Segregation and Death:
The Consequences of Slum Clearance on Mortality*

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Abstract

We study the effects of forced relocation on adults' mortality. We use evidence from a slum clearance program implemented in Santiago, Chile, between 1979 and 1985 that forced slum-dwelling families to relocate to public housing in low-income areas. Two-thirds of the families were relocated to new housing projects on the periphery of the city, while the rest received housing at their initial location. We compare the outcomes of displaced and non-displaced adults from slums with the same probability of being cleared and find that displacement increases mortality: displaced adults die 30% more each year for the next 40 years after the intervention and have a shorter lifespan by 0.376 years. The effects on causes of death are gender-specific: women are more likely to die from disease-related conditions such as heart disease or diabetes, while men are more likely to die from cancer, external causes, and tobacco addiction. In the long run, displaced individuals have lower pensions, suggesting more labor informality throughout individuals' lifetimes. Mechanisms indicate that distance from the origin, the reduction of social networks, and higher unemployment at the destination increase the risk of death for displaced individuals.

Keywords: slum clearance, mortality, neighborhood effects, forced relocation

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1 Introduction

Segregation and poverty correlate negatively with health outcomes, as individuals in poorer areas have lower life expectancy compared to adults in richer areas (Lleras-Muney et al., 2024). This relationship, however, could be due to individuals sorting into place rather than the causal effect of segregation on health (Deryugina and Molitor, 2020). In developing countries, these patterns can be exacerbated when the availability of neighborhoods for low-income individuals is limited and policy contributes to building housing in poorer and segregated areas. A common policy to deal with the lack of housing for low-income individuals has been to build public housing in city peripheries; however, the welfare consequences of these policies are not well-understood. On the one hand, the poor obtain access to better-quality housing, but on the other, the locations come with worse access to labor markets and public services, which can have negative consequences on health in the longer-term.

In this paper, we study the long-term effects of a forced relocation on mortality. To study this question, we examine the impact of a large-scale slum clearance and urban renewal program, the Program for Urban Marginality (Programa para la Marginalidad Urbana), that was implemented during the Chilean dictatorship between 1979 and 1985. The program was large in scope, affecting more than 5% of the total population of Greater Santiago (the capital). All of the slum dwellers in the program became homeowners of similar housing units, but whereas some slums were upgraded into neighborhoods, others were relocated to suburban areas. The program consisted of two types of intervention. In the first, whenever urban conditions permitted it, a slum was upgraded into a formal neighborhood and families remained in the same place (i.e., were non-displaced). In the second, when upgrading was not possible, families were evicted and forced to move in groups to new public housing projects (i.e., were displaced).

We collect archival records of slum-dwelling families that we match to administrative records to create a novel dataset that follows individuals from non-displaced

(redeveloped) and displaced (relocated) slums for 40 years after the policy ended. We take advantage of the fact that slum-dwelling families received a property deed associated with a unique national identifier. Using these identifiers, we can determine where families were sent, match individuals to death certificates, and then match individuals with data on employment, labor earnings, and years of schooling. Our final sample contains 27,810 adults who were treated between 1979 and 1985, and who we follow until 2019.

We use variation in treatment to estimate a displacement effect that compares displaced adults to non-displaced adults. An important identification concern is that displaced and non-displaced slum residents were different. The selection of slums for displacement or non-displacement was based on the feasibility of urban renewal rather than on individual family characteristics, such as slum density, geographic location, and price of land. To address this concern, we leverage the program's selection rule and our rich dataset to estimate a policy function that estimates the probability of a slum being cleared versus being redeveloped, and then compare displaced and non-displaced individuals from slums with the same probability of being relocated. Conditional on the probability of a slum being relocated, we find no correlation between the selection of slums for displacement and families' demographic and socioeconomic characteristics, such as age, gender, family composition, or formal employment before the program's implementation.

Our results show that displacement increases the risk of mortality for both sexes. Compared to non-displaced, displaced women face a 26.6% increase in their average yearly-mortality rate, and displaced men have a 37.6% increase in mortality compared to non-displaced, 40 years after the intervention. These large average effects on yearly-mortality are found immediately after the displacement and are fairly constant across years, but increase as individuals age.

Increases in mortality due to displacement are found in the entire age distribution. These effects are strengthen after the age of 50, especially for men, while displaced

women are more likely to die in the longer-term. However, the mortality impacts by cause are gender-specific: Displaced women are more likely to die due to diabetes, or cardiovascular disease, especially after the age of 60, which are chronic conditional that develop with time. For displaced men, excess mortality risk is associated to cancer, tobacco use, and to external causes, of which one-third are classified as accidents.

Because many displaced families reported losing their jobs after relocation, we explore heterogeneity of displacement effects by employment at baseline. We find that the positive effects on mortality are larger for individuals with higher formal employment at baseline, especially men. In our sample, 70% of head of households are men, and they are also more likely to be formally employed before treatment. compared to women. Because displaced families were disproportionately relocated to low employment areas, it is more likely that men who already worked were more likely to experience a negative employment effect after relocation. This result is consistent with the evidence on the relationship between employment and mortality found in the previous papers (Sullivan and von Wachter, 2009),

In addition to being forcibly moved, displaced families were assigned specific destinations, mostly in low-income municipalities on the city's periphery. These areas were generally characterized by high poverty rates and low provision of public goods, but the degree of change varied between the destinations and origins. This variation allows us to study place effects by investigating which neighborhood characteristics predict adults' mortality. Importantly, displaced families had no choice in their relocation, limiting potential selection at destination. We also show that family demographics do not systematically predict the attributes of their destination locations.

