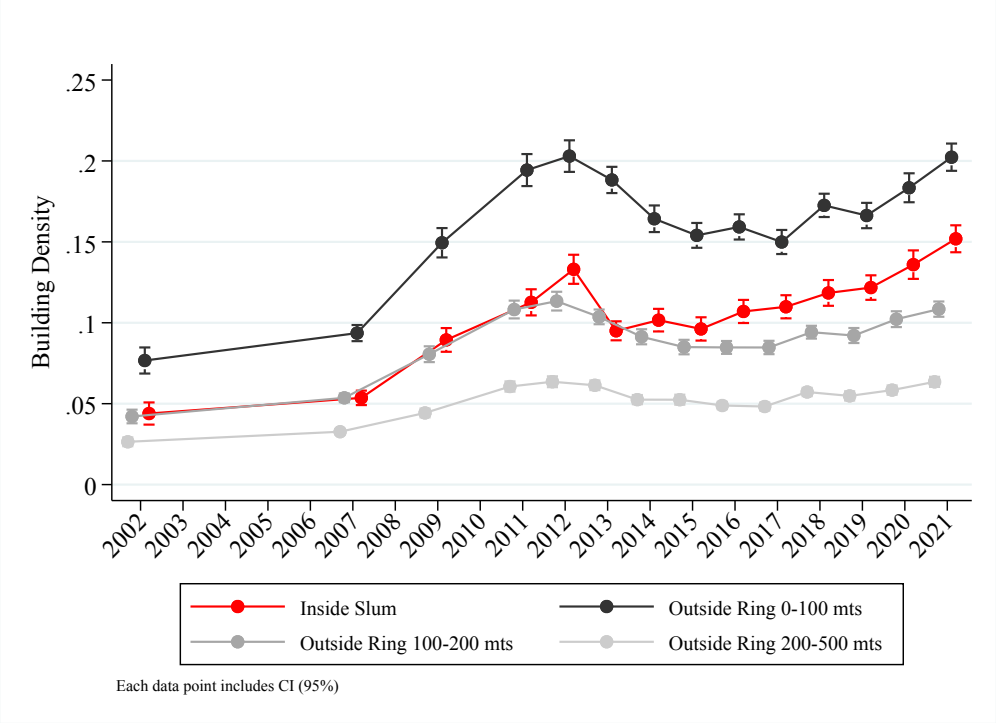


2020 City Boundaries



Normalized distance to the city center is calculated as the distance from the slum to the city center over the distance from the city center to the city boundary. Values close to zero indicate slum in the city center. Values of one represent location at the city border. City boundaries for 1993 and 2020 refer to the city continued urban construction (CUC). City centers are obtained from the Urban Functional Areas project (AUF for its Spanish acronym) by INE, MINVU, SECTRA and SUBDERE.

Figure B3: Evolution Building Density Inside Slums and Adjacent Neighborhoods



Building density is calculated using the building footprints obtained from Google Earth images.

C 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.[19] We explain below the four-stage process to identify polygons representing building footprints.

[19]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.

C.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 C1. 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.

C.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.

C.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 C1; 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.

C.4 Computing measures using building footprints

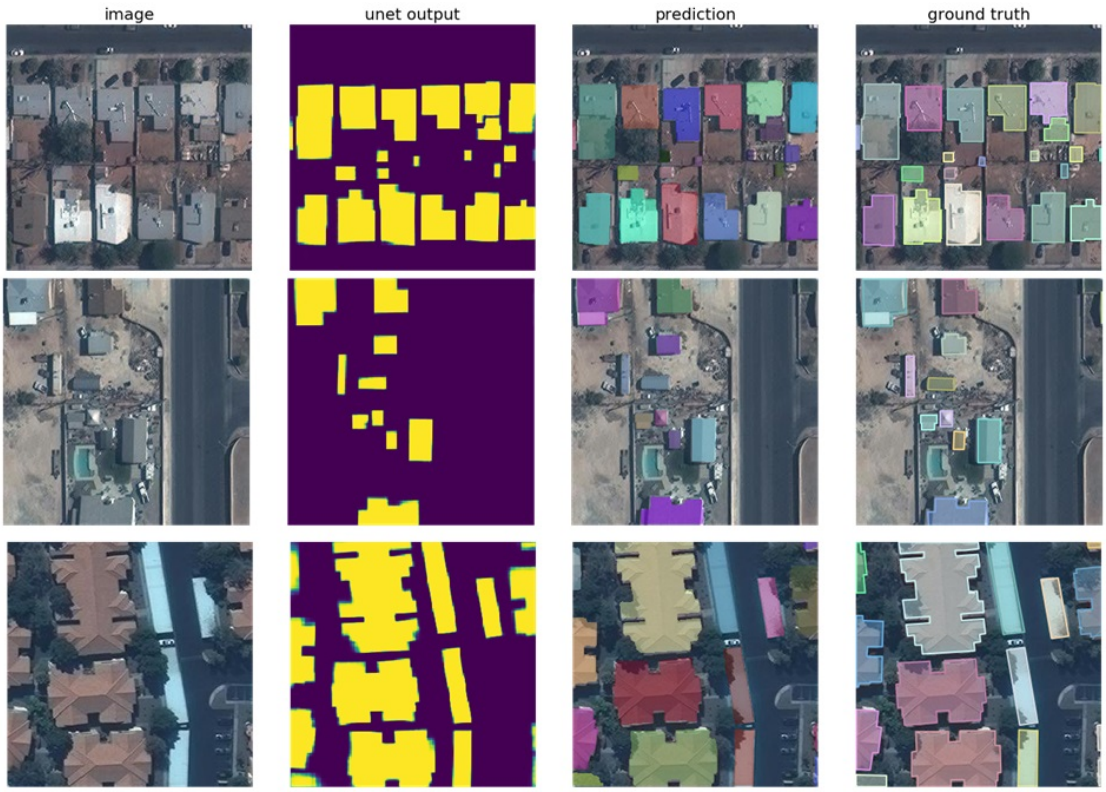
We computed different metrics to measure building activity and regularity inside and outside the slums. We began by calculating the total building area and building density within the slums. We also calculated these measures for areas within a certain distance of the slum border. Additional statistics 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.

