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

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Abstract

Policies for existing slums in developing countries can generally be classified into two categories: 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 onto 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. We rely on Synthetic Difference-in-Difference for causal identification, and 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.

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1 Introduction

Slums continue to be a defining feature of urban life in low- and middle-income countries, as one in four urban residents - more than a billion people - live in slum conditions (UN-Habitat, 2020).[1] Slums are generally viewed as spaces of disadvantage, characterized by substandard housing and inadequate access to essential services such as clean water and sanitation, and as sources of negative externalities for nearby neighborhoods, limiting local economic development. Many governments invest heavily in large slum renewal policies to improve living conditions in slums and promote growth and development in surrounding areas. They traditionally pursue two main approaches: (1) *in-situ* upgrading programs that aim to improve slum living conditions by providing basic services such as land titling, safe water, electricity, and sanitation infrastructure, and, in many cases, improving the housing infrastructure itself; and (2) population relocation strategies that depopulate slums by resettling residents into formal housing located elsewhere. As rapid urbanization continues to strain housing markets and infrastructure, there is a pressing need for credible evidence on the cost-effectiveness of these policies. We help to fill this gap by examining the direct and spillover effects of slum renewal policies in the Chilean context, where both *in-situ* upgrading and population relocation interventions have been implemented simultaneously since 2011.

One of the primary challenges to generating rigorous evidence on slum policy is the absence of high-quality representative data that track the evolution of slums over time and space (Marx et al., 2013). A central contribution of this study is to assemble a panel of the universe of slum areas that spans more than two decades. The starting point is the set of georeferenced polygons that were ever officially designated as slums at any point in time between 2011 and 2021. Each year, active slums were identified based on three conditions: (i) an area that is home to at least 8 spatially close households, (ii) households do not have property rights, and (iii) houses are of substandard quality and lack access to at least one of the basic services (water, sanitation, and/or electricity). Since slum boundaries change over time, we define each slum's area as the combined footprint of all its observed polygons across years.

We used historical Google Earth satellite images to track the evolution of land use within these polygons beginning in 2000 and follow them up to 2021. Using mask image-processing CNN algorithms, we identify built structures inside slums and up to 500 meters just outside slums. We measure physical characteristics such as building area, building density,

[1] The literature has identified several structural determinants of slum formation, including weak enforcement of property rights, underdeveloped capital and housing markets, and low levels of human capital (Field and Kremer, 2008; Glaeser, 2011; Marx et al., 2013; Collier and Venables, 2015; Brueckner and Lall, 2015; Duranton and Venables, 2020; Henderson et al., 2021).

similarities in orientation angle, and proximity between buildings. We merge building investment information from georeferenced building permits and property tax records for all formal housing in surrounding formal neighborhoods adjacent to slums. We also merge socio-economic information on residents from population censuses, as well as information on criminal activity using geocoded administrative crime records.

The data provide a nuanced picture of the formation and evolution of slums that is consistent with several of the central themes in the theoretical literature.[2] When slums appear, they form overwhelmingly at city boundaries in areas situated at higher elevations, on steeper slopes, in locations with greater overall ruggedness, closer to rivers and closer to firms that employ low-skill workers. Slums on average have worse access to public amenities such as schools, supermarkets, and public safety services. Initially, slums are populated with low-educated single males. However, over time the socio-economic characteristics of slum residents (e.g., education, gender, and marital status) converge to those of their nearby non-slum counterparts. Slum populations grow faster in cities where quality-adjusted housing rents increase rapidly, but wages for low-skilled workers do not keep up.

This paper's main objective is to evaluate and compare the impacts of *in-situ* upgrading and population relocation policies on living conditions in slums and spillovers to adjacent formal neighborhoods. We use Synthetic Difference-in-Differences (SDiD) to estimate the causal effects (Arkhangelsky et al., 2021; Clarke et al., 2023). Both policies began implementation in 2011, but were rolled out staggeredly across slum areas. Our 20-year panel dataset enables us to repeatedly observe each slum for 10 years before and 10 years after this initial implementation date. By tracking whether and when each slum was affected by one of the two renewal policies or remained untreated, the SDiD estimator combines Difference-in-Differences with Synthetic Controls (Abadie and Gardeazabal, 2003; Abadie, 2021) and accounts for differential timing of treatment. In this approach, the control group for each treatment is chosen from the set of slums that have not yet been treated. SDiD assigns an optimal weight to each potential control, so that the control group looks similar to treated group in terms of the pre-intervention trends. Since projects typically take between two and four years from assignment to implementation, we measure policy impacts six years after treatment assignment to ensure sufficient time for effects to materialize.

We find that population relocation reduces the slum population by 16 percent, which in turn leads to a 12 percent reduction in the amount of land used for residential purposes, on

[2]For models of slum formation, see Jimenez, 1984, 1985; Duranton, 2008; Brueckner and Selod, 2009; Brueckner, 2013; Duranton and Puga, 2015; Cavalcanti et al., 2019; Henderson et al., 2021; Duranton and Puga, 2023 and Cavalcanti et al., 2024. For studies focusing on how location and economic conditions (labor and housing markets) can explain the formation and evolution of slums, see Glaeser, 2011; Marx et al., 2013; Wong, 2019; Cavalcanti et al., 2019; Henderson et al., 2021; Alves, 2021; and Gechter and Tsivanidis, 2023).

average. While consistent with the main program objective of relocating slum dwellers to non-slum areas, it falls well short of the stated objective of clearing the slums completely of inhabitants. This is partly because the program is voluntary and most residents choose not to leave (often due to social ties or proximity to employment) and partly because cleared slums are typically quickly repopulated with new slum dwellers. In contrast, we find no effect of *in-situ* upgrading on population, consistent with the program's objective of enabling residents to stay in place in better living conditions.

We also find that *in-situ* upgrading has significant positive effects on both housing quality and infrastructure. Specifically, the share of paved streets in upgraded slums is double relative to that in control slums. Upgraded sites are more likely to have new formal housing and improvements in existing structures. Housing units in upgraded slums are also more likely to be larger and have two or more bedrooms. *In-situ* upgrading also generates more regularly oriented structures that are spaced further apart, suggesting coordinated formalization. Finally, upgraded slums attract a better educated population. In contrast, we find no effect of population relocation on housing quality or the composition of slum residents.

What impacts do the two policies have on the areas surrounding the treated slums? We find that *in-situ* upgrading has strong positive spillover effects in adjacent neighborhoods across a range of outcomes. Specifically, there is an increase in investment in both new and existing housing. New housing starts are 10 percent higher and existing buildings are more likely to have undergone renovation. These improvements in housing attracted higher-SES residents in terms of education and employment. Finally, we find a significant reduction in both violent and property crimes. On average, there was 15 percent less property crime, 25 percent less violent crime, and the number of homicides dropped precipitously. In contrast, there were no significant and sizable effects of population relocation in formal neighborhoods adjacent to treated slums.

Taken together, the evidence on direct impacts and spillover effects provides strong support for *in-situ* upgrading as a more effective strategy than population relocation to promote the development of more desirable neighborhoods. Furthermore, the average fiscal expenditure per slum household is approximately one third lower for *in-situ* upgrading relative to population relocation, implying that upgrading is more cost-effective, further strengthening its policy appeal. However, it is important to acknowledge that *in-situ* upgrading may not be feasible or appropriate in all contexts. For instance, upgrading may be impractical or cost-prohibitive when the land is privately owned and subject to ongoing legal disputes. Similarly, in cases where informal settlements are located in areas that are vulnerable to natural hazards, such as flood-prone zones, relocation may represent the only viable policy alternative.

The main contribution of this research is to directly compare the two main slum renewal policies that address the challenges of slum growth. A key input for this analysis is a high-resolution, yearly panel of slum areas spanning more than two decades, which requires methodological advances not only in policy evaluation but also in slum detection and spatial analysis. We build on recent advances in earth science, computer science, and economics that have led to powerful analytical tools to map spatial development patterns (Michalopoulos and Papaioannou, 2018), and particularly innovative methods for identifying and delineating the spatial extent of slums (Gechter and Tsivanidis, 2023; Montana et al., 2016; Friesen et al., 2018; Ansari et al., 2020; Abascal et al., 2022; Najmi et al., 2022; Fisher et al., 2022; Garnica-Peña and Delikostidis, 2024; Prabhu, 2024; Arndt et al., 2024; Büttner et al., 2024).

Previous work has studied the impact of slum renewal policies, yet only individually, 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); and Franklin (2020).[3] There is also evidence on policies aimed at preventing the emergence of slums through infrastructure planning (Michaels et al., 2021) and land titling programs (Field, 2005, 2007; Galiani and Schargrodsky, 2010).

Our work is closely related to Harari and Wong (2024), who examine the long-term impact of an extensive slum upgrading program in Jakarta, the Kampung Improvement Program (KIP). They find that areas that underwent KIP upgrades have, on average, 15% lower land values and 50% fewer high-rises 40 years later. Importantly, while the KIP program improved access to basic public services, it did not formalize property rights in terms of ownership titles —unlike the Chilean *in situ* upgrading program. The authors hypothesize that the absence of land titles may have delayed formalization. However, KIP did deliver significant positive spillover effects in nearby locations, suggesting a trade-off between upgrading and preserving slums as cities expand.

Our results differ from the KIP program, in part due to the fact that the *in-situ* upgrading program in Chile *de facto* formalized property rights by providing beneficiaries with land titles along with formal housing. In fact, after the intervention, the slum was no longer considered a slum. Inhabitants obtained formal property rights and live in a neighborhood with access to all public services.

Another closely related study is Rojas-Ampuero and Carrera (2023), which examines an involuntary slum clearance program implemented in Santiago, Chile during the 1980s. Some slum households were forcibly relocated to formal neighborhoods elsewhere, while others received improved housing through *in-situ* provision. They find that children from relocated

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

households experienced significantly lower educational attainment and earnings compared to those who remained in their original locations but benefited from improved conditions. Our findings are not comparable by design, but are complementary. While Rojas-Ampuero and Carrera (2023) focus on individual outcomes, our paper examines outcomes for slum areas, i.e., our unit of analysis are not individuals, but rather spatial units whose characteristics reflect the conditions of their residents. Second, they compare *in-situ* upgrading versus population relocation in a non-voluntary setting, where relocated slum dwellers were evicted and forced to move to public housing projects elsewhere. Finally, their research design allows to compare displaced (relocated) versus non-displaced (in-situ upgrading) groups, yet no control group is available to test for the effect of each intervention separately.

2 A Brief Overview of Slum Renewal Policy in Chile

Adequate housing for slum dwellers, estimated at 10–20% of the population in the 1960s (Hidalgo, 2019), has been a long-standing policy issue in Chile. The government established the Ministry of Housing and Urbanism (MINVU) in 1965 to address housing conditions. Its first major program, "Operación Sitio," provided low-income households with urban plots equipped with basic infrastructure such as water, electricity, and sanitation, on which residents built their homes. Public housing expanded significantly with slum dwellers given priority for access to new housing during President Allende's administration (1970–1973). However, due to massive rural-to-urban migration, the demand for housing continued to overwhelm supply, so that slums continued to expand.

Under the Pinochet dictatorship (1973–1989), housing policies underwent extensive neoliberal reform (Rojas-Ampuero, 2025). New public housing was often located on the periphery of cities in areas with low land costs but high unemployment and limited access to public services. The average size of public housing units decreased from an average of 60 square meters in the 1960s to less than 30 in the 1980s. A signature policy of Pinochet was the "Program for Urban Marginality" (1979–1985), a large-scale slum clearance and relocation initiative that affected 340 slums and more than 40,000 residents. The program provided formal housing ownership to slum dwellers, but was implemented through forced relocation.[4]

Following the return to democracy in 1990, the supply of public housing again expanded. For the first time, private firms developed most of the new public housing units financed through demand-side subsidies. Although the new housing helped contain the expansion of

[4]Rojas-Ampuero and Carrera (2023) assess the long-term effects of such displacements. By comparing forcibly relocated households with those who received on-site public housing, they find that displaced children earn 9% less and complete 0.8 fewer years of education on average. They also tend to work in more precarious, informal jobs and are more likely to live in high-poverty neighborhoods as adults.

slums, informal settlements remained a prominent feature of urban landscapes (Celhay and Undurraga, 2022).

Slum renewal policy returned to the center of Chile's policy agenda after MINVU implemented a national slum census in 2011 (MINVU, 2011). Contemporary slum renewal policy centers on two main interventions: *in-situ* upgrading and population relocation. *In-situ* upgrading is a slum renewal policy that improves infrastructure and housing conditions within slum areas without displacing residents. In contrast, the population relocation policy offers residents of informal settlements the option to move to formal housing outside the slum. In some cases, the policy also includes public investment in demolishing the original slum structures and repurposing the cleared land for public use. Contrary to the Pinochet years, both approaches are voluntary and seek to incorporate informal settlements into the formal urban fabric. Since 2011, MINVU has invested more than US$400 million in these interventions.

3 Data and Description

One of the major contributions of this paper is to assemble a long panel of time-varying characteristics of the universe of slums in Chile. The first step is to identify areas that have, at any point in time, been identified as a slum, where a slum is defined as a cluster of at least eight houses that lack access to basic services and property rights. Chile used this definition to identify slums as part of a set of national censuses of slums conducted between 2011 and 2020.[5] Census staff worked with municipalities to locate and geo-code potential slum sites, and then sent enumerators to visit those sites to verify that they met the definition of a slum and conduct a short survey of all households. The number of slums increased from around 650 in 2011 to almost 900 (a 36 percent increase) in 2020, while the number of households living in slums more than doubled from approximately 31,000 to more than 80,000 over the same period (see Appendix Figure C1).

3.1 Slum Location

The geo-coded data allow us to visualize location of slums within the urban footprint. For example, Figure 1 illustrates where slums are located in one particular city,Valparaiso, along with the urban footprint in 1993 and 2020. In this case, slums are primarily located in the city's periphery. In addition, newer slums – those established after 2010 – tend to be

[5]The censuses were conducted by MINVU and TECHO, a local housing NGO, and are available for the years 2011, 2016, 2017, 2018, 2019, and 2020.

located in the expansion areas of the urban footprint. These patterns are present in the entire country.

Slums tend to occupy less advantageous terrain than non-slum areas. This is presented in the bottom panel of Table 1, where we report the results of regressions of the terrain characteristics of census blocks against a dummy that equals one if the census-block area overlaps an ever-slum area and is zero otherwise. Specifically, the results confirm that slums are located at higher elevations, on steeper slopes, and They are also closer to rivers, which is consistent with a higher risk of flooding. overall, slums are located in areas of greater ruggedness and risk.

The slum census blocks are also located farther from essential public and private amenities than are non-slum census blocks. The top panel of Table 1 reports the results of regressions of the distance to each amenity against a dummy that equals one if the census-block area overlaps an ever-slum area and is zero otherwise.[6] The results show that slums indeed tend to be located further away from essential amenities such as schools, supermarkets, financial institutions, fire stations, and police stations.[7] Using a standardized index of distance to amenities, slums are 0.6 standard deviations further away from urban amenities than the average non-slum block.

3.2 Built Structures and Land Use in and around Slums

An important part of the data is the evolution of the built environment within and around slums. This requires knowing the geographic boundaries of the slums ever-identified in the censuses. The perimeter of each slum was geo-coded in each census enabling us to track a slum's boundary as it expands or contracts over time. We define the unit of analysis as the spatial union of all observed boundaries associated with each slum —which we refer to as an "ever-slum area". As illustrated in Figure 2, the constructed polygon captures the maximal footprint throughout the study period.

We used satellite images for the period 2000 to 2022 to measure built structures within and around the ever-slum areas. We downloaded approximately 90,000 satellite images from Google Earth following Huang et al. (2021).[8] Each image covers approximately 1 km^2 and captures the area where the ever-slum polygon is located, as well as the adjacent non-slum neighborhoods. This allows us to study changes in the built environment in years before an area is identified as a slum in the 2011 slum census.

[6]For references to the data sources used to compute distance to amenities, see Appendix Table B.

[7]The only exceptions being distance to health centers, where the coefficient on distance is positive but not significantly different from zero.

[8]Code to download images from Google Earth is available at GitHub website.

To identify building structures from the satellite images, we trained a machine learning (ML) algorithm that leverages recent advancements in image processing. 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) and achieves high accuracy, with a precision level of 0.94. Details on the image processing procedure and model calibration are provided in Appendix D.[9] With predicted building footprints obtained from the time-stamped images, we computed metrics such as total building area, building density, and measures of building regularity for both structures inside and outside slum polygons over time.

We complemented the machine learning analysis with human observational data (HOD). Six research assistants were tasked with viewing and selecting the first image with sufficient quality to clearly identify building structures for each slum and each year. For each images, they reported the number of recreational facilities, the presence of paved roads, and the coverage of residential and vacant land using four categories: none (<5%), some (5–49%), most (50–95%), and all (>95%). Each image was processed by two different research assistants, and any discrepancies were resolved by a supervisor.

Using these data, Figure 3 shows the evolution of building density inside and outside slums over the last 20 years. In the early 2000s, the typical slum and surrounding non-slum area were mostly vacant land with limited development. Between 2007 and 2012, there was a rapid increase in building density inside slums, a lull until 2016, and then a rapid rise again until 2021. This suggests a dynamic of slum development that, while in general increasing, can also observe periods of reduced activity.

We combined the satellite-gleaned data with detailed information about building structures from the Chilean Internal Revenue Service. This dataset includes variables such as building size, primary construction material, year of construction, year of last renovation, and assessed property value. However, it does not offer information about the internal configuration of buildings —such as the number of bedrooms, bathrooms, or floors.[10]

[9] The ML strategy involves a four-stage process. First, we pre-processed high-resolution images by fragmenting each $4,800 \times 4,800$-pixel image into 256 tiles of 300×300 pixels to optimize the model's performance and manage computational resources efficiently. Second, the 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.

[10] Although assessed value is included in the dataset, it follows an appreciation formula that does not fully capture changes in the real estate market. This data was obtained through a partnership between the University of California - Berkeley and the ESE School of Business of Universidad de los Andes, Santiago de Chile.

Finally, we integrated data on construction of residential and commercial buildings from 2010 to 2022 available from the National Statistics Institute (INE). These data are compiled from building permits submitted to municipal planning departments and subsequently reported to INE, which consolidates them into a nationwide dataset. We successfully obtained permit data for approximately 90% of municipalities.