We examine where families were relocated using archival records. The data confirm that displaced families were relocated to peripheral neighborhoods with higher unemployment rates and greater distances from the city center compared to non-displaced families, who remained in their original locations. Consequently, displaced families received homes of 12% lower value compared to non-displaced.

To study the mechanisms that determine the displacement effect by exploring which characteristics of the new locations explain the observed variation in adults' mortality. We find that distance from origin and the disruption of slum network (measured as the share of original slum families at the destination) increase the risk of dying for women, with a small share being explained by the lack of primary care centers at destination. Overall, disrupted slum networks and distance from origin explain 40% of the total effect of the displacement on women. For men, we find that distance from origin and higher unemployment rates at destination locations explain 50% of the total displacement effect on mortality.

Finally, we study the labor market outcomes of adults that have not died by 2007, and who we match with administrative data between 2007 and 2019. We find that displaced individuals are more likely to be employed after the age of 65 compared to non-displaced adults, but their total income is lower. This effect is mainly driven by displaced individuals having lower pensions and higher labor informality compared to non-displaced. We also find that the program had persistent effects on families' locations. Thirty years after the program ended, 60% of adults remain in the same destination municipality, and their current neighborhoods are 7% poorer compared to those of non-displaced individuals.

This paper contributes to several strands of literature. Our results are related to the literature that studies policies that target slums (Marx et al., 2013). Slum clearance and housing upgrading programs were common in developed countries (LaVoice, 2023; Collins and Shester, 2013) and are still common practice in developing countries, where low-income housing is usually built in suburban areas (Dasgupta and Lall, 2009). Prior research has mainly focused on the effects of slum clearance on neighborhood quality, but little evidence has been provided for the effects of slum clearance policies on individuals, especially on health outcomes.[1] Barnhardt et al. (2016) and Picarelli (2019)

[1]Most of the literature has focused on property rights (Field, 2007; Franklin, 2020), improvements on-site (Galiani et al., 2017, Harari and Wong, 2021), or aggregate effects on urban development (Michaels et al., 2021).

are the most similar to our paper but they focus on employment and earnings in the short-term, while we study mortality and income effects associated to building public housing in low-quality neighborhoods in the longer-term.[2]

We also contribute to a recent literature that studies the role of place on mortality (Deryugina and Molitor, 2020; Finkelstein et al., 2021; Deryugina and Molitor, 2021). In this paper we contribute to the literature by studying adults that are forced to move to worse and isolated neighborhoods. We study individuals by gender, age and causes of deaths, and our results suggest different mechanisms play a role in explaining mortality patterns. Displacement could operate through a disruption and a place effect, as some individuals die immediately after the forced move, but the displacement effect on mortality is positive for all the ages in our sample.

The rest of the paper is organized as follows. Section 2 describes the historical background and the program. Section 3 explains the data collection process, and Section 4 presents the empirical framework. Section 5 presents our baseline results on mortality by age and causes of death. Section 6 discusses mechanisms, and section 7 presents a short discussion on future steps.

2 Historical Background: The Program for Urban Marginality

In the late 1970s, Chile had high levels of urban poverty after decades of urbanization. In Greater Santiago, the country's main metropolitan area,[3] approximately 15% of the population lived in a slum (INE, 1970; INE, 1982). A slum was defined as a squatter settlement without access to drinking water, electricity, or sewage (MINVU,

[2]Both Barnhardt et al. (2016) and Picarelli (2019) find a negative relationship between distance and adults' outcomes.This is also related to the literature on uneven geographical access to jobs and the spatial mismatch hypothesis (Kain, 1968; Kain, 2004; Andersson et al., 2018); Haltiwanger et al., 2020.

[3]Santiago is the capital of Chile, and at the time it contained 34.8% of the country's population.

1979).[4] Besides housing a large fraction of the population, slums were geographically ubiquitous: Every municipality in the city contained at least one. After the beginning of the Pinochet dictatorship in 1973, any attempt to create a new slum faced a strong military response.[5]

Motivated by this housing crisis, between 1979 to 1985, Chile's Ministry of Housing and Urban Development (MINVU) implemented the Program for Urban Marginality, a massive slum clearance and urban renewal policy. Proponents of this program believed the most effective way to end poverty was to house poor families by making them homeowners regardless of the attributes of the new housing units or neighborhoods (Murphy, 2015). At the onset of the program in 1979, the government conducted a census of slums and targeted 340 slums to be cleared.[6] According to Molina (1986) and Morales and Rojas (1986), by 1985, between 40,000 and 50,000 families participated in the program, accounting for 5% of the population of Greater Santiago. The average housing unit cost was US$10,148, and the program's average total annual cost was US$63 million, which corresponds to approximately 0.25% of the Chilean GDP in 1982.[7]

The Program for Urban Marginality had two features. First, it aimed to build public housing for low-income families where land was cheap. Second, it aimed to provide families with housing in places where they could afford it. With these goals, MINVU implemented two different types of interventions for slum dwellers: Whenever conditions permitted, families would remain in their original location, and their slum would go through an urban renewal process to provide them with housing on-site (i.e.,

[4]The median slum had around 250 families, with an average size of 5.2 persons per family.