C.5 Example building footprints

Figure C2 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 C2 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%.[20] 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.

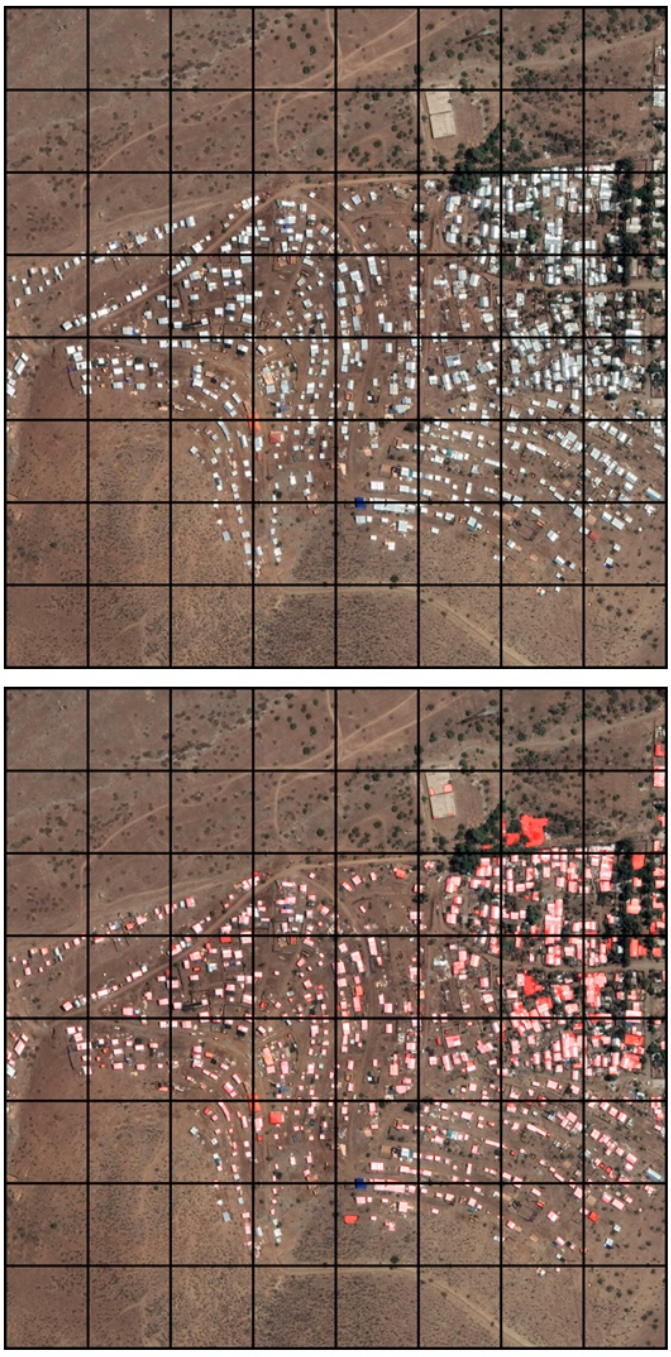
[20]Precision is calculated as the number of true predicted building footprints over the total number of predicted footprints. Recall has the same numerator but uses the actual number of building footprints as the denominator.

Figure C1: Performance ML Algorithm to Identify Building Footprints



Source: Czakon et al. (2021).