3.3 Population and Slum Growth

We merge the WorldPop 100mX100m dataset to the ever-slums for the years 2011-2017. We can use both the WorldPop and block-level Population Census data to perform one of the first descriptive cross-city analyses of municipal slum population growth. We can estimate a long difference regression of slum population against a series of variables that have been suggested in the literature as drivers of slum growth. These are housing costs, wages, employment, and municipal expenditures.

Table 2 shows the results. Column (1) uses WorldPop's 100-meter resolution estimates for the years 2011 to 2017, while column (2) relies on census data from 2002 to 2017. This analysis suggests that, as expected from extant literature, quality adjusted housing rents are an important driver of municipal slum population growth. A one standard deviation increase in quality-adjusted rent is associated with a 24-29 percent increase in the slum population.[11] Given lower income households' limited ability to afford housing, as formal housing becomes more expensive, some may turn to informal settlements as a way of reducing housing cost burdens.

Also as expected, higher wages for low-skilled workers (less than high school) reduce the growth of populations living in slums. A one standard deviation increase in wages is associated with a 21–22% reduction in the slum population, on average. This suggests that higher earnings enable low-income households —arguably those most at risk of residing in informal settlements— to avoid living in slums. Finally, employment growth and municipal expenditure growth do not predict slum population growth in the data.

3.4 Socio-economic Composition in and around Slums

We next merged in data from the 2002 and 2017 population censuses at the block level. On average, each block contains 100 people and 33 households. We use the geocoded block centroid to determine if it falls inside the slum boundary or not. If the block's centroid is

[11] Our quality-adjusted rent measure is built using the CASEN household survey, and 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), which capture municipality-specific rental prices after controlling for housing characteristics.

inside a slum, we label that block as representing slum population. If it falls outside the slum perimeter, we classify it as a non-slum population.

These data shed light on how slums compare to nearby non-slum areas in terms of socioeconomic characteristics. Table 3 presents descriptive statistics, comparing census blocks in slum areas with blocks located between 200 and 500 meters from the slums' borders. We ignore blocks exactly adjacent to the slum, as they may suffer from misclassification issues.

The table shows that the average population living in ever-slum areas increased by 11.2% between 2002 and 2017, more than twice the rate of growth in nearby blocks (4.9%). Another notable pattern is the shift in the demographic composition of slums: whereas in 2002 slums exhibited a pronounced over-representation of adult males—reflected in an adult male-to-female ratio of 1.3—by 2017 this ratio had declined to 0.97, aligning closely with that of adjacent non-slum areas. This suggests a dynamic in family structure in which males initially populate slums and families follow. In terms of education, slum dwellers also show some convergence in secondary and tertiary education. Overall, the economic census data suggests a dynamic for slum inhabitants whereby, as time passes, their socioeconomic characteristics catch up to those of their nearby non-slum counterparts.

3.5 Crime

We obtained crime incident reports compiled by the Under-Secretary for Crime Prevention (Subsecretaría de Prevención del Delito, SPD), based on records filed by the national police and geocoded ex-post using address information. The dataset covers the entire country and includes georeferenced crime events occurring between 2013 and 2021 within a 500-meter radius of all identified slum polygons. A key limitation of this dataset is that, due to the reliance on address-based geocoding, crimes occurring within slums themselves are systematically underreported or entirely excluded, given the lack of standardized addresses in these informal areas. Consequently, the dataset is only suitable for analyzing spillover effects into surrounding formal neighborhoods, rather than for estimating direct crime impacts within slums. As such, in our results we can only report impacts on crime for areas outside slums.

4 *In-situ* Upgrading vs Population Relocation

The slum renewal policies examined in this study emerged from the Chilean government's mandate, through the Ministry of Housing and Urban Development (MINVU), to address the substandard living conditions identified in informal settlements during the 2011 Na-

tional Slum Census. These policies consist of two principal strategies: in-situ upgrading and population relocation.

These policies were initiated following the 2011 census, which identified and verified areas that met the official criteria for classification as slums: (i) the presence of at least eight households living in close proximity, (ii) the absence of formal property rights, and (iii) the lack of access to at least one basic service—water, sanitation, or electricity. MINVU then performed a territorial diagnosis to assess local conditions, selected an intervention strategy, and confirmed that residents agreed to the intervention.[12] The complete process is summarized in Figure A1. Given budgetary constraints, progress on roll out has been incremental, with the pace of advancement being dictated by the annual allocations approved by the National Congress.

4.1 *In-situ* Upgrading

In-situ upgrading addresses deficient or missing infrastructure and improves housing conditions without displacing existing residents. The intervention finances and contracts for the provision of basic infrastructure, including street paving, piped water, sewerage, and electricity. This component is provided at no cost to households. The program supports the construction of improved housing in cases in which existing housing is considered substandard. The housing component is funded through demand-side subsidies.[13] The average subsidy is approximately USD 15,000 per household. Beneficiaries are required to contribute an additional USD 800 copay. These funds are used to construct single-family or multifamily housing units within the slum polygon, often involving the partial or complete demolition of existing structures and the on-site construction of new units. Implementation is considerably simplified when the slum is on publicly owned land, which can be transferred to beneficiaries through individual property titles. Although the subsidy terms prohibit the sale or rental of ousing units, intergenerational transfers are permitted.

We obtained detailed intervention cost data from MINVU, summarized in Table 4. A third of treated slums received the *in-situ* upgrading intervention, with an average cost per household of USD $20,177. These average costs confirm that *in-situ* upgrading relies on a combination of direct public investment and housing subsidies. Notably, over half of the beneficiary households received a DS49 housing voucher as part of the intervention.

[12]The original list of target slums was established in 2011 and then updated 2018 (Hanne et al. (2019).

[13]The subsidies use DS49 vouchers which are means tested and targeted to households in the lowest 40% of the national income distribution. MINVU provides slum residents with technical assistance and guidance for DS49 application.

4.2 Population Relocation

Population relocation entails offering residents of informal settlements access to formal housing located in non-slum areas of the city. This strategy comprises two primary components. The first involves the provision of DS49 housing vouchers, which recipients may use to acquire formal housing units outside the original slum area. These units may be newly constructed or part of the existing housing stock, but must be priced below the eligibility threshold defined by the subsidy program. This component depends on the supply of privately developed housing or on government-subsidized housing projects explicitly designed to align with DS49 affordability criteria.

The second potential component of this strategy consists of direct public investment by MINVU in the original slum area. This includes the demolition of existing structures, debris removal, and, in some cases, the reallocation of the cleared land for alternative public uses such as parks or community facilities. In instances where the slum was located on privately owned land, the land is usually returned to its original owners, who may develop it at a later stage.

An important feature of the population relocation strategy is its voluntary nature: although the intervention is designed and implemented at the slum level, individual households are not mandated to participate. Relocation decisions are made independently by each household, and in practice, a substantial proportion may choose not to accept the offer extended by MINVU. As a result, some intervened slum polygons may persist as informal settlements even after relocation efforts, due to either individual non-compliance or repopulation dynamics. Vacated homes may attract new informal settlers, or in other cases some household members may relocate while others remain, thereby perpetuating the presence of the slum.

Although population relocation was the most widely implemented intervention –two-thirds of treated slums– it is, on average, one-third more expensive than *in-situ* upgrading, as shown in Table 4. Table 4 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.

4.3 Determinants of Treatment and Treatment Type

MINVU internal documents mention which factors are considered when deciding a slum's treatment strategy. These include feasibility for new construction, basic service connectivity (piped water, sewage, and electrical grid), dispersion of households, household eligibility for subsidies, housing materials, natural hazards, location within the city structure, public

transit access, green and public space, social and cultural attachment and political concerns Hanne et al., 2019. While some of these factors are unobservable to us, we have access to many of these in our data, which allows us to estimate logistic regressions of determinants of any treatment and determinants of *in-situ* upgrading conditional on any treatment.

In our analysis, we considered three sets of variables: Slum characteristics, terrain characteristics and location characteristics.[14] These results are presented in Table 5, which show marginal effects at the mean in specifications with and without region fixed effects.

Columns (1) and (2) examine the determinants of whether a slum receives any type of intervention. The results suggest that cost considerations play a role in intervention decisions. Specifically, slums located on terrain unsuitable for construction and those with a larger number of households are significantly less likely to be treated. We interpret these findings as indicative of a larger fiscal burden associated with larger-scale interventions on difficult terrain, both of which may discourage government action. Supporting this interpretation, the probability of intervention increases with distance from the city center, consistent with lower land values and, thus, lower intervention costs in peripheral areas.

A second key finding is the strong positive association between inclusion in the 2011 slum census and the likelihood of treatment, highlighting the program's political mandate to rely on this registry to allocate resources. Lastly, it is noteworthy that some variables referenced in program guidelines—such as proximity to urban amenities—do not appear to influence the probability of receiving any intervention.

Columns (4) and (5) analyze the determinants of receiving *in-situ* upgrading, conditional on a slum being selected for intervention. The results indicate that slums located within 250 meters of a river are significantly more likely to be assigned to population relocation rather than *in-situ* upgrading, consistent with MINVU's objective of mitigating flood risk. Similarly, slums situated on terrain deemed unsuitable for construction are also more likely to be targeted for relocation.

In contrast, rugged terrain is positively associated with the likelihood of receiving *in-situ* upgrading, suggesting that adaptation of existing structures may be preferred over new construction in such contexts. Additionally, slums with larger geographic footprints and greater numbers of households are more likely to undergo *in-situ* upgrading. This pattern

[14]Slum characteristics are: inclusion in the 2011 slum census, slum area and number of households. Terrain characteristics are: lack of suitability for construction, within 250m of a river, elevation, slope and terrain roughness. Location characteristics are: slum located at the city border or beyond, distance to the city center, distance to amenities index, building density in areas within 200 meters of the slum and municipality expenditures. The distance to amenities index is an Anderson (2008) index of 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. See the Data section and Appendix Table B for a complete list of variables used in this paper, along with their definitions and data sources.

also extends to slums located near or beyond the urban periphery, which exhibit a higher probability of receiving *in-situ* interventions. These findings align with the view that cost considerations influence intervention strategy, given that *in-situ* upgrading typically entails lower public expenditure than relocation.

Overall, this analysis shows that cost considerations matter when deciding whether to intervene a slum. Once a slum is slated for intervention, we observe evidence consistent with relocation being a preferred tool when flood risk is higher. In contrast, *in-situ* upgrading is preferred for larger and more populated slums, and this is consistent with this treatment being the lower-cost intervention.

5 Empirical Strategy

This section outlines the empirical strategies used to estimate the effects of the two policy interventions—*in-situ* upgrading and population relocation—on slum characteristics and potential spillovers to adjacent non-slum neighborhoods. The methodological approach is guided by the non-random assignment of treatments, as documented in the previous section, as well as by data availability. For most of our primary outcomes, we exploit a long panel structure that allows the application of the Synthetic Difference-in-Differences (SDiD) approach developed by Arkhangelsky et al. (2021). However, for outcomes derived from the two waves of the population census, the data structure limits us to standard two-way fixed effects (TWFE) models. We present each empirical strategy in detail below.

5.1 Synthetic Difference-in-Differences

To address non-random treatment assignment and systematic differences between treated and untreated units, we employ the Synthetic Difference-in-Differences (SDiD) approach developed by Arkhangelsky et al. (2021), which is particularly well-suited for settings where standard DiD assumptions, such as parallel trends, are likely to be violated. As documented earlier, slums selected for intervention tend to be smaller, located on terrain more suitable for development, and farther from the city center—characteristics that challenge the plausibility of the parallel trends assumption. SDiD mitigates these concerns by combining the strengths of synthetic control and difference-in-differences, improving balance in both levels and trends. This method is feasible in our context given the availability of a long panel of slum characteristics for both treated and untreated units.[15]

[15] See Dench et al. (2024); Ling et al. (2024); Sun et al. (2024) for other applications of the SDiD methodology in settings with non-random treatment assignment.

SDiD combines the core features of Synthetic Control (SC) and Difference-in-Differences (DiD) framework. It constructs a weighted counterfactual for the treated units by assigning both unit and time weights to untreated slums, ensuring that the synthetic control group closely replicates the pre-treatment trends of the treated group. While traditional SC methods focus primarily on matching levels, SDiD emphasizes matching trends in the pre-intervention period. In doing so, SDiD reduces reliance on the parallel trends assumption.

A key advantage of SDiD is its ability to accommodate staggered treatment timing. In our setting, slums were treated between 2011 and 2017. SDiD constructs a separate synthetic control for each treated cohort using weighted combinations of untreated slums observed over the same period.

Consider the following standard equation for the outcomes of interest, y_{it}, which are measured annually. The set of potential outcomes is drawn from our panel of slums and includes variables measured both at the slum level and in adjacent non-slum neighborhoods. Our main outcomes come from satellite imagery, land tax records, and crime reports.[16]

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

α_0, α_i and α_t represent the constant term, and the slum- and time-fixed effects, respectively. X_{it} represents time-variant slum characteristics used as controls. $\mathbb{D}_{it}$ is a treatment indicator equal to one in the year slum i is first treated and thereafter. Following the systematic differences in slum characteristics for each intervention documented in the previous section, we estimate two separate models: one for slums under *in-situ* upgrading and one for the population relocation treatment.

We can express the objective optimization function for the SDiD model using equation (1), assuming there are N slums and T time periods, as follows:

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

$\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ represent the individual slum and time weights, respectively. The weights $\hat{\omega}_i^{sdid}$ are chosen to minimize the average squared difference in pre-treatment trends between slums exposed to a given treatment strategy and non-treated slums. This is conceptually similar to the Synthetic Control method, although SC focuses on matching levels of the outcome

[16]The list of outcomes includes population, residential land coverage, streets paved, number of building permits, number of large buildings, standard deviation of building main angle, average distance between building footprints, violent and property crime rates in adjacent neighborhoods, and buildings undergoing renovations in adjacent neighborhoods.

rather than trends. As for the time weights, $\hat{\lambda}_t^{sdid}$, they are selected to minimize the sum of squared differences between the time-weighted pre-treatment outcomes of the control slums and the simple average of their post-treatment outcomes. In other words, SDiD assigns more weight to pre-treatment periods that are more predictive of post-treatment outcomes (and less weight to those that are less predictive) for the control group. Notice that, depending on the values assigned to the weights, the SDiD estimator nests other well-known estimators: standard DiD (when $\hat{\omega}_i^{sdid} = 1$ and $\hat{\lambda}_t^{sdid} = 1$) and SC (when only $\hat{\lambda}_t^{sdid} = 1$).

Both sets of weights, $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$, are optimally chosen to construct a counterfactual slum for each cohort-treatment combination. Although this weighting is implemented directly through the SDiD model, researchers can refine the pool of control slums to improve comparability. As shown in Table 5, the two most relevant variables predicting the probability of receiving treatment are inclusion in the 2011 slum census and the number of slum households. We restrict the sample to slums created before 2017, ensuring never-treated slums were either listed in the 2011 census or excluded only because they formed a few years later. SDiD also allows for the inclusion of time-varying confounding controls to further strengthen the robustness of the estimates. We include one-year lagged LandScan population data, which helps account for differences in outcome trends related to slum size and the likelihood of receiving any treatment. LandScan population covers a 1 km^2 area centered on the slum, capturing broader population trends while preserving local geographic variation.

We estimate event-study effects within the SDiD framework, drawing on the approach of Clarke et al. (2023), which compares treated and synthetic control slums over time relative to their time-weighted pre-treatment outcomes. Confidence intervals are constructed using a nonparametric bootstrap, also following Clarke et al. (2023). SDiD is estimated separately for each intervention type —*in-situ* upgrading and population relocation— and within each, for each treated cohort corresponding to the years 2011 to 2017. This procedure produces cohort-specific synthetic controls tailored to the timing and nature of the intervention. After estimating the optimal weights, we compute post-treatment effects by directly comparing treated slums with their synthetic counterparts. While this yields point estimates, we assess statistical significance by repeating the entire estimation procedure 250 times to generate standard errors and 95 percent confidence intervals. The bootstrapped distribution supports hypothesis testing across intervention types.

Aspects of the program design help mitigate concerns associated with evaluating these types of interventions, thereby strengthening our empirical strategy. First, the structure of the intervention reduces the risk of systematic bias arising from the pool of eligible slums and from community interference. All potential beneficiary slums are drawn from the 2011 census, which remained unchanged until 2018/2019, ensuring newer slums shaped by different

dynamics are excluded. Second, once a slum is identified as eligible, community participation is required for the intervention to proceed. Importantly, slum residents decide whether to participate in the program before the specific type of intervention (*in-situ* upgrading or relocation) is determined. This institutional feature makes it unlikely that unobserved community characteristics influencing preferences for one type of treatment over another would affect the probability of receiving a particular intervention (see Figure A1 for details on the treatment process).

There is typically a two- to four-year lag between the selection of an intervention strategy and its implementation. While we observe the timing and magnitude of government investments, as well as the number of subsidies allocated to each slum, we do not have precise data on the completion dates of infrastructure works or the timing of subsidy disbursement and uptake by beneficiary households. Accordingly, our SDiD estimates capture Intent-to-Treat (ITT) effects.

5.2 Two-Way Fixed Effects

While the SDiD approach is well-suited to analyzing our annual panel data on slum and neighborhood physical characteristics, it cannot be applied to outcomes available only in population censuses. Key socioeconomic variables—such as employment rates and the share of the population with more than secondary education—are only observed in the 2002 and 2017 census rounds. Because these outcomes are measured at just two points in time, before and after the interventions, we rely on a canonical Two-Way Fixed Effects (TWFE) framework instead. In this specification, we allow treatment effects to vary by intervention type and estimate the following pooled model:

$$y_{it} = \alpha_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \alpha_i + \alpha_t + \gamma X_{it} + \varepsilon_{it} \tag{3}$$

where y_{it} is the outcome of interest measured using population census data, with $t \in 2002, 2017$. D_{1i} is a dummy variable equal to one if slum i received the *in-situ* upgrading treatment, and D_{2i} equals one if it was subject to the population relocation strategy. X_{it} is a set of baseline covariates. As in the SDiD specification, we include lagged LandScan population as a control to account for differences in slum size and potential confounding trends.