[5]Between 1973 and 1990, Chile was under a military dictatorship headed by Augusto Pinochet. The slums originated between 1960 and 1973 as land seizures.

[6]Some slums families had received housing starting in 1977 but did not have the property on the new homes, they were renting. At the onset of the program in 1979 they were included in the group of families to become homeowners, thus we include them in our sample. But there were other evictions that occurred between 1976 and 1978, and were considered a precedent for the Program for Urban Marginality. They were called Operaciones Confraternidad I, II, and III. These were politically motivated forced evictions, and hence we do not include them in our analysis (for more information, see Celedón, 2019).

[7]Computation made by the authors based on average home value and subsidy from archival data. This number is similar to current expenditure in homeownership subsidies in Chile (see here).

non-displaced group). If this was not possible, the slum's residents would be evicted from their original location, and families would receive a housing unit in a different location (i.e., displaced group). All families in the same slum would receive the same treatment, and all of them would become homeowners.[8]

The features of each intervention are as follows. Non-displaced families accounted for one-third of the total number of families in the program, and their slums went through a process of urban renewal. In some cases, these families would get an apartment in projects constructed very close to their original site; in other cases, the slum's land was subdivided among all the residents, and families received a "starting-kit unit."[9] These new neighborhoods were provided with all of the basic services of a formal neighborhood (water, electricity, and sewage).

Displaced families accounted for two-thirds of the total number of families. These families were evicted and moved in groups to public housing projects located in peripheral sectors of the city. They received a house or an apartment in these new neighborhoods and became the owners of a new housing unit. The land used by the slum was then cleared and used for a different purpose.[10] The destination neighborhoods were not prepared to receive the large number of displaced families involved in this program (Molina, 1986; Aldunate et al., 1987). A large fraction lacked access to public transportation and public goods and services, such as schools and health care centers, and many were located in former rural areas recently added to the metropolitan limits.

Funding for the homes provided by the program came from a direct government subsidy that was designed to cover 75% of the cost of construction but capped at

[8]Both groups of residents were granted property rights to the new housing unit they received, and thus we cannot study the effect of property rights and land security on labor market outcomes. Field (2007) provides a good example of the effects of granting property rights to slum dwellers on labor force participation.

[9]A starting kit consisted of a living room, a bathroom, and a kitchen. Families would add bedrooms to the kit, completing the home.

[10]All families would be evicted, and if they did not want to move, they would be excluded from the program. According to social workers, it was unheard of for families to not accept the subsidy because for most of them, it was their only chance to become homeowners.

200UF (inflation adjusted index).[11] That is, a family would receive a subsidy equal to the minimum between 200UF and 75% of the value of the new housing unit. The remaining amount corresponded to a copay that was paid in monthly installments to MINVU over a term of 12 years.[12] Although the design of the policy considered the previous rule for the subsidy, in our data we find evidence that suggests there was discretion: Some housing projects had a subsidy capped at 200UF, that was above the 75% value of the new housing unit.[13]

Decisions regarding the program's implementation were made directly at the central government level by MINVU. Santiago lacked a citywide government; instead, there were 30 local municipalities that managed each territory. Under this governance structure, citywide policies such as social housing were defined at the central government level. Moreover, the dictatorial regime of Pinochet appointed all local-level authorities. Hence, government directives were uniformly followed at the municipal level (González et al., 2021).

Families did not participate in the decisions made by MINVU, and given the political circumstances, they could not oppose the policy. Instead, displaced families were assigned to destination locations based on the current availability of finished projects across the city. This also implied that in some cases, displaced families of a single slum were assigned to more than one housing project.[14] Destination municipalities could not influence how the Program for Urban Marginality was implemented in their territories. As Labbé et al. (1986) explain, "municipalities have not had a direct responsibility regarding the location and quantity of the displaced families, as construction

[11]The average home value in our sample is 254UF equivalent to US$10,148 in 2018.

[12]In our data we observe that sometimes families pay over a term of 25 years, but their subsidies are lower.

[13]An example of this are slum dwellers that were moved from the Rio Mapocho riverbank in 1982 due to a flood. These families received a house with a value of 220UF, but a subsidy of 200UF, possibly due to the emergency situation associated to their displacement. However, we do not find systematic evidence of families' demographics predicting the subsidy amount nor the home value. See Table A.4.

[14]Housing projects were not planned specifically to house families of any given slum. We interviewed social workers who accompanied families during the eviction processes and asked them how the new locations were determined. In most cases they reported that it depended on which public housing projects were available to receive families at a given point in time.

and relocation did not have to be approved by the municipality of destination."

The decision to clear a slum stemmed from a variety of circumstances that prevented families from staying in their original locations. These circumstances ranged from slums being too close to freeways to being on a riverbank—especially the Mapocho River, which had a high risk of flooding during winter months. Other circumstances were related to features of the land itself, such as public versus private property, the density of a slum (number of families per site), and potential difficulties for the provision of sewage, water, and electricity. Land value also mattered; as Rodríguez and Icaza (1998) explain, "other criteria included the reputation of the municipality of origin, their land values, and the speculation about future prices." This is consistent with the fact that evictions were more common than urban renewal projects in high-income municipalities.