Figure C2: Example Predicted Building Footprints - Slum in Santiago Metropolitan Area



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.

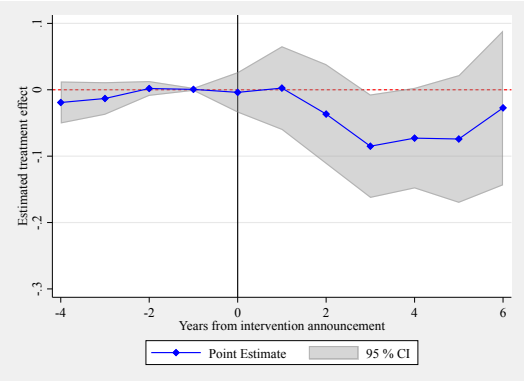
D Dynamics of SDiD Effects

We present here the event-study graphs for the different dependent variables presented in the main text in Tables 6 and 8. All of which were estimated using SDiD.

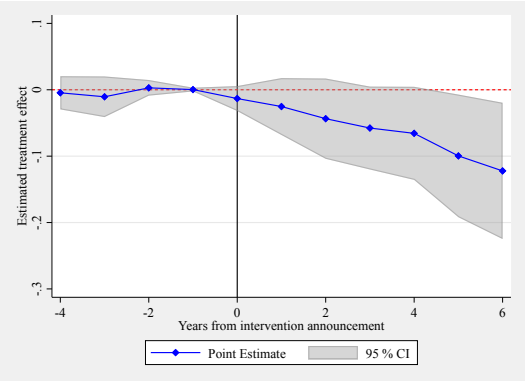
Figure D1: SDiD Direct Effects of Slum Policies

(a) Share of Land Devoted to Residential Housing

In-situ Upgrading

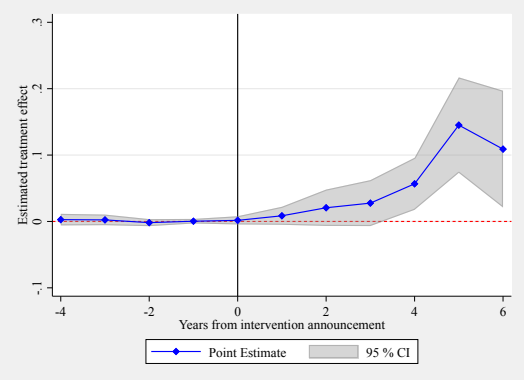


Population Relocation

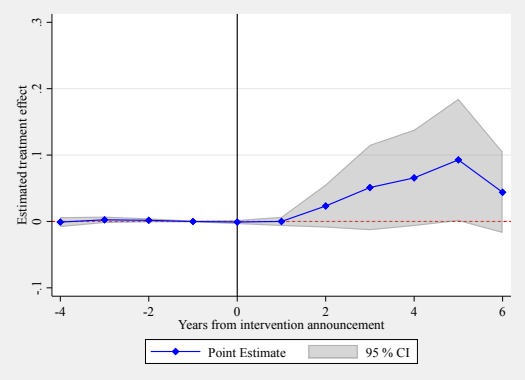


(b) Share of Streets Paved

In-situ Upgrading

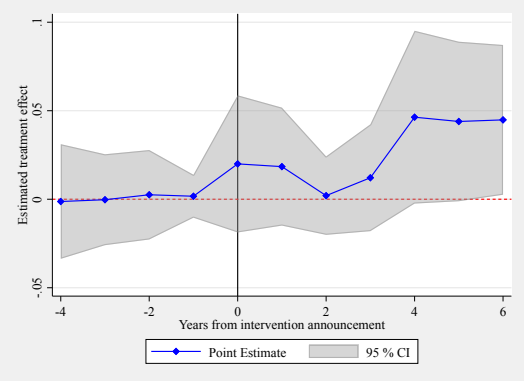


Population Relocation



(c) Pr(Building Permits > 0)

In-situ Upgrading



Population Relocation

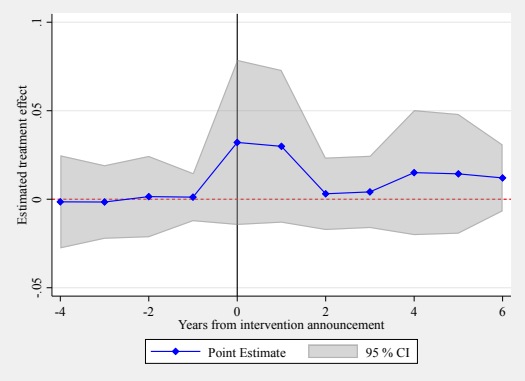
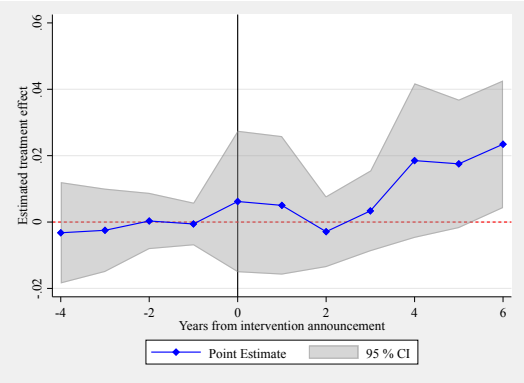