The credibility of the TWFE estimates hinges on how comparable never-treated slums are to those that received interventions before 2017. To strengthen identification, we restrict the sample in two ways. First, we include only slums that existed by 2017, ensuring all units had a similar baseline probability of being treated. Second, we focus on treated slums that

had been exposed to their assigned intervention for at least three years prior to the 2017 census, allowing time for effects to materialize. These restrictions help mitigate concerns about differential selection and ensure a more balanced comparison. While this strategy cannot exploit the rich temporal variation used in the SDiD analysis, it offers a feasible alternative for estimating the effects of the interventions on socioeconomic outcomes that are only captured in census years. By including slum-fixed effects and controlling for lagged population, the model absorbs much of the cross-sectional variation in treatment probability documented earlier.

6 Results

In this section, we first present estimates of the effects of both policy interventions on outcomes within the treated slum polygons. We then examine potential spillover effects on adjacent non-slum neighborhoods.

6.1 Direct Effects of the Policies

We begin by examining the effects of the interventions on slum population, using an event-study specification implemented within the Synthetic Difference-in-Differences (SDiD) framework. Figure 6 presents the estimated dynamic effects of treatment assignment, with the top panel showing results for *in-situ* upgrading and the bottom panel for population relocation. Estimates are plotted from four years prior to treatment assignment to six years after. The pre-treatment coefficients serve as a diagnostic for the credibility of the counterfactual constructed by SDiD. The absence of pre-trends and the presence of narrow confidence intervals indicate that the method achieves a close match between treated and synthetic control units prior to intervention. Following treatment assignment, we find that *in-situ* upgrading does not lead to significant changes in population—consistent with the program's objective of improving conditions without displacing residents. In contrast, population relocation, shown in the bottom panel, is associated with a gradual decline in population, reaching statistical significance by year six, with an estimated reduction of 0.16 log points—equivalent to approximately 17 percent. While the direction of the effect aligns with the program's stated objective of depopulating slum areas, the magnitude falls substantially short of full relocation. As discussed earlier, this attenuated impact may reflect incomplete program take-up, partial household movements, or re-occupation of vacated slum areas by new residents.

For brevity, we report year-six impacts in table format. Table 6 summarizes the main results across three domains: Slum Characteristics, Housing Investment, and Housing Quality.

In each panel, the first row presents the estimated effect on a composite index constructed following the methodology of Anderson (2008). Specifically, each outcome is standardized using the control group's mean and standard deviation and combined using inverse covariance weights. Variable signs are adjusted so that higher index values correspond to more desirable outcomes.

Beginning with the top panel on Slum Characteristics, Table 6 indicates that population density is 16 log points lower in areas assigned to population relocation, while no statistically significant change is observed under *in-situ* upgrading—consistent with the patterns previously shown in Figure 6. The subsequent row shows that the share of the slum polygon devoted to residential use—including built structures and private-use spaces such as driveways and patios—declines by 12 percentage points following relocation, with no detectable change under upgrading. These directional effects are in line with the relocation program's objective of reducing residential occupancy in targeted areas, although the estimated magnitudes fall short of what might be expected given the program's stated goals. Finally, in the third row, we observe that the share of paved streets increases by 11 percentage points under *in-situ* upgrading, whereas no significant effect is found for population relocation. This result is consistent with the design of the upgrading intervention, which includes infrastructure improvements such as street paving, whereas relocation programs do not involve such investments. In all cases, the null hypothesis of equal effects across treatment arms is rejected, as shown in column 4.

We next present results from administrative data on two important outcomes that reflect investment in housing within the slum polygon: The probability of having any formal housing building permits issued within the slum polygon increases by 5 percentage points, a 5 fold increase from the mean in the control group. This points to *In-situ* upgrading not only increasing housing quality but also initiating a neighborhood transformation that attracts formal housing investment. We do not detect significant changes for the population relocation program. Qualitatively similar differences are found when we use the number of building permits.

The bottom panel of Table 6 presents results for satellite-derived measures of housing quality. We begin with the average distance between a dwelling and its nearest eight neighbors, a proxy for residential spaciousness (the opposite of crowding) within slum areas. Slum dwellings are typically built very close to each other; thus, increases in the distance between a building and its neighbors can be interpreted as higher neighborhood quality. The estimated effects reveal significant heterogeneity across interventions. *In-situ* upgrading leads to a statistically significant increase of 8.7 meters—equivalent to a 14 percent rise—in the average inter-household distance, indicative of reduced crowding and consistent with improvements

in urban form and housing quality. By contrast, the effect of population relocation on this measure is small in magnitude and statistically indistinguishable from zero.

The second outcome we examine is the similarity in building orientation, measured using the angle of the principal axis of the minimum bounding rectangle enclosing each slum structure, following the methodology of Michaels et al. (2021). We compute the standard deviation of the angles between an observation and its eight nearest neighboring structures and then average this measure across the whole polygon. This serves as an indicator of building layout regularity. Higher values of this measure correspond to greater heterogeneity in building orientation and are interpreted as indicative of more disorderly or unplanned construction patterns. In more orderly neighborhoods, most houses tend to face the same direction, resulting in a standard deviation of orientation angles close to zero. As shown in the table, *in-situ* upgrading is associated with significantly more orderly urban development relative to population relocation. Specifically, the standard deviation in building orientation declines by 15 percent following upgrading, indicating increased alignment of structures, whereas the corresponding estimate for the population relocation intervention is small and not statistically distinguishable from zero.

Finally, we examine the prevalence of large structures, defined as buildings with a footprint exceeding 64 m^2. Such structures are unlikely to correspond to single-family dwellings and more plausibly reflect formal constructions intended for commercial use or multi-unit residential occupancy, including multi-story buildings. In this case, we also evidence that *in-situ* upgrading led to a 16 percent ($p < 0.10$) increase in large buildings within the slum perimeter and no statistically detectable change for the population relocation.

Overall, the results in Table 6 provide compelling evidence that Chile's two principal slum policy interventions yield markedly different impacts on the physical characteristics of slum areas. *In-situ* upgrading is associated with significant improvements in urban quality, including increased prevalence of paved streets, greater building investment, increased spacing between structures, and more orderly construction patterns. In contrast, the population relocation program does not produce statistically significant improvements in any of these dimensions relative to the synthetic control. Its primary effects are limited to a reduction in population—approximately 15 percent—and a decline in the share of land allocated to residential use.

We next examine the effects of slum interventions on the sociodemographic characteristics of residents using data from the 2002 and 2017 population censuses. In addition to demographic indicators, these censuses provide information on aspects of housing quality not observable in satellite imagery, such as the number of bedrooms and the quality of wall materials. Given the availability of only two time periods, we estimate treatment effects

using a Two-Way Fixed Effects (TWFE) specification, as described in Equation (4). The corresponding results are reported in Table 7.

The two housing quality indicators available from the population censuses are (i) the proportion of dwellings with two or more bedrooms, and (ii) the proportion of dwellings constructed with high-quality wall materials, defined as concrete, stone, brick, or prefabricated blocks. These results, reported in the top panel of Table 7, reinforce the findings presented in the preceding table. Consistent with improved housing conditions, *in-situ* upgrading is associated with a statistically significant increase of approximately 4.5 percentage points in the share of dwellings with two or more bedrooms. By contrast, we find no evidence that population relocation leads to improvements in housing quality. In fact, the share of dwellings constructed with high-quality wall materials exhibits a modest decline in areas subject to the relocation program.

Turning to sociodemographic outcomes, reported in the bottom panel of Table 7, we find that the share of adults with at least a high school education is approximately 3 percentage points higher in slums that received *in-situ* upgrading, relative to the synthetic control group. No statistically significant differences are observed for slums exposed to the population relocation program.[17] Employment rates among adults in the control group are already high—around 83 percent—and we detect no significant differences in unemployment rates under either intervention.

An important caveat should be noted regarding the census-based results reported in Table 7. Given that the interventions were initiated only after 2011 and typically require two to four years for full implementation, the 2017 census may capture outcomes that reflect only partial treatment exposure. As a result, the estimated effects may be attenuated toward zero due to the lag between treatment assignment and actual program completion.

In sum, the evidence presented in this subsection demonstrates that *in-situ* upgrading is consistently more effective than population relocation at improving conditions within slum polygons, across multiple outcomes and empirical strategies. *In-situ* upgrading is associated with significant enhancements in housing and neighborhood quality, including a higher prevalence of paved streets, the construction of larger and more uniformly oriented structures, and increased spacing between dwellings. Moreover, it appears to catalyze neighborhood transformation by attracting formal housing investment, as indicated by an uptick in building permits. The intervention also contributes to shifts in the sociodemographic profile of slum areas, with evidence of increasing residence by higher socioeconomic status (SES) individuals. In contrast, the population relocation program fails to produce measurable improvements in

[17]Estimates are robust to restricting the sample to individuals aged 30, 35, or 40, with point estimates remaining stable across age thresholds.

housing and neighborhood quality and achieves only limited success in reducing population within slum perimeters—its primary stated objective.

6.2 Spillovers onto Nearby Formal Neighborhoods

In this subsection, we examine the critical issue of spatial spillovers from slum renewal policies onto adjacent non-slum neighborhoods. This question is of critical importance, as formal areas neighboring slums are likely to experience the externalities —positive or negative— associated with these interventions. Despite the relevance of such spillovers, empirical evidence remains scarce. We contribute to filling this gap by providing novel estimates of the external impacts of both in-situ upgrading and population relocation on surrounding formal neighborhoods. We present results on crime, housing investment and housing quality using the SDiD method as well as sociodemographic changes and housing quality using TWFE.

This analysis focuses on two spatial buffers surrounding slum boundaries: 0–200 meters and 200–500 meters. The first, immediately adjacent buffer is expected to capture the strongest spillover effects due to its proximity to the treated areas.

We begin by presenting estimates of spillovers from both programs on crime reports in neighboring non-slum neighborhoods. Table 8 reports effects of each policy in the 0-200m distance band in columns 1-4 and in the 200-500m distance band in columns 5-8 after five years of assignment to treatment using the SDiD methodology. We focus on five years post-intervention due to data availability (crime records only cover 2013-2023).

The top row reports results for an aggregate crime index, standardized such that estimated coefficients can be interpreted in units of standard deviations. Notably, we find that *in-situ* upgrading is associated with a statistically significant reduction in crime in the 0–200 meter buffer surrounding treated slums ($p < 0.01$). The coefficient estimate of –0.09 standard deviations corresponds to a substantial 69 percent decline in reported crime incidents relative to synthetic control areas. In contrast, the estimated effect of population relocation on crime is positive and statistically indistinguishable from zero. Moreover, we can reject the null hypothesis of equality between the two policy coefficients ($p < 0.01$), as reported in column 4.

Disaggregating the crime index into its three constituent components —property crimes, violent crimes, and homicides per square kilometer— we find that *in-situ* upgrading consistently leads to statistically significant reductions across all categories. It is important to exercise caution when interpreting crime reports as proxies for actual crime levels, due to well-known issues with underreporting. With this in mind, among all crime categories,

homicide is generally considered the least susceptible to such reporting biases. It is therefore reassuring that our findings hold even for homicides.

In contrast to our findings for *in-situ* upgrading, population relocation is associated with statistically insignificant changes in each category. Even so, we can reject the null hypothesis of coefficient equality across policies in all three domains.

Taken together these results are striking: to the extent that residents of formal neighborhoods adjacent to slums are sensitive to local crime conditions, *in-situ* upgrading emerges as a clearly superior policy intervention.

Columns 5 through 8 present estimates for the 200–500 meter buffer surrounding slum perimeters. While point estimates remain directionally consistent with those observed in the adjacent buffer, neither policy exhibits statistically significant effects at conventional levels. Nonetheless, we continue to reject the null hypothesis of coefficient equality between the two interventions (column 8), consistent with *in-situ* upgrading being a superior policy even at 200-500m away from the slum perimeter.

The observed reduction in crime in areas adjacent to slums that undergo *in-situ* upgrading is a plausible consequence of the improvements in slum conditions documented in the preceding subsection. Individuals with higher socioeconomic status are generally less likely to engage in criminal behavior, particularly due to stronger attachment to the formal labor market, which diminishes incentives to participate in illicit activities. Importantly, this mechanism does not depend on the assumption that offenders disproportionately reside within slum areas. Were that the case, the population relocation strategy would similarly be expected to reduce criminal activity, owing to the decline in population density following relocation.[18]

After showing spillover effects in terms of crime, we now present results on housing investment and housing quality in slum-surrounding areas using the SDiD method. The top panel of Table 9 begins with an index of housing investments. Within 200m of a slum, we find a 0.22SD ($p < 0.01$) increase in the housing investment index from *in-situ* upgrading, which is significantly larger than the 0.14SD increase observed for population relocation.

When we consider individual components of the index within 200 meters of *in-situ* upgraded slums, a similar pattern holds. Specifically, there is a 4 percentage point increase in new buildings (less than five years old) and a 30% increase in renovated buildings. For areas near population relocation slums, we find a smaller effect on new buildings and no significant effect on building renovations. This suggests that communities near upgraded slums end up seeing more housing investment and maintenance in their properties.

Analyzing the georeferenced building permits data also indicate greater neighborhood

[18]See Appendix F for the spillover crime results using event study figures.

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% and there is a 13% increase in the number of building permits. For formal neighborhoods near population relocation slums, we still find positive but smaller point estimates, and only the latter outcome is statistically different from zero.

When we consider areas at a 200-500m distance to a slum, shown in columns 5-8, we observe similar patterns. The effects are always larger for in-situ upgrading than for population relocation and the index of housing investments is double that of population relocation and significantly different from zero.

Overall, the top panel portrays a pattern of improved neighborhood conditions, in line with the crime externalities presented above.

While housing investment suggests improvements at the margin, the bottom panel of Table 9 reports outcomes for *all* housing stock at different distance bands. In this case, impacts are more muted. In particular, the overall index is not significantly different from zero for either policy. When looking at the different subcomponents, we do not find significant effects on building orientation angle and distance between buildings, although this result is not surprising in more established neighborhoods where changes in building regularity and distribution take much longer to appear. We do find a significant reduction in the average building age in areas within 200 meters of *in-situ* upgraded slums. And while we also find positive spillovers in building age for population relocation areas, the effect is about 60% of that near *in-situ* upgraded slums, and we can reject that the coefficients are equal ($p < 0.01$).

In Table 10, we use the two population census rounds using the TWFE specification. Recall that, in this analysis, results are measured 15 years apart and are useful because they allow us to examine whether the interventions generated changes in the socioeconomic characteristics of individuals who decided to live close to slums.

First, note that adults living near *in-situ* upgraded areas are statistically more likely to have high school or higher education than adults living near never-treated slums. They are also more likely to be employed. In contrast, adults living close to population relocation slums are not statistically different from those living near never-treated slums. This is true whether we consider the 0-200m or the 200-500m distance band.

The third row of the table shows that population growth in areas near slums subject to population relocation is significantly lower than in areas near never-treated slums. Specifically, population is 21 percent lower within 200 meters and 18 percent lower between 200 and 500 meters from the slum perimeter. This finding is consistent with the view that slums subject to population relocation interventions are, in equilibrium, less attractive in terms of amenities than even untreated slums.

The lower panel in Table 10 revisits housing quality outcomes, this time using the TWFE specification. It confirms the findings of the SDiD specification discsussed previously. Namely, *in-situ* upgrading results in improved housing quality in surrounding areas as measured by an index of housing quality (0.14SD within 200m and 0.15SD between 200-500m).

Our analysis demonstrates that *in-situ* upgrading generates substantial positive spillover effects in adjacent formal neighborhoods, whereas population relocation strategies yield no comparable benefits. Notably, we document significant reductions in both property and violent crime rates, pointing to improvements in local safety. Together with greater public safety, areas within 200 meters of *in-situ* upgraded slums exhibit increased building activity and housing investment, as indicated by higher probabilities of approved building permits and a marked rise in building renovations. These neighborhoods also undergo favorable sociodemographic changes, attracting a greater share of high socioeconomic status (SES) residents. Taken together, these findings underscore the broader effectiveness of *in-situ* upgrading—not only in enhancing conditions within targeted slums but also in catalyzing positive transformations in the surrounding urban fabric.

7 Conclusion

Rapid urbanization in low- and middle-income countries has led to the proliferation of informal settlements, with over one billion people now residing in slums worldwide —a number projected to grow in the coming decades. In response, governments have implemented a range of slum policies, including in-situ upgrading and population relocation. Yet despite the scale and policy relevance of these interventions, systematic evidence on their effectiveness for the development of slum areas remains limited. Studying slum policies at scale is therefore critical for understanding how cities can improve housing quality and guide efficient land use. This paper contributes to this agenda by rigorously evaluating the direct and spillover effects of two major slum policies implemented at scale in Chile: in-situ upgrading and population relocation.

To undertake our study, we amassed an unprecedented amount of Chilean data to study the direct effects of the two slum policies on slum polygons, as well as their spillover effects on surrounding formal neighborhoods.

Starting from a unique georeferenced national panel census of slums, we merge in outcomes derived from satellite imagery analysis, building permits, population censuses and crime reports. Our descriptive statistics reveal that slums are typically located on the outskirts of cities, on worse terrain and further away from essential amenities such as schools

and supermarkets compared to non-slum areas.

Our descriptive analysis of slums is consistent with longstanding hypotheses about drivers of slum growth: high cost rental housing prices and low wages for unskilled workers.

Since 2011, Chile has simultaneously implemented two distinct slum renewal strategies. The *in-situ* upgrading approach seeks to address the fundamental deficiencies that characterize informal settlements, including the absence of piped water, sewerage, electricity, formal land tenure, paved streets, and adequate housing structures. This strategy is less costly on a per-beneficiary basis and we know from previous literature that it is less disruptive to existing social networks and employment arrangements, as beneficiaries have voluntarily settled in these locations. In contrast, the population relocation strategy offers eligible households free formal housing outside the original slum polygon. Our analysis focuses on the trajectory of the slum polygon itself, allowing us to trace the impacts of this policy over time.

While slums agree to participate in the program without knowing which specific policy they will end up receiving, it is not randomly assigned. We find that more populated slums and those in areas where construction is more difficult are less likely to be treated at all. Furthermore, being close to a river and being in terrain where construction is more difficult predict relocation. Whereas slums with more households are more likely to receive slum upgrading. 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. We leverage the staggered nature of treatment assignment and employ Synthetic Difference-in-Differences (SDiD) methodology.

Our findings indicate that *in-situ* upgrading is more effective than population relocation at improving slum polygon conditions and generating positive spillovers onto 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 (partial) removal 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.