A well-documented example of how MINVU decided to clear a slum and relocate its dwellers is presented by Murphy (2015) for Las Palmeras, a slum in a low-income municipality. Originally, MINVU's official plan was to create a neighborhood for families on the original location. However, by 1981, the high density of Las Palmeras made it impossible to allocate plots inside the slum in a way that guaranteed a minimum size for all the plots. Thus, the authorities decided to include Las Palmeras among the slums to be displaced. In late 1983, residents were moved to a new neighborhood built on the outskirts of the municipality, and the former slum became a park. A second example is the slum dwellers located in the riverbank of the Mapocho River, who were displaced in 1982 after it flooded. More than 3,000 families from the slums El Ejemplo, El Esfuerzo, El Trabajo—originally located in Las Condes, a rich municipality—were relocated to La Pintana and San Ramón, two low-income municipalities in the south of the city.[15]

Using data on slum characteristics collected by Morales and Rojas (1986) and from the MINVU's slum censuses, we find the same patterns established by previous researchers. We report means by intervention in columns (1) and (2) of Table 1, and

[15]Most of these families were relocated to El Castillo and La Bandera neighborhoods.

column (3) reports the simple difference between treatments. Panel A shows that displaced slums are denser as they house fewer families in smaller land areas. They are located in more elevated areas with higher slopes, are closer to rivers or canals, and have a higher risk of flooding. They are also closer to the central business district (CBD), but the difference between the treatments is small. Additionally, in Panel A we classify slums' names as either military related or not related as a proxy for support for the dictatorial regime, finding that displaced slums are less likely to have a military-related name.[16]

In Panel B we report attributes of the census districts where slums were originally located to proxy for neighborhood characteristics. We find that displaced slums are located in areas with higher average schooling, lower unemployment rates, and slightly higher property prices but fewer schools. In column (4) we report the difference in slum characteristics within municipalities of origin. Municipality fixed effects do not systematically reduce the difference in slum characteristics, indicating that even within municipalities, the urban attributes of slums determined their probability of relocation. This finding is consistent with the discussion by Rodríguez and Icaza (1998).

Figure 1 plots the urban limits of Greater Santiago and its municipalities. Panel (a) depicts the location of slums in 1979, showing they were located throughout with no particular concentration in any municipality. Panels (b) and (c) show the location of the housing projects built to receive slum families in 1985. The neighborhoods where housing projects were built for the displaced are represented by purple areas, and housing projects for the non-displaced are represented by blue areas. Two important conclusions can be drawn from this figure: the new housing projects were disproportionately built in the city's peripheral areas, and public housing projects were farther from job opportunities (in gray scale).

After 1985, Aldunate et al. (1987) surveyed 592 displaced families, who reported

[16]We classify the name of each slum as being military related if it refers to any military historical event, such as wars or the coup d'etat of September 11 of 1973, or names of heroes of the country who were in the military.

that they thought their homes were better than their previous ones. However, they reported that the quality of their new neighborhoods was worse than the slums, citing fewer job market opportunities and limited access to transportation, education, and health care services. They also perceived their new neighborhoods as more dangerous and lacking public services (see Figure B.2 for a summary).

3 Data

We construct a novel dataset that tracks slum dwellers that become homeowners, their slum of origin and destination neighborhood, and then we match these individual records to birth, marriage and death certificates.[17]

3.1 Archival data: Slums and homeowners

We digitize two slum censuses conducted by MINVU in 1979 and 1980 that contain information on slums' names, their locations, and destination projects. We classify each slum as displaced or non-displaced and the final destination of the displaced families. We then complement these data with information collected by Molina (1986) and Morales and Rojas (1986), who compiled a full list of slums, locations, and destination neighborhoods by year.

Next, we find the families in the program. We collect and digitize archival data from the Regional Housing and Urban Planning Service and historical records kept by the Municipality of Santiago.[18] These records correspond to the lists of homeowners and their spouses who received a property deed through the Program for Urban Marginality. We collect data for 18,337 unique recipients of social housing, representing 50% of the

[17] See Appendix D in Rojas-Ampuero and Carrera (2023) for a detailed description of the process and variables.

[18] Each region of Chile (equivalent to a state) has an Urban Development and Housing Service, which is dependent on the MINVU. These agencies administer and implement housing policies at the local level.

total number of recipients (Molina, 1986).[19] We focus on individuals in Greater Santiago, excluding rural municipalities, and for internal validity we exclude municipalities without variation in treatment (all families were displaced or all were non-displaced), this leaves us with 16,929 unique households that were recipients of social housing from 14 different municipalities.[20]

The archival data contain information of the recipients of the property deed (heads of the household) and their spouses, full names, national identification numbers (NIDs), and new addresses. These records are grouped by year of eviction/urban renewal and project of destination, and we match them to their slum of origin using the slum censuses of 1979 and 1980. We lose households with a missing NID due to mistakes or older versions that we could not validate using contemporaneous data.[21] Of the 16,929 households in our sample we observe 16,901 women and 16,896 men with a valid NID. Because missing NIDs were more common among older people or single individuals, in our matched data we are more likely to observe younger adults and married couples.

3.2 Death and marriage certificates

We worked with Genealog Chile and web scraped birth, marriage, and death certificates for the dwellers in our sample.[22] We used marriage certificates to find spouses that were not in the archival data, and to study marital status after the intervention. We also matched homeowners' archival data with their children using NID to compute the number of children per household. The death certificates include date of death, municipality of death, and cause of death.

[19] We could not find all of the records; details can be found in Data Appendix.