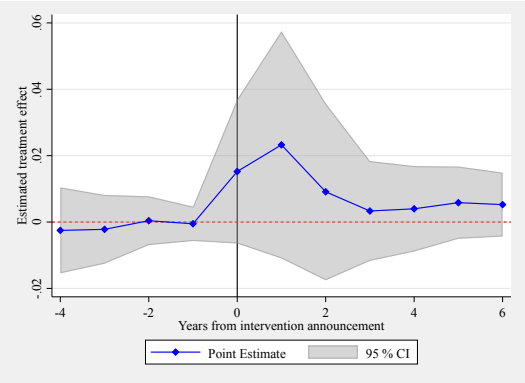
Figure D1: SDiD Direct Effects of Slum Policies (*continued*)

(d) Log # of Building Permits

In-situ Upgrading

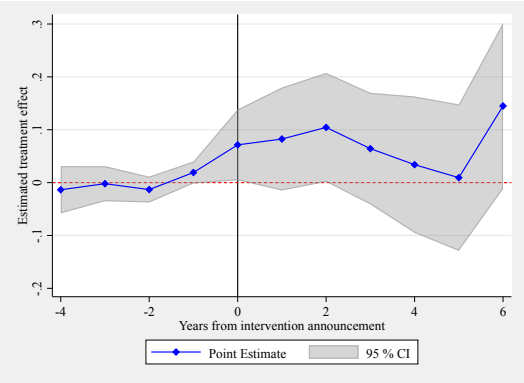


Population Relocation

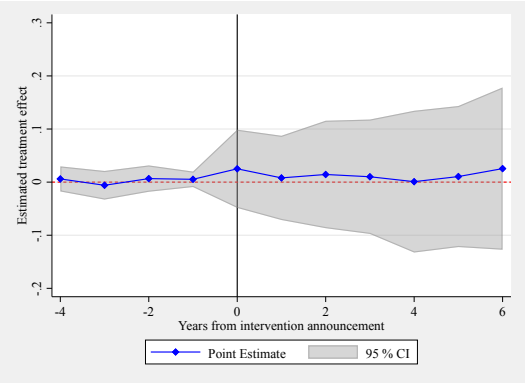


(e) Log # of Large Buildings (size $> 64\text{m}^2$)

In-situ Upgrading

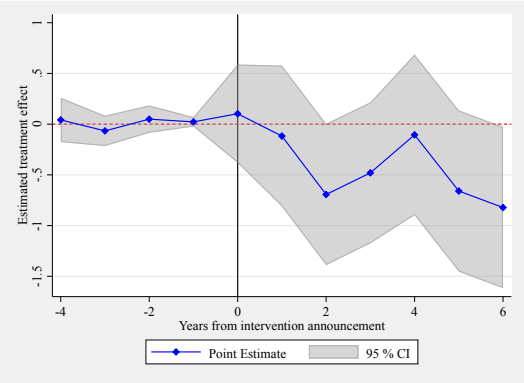


Population Relocation

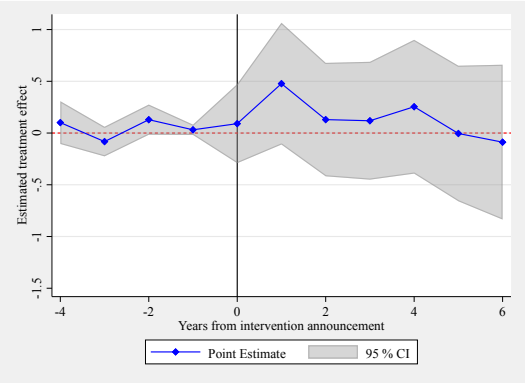


(f) SD Building Main Angle Across Neighbors

In-situ Upgrading



Population Relocation

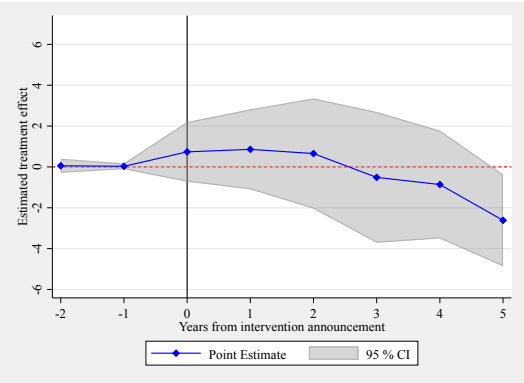


SDiD - Synthetic Difference-in-Difference methodology developed by Arkhangelsky et al. (2021). Confidence intervals are obtained using bootstrapping. We focus on slums treated between 2011 and 2017.