Our findings indicate that in-situ upgrading is more effective than population relocation

at improving conditions within slum polygons and in generating positive spillover effects in surrounding formal neighborhoods. In-situ upgrading yields substantial improvements in housing quality, including a higher incidence of paved streets, larger and more regularly oriented buildings, and increased spacing between dwellings. It also catalyzes neighborhood transformation by attracting formal housing investment. In adjacent formal areas, we observe favorable changes in sociodemographic composition as well as significant reductions in property and violent crime. In contrast, population relocation produces limited improvements in housing quality and sociodemographic outcomes, beyond the expected—though only partial—reduction in population within the treated slum polygon. The relative advantages of in-situ upgrading become particularly salient when considering its cost: on average, it is one-third less expensive per beneficiary than population relocation. This makes in-situ upgrading a more cost-effective strategy in contexts where both options are feasible. Nonetheless, these findings should be interpreted with a caveat, as the applicability of each strategy is contingent on local conditions. In particular, in-situ upgrading may not be viable for slums located in areas exposed to natural hazards, where relocation remains the only safe alternative.

This paper evaluates the effectiveness of two major remedial slum policies, offering important insights for public policy aimed at addressing the challenges posed by existing informal settlements. However, it is equally critical to examine preventive approaches that reduce the likelihood of slum formation in the first place. Promising strategies include the provision of serviced land and the implementation of sites-and-services programs (**?**), as well as the development of efficient rental housing markets and well-functioning formal housing systems. Future research should focus on identifying and assessing policies that expand access to affordable, well-located formal housing and promote inclusive urban planning frameworks capable of accommodating population growth while limiting the emergence of new informal settlements.

This paper sheds light on the implications of slum policies for slum polygons themselves. Previous work focusing on slum interventions has focused on tracking individuals as they are relocated (Rojas-Ampuero and Carrera, 2023), but that literature has mostly found that population relocation strategies are costly for individuals, who see their social networks interrupted and even outcomes such as longevity are worse for relocated individuals. In one case of India, 1/3 of individuals prefer to go back to slums instead of staying in improved housing in non-slum areas. Taken together with our results, this suggests that contrary to its usual perception among policymakers as as a higher cost but superior alternative, population relocation is not only worse for individuals, but is also worse for the outcomes of the polygon that is intervened, as well as surrounding neighborhoods.

This paper contributes to the literature by examining the implications of slum policies for the physical trajectories of the slum polygons themselves. While much of the existing research on slum interventions has focused on tracking outcomes for individuals who are relocated—such as in Rojas-Ampuero and Carrera (2023)—the evidence generally indicates that population relocation strategies impose substantial costs on affected households. Relocated individuals often experience the disruption of social networks and, in some cases, adverse outcomes such as reduced longevity. In one study from India (Barnhardt et al 2017), on third of families never took up subsidized formal housing outside the slum and on third eventually returned to informal settlements rather than remain in improved but distant housing. Combined with our findings, this body of evidence suggests that population relocation —often perceived by policymakers as a more costly but more effective intervention— may in fact be inferior across multiple dimensions. Not only does it often result in worse outcomes for individuals, but it also fails to improve conditions within the treated slum polygon and generates limited or no positive spillovers in adjacent neighborhoods.

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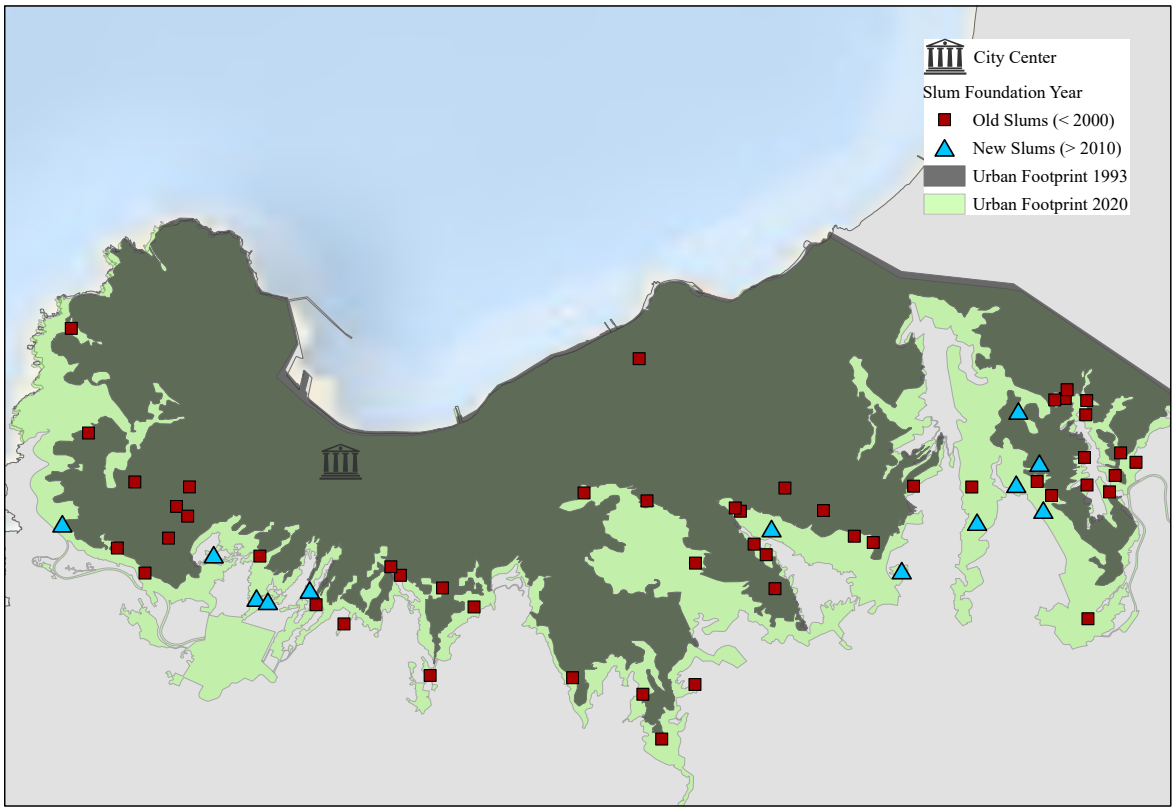
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8 Figures and Tables

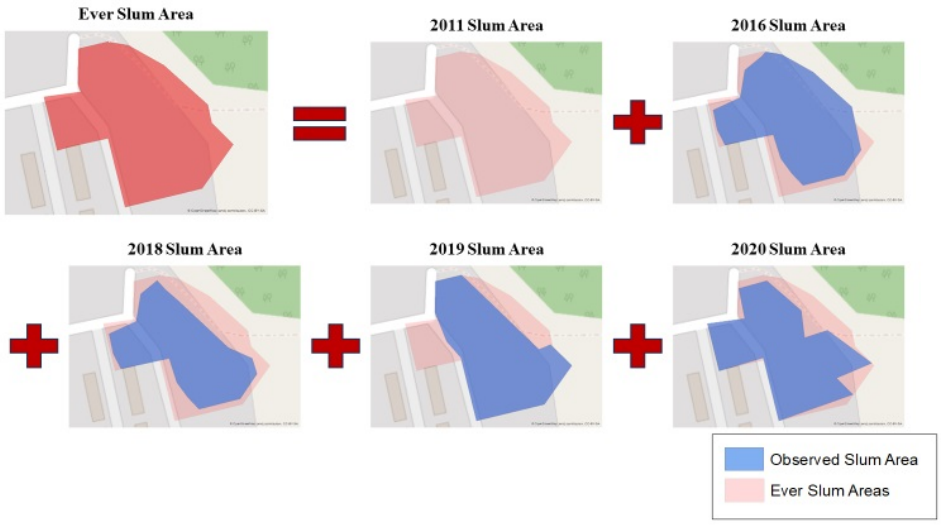
Figure 1: Location of Slums in Valparaiso, Urban Footprints in 1993 vs. 2020



Notes: City boundaries for 1993 and 2020 refer to the city continued urban construction (CUC). City center is obtained from the Urban Functional Areas project (AUF for its Spanish acronym) by INE, MINVU, SECTRA and SUBDERE. Slums that existed before 2000 are marked in red squares, while those that emerged after 2010 are marked in light blue triangles.

Figure 2: Unit of Analysis - Ever-Slum Areas

(a) Geographical Union of Observed Slum Areas over Time

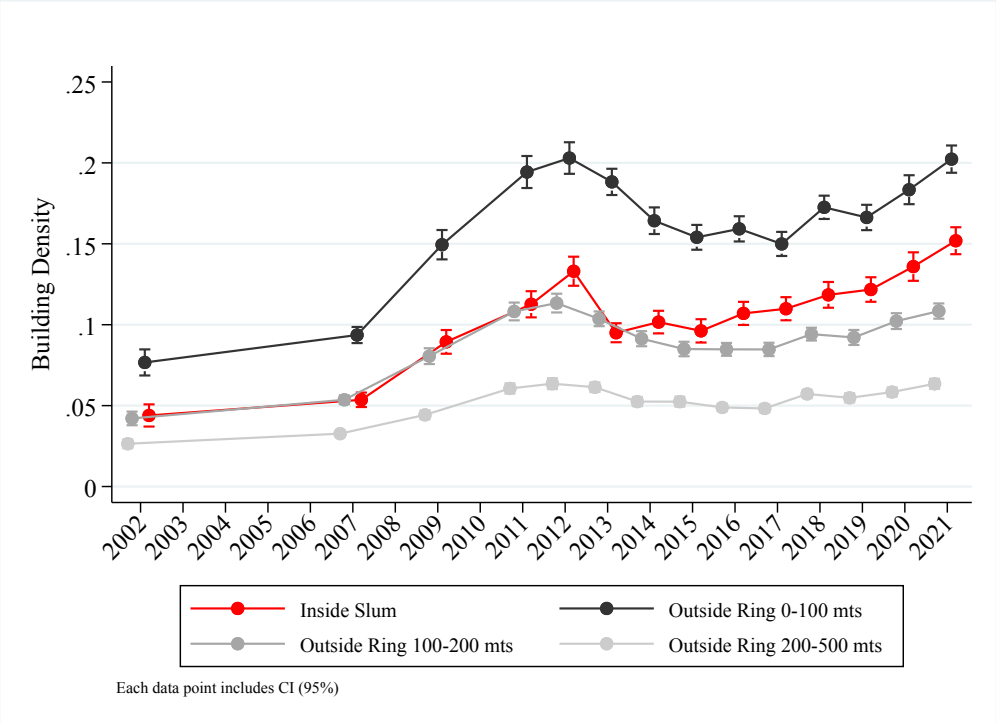


(b) Satellite Images of the Fixed Slum Area



Notes: Representation of the slum La Iglesia in the municipality of Tome. Panel (a) shows the slum boundaries provided by MINVU (2011 and 2019) and TECHO (2016, 2018, 2020). The slum did not exist in 2011 and was included for the first time in the 2016 slum census. The red shaded area is the ever slum area calculated as the union of all observed boundaries (blue polygons). Panel (b) shows satellite images from Google Earth with the ever slum area delineated in red.

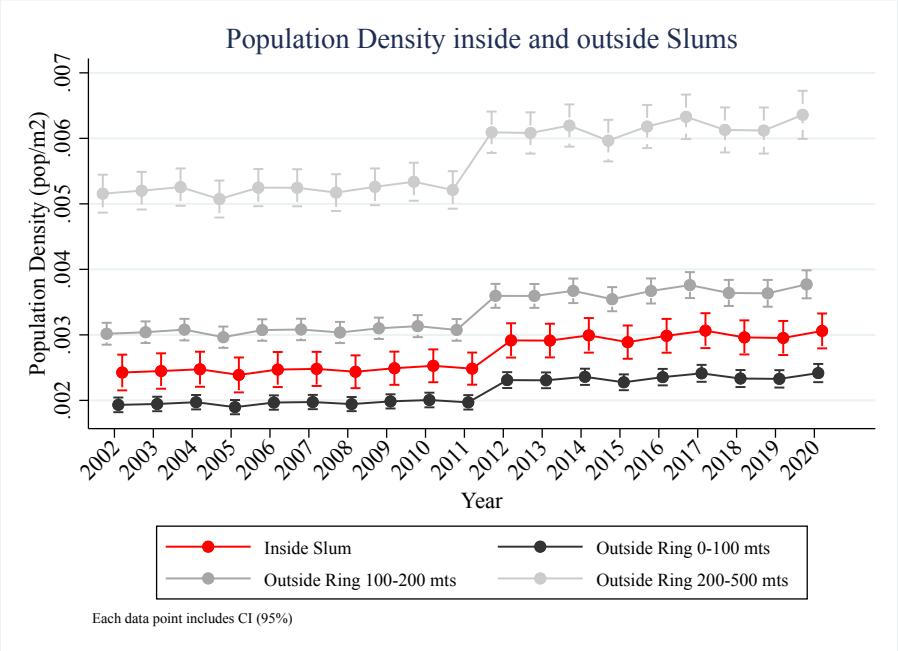
Figure 3: Evolution of Building Density Inside Slums and Adjacent Neighborhoods



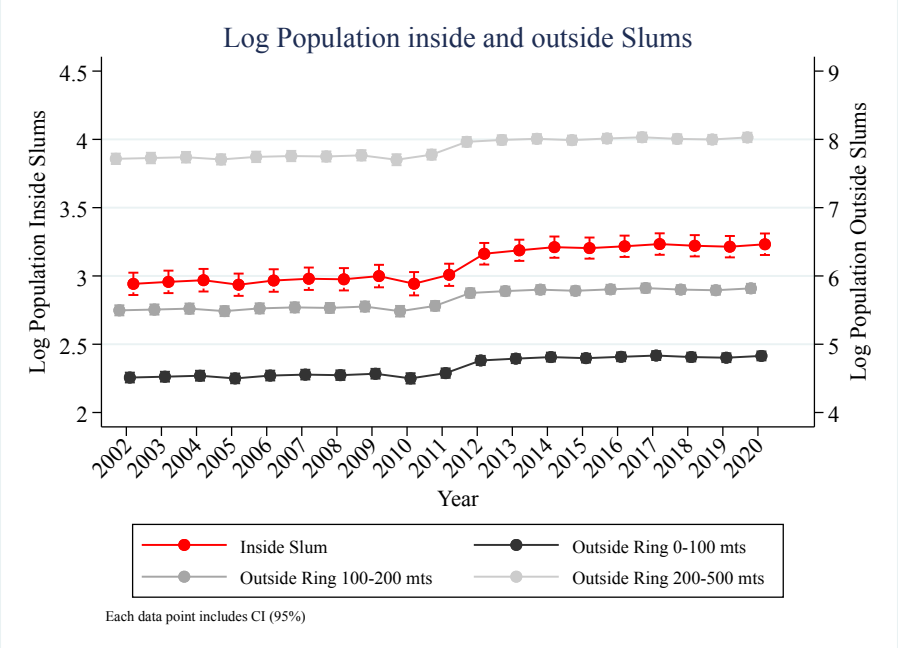
Notes: Building density is calculated using the building footprints obtained from Google Earth images. Building density in slums is the proportion of the area occupied by building footprints. The outer rings are defined by distance from the slum boundary: the first ring (0-100 meters) measures density within 100 meters, the second ring (100-200 meters) covers the next 100 meters, and the third ring (200-500 meters) extends to 500 meters.

Figure 4: Evolution Population Density and Log Population

(a) Population Density (people per m2)

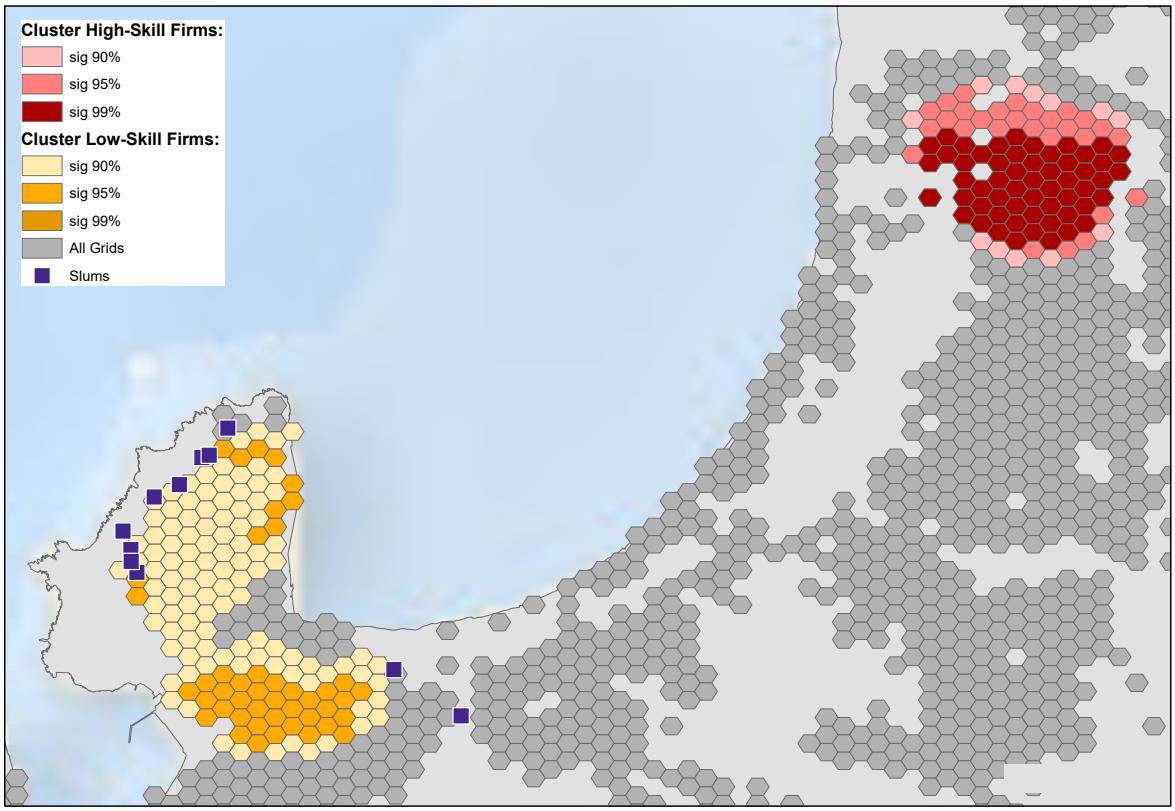


(b) Log of Population



Notes: Population data is obtained from WorldPop, which provides estimates of gridded populations within 100-meter grids for all countries. Grids are assigned to slums and nearby neighborhoods based on the grid's centroid; a grid's population is considered part of the area only if the centroid falls within its boundaries. If an area has a population estimate of fewer than four people, it is assumed to be zero, as such low numbers may be affected by the smoothing algorithm used for estimating populations at this scale.