[20] We exclude rural municipalities because most of the neighborhoods' characteristics we can measure in the 1980s are only available in urban areas.

[21] To validate NID we use data from Chilean electoral records in 2016.

[22] We web scraped certificates from Chile's Civil Registration and Identification Service.

3.3 Earnings and employment data

In addition to death certificates, we match individuals to administrative data sources using NID numbers. We use data from the Social Household Registry, or the RSH (Registro Social de Hogares), which is an information system managed by the Ministry of Social Development. The RSH used to provide information on a family's needs and use of social and governmental benefits for income, housing, and education. Approximately 70% of all Chilean households voluntarily register to be in it. We have access to biannual data from June 2007 to December 2019 and observe self-reported income, employment status, pensions, and family composition and dwelling characteristics. A caveat of this dataset is it only starts in 2007, thus matching will include attrition directly related to treatment if displaced and non-displaced individuals die at different rates prior to the beginning of the sample.

3.4 Municipality and district attributes

We measure location attributes, such as education and employment, by municipality and by census district, which come from the 1982 Census of Population, in which we observe variables such as years of education and employment status. We combine these measures with historical records from the Ministry of Education and the Ministry of Health in 1985 or earlier on schools, hospitals, and family health care centers. In addition, we have information on subway stations built in Santiago and their opening dates and locations; these are publicly available from Greater Santiago's subway system. Finally, we measure property prices at the neighborhood level from newspaper listings that we collect and digitize from 1978 to 1985.

4 Empirical Strategy

4.1 Identifying a displacement effect

To estimate the impact of the forced displacement on adults mortality, we exploit the fact that treatment was determined at the slum level and not based on individual family demographics. The empirical strategy involves comparing displaced individuals with non-displaced who come from slums with the same probability of being relocated. The process of selecting slums into displaced and non-displaced groups did not depend on households' characteristics but rather on the feasibility of renewal on-site.

Under the assumption that we know and observe the slum characteristics that determine treatment, we can compute the probability of a slum being relocated as a function of its urban characteristics. Then, we can compare the outcomes of individuals in a set where they have the same propensity of being displaced (relocated). Thus, any differences between individuals in the displaced and non-displaced groups are attributed to the eviction process and subsequent relocation to a new housing project.

We estimate a linear model to study the impact of the displacement on mortality, using the following specification (Deryugina and Molitor, 2020):

$$Died_{it} = \alpha + \beta Displaced_{s\{i\}} + \psi_o + p(X_s) + \psi_o \times p(X_s) + \phi_t + \chi_{a(i,t)} + X_i'\theta + \varepsilon_{it}, \tag{1}$$

we define the time dimension of the data to be a year panel since the year of treatment, where $Died_{it}$ is a dummy that equals zero if individual i survived through year t, and equals one if the individual died in year t. If the individual dies in year t then $Died_{it}$ is missing in all years after t; $s(i)$ indexes the slum of origin for individual i and the variable $Displaced_{s\{i\}}$ equals 1 if an individual lived in a displaced slum and 0 otherwise.

ψ_o are municipality of origin fixed effects that control for any initial differences between families living in slums located in different municipalities; $p(X_s)$ is the set of deciles of the propensity score of the probability of being cleared and relocated on X_s that incluye slums' characteristics; ϕ_t are calendar year fixed effects from first year of intervention through 2019; and $\chi_{a(i,t)}$ are age fixed effects. For precision, in (1) we add baseline controls for individual and family characteristics at the time of intervention, X_i, that include cohort fixed effects, dummy for head of household, married head of household, marital status unknown, indigenous last name, number of children at baseline, head of household's formal employment before treatment, and year of intervention fixed effects (1979 to 1985) that control for aggregate temporal differences across the six years this housing program was in effect. We cluster standard errors at the level of slum of origin; however, later in the text we show robustness to other clustering methods.[23]

In addition, estimating a propensity score model requires the unconfoundness assumption to hold, which means that conditional on the propensity score, the outcome Y is independent of displacement. Moreover, the overlap condition means that we can compare displaced and non-displaced children within the common support of the propensity score (Rosenbaum and Rubin, 1983). Note that our propensity score is only a function of slum characteristics (s), not individual characteristics (i), because the policy function was at the slum level rather than the individual level.

Equation (1) implies that we match on the propensity score, which requires first estimating the propensity score function (**?**). We choose matching instead of propensity score re-weighting because it offers greater flexibility and is more effective in cases where the overlap of the common support is imperfect (**?**). In the next section we show robustness of our results to different versions of the propensity score method.

[23] Additional clustering methods, such as Conley and bootstrapped standard errors, are discussed in the next section.

4.2 Propensity score estimation

To estimate the probability of relocation, we use data from Morales and Rojas (1986), who compiled the most complete sample of slums and their characteristics in urban areas. In these data we observe 222 slums with information on their characteristics (Table 1). We estimate the probability of relocation using a logit function on the following set of characteristics: density (families per hectare), military name, elevation, slope, proximity to a river or canal, flooding risk, distance to the CBD, population's schooling, unemployment rate, and number of schools per census district. We exclude the price index from the propensity score because it might reflect expectations of future land prices due to slum clearance, as well as municipality-of-origin fixed effects since differences between slums within the same treatment remained within municipalities.[24] The estimates of this exercise are presented in Table **??**, column (1).