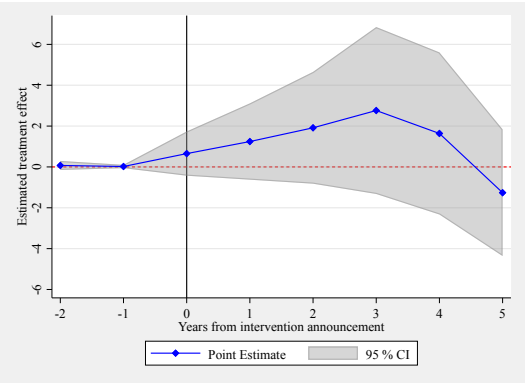
Figure D2: SDiD Spillovers of Slum Policies on Crime -Adjacent Neighborhoods

(a) Violent Crime per Km^2 within 200m of a Slum

In-situ Upgrading

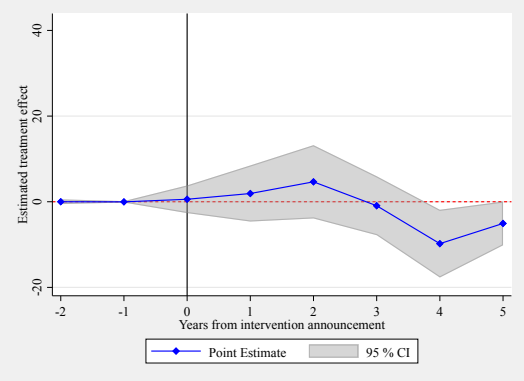


Population Relocation

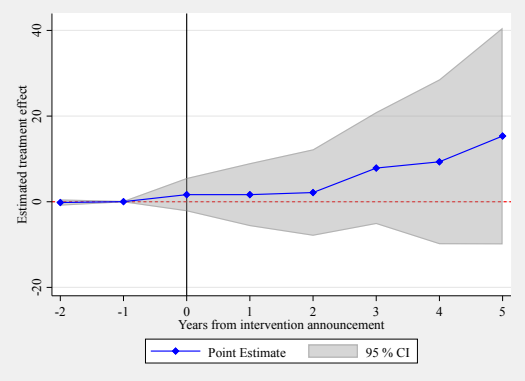


(b) Property Crime per Km^2 within 200m of a Slum

In-situ Upgrading

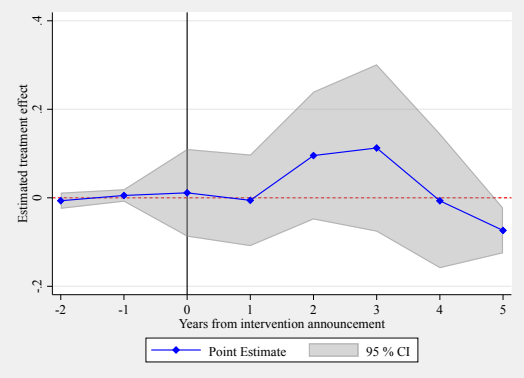


Population Relocation

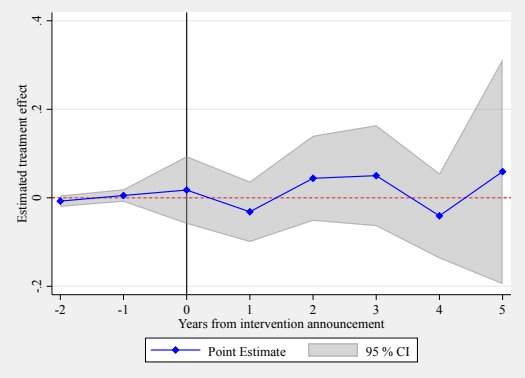


(c) Homicides per Km^2 within 200m of a Slum

In-situ Upgrading



Population Relocation

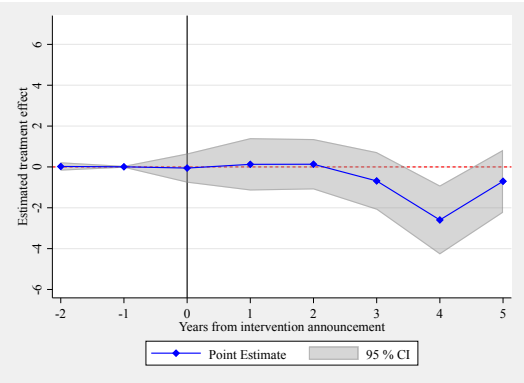


[a]SDiD - Synthetic Difference-in-Difference (Arkhangelsky et al., 2021). Confidence intervals are obtained using bootstrapping. Crime data come from the Subsecretaria de Prevencion del Delito, and data covers the sample of slums treated between 2015-2018.