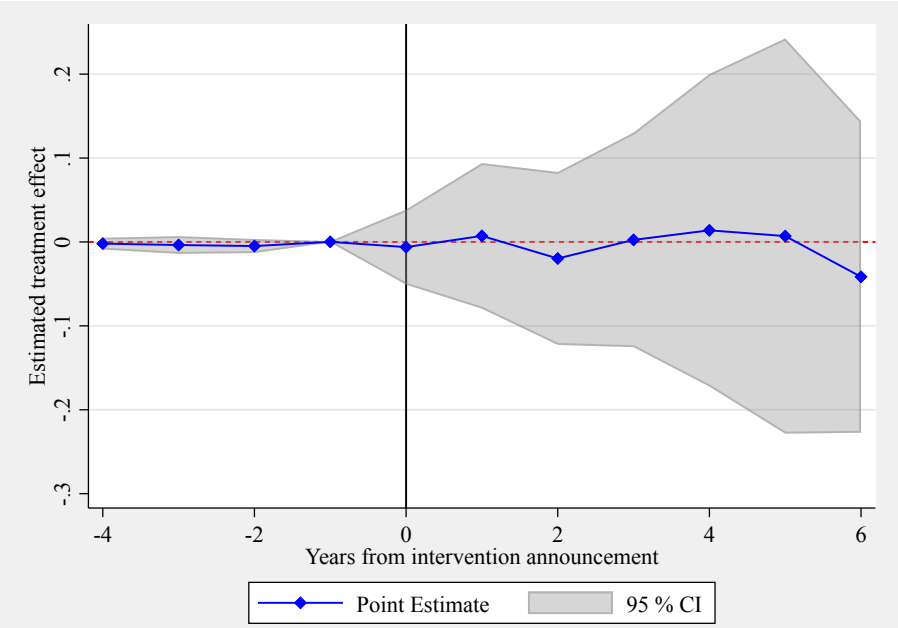
Figure 5: Proximity of Slums to Centers of Low- and High-Skill Employment, Coquimbo



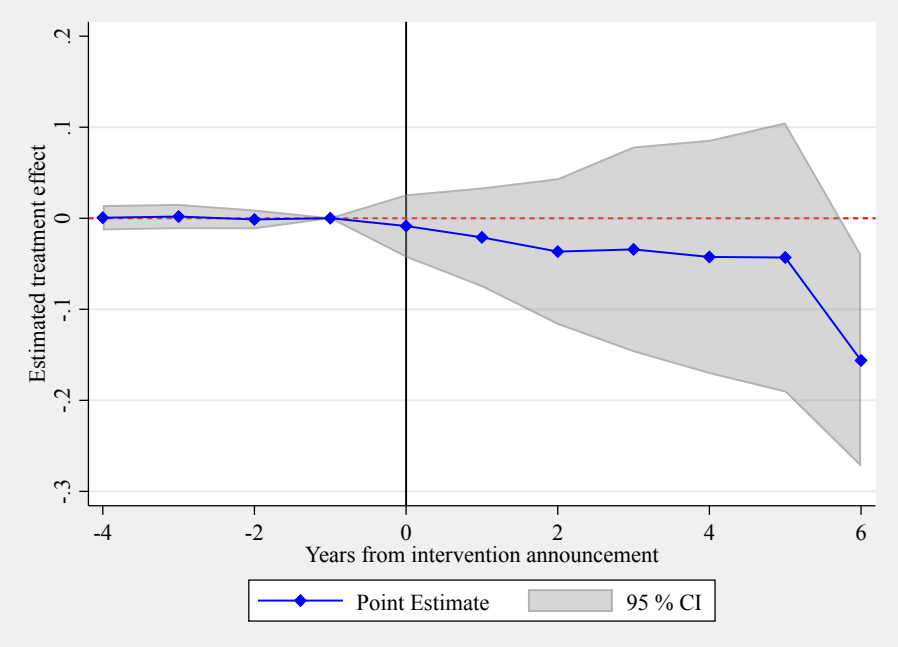
Notes: firms' location comes from the 2017 National Firms Census. Chile is divided into hexagons with sides of approximately 125 m and count the number of firms within each hexagon. Clusters are identified through hot-spot analysis, which detects statistically significant spatial clusters of high and low concentrations of firms at the 90, 95, and 99 percent confidence intervals (see ArcGIS description). Low-skill industries are agriculture, mining, manufacturing (food, beverages, leather, wood, paper, plastic, minerals, and furniture), construction, retail, and transportation. High-skill industries are other manufacturing (chemicals, pharmaceuticals, electronics, machinery, automobiles), services, teaching, professional and scientific activities.

Figure 6: Effects of Slum Renewal Policies on Log Slum Population (SDiD)

(a) *In-situ* Upgrading



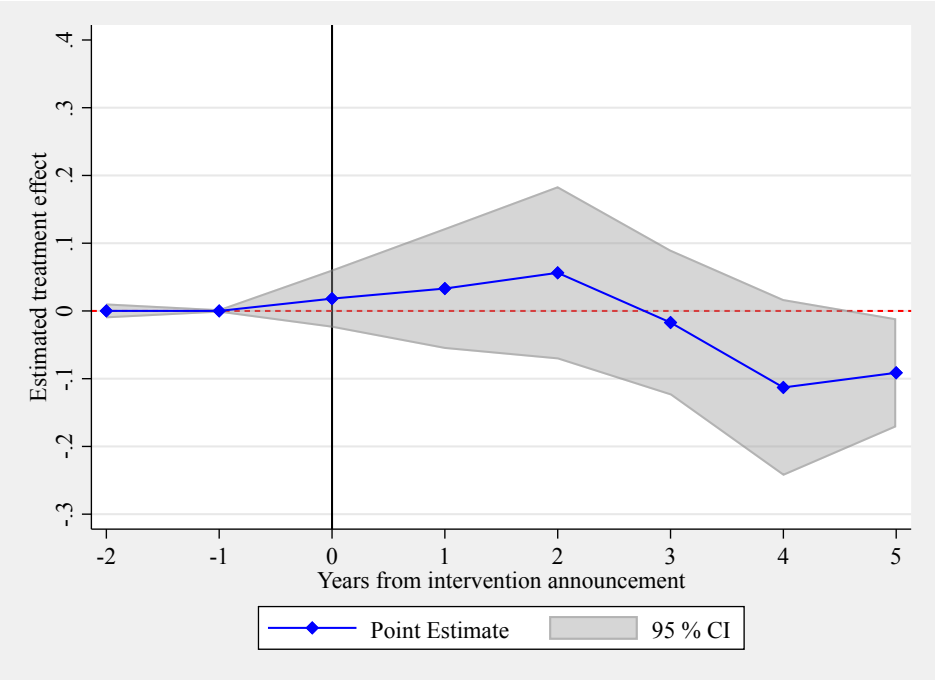
(b) Population Relocation



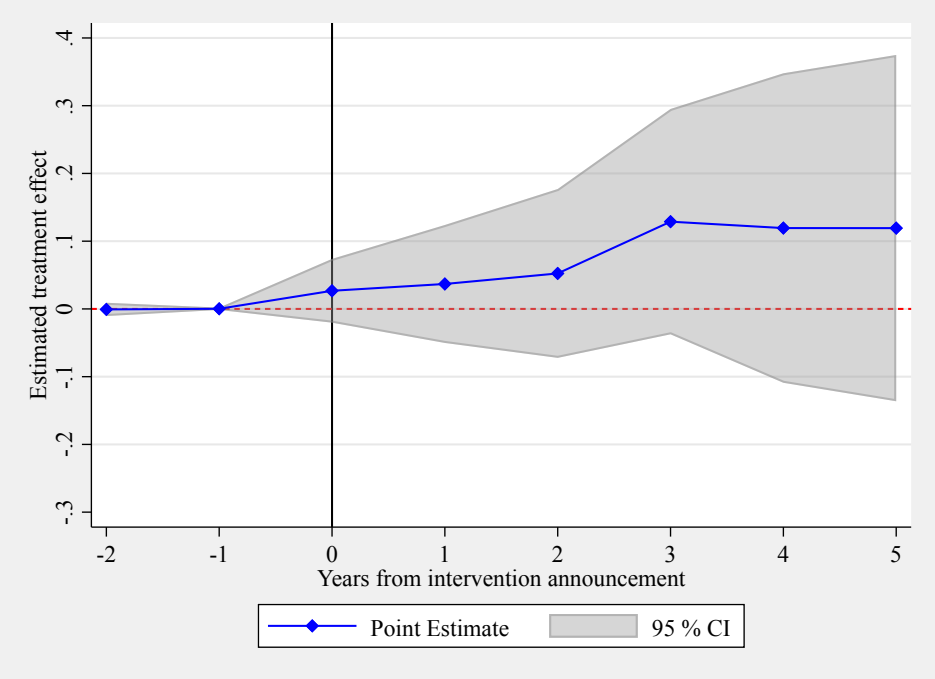
Notes: These are event-study graphs showing the effects of in-situ upgrading (Panel a) and population relocation (Panel b) on the log of slum population using the SDiD estimator (Arkhangelsky et al., 2021). Slum population is obtained through LandScan (gridded population estimates for 1 km^2) based on the grid containing the slum polygon. For each cohort of treated slums, we find a synthetic control group using never-treated slums to match the pre-treatment trends of treated slums. Once the synthetic control is chosen the standard DiD interpretation applies. Inference is constructed using bootstrapping with replacement. Year zero is the moment the intervention is determined. Only slums treated between 2011 and 2017 are considered.

Figure 7: Effect of Slum Renewal Policies on Crime Index (sd) in Adjacent Formal Areas

(a) *In-situ* Upgrading



(b) Population Relocation



Notes: These are event-study graphs showing the effects of in-situ upgrading (Panel a) and population relocation (Panel b) on the crime index in neighborhoods within 200 m of the slum using the SDiD estimator (Arkhangelsky et al., 2021). The crime index follows Anderson (2008) and combines property and violent crime per square kilometer. For each cohort of treated slums, we find a synthetic control group using never-treated slums to match the pre-treatment trends of treated slums. Once the synthetic control is chosen the standard DiD interpretation applies. Inference is constructed using bootstrapping with replacement. Year zero is the moment the intervention is determined. Only slums treated between 2015 and 2018 are considered.

Table 1: Distance to Amenities & Differences in Terrain, Slum vs Non-Slum Census Areas

Dependent Variable:	Mean Dep. Var. Control (1)	Slum Indicator (2)	Romano-Wolf (p-value) (3)
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)	

Notes: Units of analysis are slums and non-slum census-blocks. Sample size = 156,654. Significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the Municipality level. 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. Amenities' locations are for 2022. School information includes build year, and distance to the nearest school reflects the proximity at the time the slum was established. Column 1 is the mean of the dependent variable for the non-slum areas. Column 2 shows the regression coefficient of the slum indicator. Column 3 presents the Romano-Wolf p-values correcting for multiple hypothesis testing. The Amenities Distance index follows Anderson (2008) and combines all reported individual amenities in the table.

Table 2: Correlates of Municipal Slum Population Growth

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

Notes: OLS estimates of regressing the log change in the slum population per municipality against the log change in rents, employment, salaries, and public expenditure, with $\underset{a-b}{\Delta} X$ representing the log change of variable X between year a and b. Each column uses a different data source for calculating slum population growth. Column 1 uses WorldPop's 100-meter resolution estimates for the years 2011 to 2017. Column 2 relies on census data from 2002 to 2017. Both WorldPop grids and Census blocks are classified as slums based on their centroid locations, i.e., if a centroid is within slum boundaries, the population is counted as living in slums. WorldPop 100m cells with fewer than four people are set to zero, likely due to the smoothing algorithm. All regressions control for the log of baseline municipality population (2011 in Column 1 and 2002 in Column 2) and the municipality population growth during the same period. For a detailed definition of variables, see Table B1. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3: Sociodemographic Changes - Population Censuses 2002 and 2017

	Census Year		Δ_t
	2002	2017	(2017-2002)
	(1)	(2)	(3)
Population			
Slums	277	308	31
Adjacent Non-Slum Blocks	6,870	7,206	336
Δ_i (Slums - Non-Slums)	-6,593	-6,898	-305
Ratio Adult Males/Females (25-64 yo)			
Slums	1.30	0.97	-0.33
Adjacent Non-Slum Blocks	0.96	0.95	-0.01
Δ_i (Slums - Non-Slums)	0.34	0.02	-0.32
% Pop w Secondary Education			
Slums	39.58%	51.03%	11.4%
Adjacent Non-Slum Blocks	43.21%	50.65%	7.4%
Δ_i (Slums - Non-Slums)	-3.62%	0.38%	4.0%
% Pop w some Tertiary Education			
Slums	10.20%	18.45%	8.3%
Adjacent Non-Slum Blocks	14.45%	20.24%	5.8%
Δ_i (Slums - Non-Slums)	-4.25%	-1.79%	2.5%
% Employed			
Slums	80.63%	90.19%	9.6%
Adjacent Non-Slum Blocks	82.41%	90.31%	7.9%
Δ_i (Slums - Non-Slums)	-1.79%	-0.11%	1.7%

Notes: census blocks are assigned to slums if their centroid falls inside the slum area. Adjacent non-slum census blocks are within 200 to 500 m of the slum border. Each grouping represents a variable from the population census. The first grouping is Population and columns 1, 2, and 3 represent the average population in the 2002 census, 2017 census, and population change for slums and adjacent non-slum blocks. The last row of each grouping presents the across-group difference for the given census year.

Table 4: *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	$36,672	$16,534	$34,487
Voucher Value per Slum HH	$19,580	$18,126	$15,917
Infrastructure Investment per Slum HH	$9,057	$14,389	$2,599
Total Expenditure per Beneficiary HH	$45,407	$24,080	$37,469
Total Expenditure per Slum HH	$28,636	$27,307	$23,021
Population Relocation (N Slums = 440)			
# Households (HH) per Slum	34.43	46.92	23
Share HH Receiving Housing Voucher	0.82	0.63	0.79
Voucher Value per Beneficiary HH	$46,710	$2,867	$45,415
Voucher Value per Slum HH	$38,317	$29,087	$36,605
Infrastructure Investment per Slum HH	$4,215	$9,112	$773
Total Expenditure per Beneficiary HH	$50,881	$10,032	$47,209
Total Expenditure per Slum HH	$42,532	$32,620	$40,138

Data source: MINVU. Data covers the period 2011-2020. Monetary values are in 2017 US dollars. Households (HH) residing in slums correspond to the first slum census in which the slum appears.

Table 5: Determinants of Treatment Assignment

	Pr(Any Treatment)			Pr(In-situ Upgrading | Any Treatment)		
	Marginal Effect (at the mean)		Covariate Mean	Marginal Effect (at the mean)		Covariate Mean
	(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)		(0.02)	(0.02)	
Log Slum Households	-0.12***	-0.15***	3.45	0.06	0.07**	3.37
	(0.03)	(0.04)		(0.04)	(0.03)	
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)		(0.09)	(0.16)	
Elevation Slope, percentage rise	0.00	0.00	4.90	0.01	0.00	4.71
	(0.01)	(0.01)		(0.01)	(0.01)	
Terrain Ruggedness Index (km)	0.01	0.00	0.12	0.62**	0.54***	0.11
	(0.24)	(0.18)		(0.27)	(0.19)	
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)		(0.00)	(0.00)	
Amenities Distance Index	0.00	0.01	0.00	0.01	-0.03	0.03
	(0.02)	(0.02)		(0.02)	(0.04)	
Building Density within 200m	0.60*	0.59	0.10	-0.04	-0.25	0.11
	(0.36)	(0.36)		(0.36)	(0.24)	
Log Municipality Expenditures	0.00	0.10***	16.57	-0.07***	-0.01	16.54
	(0.01)	(0.03)		(0.01)	(0.02)	
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	

Notes: Columns 1 and 2 present the marginal effects from logit models analyzing the probability of receiving any treatment, using a sample of treated and never-treated slums. Column 3 shows the mean values for each covariate (row) to help interpret the marginal effects reported in columns 1 and 2. Columns 4 and 5 display the marginal effects from the probability of receiving in-situ upgrading, using only treated slums. Column 6 represents a similar counterpart to column 3. Significance: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors. The Pr(Population Relocation|Any Treatment) is the converse of the Pr(In-situ Upgrading|Any Treatment). For a detailed definition of the regressors see Table B1.

Table 6: Direct Effect of Slum Renewal Policies —SDiD

Dependent variable:	Mean Control (Level) (1)	*In-situ* Upgrading β_1 (2)	Population Relocation β_2 (3)	p-value $\beta_1 = \beta_2$ (4)
Slum Characteristics				
Index Slum Characteristics (sd)	0.00	0.16***	0.21***	0.00
		(0.04)	(0.03)	
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				
Index Housing Investment (sd)	0.00	0.56**	0.14	0.00
		(0.25)	(0.11)	
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				
Index Housing Quality (sd)	0.00	0.09***	0.05	0.00
		(0.04)	(0.04)	
Log # Buildings, size > 64m^2	(4.60)	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)	

Notes: Unit of analysis is the slum. Significance: * p<0.1, ** p<0.05, *** p<0.01. Each coefficient is from a different SDiD regression (Arkhangelsky et al., 2021) for the dependent variable (row) six years after the indicated treatment (columns 2 and 3). Column 1 shows the control group's dependent variable mean; those in parentheses are means in levels instead of logs. SDiD identifies a synthetic control group from never-treated slums to match pre-treatment trends. It also accounts for slum fixed effects, time fixed effects, and lagged slum population data from LandScan (1 km^2 estimates). Inference is built using bootstrapping with replacement, creating a distribution for each estimated coefficient. Column 4 tests the equality of the effects for both policies using the bootstrapped distribution of each estimated effect. *Slum Characteristics* and *Housing Quality* variables come from satellite images. *Housing Investment* variables are from building permits. Indexes for each grouping follow Anderson (2008). Baseline mean corresponds to 2009, except for building permits, which is 2010.