We use the estimates from the previous regression to predict the probability of slum relocation in our archival sample of 99 slums. This approach increases statistical power and reduces selection on observables, as the slums in the archives are less peripheral and show more similarity between treatments. Figure A.1 presents the results of the estimation. Panel (a) shows the propensity score densities by treatment in Morales and Rojas (1986)'s sample, and panel (b) depicts the same figure for slums in our archival sample. Importantly, in both figures there is common support.

We implement the propensity score method in four steps. First, we estimate the propensity score $\hat{p}(X_s)$ at the slum level using a logit function. Second, we impose common support. Based on the propensity score densities by treatment in Figure A.1, panel (b), we keep slums where $0.15 < \hat{p}(X_s) < 0.70$: from the 99 slums in our archival sample, 90 are in the common support. Third, we generate dummies for each decile of the distribution of the estimated propensity score. Last, we run equation (1) on the outcomes of interest where $p(X_s)$ is included as a full set of propensity

[24] In Section **??** we perform robustness checks where we include these variables in the propensity score. The results are very similar to the main results on children's outcomes.

score dummies interacted with municipality-of-origin fixed effects. This ensures that we compare displaced and non-displaced children within the same municipality in the same decile of the propensity score estimate.[25]

4.3 Evaluation of the identification strategy

The validity of our research design depends on whether the decision to displace a slum was uncorrelated with the characteristics of families conditional on the probability their slum was cleared. Under the assumption that conditional on the policy function, $p(X_s)$, the covariance between $Displaced_{s\{i\}}$ and ε_{it} is 0, the coefficient β estimates the causal effect of the displacement on adults' mortality. We first compare the demographics of the displaced and non-displaced adults at the time of the intervention (baseline).

Table 2, columns (1) and (2) report means for the demographics of adults in the sample with common support for the non-displaced and displaced groups, respectively. Column (3) reports the difference between groups conditional on $p(X_s) \times \psi_o$. Based on these adjusted differences, displaced and non-displaced individuals with similar probabilities of experiencing relocation have similar demographics at baseline, with no statistical differences between both groups for 12 out of 14 observables. There are two variables that show a statistically significant difference from 0, though the size of the coefficients is small. The table shows in the sample with common support, displaced individuals are slightly less likely to be women, and more likely to have an indigenous last name (Mapuche). Columns (4)–(6) and (7)–(9) repeat the previous exercise for women and men, respectively. The results show that in the sample of women, displaced and non-displaced adults are more similar than in the sample of men. Displaced men compared to non-displaced men are less likely to be married, are more likely to have a Mapuche last name, and have fewer children. These differences are statistically different from 0; however, the size of the effects for married and number of children are

[25] A more strict approach would be to perform a block propensity score by municipality of origin (Heckman et al., 1998). In our data this is not possible, as we would require a larger number of slums per municipality to estimate a different propensity score density in each municipality of origin.

small in economic terms. Overall, we find that displaced and non-displaced individuals look similar in their demographics conditional on the probability of their slum being relocated.

5 Main Results

5.1 Displacement effect on new location attributes

To estimate the program's displacement effects on new neighborhood attributes, we analyze the densities of various characteristics in the relocation areas of both displaced and non-displaced households. Figure 2 illustrates these densities, with panel (a) reporting unemployment rates. The analysis shows that displaced families were more likely to be relocated to areas where the unemployment rate is 3 percentage points higher, or 15% higher compared to those of non-displaced households. Panel (b) plots densities for the prices of properties surrounding the new public housing projects, and on average, displaced families were relocated to areas with lower price values. In addition, their homes were 12% cheaper, on average (panel (c)). Most displaced families received a house that cost 220 UF, and while the variance in cost for non-displaced families is larger, most non-displaced received houses above 250 UF.

These patterns, consistently align with the fact that compared to non-displaced families, displaced families were relocated farther from the city center, by an average 2.5 kilometers (panel (d)), and even farther away from their slums of origin, by 8.6 kilometers (panel (e)).

5.2 Displacement effect on annual mortality

We continue our analysis by estimating the average displacement effect on mortality in Table 3. The dependent variable is annual mortality in year t, conditional on having

survived until year $t-1$, expressed as percentage points.[26] The results in column (1) when we only control for municipality fixed effect, indicate displaced adults die 0.11 percentage points more per year, which represents 16.6% more relative to the non-displaced mean. In column (2) we had baseline controls and the effect is almost doubled to 0.214 percentage points, suggesting the importance of controlling for demographic characteristics. Column (3) adds slums characteristics at baseline, which leaves the displacement effect almost unchanged, and column (4) replaces the slums characteristics for a full set of interactions between the deciles of the propensity score and municipality of origin fixed effects (equation (1)). This result in column (4) indicates displaced individuals die 0.2 percentage points more per year, which represents a 29.9% higher risk of mortality relative to non-displaced adults. This is our preferred specification.

Next, we compute separate regressions for women and men. Table 4 shows the effect of the displacement on mortality. Columns (1) and (2) summarize the results for women, and columns (3) and (4) present the results for men. Columns (1) and (3) report the difference in outcomes between displaced and non-displaced adults conditional on the full set of interactions between the deciles of the propensity score and municipality of origin fixed effects. Meanwhile, columns (2) and (4) also include baseline demographic controls and family composition at baseline. We report the results with and without baseline demographics to show how the displacement effect becomes larger with their inclusion, and this is the case for both sexes.