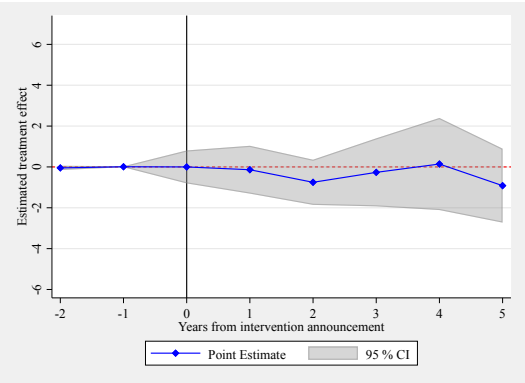
Figure D3: SDiD Spillovers of Slum Policies on Crime -Neighborhoods >200m

(a) Violent Crime per Km^2 within 200-500m of a Slum

In-situ Upgrading

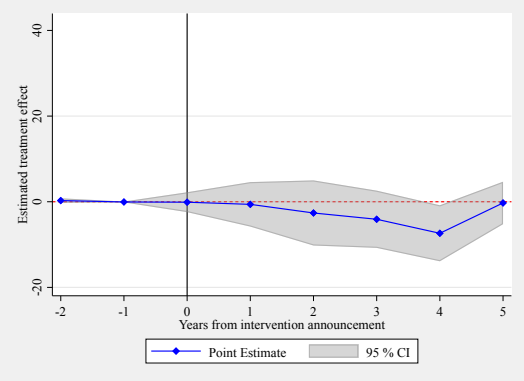


Population Relocation

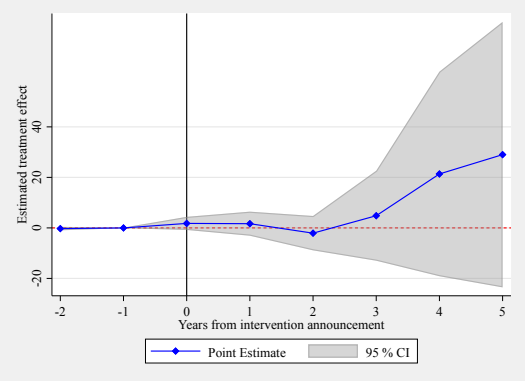


(b) Property Crime per Km^2 within 200-500m of a Slum

In-situ Upgrading

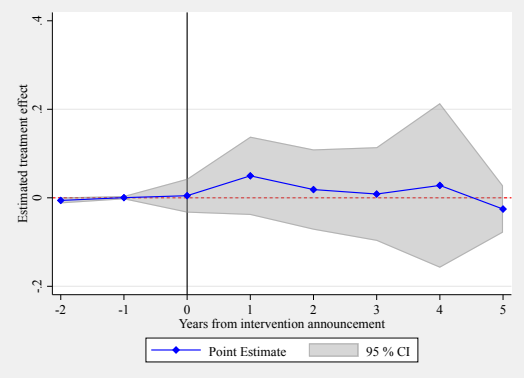


Population Relocation

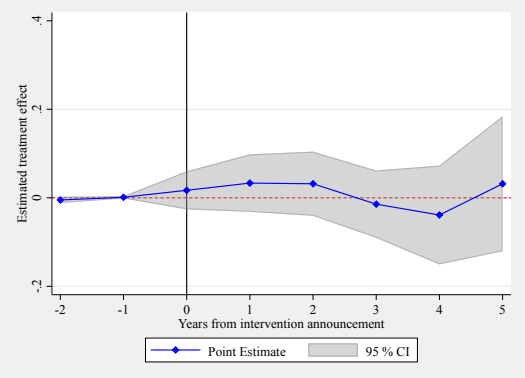


(c) Homicides per Km^2 within 200-500m of a Slum

In-situ Upgrading



Population Relocation



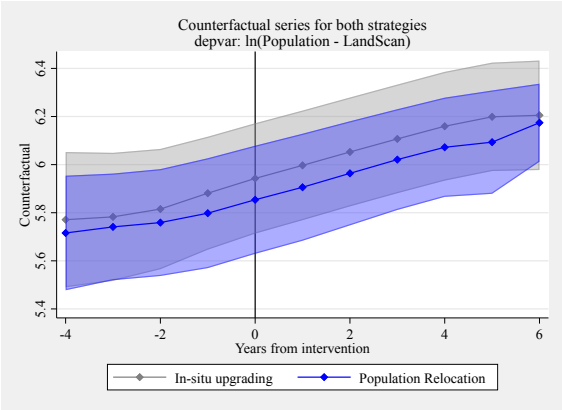
[a]SDiD - Synthetic Difference-in-Difference (Arkhangelsky et al., 2021). Confidence intervals are obtained using bootstrapping. Crime data come from the Subsecretaria de Prevencion del Delito, and data covers the sample of slums treated between 2015-2018.