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

Dependent variable:	Mean Control (Level) (1)	*In-situ* Upgrading β_1 (2)	Population Relocation β_2 (3)	p-value $\beta_1 = \beta_2$ (4)
Sociodemographics				
Index Sociodemographics (sd)	0.00	0.14	-0.02	0.09
		(0.09)	(0.08)	
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				
Index Housing Quality (sd)	0.00	0.15	-0.09	0.06
		(0.13)	(0.08)	
% 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)	

Notes: Unit of analysis is the slum. Significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors are clustered at the municipality level. Sample size = 920. Outcome variables are from the 2002 and 2017 population censuses. Column 1 shows the control group's dependent variable mean; those in parentheses are means in levels instead of logs. Each row corresponds to one pooled TWFE regression of the dependent variable indicated, including two dummy treatment variables, one for in-situ upgrading (column 2) and another for slums receiving population relocation (column 3). The TWFE regression controls for slum and year FE. Only slums treated between 2011 and 2015 are included in the treated sample. Column 4 reports p-values from Wald tests to determine if the treatment coefficients are statistically similar. Indexes for each grouping follow Anderson (2008).

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

	0 - 200 m				200 - 500 m			
	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 $\gamma_1 = \gamma_2$
Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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)	

Notes: Unit of analysis is the nearby neighborhoods of the slums. Significance: * p<0.1, ** p<0.05, *** p<0.01. Each coefficient is from a different SDiD regression (Arkhangelsky et al., 2021) for the dependent variable (row) five years after the indicated treatment (columns 2 and 3, and columns 6 and 7). Columns 1 and 5 show the control group's dependent variable mean. For each cohort of adjacent areas of treated slums, SDiD finds a synthetic control group using adjacent areas of never-treated slums to match the pre-treatment trends of the treated locations. In addition to matching the pre-treatment trends in the outcome of interest, SDiD also controls for individual FE, time FE, and the lag of slum population measured using LandScan (gridded population estimates for 1 km^2) based on the grid containing the slum polygon. Inference is constructed using bootstrapping with replacement, which allows for the construction of a distribution for each estimated coefficient. Columns 4 and 8 test the equality of the effects for both policies using the bootstrapped distribution of each estimated effect. 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.

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) (1)	*In-situ* Upgra. β_1 (2)	Pop. Reloc. β_2 (3)	p-value $\beta_1 = \beta_2$ (4)	Mean Control (Level) (5)	*In-situ* Upgra. γ_1 (6)	Pop. Reloc. γ_2 (7)	p-value $\gamma_1 = \gamma_2$ (8)
Housing Investment								
Index Housing Investment (sd)	0.01	0.22***	0.14**	0.00	0.00	0.13***	0.06	0.00
		(0.05)	(0.06)			(0.03)	(0.04)	
% 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								
Index Housing Quality (sd)	0.00	0.03	0.02	0.01	0.00	-0.02	0.016	0.00
		(0.04)	(0.02)			(0.05)	(0.03)	
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)	

Notes: Unit of analysis is the nearby neighborhoods of the slums. Significance: * p<0.1, ** p<0.05, *** p<0.01. Each coefficient is from a different SDiD regression (Arkhangelsky et al., 2021) for the dependent variable (row) five years after the indicated treatment (columns 2 and 3, and columns 6 and 7). Columns 1 and 5 show the control group's dependent variable mean. For each cohort of adjacent areas of treated slums, SDiD finds a synthetic control group using adjacent areas of never-treated slums to match the pre-treatment trends of the treated locations. In addition to matching the pre-treatment trends in the outcome of interest, SDiD also controls for individual FE, time FE, and the lag of slum population measured using LandScan (gridded population estimates for 1 km^2) based on the grid containing the slum polygon. Inference is constructed using bootstrapping with replacement, which allows for the construction of a distribution for each estimated coefficient. Columns 4 and 8 test the equality of the effects for both policies using the bootstrapped distribution of each estimated effect. 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. Indexes for each grouping follow Anderson (2008). Baseline mean corresponds to 2009, except for building permits, which is 2010.

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

	0 - 200 m				200 - 500 m			
Dependent variable:	Mean Control (Level) (1)	*In-situ* Upgra. β_1 (2)	Pop. Reloc. β_2 (3)	p-value $\beta_1 = \beta_2$ (4)	Mean Control (Level) (5)	*In-situ* Upgra. γ_1 (6)	Pop. Reloc. γ_2 (7)	p-value $\gamma_1 = \gamma_2$ (8)
Sociodemographics								
Index Sociodemographics (sd)	0.00	0.07	-0.11***	0.00	0.00	0.05	-0.11***	0.00
		(0.04)	(0.04)			(0.03)	(0.03)	
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								
Index Housing Quality (sd)	0.00	0.14**	-0.01	0.05	0.00	0.15***	0.01	0.02
		(0.06)	(0.04)			(0.05)	(0.04)	
% 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)	

Notes: Unit of analysis is the nearby neighborhoods of the slums. Significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered at the municipality level. Outcome variables are from the 2002 and 2017 population censuses. Columns 1 and 5 show the mean values of the dependent variable for the control group, with parentheses indicating means in levels. Pooled TWFE regressions for each dependent variable (listed in rows) use two dummy treatment variables: one for in-situ upgrading and another for slums receiving population relocation. Columns 2 and 3 show coefficients for areas within 200 m of slum boundaries, while Columns 6 and 7 present results for areas between 200 and 500 m. The regressions control for slum and year FE. Only the nearby areas of slums treated between 2011 and 2015 are included. Columns 4 and 8 report p-values from Wald tests to determine if the treatment coefficients are statistically similar. Indexes for each grouping follow Anderson (2008).

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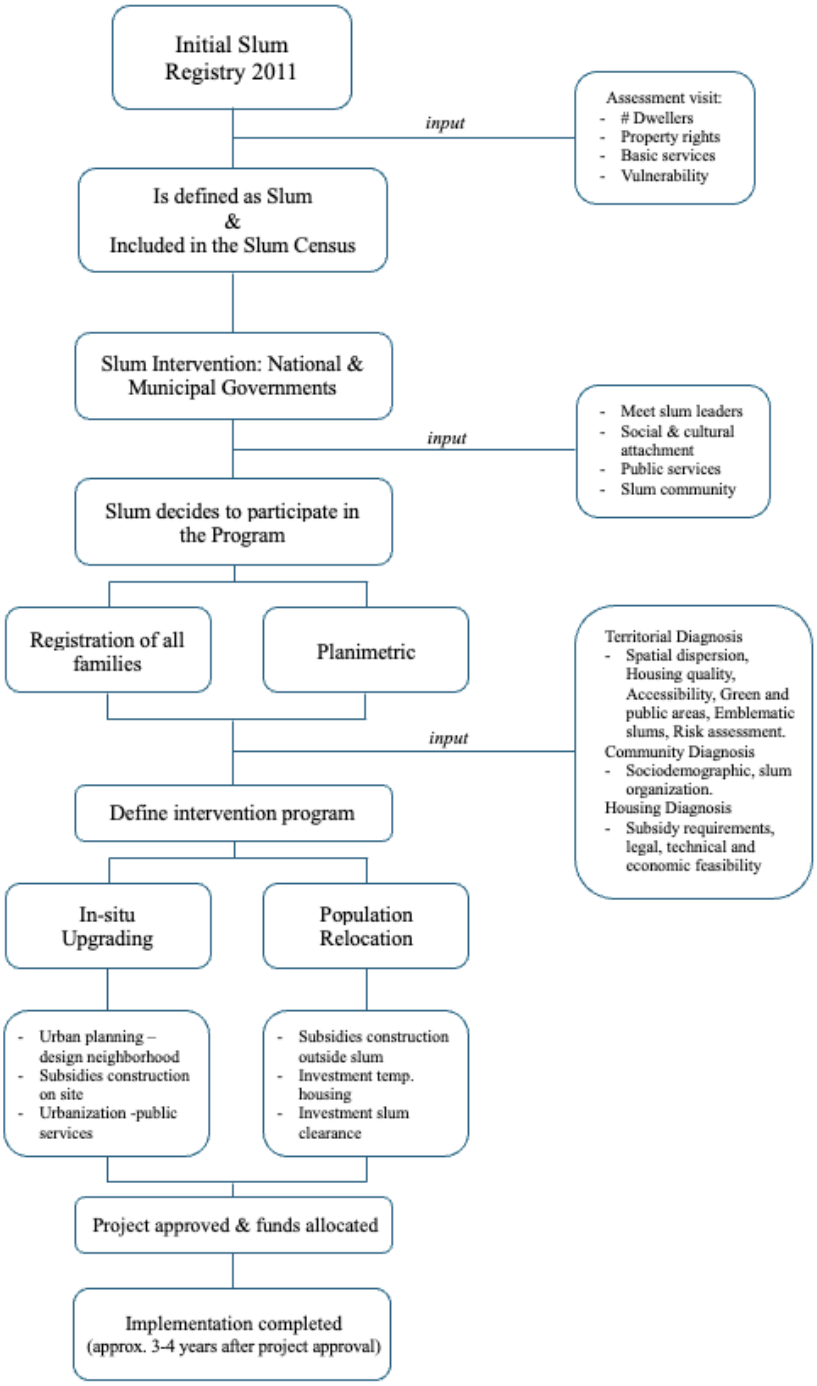
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A Flowchart Government Interventions

Figure A1: Flowchart Government Intervention



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

B List of Variables and Datasets

Table B1: List of Variables and Data Sources

Variable	Definition	Units	Source	Years	Tables
# Building Permits	Number of building permits registered inside the slum polygon	Count	Instituto Nacional de Estadistica (INE)	2010-2021	6, 9
# Buildings size > 64m2	Number of building footprints larger than 64 square meters	Count	Building footprints - Satellite images	2000-2021	6, 9
# employees	Count of employees in the municipality	Count	Encuesta Nacional de Empleo - INE	2010-2020	5
# employees - high school or more	Count of employees with high school education or more in the municipality	Count	Encuesta Nacional de Empleo - INE	2010-2020	5
# Homicide crime per km2	Homicides divided by the area in square kilometers	# per square kilometer	Subsecretaria de Prevencion del Delito	2013-2022	8
# Property crime per km2	Property crimes (burglary, theft, auto theft, theft from non-residential areas, and other economically motivated crimes) divided by the area in square kilometers	# per square kilometer	Subsecretaria de Prevencion del Delito	2013-2022	8
# Violent crime per km2	Violent crimes (homicides and assault) divided by the area in square kilometers	# per square kilometer	Subsecretaria de Prevencion del Delito	2013-2022	8
% adults high-school or more educ	Percentage of adults over 25 years with secondary education completed or more	Percentage	Population Census	2002, 2017	7, 10
% houses with high quality walls	Percentage of houses that have concrete, stone, brick, or steel as predominant wall materials	Percentage	Population Census	2002, 2017	7, 10
% houses with two or more bedrooms	Percentage of houses with two or more bedrooms	Percentage	Population Census	2002, 2017	7, 10
% new buildings	Percentage of buildings constructed in the last 5 years	Percentage	Servicio de Impuestos Internos (SII) Cadastro	2009-2024	9
% population with secondary education	Percentage of adults over 25 years with secondary education completed (high school graduates)	Percentage	Population Census	2002, 2017	4
% population with tertiary education	Percentage of adults over 25 years with some tertiary education (vocational training, 2yrs training, colleges)	Percentage	Population Census	2002, 2017	4
% renovated buildings	Percentage of buildings that undergo renovations during a given year (reported alterations to building characteristics)	Percentage	Servicio de Impuestos Internos (SII) Cadastro	2009-2024	9
Aggregate crime index	Anderson (2008) index combining number of property crime per square kilometer and violent crime per square kilometer	Standard deviations	Subsecretaria de Prevencion del Delito	2013-2022	8
Amenities Distance Index	Anderson (2008) index combining distance to the nearest bus stop, supermarket, library, fire station, police station, school, health center, and finance institution.	Standard deviations	See each component data source	circa 2022	2
Average distance to neighbors	Average distance between a building footprint and its nearest eight neighbors	Meters	Building footprints - Satellite images	2000-2021	6, 9
Building age	Average age of buildings	Years	Servicio de Impuestos Internos (SII) Cadastro	2009-2024	9
Building Density within 200 m	Total building footprints area in formal neighborhoods within 200 m of the slum over the area	Share	Building footprints - Satellite images	2000-2021	2

Table B2: List of Variables and Data Sources

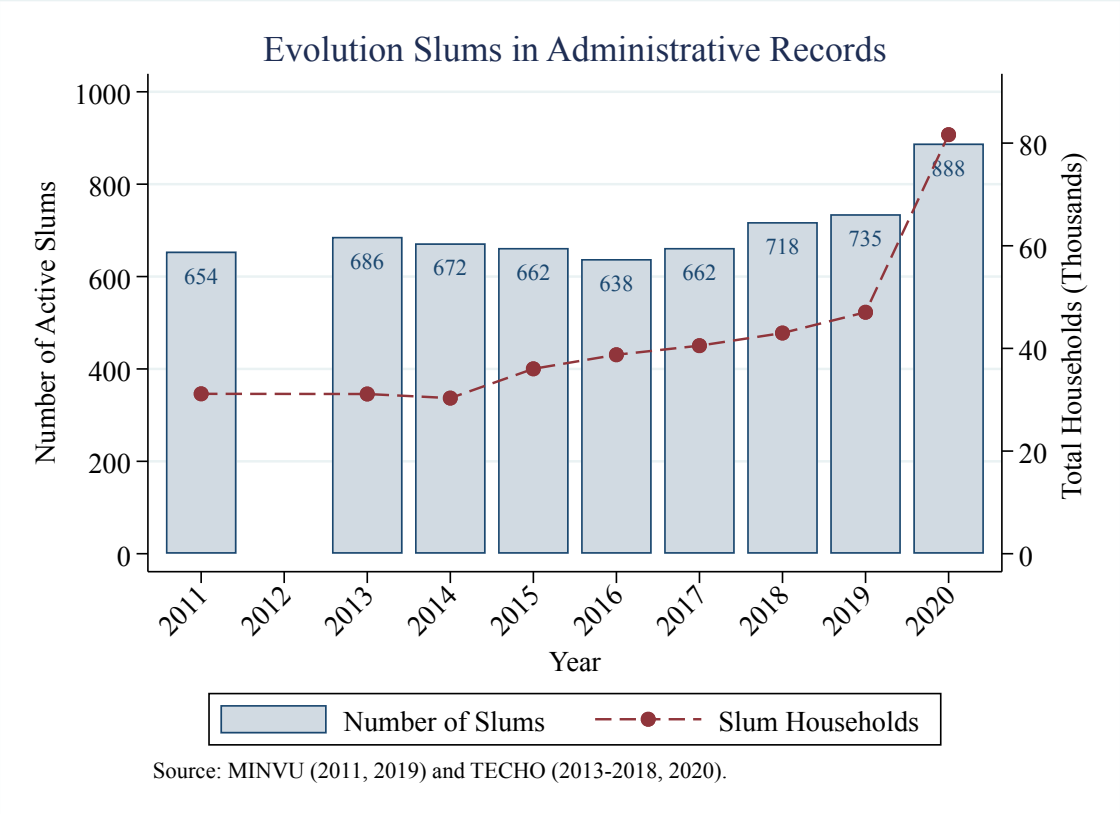
Variable	Definition	Units	Source	Years	Tables
Building Permits > 0	Dummy variable equals one if there are at least one building permit registered inside the slum polygon, zero otherwise	Indicator	Instituto Nacional de Estadistica (INE)	2010-2021	6, 9
Building size	Average reported building size	Years	Servicio de Impuestos Internos (SII) Cadastro	2009-2024	9
Distance to City Center	Euclidean distance to the nearest city center	Kilometers	Urban Functional Areas project	2021	2
Distance to Nearest Bus Stop	Euclidean distance to the nearest bus stop	Kilometers	XX	2022	3
Distance to Nearest Finance Institution	Euclidean distance to the nearest finance institution (bank, atms, money transfer, or post office)	Kilometers	OpenStreetMap	2023	3
Distance to Nearest Fire Station	Euclidean distance to the nearest fire station	Kilometers	Geoportal IDE MINVU	2022	3
Distance to Nearest Health Center	Euclidean distance to the nearest health center	Kilometers	Geoportal IDE MINVU	2022	3
Distance to Nearest Police Station	Euclidean distance to the nearest police station	Kilometers	Geoportal IDE MINVU	2022	3
Distance to Nearest River	Euclidean distance to the nearest water body (river, ravine or estuary)	Kilometers	Biblioteca del Congreso Nacional de Chile	2018	3
Distance to Nearest School	Euclidean distance to the nearest school by the time the slum was founded	Kilometers	Centro de Estudios MinEduc	2000-2023	3
Distance to Nearest Supermarket	Euclidean distance to the nearest supermarket	Kilometers	XX	2022	3
Elevation	Distance above sea level	Kilometers	View Finder Panoramas & DIVA-GIS	2022	2, 3
Elevation Slope, percentage rise	Percent of slope is determined by dividing the amount of elevation change by the amount of horizontal distance covered	Percentage	View Finder Panoramas & DIVA-GIS	2022	2, 3
Employment rate	Percentage of the population of working age that is employed	Percentage	Population Census	2002, 2017	4, 7, 10
Housing subsidies in slums	Count of the number of housing subsidies allocated to a slum	Count	MINVU	2011-2020	1.5
Identified as Slum in 2011	Dummy variable equals one if the slum is included in MINVU 2011 census of slums, zero otherwise	Indicator	MINVU Slum Census	2011	2
Index Housing Investment	Anderson (2008) index combining the indicator of whether there is at least one building permit and the # of building permits	Standard deviations	See each component data source	2010-2021	6
Index Housing Quality	Anderson (2008) index combining the # buildings size > 64m2, SD building main angle across neighbors, and average distance to neighbors. The SD building main angle is flipped, so positive index values indicate better outcomes.	Standard deviations	See each component data source	2010-2021	6
Index Housing Quality (Census)	Anderson (2008) index combining the % of houses with two or more bedrooms and the % of houses with high-quality walls.	Standard deviations	See each component data source	2002, 2017	7
Index Slum Characteristics	Anderson (2008) index combining log slum population, share of residential land, and share of streets paved. The first two variables are flipped, so positive index values indicate better outcomes.	Standard deviations	See each component data source	2009-2021	6
Index Sociodemographics	Anderson (2008) index combining the log of population, the % of adults with high school or more education, and the % employed. The log of population is flipped, so positive index values indicate better outcomes	Standard deviations	See each component data source	2002, 2017	7
Investment in slums	Amount of direct investments allocated to a slum	Currency	MINVU	2011-2020	1.5
Labor salary	Payments received as compensation of work for those employed (not including self-employment)	Currency	Encuesta Suplementaria de Ingresos - INE	2010-2020	5