Table 4 shows that the displacement effect due to the slum clearance program had a positive effect on mortality. The coefficient of 0.214 in column (2) for women is statistically significant at 1% and represents an increase in the annual risk of mortality for the displaced of 26.6%, relative to non-displaced women. In the case of men, the coefficient of 0.297 is also significant at 1% and corresponds to an even larger percentage effect of 37.6% increased mortality with respect to non-displaced men.

[26]For better exposition we multiply the displacement coefficient by 100, so it should be interpreted as percentage points.

We turn next to study the effects of the displacement on mortality by years since intervention to understand when the displacement effect is larger. Panel (a) of Figure 3 presents the displacement effect estimates for mortality in year t after the intervention, computed separately by sex. Although the estimates differ on their precision, the effect on mortality for both sexes is statistically different from zero in some periods immediately after the intervention. We use these year-estimates to compute the cumulative effects by year after the intervention by following Deryugina and Molitor (2020). In Figure 3 panel (b), we show the cumulated mortality effect by sex t years after the move. The cumulative negative effect on mortality for women is accumulated gradually at a relatively constant rate (panel (c)) while, in the case of men (panel (d)) the cumulative effect increases more rapidly than for women. Eventually, the cumulative effect will be zero when all individuals in our sample have died. In panel (c) we can observe that by year 36, non-displaced women die at higher rates more than displaced, as the cumulative effect start to decrease, but for men the trend has not changed after 40 years yet. These positive cumulative effects on mortality suggest displaced individuals die younger than non-displaced because they had similar ages at baseline. We study these patterns next.

5.3 Displacement effect by age and cohort

Another important dimension is the relationship between the displacement effect on mortality and age. Figure 4 plots the estimated displacement effect (in percentage points) by age for women and men in panels (a) and (b), respectively. The results show individuals die more as they age. The effects for women are positive and different from zero for ages after 60, while for men the increased mortality start at earlier ages, specifically at the age of 40.

We ask who is more likely to die relative to years since intervention. Figure **??** repeats the cumulative results from Figure 3 stratified by age at intervention. We split the sample between adults below and above the age of 35 at baseline (35 is the median

age in our sample). The results show older individuals at baseline are more likely to die in the first years after the relocation. Older women die more rapidly than younger women, but in the longer term. For men the effects are short- and medium term. While older men die more quickly than younger men, men below the age of 35 have a higher risk of mortality 12 years after the intervention and this effect increases with time.

5.4 Displacement effect by causes of death

We study the displacement effects by causes of death. In the death certificates we observe causes of death; however, these are not standardized, specially among people who died in the 1980s, we clean them to make them comparable to current causes of death categories using ICD-codes. In many cases, we observe more than one cause of death or chronic condition, thus our categories are not mutually exclusive.

In Figure 7 we repeat the cumulative effect analysis by cause and sex. The results suggest that for displaced women increased mortality is more likely to be observed for individuals who died of diabetes or high blood pressure, which are conditions that develop chronically. For displaced men we observe higher risks of dying of cancer, causes related to tobacco use, and a higher share of deaths due to external causes, compared to non-displaced men. Among the external causes of death, 1/3 of them are deaths associated to accidents.

5.5 Robustness checks

In this section we show our baseline results on annual-mortality displacement effects are robust to other propensity score methods and to different parametric models to estimate the risk of dying.

In Table A.3 we show robustness of our baseline result to variations in the propensity score method. We find very similar results if we restrict our common support to include slums in the 1–99 percentiles of the common support or 2.5–97.5 percentiles of the

propensity score. We also run or baseline results by re-weighting the observations by the inverse probability of relocation, and the results are very similar. And finally, we estimate equation (1) by adding to the propensity score the municipality-of-origin fixed effects, and the results are not changed.

Figure A.2 we run our baseline results using a parametric approach, using a Kaplan-Meier survival function since years of intervention. The figure shows displaced individuals have higher risk of dying (or lower risk of surviving) compared to non-displaced individuals as years pass since the initial year of intervention. We reject equality of functions. Figure A.3 presents a similar figure by age, showing that displaced individuals die younger than non displaced, and we also reject equality of survival functions between groups.

6 Mechanisms

In this section we investigate the mechanisms behind our baseline results on mortality. Based on families' impressions after relocation and the lower-quality attributes of destination neighborhoods, we study which changes in neighborhood attributes explain the average displacement effect on mortality. We then examine how the displacement effect on mortality relates to long-term negative effects on income for the adults we find in the administrative data after 2007.

6.1 Destination characteristics at baseline

We first explore which characteristics of the new locations explain the average effect on increased mortality. To do so, we investigate how the displacement estimate decreases when location changes are included in the regression. Table 5 column (1) shows our baseline results on mortality for all adults in the sample, and column (2) controls for determinants of the displacement itself and changes to neighborhood characteristics, slum network (measured as the share of slum-dwelling families from a slum of origin

moved together to a new project), distance from origin, change in distance to the central business district (relative to origin). For both women and men, the inclusion of these characteristics changes the displacement effect to the point that the average effect is small and no longer statistically different from zero.

We can use these results to conduct an accounting exercise that decomposes the displacement effect by characteristic following the procedure proposed by Gelbach (2016). This procedure states that the total displacement effect in column (1) and (4) are the sum of the contributions arising from each of the neighborhood attributes we consider in columns (2) and (5) and from a residual contribution not captured by neighborhood changes. The observed contribution of each attribute is obtained by multiplying the corresponding coefficient in column (2) or (5) with the corresponding change in attribute due to displacement, that is, the correlation between the displacement dummy and the neighborhood attribute. We report these auxiliary correlations in columns (3) and (6) of Table 5 and the decomposition results after the equal sign.