E Counterfactuals for Both Policies

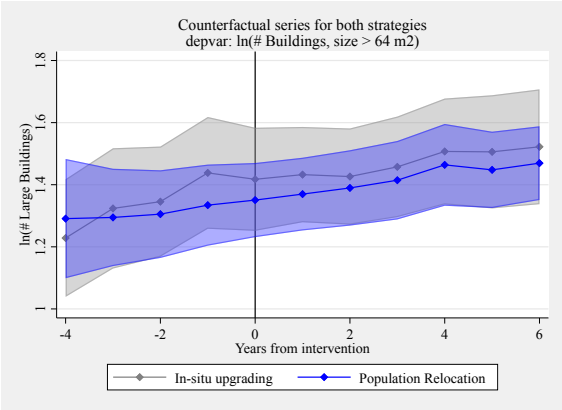
We plot the estimated counterfactuals under the SDiD estimation for both treatment strategies. Each estimation is done separately for each slum policy, meaning that the objective function for the optimal weights does not take into account the pre-treatment trends of the other treatment arm.

Figure E1: Counterfactual Synthetic Controls for the Two Policies

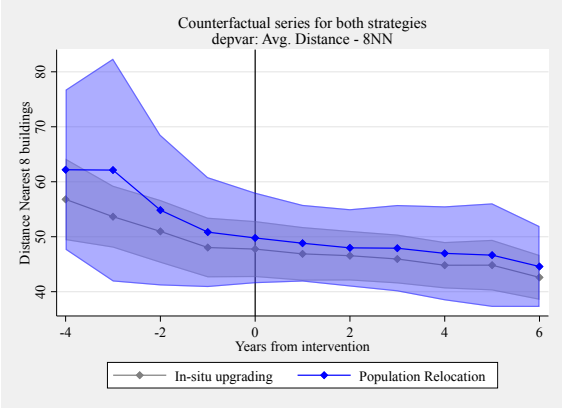
(a) ln(Population - LandScan)



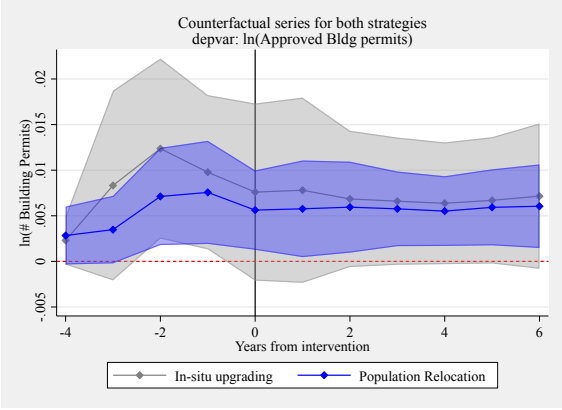
(b) ln(Large Buildings)



(c) Avg. Distance - 8NN



(d) ln(Approved Bldg permits)



Counterfactual Synthetic Controls correspond to the SDiD estimated series for the control group.

F Location Characteristics: Amenities & Terrain

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 F1 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.

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.

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 **??** 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.[21] 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.

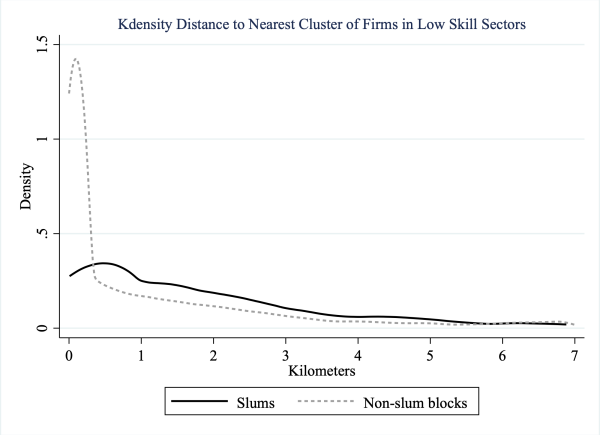
These results raise the question of why slums in big cities face riskier locations compared to those in small cities. The answer may lie in some of the findings documented in this

[21] TRI classification by ESRI is available here.