Table B3: List of Variables and Data Sources

Variable	Definition	Units	Source	Years	Tables
Labor salary - High school or more	Payments received as compensation of work for those employed (not including self-employment) with high school education or more	Currency	Encuesta Suplementaria de Ingresos - INE	2010-2020	5
Located at City Border or Beyond	Dummy variable equals one if the normalized distance to the city center is greater or equal 0.9	Indicator	Urban Functional Areas project	1993, 2011, 2017, 2019, 2020	2
Municipal social expenditures	Local municipal government expenditures in social assitance	Currency	SINIM	2010-2020	5
Municipality expenditures	Total expenditures by the local municipality	Currency	SINIM	2011-2020	2,5
Municipality population	Population in the municipality	Count	Population Census	2002, 2017	5
Not Suitable for Construction	Dummy variable equals one if the terrain has slopes higher than 20% or ruggedness greater than 497 mt, zero otherwise	Indicator	See slope & TRI sources		2
Population - Census	Count population using census blocks. Census blocks are assigned to each area based on their centroid.	Count	Population Census	2002, 2017	4, 7, 10
Population - LandScan	Estimated count of population in slum areas using 1km grid population estimates based on the grid where the slum is located	Count	Landscan	2000-2021	6
Population - WorldPop	Estimated count of population in slum areas using 100m grid population estimates. Grids are assigned to each area based on their centroid	Count	WorldPop	2000-2021	4
Quality adjusted rent	Municipal FE from a hedonic regression of rent including house size, bedrooms, bathrooms, basic services, and roof materials. FE are adjusted to match mean rent	Currency	CASEN	2009-2017	5
Ratio Adult Males/Females	Number of males between 25-64 years old over females between 25-65 years old	Ratio	Population Census	2002, 2017	4
SD bldg main angle across neighbors	Standard deviation between a building footprint's main angle and its eight nearest neighbors. Building main angle is the direccion angle of the minimum bounding rectangle containing the building footprint	Standard deviations	Building footprints - Satellite images	2000-2021	6, 9
Share residential land	Percentage of the slum polygon covered by residential areas. This comes from the question:	Share	HOD	2000-2021	6
Share streets paved	Percentage of the streets inside the slum polygon that are paved. This comes from the question:	Share	HOD	2000-2021	6
Slum Area	Size of the area ever occupied by a given slum (constant fixed boundary)	Square meters	MINVU & Techo		2
Slum Households	Number of households living in the slum	Number	MINVU & Techo	2011-2020	1, 2
Terrain Ruggedness Index (TRI)	TRI is used to express the amount of elevation difference between adjacent cells of a DEM.	Kilometers	Nunn and Puga	circa 2000	2, 3
Value of housing voucher	Estimated expenditures in housing vouchers:	Currency	MINVU	2011-2020	1
Within 250mt of a River	Dummy variable equals one if the slum is within 250 m of the nearest body of water	Indicator	Biblioteca del Congreso Nacional de Chile	2018	2

C Descriptive Analysis

Figure C1: 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.

D 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.

D.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 D1. 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.

D.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.

D.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 D1; 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.

D.4 Computing measures using building footprints

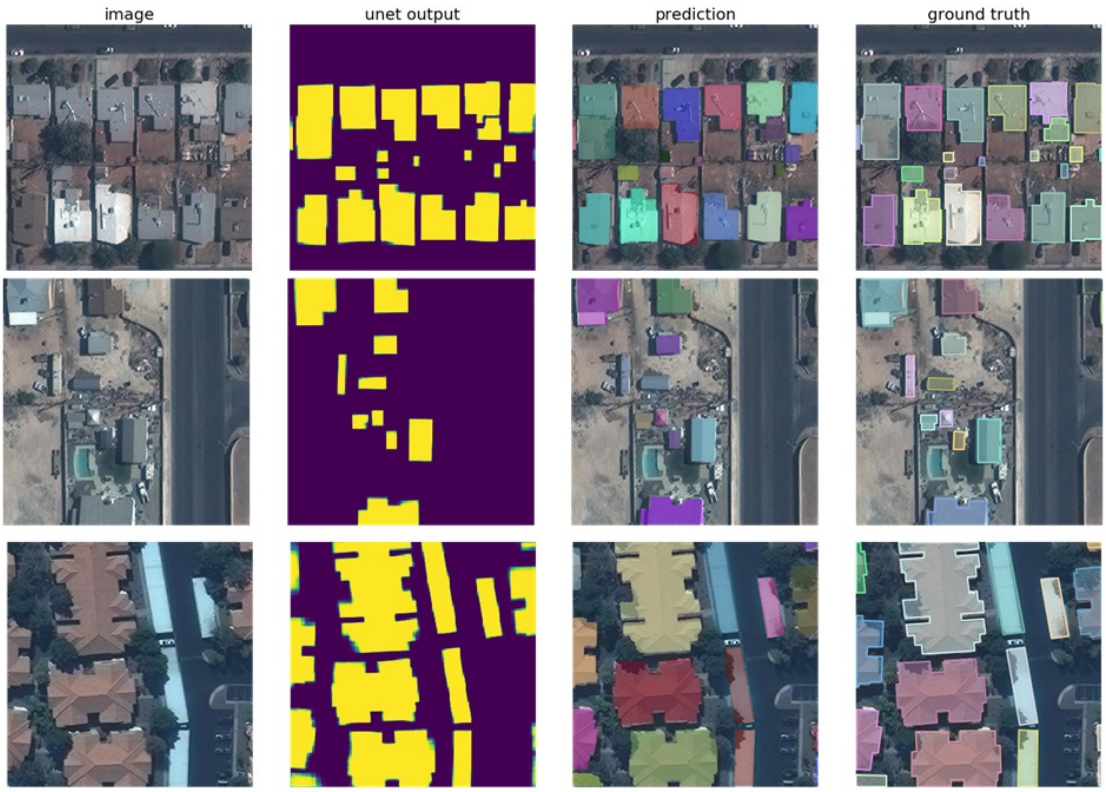
We computed different metrics to measure building activity and regularity inside and outside the slums. We began by calculating the total building area and building density within the slums. We also calculated these measures for areas within a certain distance of the slum border. Additional statistics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

D.5 Example building footprints

Figure D2 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 D2 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.

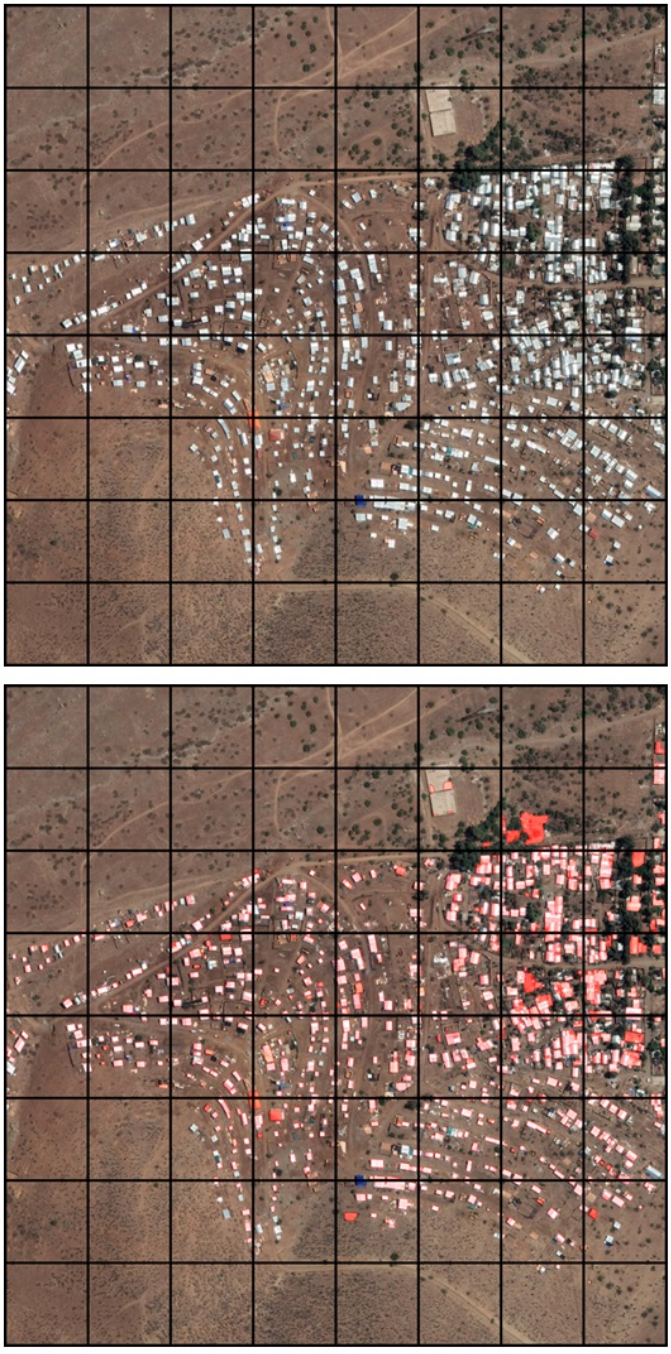
[20]Precision is calculated as the number of true predicted building footprints over the total number of predicted footprints. Recall has the same numerator but uses the actual number of building footprints as the denominator.

Figure D1: Performance ML Algorithm to Identify Building Footprints



Source: Czakon et al. (2021).

Figure D2: 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.

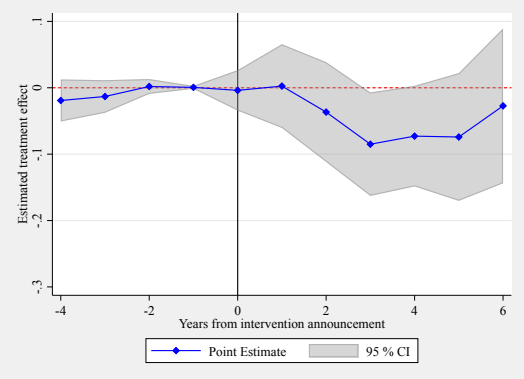
E Dynamics of SDiD Effects

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.

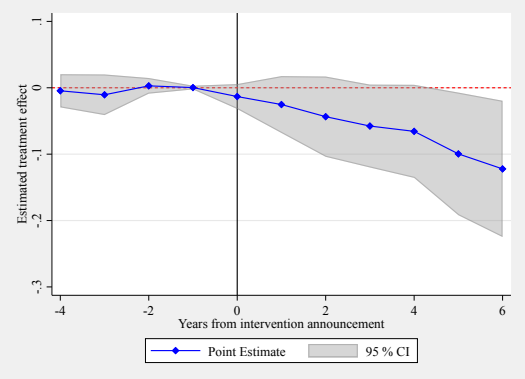
Figure E1: SDiD Direct Effects of Slum Policies

(a) Share of Land Devoted to Residential Housing

In-situ Upgrading

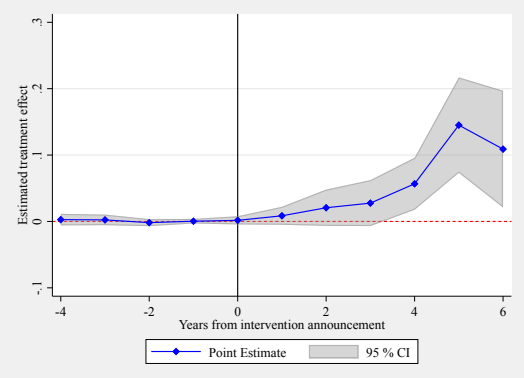


Population Relocation

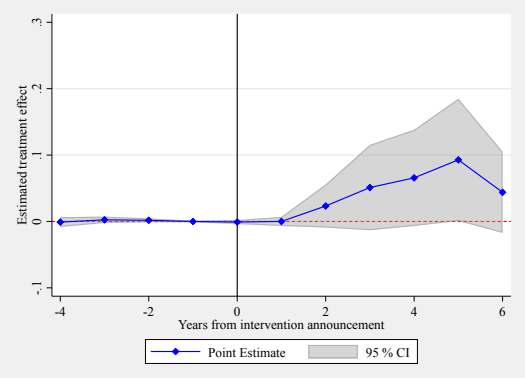


(b) Share of Streets Paved

In-situ Upgrading

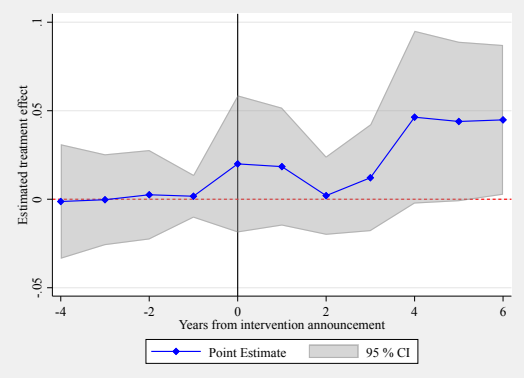


Population Relocation



(c) Pr(Building Permits > 0)

In-situ Upgrading



Population Relocation

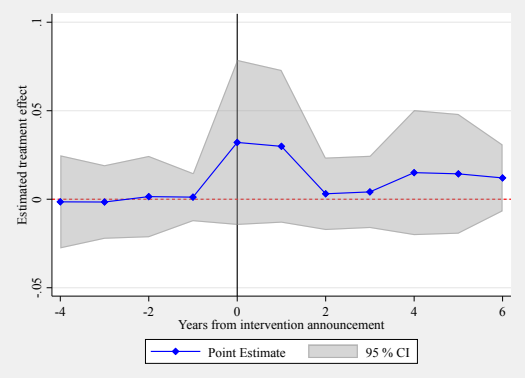
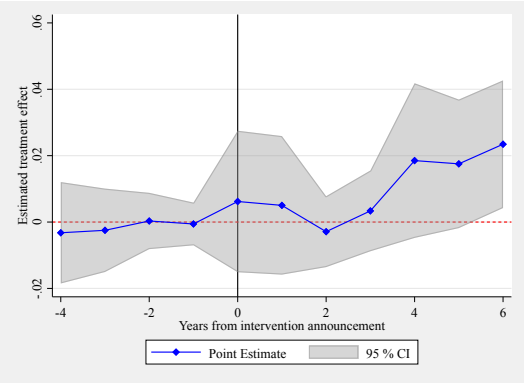


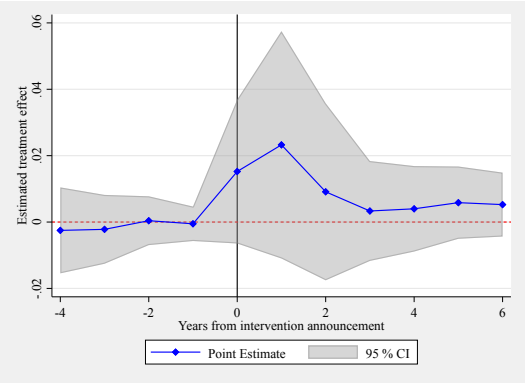
Figure E1: SDiD Direct Effects of Slum Policies (*continued*)

(d) Log # of Building Permits

In-situ Upgrading

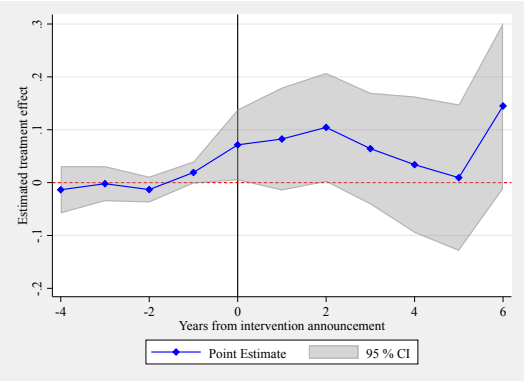


Population Relocation

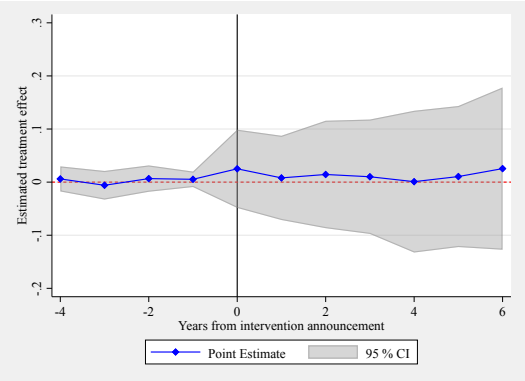


(e) Log # of Large Buildings (size $> 64\text{m}^2$)

In-situ Upgrading

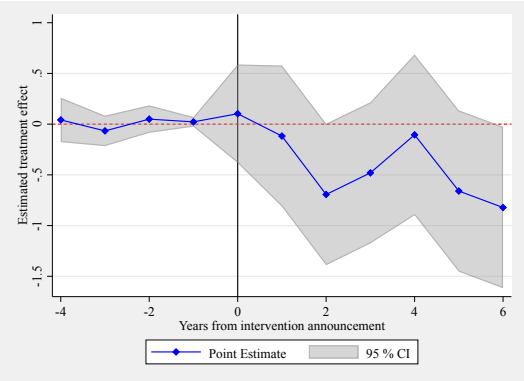


Population Relocation

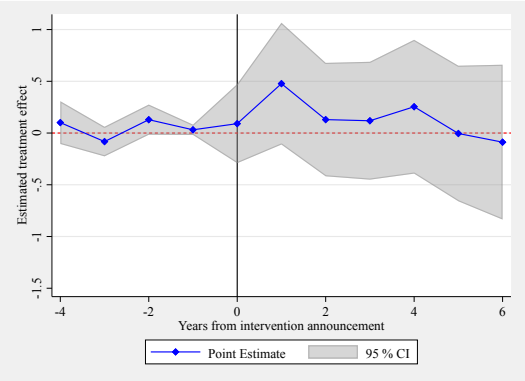


(f) SD Building Main Angle Across Neighbors

In-situ Upgrading



Population Relocation

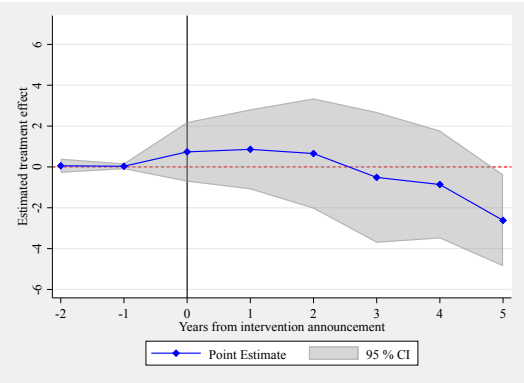


SDiD - Synthetic Difference-in-Difference methodology developed by Arkhangelsky et al. (2021). Confidence intervals are obtained using bootstrapping. We focus on slums treated between 2011 and 2017.