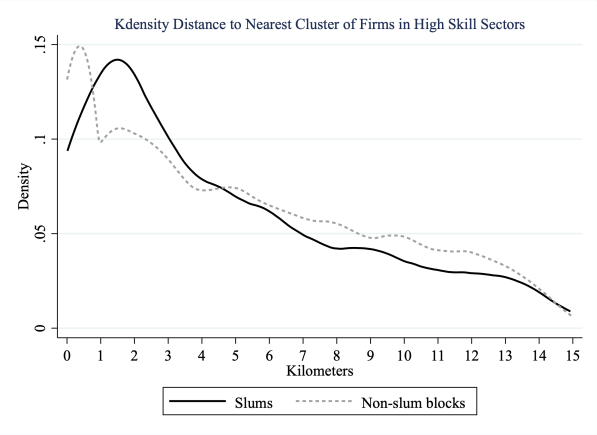
paper. Bigger cities have more competitive formal housing markets, leading to higher rents. Although larger cities offer a wider array of labor opportunities than smaller cities, they also push informal settlers to trade proximity to labor markets for access to amenities. If we consider a slum household 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 F1: Slums Proximity to Different City Amenities [a]

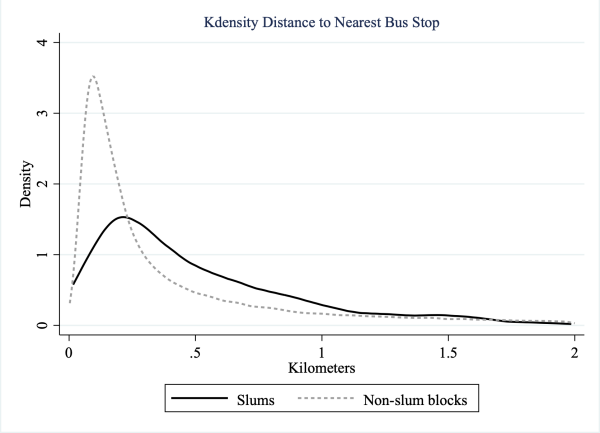
(a) Low-Skill Firms' Cluster



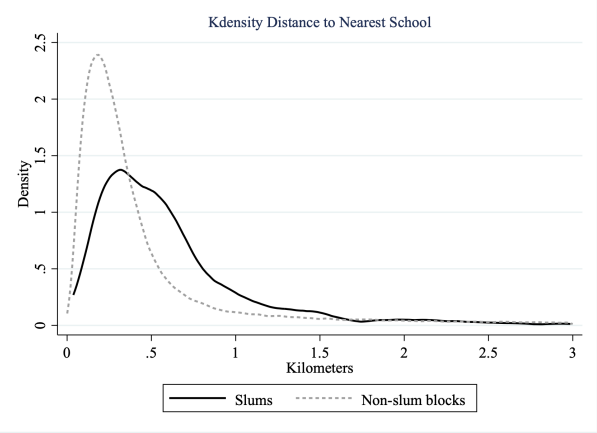
(b) High-Skill Firms' Cluster



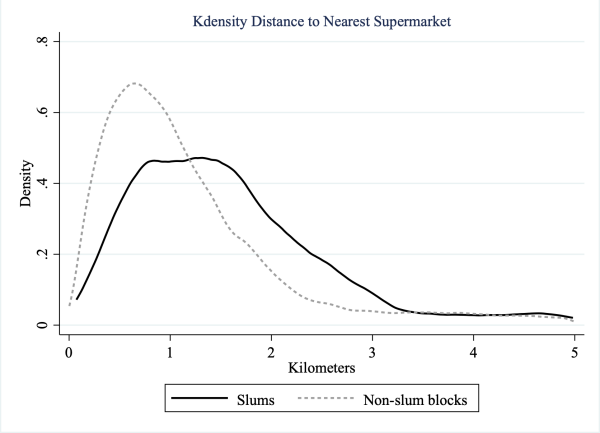
(c) Bus Stop



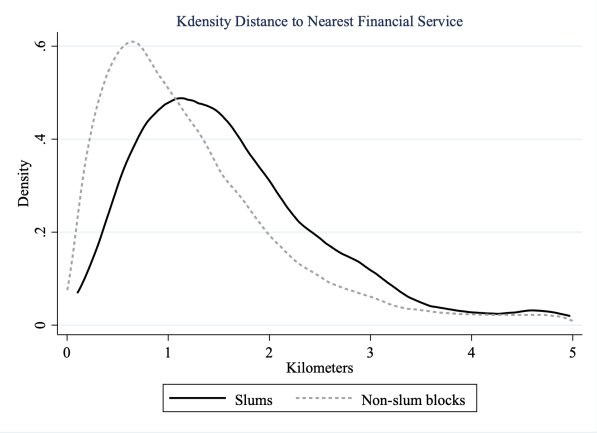
(d) School



(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.