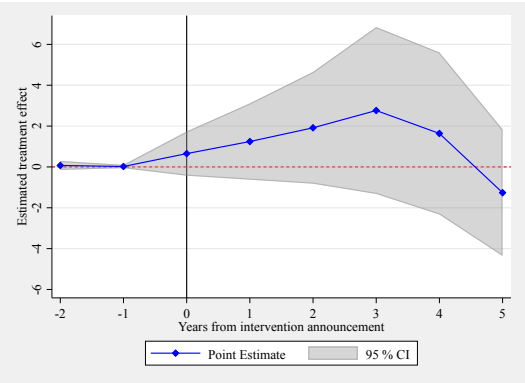
Figure E2: SDiD Spillovers of Slum Policies on Crime -Adjacent Neighborhoods

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

In-situ Upgrading

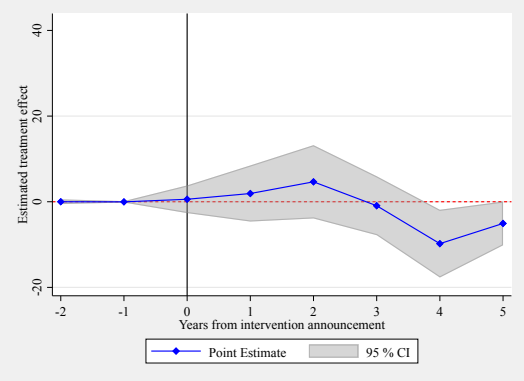


Population Relocation

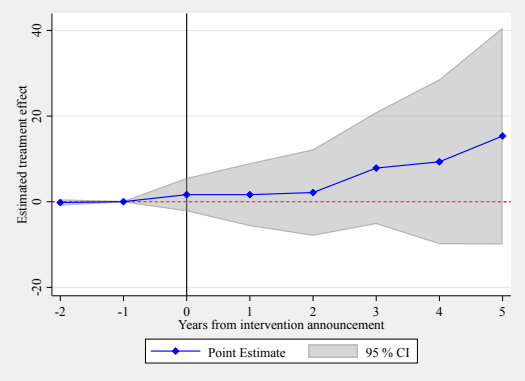


(b) Property Crime per Km^2 within 200m of a Slum

In-situ Upgrading

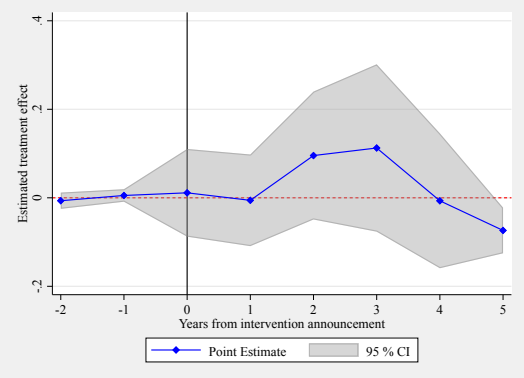


Population Relocation

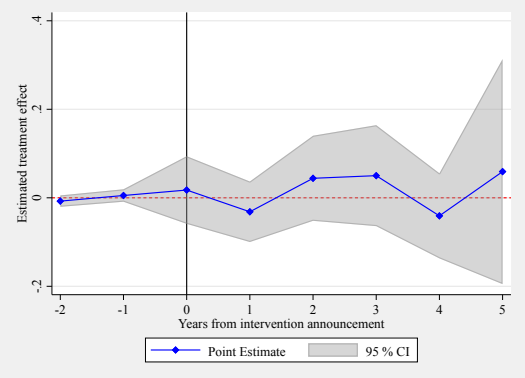


(c) Homicides per Km^2 within 200m of a Slum

In-situ Upgrading



Population Relocation

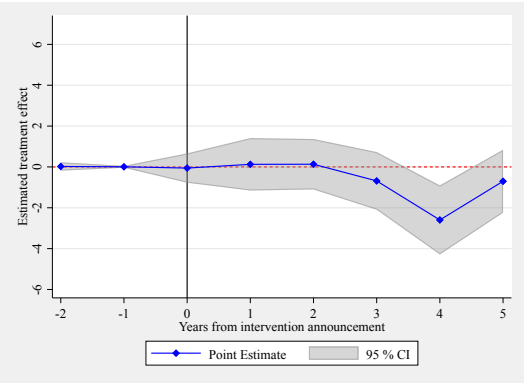


[a]SDiD - Synthetic Difference-in-Difference (Arkhangelsky et al., 2021). Confidence intervals are obtained using bootstrapping. Crime data come from the Subsecretaria de Prevencion del Delito, and data covers the sample of slums treated between 2015-2018.

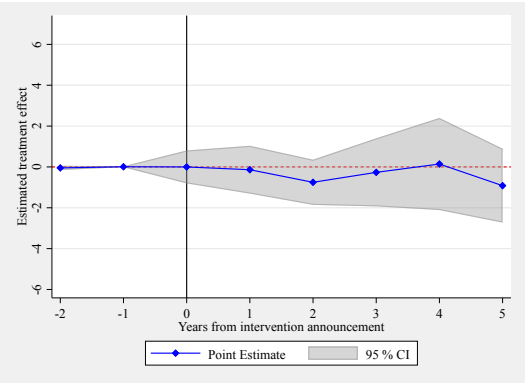
Figure E3: SDiD Spillovers of Slum Policies on Crime -Neighborhoods >200m

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

In-situ Upgrading

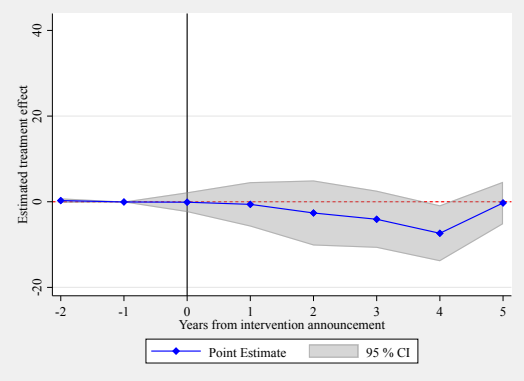


Population Relocation

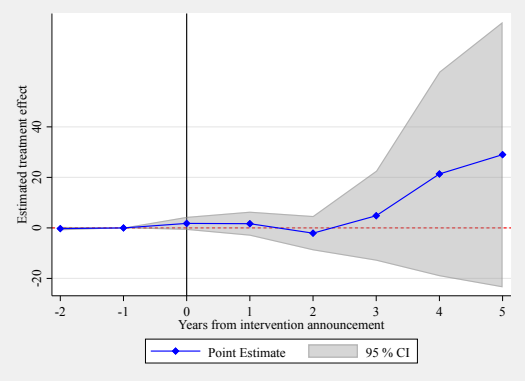


(b) Property Crime per Km^2 within 200-500m of a Slum

In-situ Upgrading

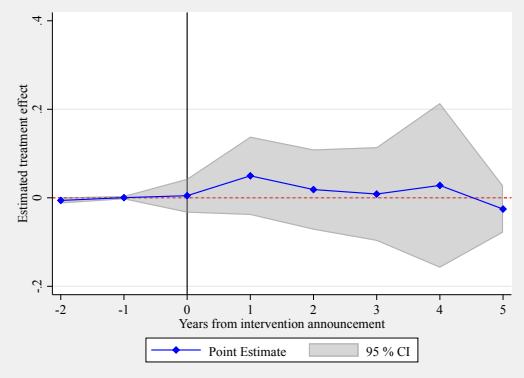


Population Relocation

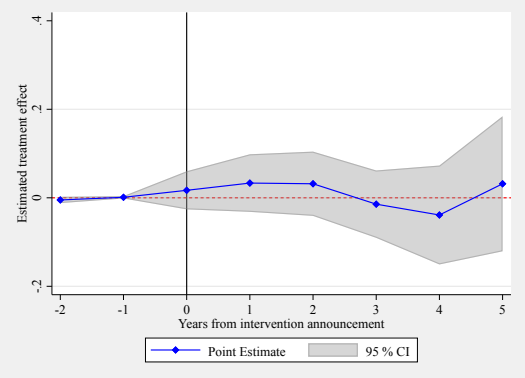


(c) Homicides per Km^2 within 200-500m of a Slum

In-situ Upgrading



Population Relocation



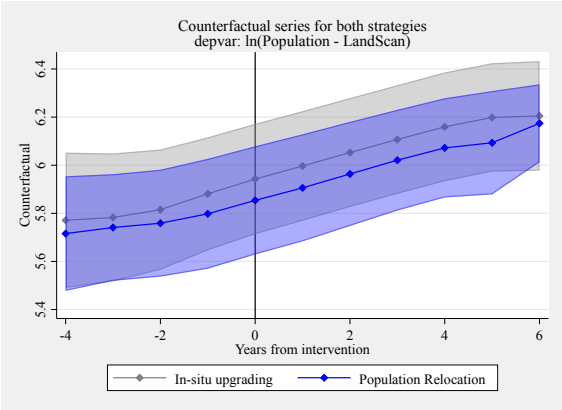
[a]SDiD - Synthetic Difference-in-Difference (Arkhangelsky et al., 2021). Confidence intervals are obtained using bootstrapping. Crime data come from the Subsecretaria de Prevencion del Delito, and data covers the sample of slums treated between 2015-2018.

F Counterfactuals for Both Policies

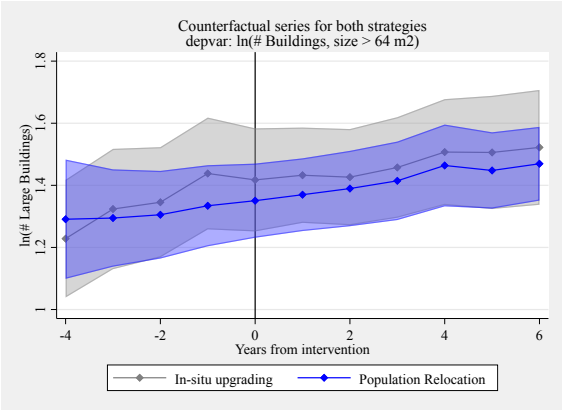
We plot the estimated counterfactuals under the SDiD estimation for both treatment strategies. Each estimation is done separately for each slum policy, meaning that the objective function for the optimal weights does not take into account the pre-treatment trends of the other treatment arm.

Figure F1: Counterfactual Synthetic Controls for the Two Policies

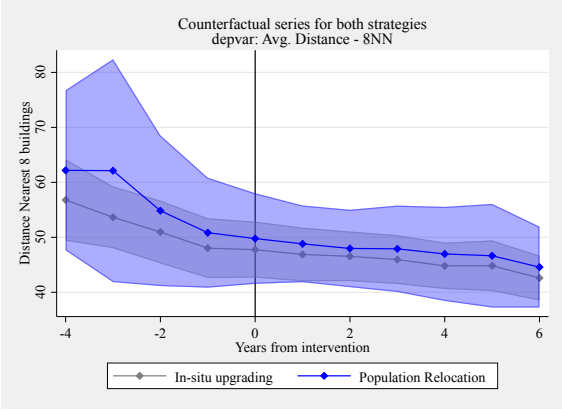
(a) ln(Population - LandScan)



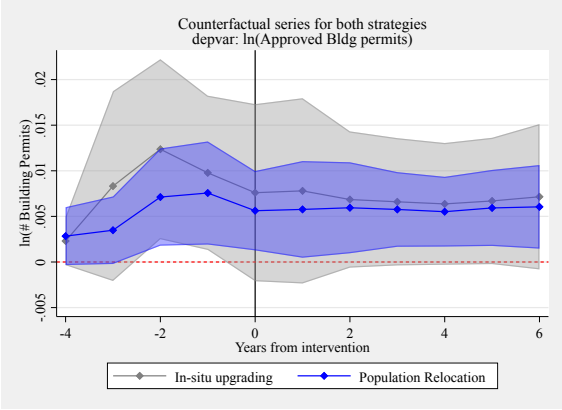
(b) ln(Large Buildings)



(c) Avg. Distance - 8NN



(d) ln(Approved Bldg permits)



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

G 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 1 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 G1 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.

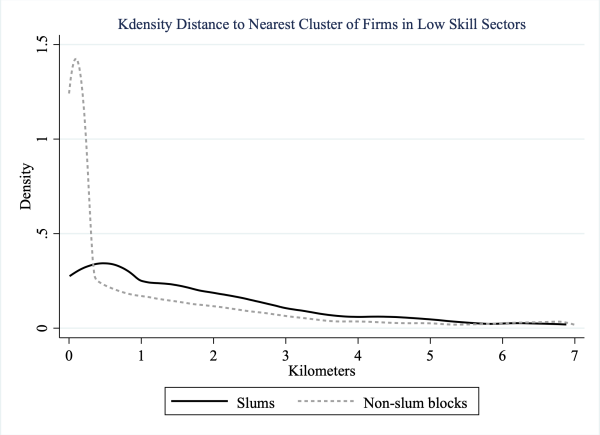
These results raise the question of why slums in big cities face riskier locations compared to those in small cities. The answer may lie in some of the findings documented in this

[21] TRI classification by ESRI is available here.

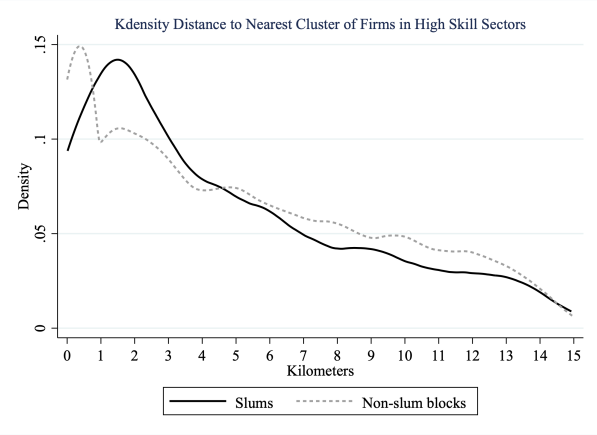
paper. Bigger cities have more competitive formal housing markets, leading to higher rents. Although larger cities offer a wider array of labor opportunities than smaller cities, they also push informal settlers to trade proximity to labor markets for access to amenities. If we consider a slum household 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 G1: Slums Proximity to Different City Amenities [a]

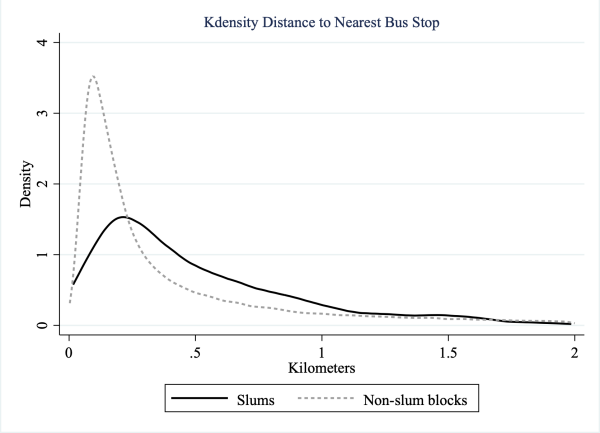
(a) Low-Skill Firms' Cluster



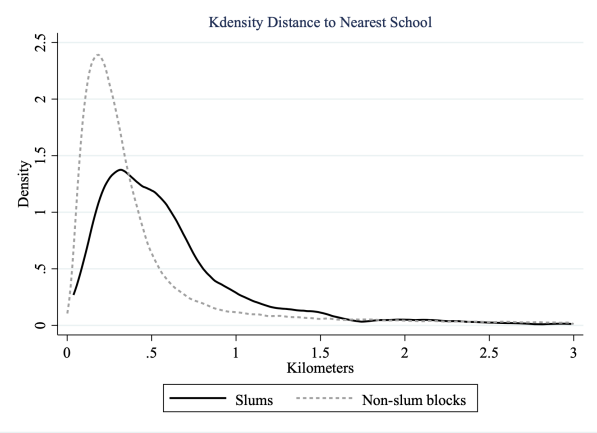
(b) High-Skill Firms' Cluster



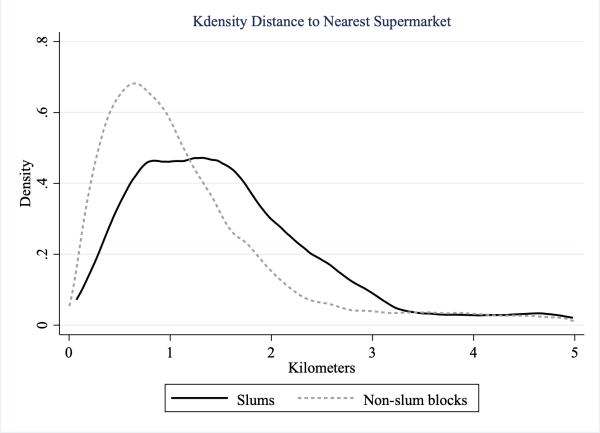
(c) Bus Stop



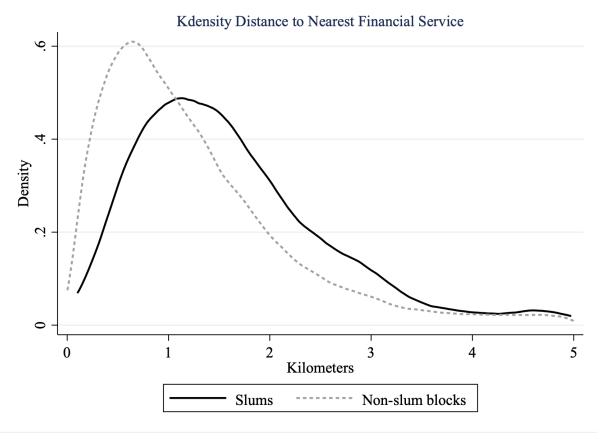
(d) School



(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.