The inclusion of these characteristics explain 49% of the displacement effect on mortality for women, and almost all the effect on mortality for men. In particular, most of the displacement effect on mortality is explained by the distance to origin (40% for women, and 37% for men). But in addition for men, the change in unemployment level at the census district level explains 13.3% of the displacement effect on mortality. This is non-trivial given the evidence provided by families supporting the lack of employment in the new destination locations, and the fact that men more than women were more likely to work for pay at baseline, 50% for men versus 13% for women (see Table 2). This result goes in line with previous evidence that links the causal relationship between employment and mortality (Sullivan and von Wachter, 2009), in the next section we investigate the relationship between displacement and long-term earnings.

6.2 Income effects

To study income effects, we merge our sample of adults to administrative data from 2007 and 2019 coming from the Social Household Registry (RSH) administered by the Chilean Ministry of Social Development, where we observe employment and earnings. A caveat of this procedure is we only observe individuals who have not died by 2007 and who are in the RSH, but it has the advantage that we observe retirement earnings which gives a measure of formal employment across people's lifetime.

We first look at displacement effects on average employment and earnings between 2007 and 2019. The results are in Table 6. Panel A shows the effects for the full sample of matched individuals. We observe that displaced individuals have higher employment rates, but their total income is lower than for non-displaced (column (2)), mainly because their pensions are lower (column (4)). This pattern is the same for both women and men (lower bottom panels B. and C.). Displaced women are also more likely to be employed as domestic workers, which is a low-pay job and highly informal. Overall, among those who are alive after 2007, displaced individuals have higher employment rates, but lower earnings, and if retired they have lower pensions, compared to non-displaced individuals. These results suggest the type of jobs that displaced individuals do are lower quality compared to non-displaced adults.

In Figure 8 we show the similar results but taking advantage of the panel structure of the data and show employment and earnings trajectories of displaced and non-displaced individuals by age. The lowest age we observe in our data is 50, and we observe individuals from 2007 until the year 2019 or until they die.

The positive employment effects come from displaced women before retirement age; however, the labor earnings of displaced individuals are not large enough to compensate for lower pensions after retirement (60 for women and 65 for men). Because the Chilean pension system is mainly through individual savings (not pay-as-you-go), the fact that displaced individuals have lower retirement income indicates worse employ-

ment trajectories, compared to non-displaced women and men.

In the two bottom panels of Figure 8, we show the probability of indicating having a disability as a reason for not working for pay. The figure shows that displaced individuals, in particular men, are more likely to report they do not work because they have a chronic condition or a disability. This results goes in line with the fact they have worse health outcomes compared to non-displaced adults after the age of 50.

7 Preliminary discussion

This paper studies the long-term effects on mortality of a housing policy that affected approximately 5% of the population of Greater Santiago during the Pinochet dictatorship. As part of the program, families that lived in a large number of slums were relocated to the periphery of the city. Because the relocation decision was made at the slum level and families did not choose their final locations, we are able to compare the mortality and earnings outcomes of displaced and non-displaced adults who lived in slums that had the same *ex-ante* probability of being relocated.

Our results show a statistically significant displacement effect on mortality for both women and men. Displaced adults have approximately a 30% higher probability of dying per year compared to non-displaced adults. However, these large mortality effects are associated to different causes of death by sex. The analysis of causes of death shows that displaced women are more likely to develop a chronic disease, such as diabetes and heart disease; while men have a larger probability of suffering a violent or an addiction-related death with respect to the non-displaced.

In our analysis three results suggest that our mortality effects are associated with segregation and isolation as potential mechanisms. Higher mortality risk is associated to longer distances from origin, and this is true for both men and women. Displaced men's increased risk of dying is associated with higher unemployment levels in the destination locations. And finally, displaced individuals have lower pensions compared

to non-displaced, which suggest more informality during their labor market trajectories (lower contributions to social security across time). All these results together point to the direction of displaced individuals having worse access to labor markets and to lower quality jobs, that are potentially related to worse health outcomes. Finally, given the high share of accidents as a cause of death in the group of displaced men, future avenues for this paper should include an analysis that studies the access to jobs and transportation infrastructure as mechanisms to explain the mortality and earnings patterns of displaced individuals relative to those of non-displaced individuals.

References

Aldunate, A., Morales, E., and Rojas, S. (1987). Evaluación social de las erradicaciones: Resultados de una encuesta. *Programa FLACSO*, (96).

Andersson, F., Haltiwanger, J. C., Kutzbach, M. J., Pollakowski, H. O., and Weinberg, D. H. (2018). Job Displacement and the Duration of Joblessness: The Role of Spatial Mismatch. *The Review of Economics and Statistics*, 100(2):203–218.

Barnhardt, S., Field, E., and Pande, R. (2016). Moving to opportunity or isolation? Network effects of a randomized housing lottery in urban India. *American Economic Journal: Applied Economics*, 9(1):1–32.

Benavides, L., Morales, E., and Rojas, S. (1982). Campamentos y poblaciones de las comunas del Gran Santiago. Una síntesis informativa. *Documento de Trabajo Programa FLACSO-Santiago*, (154).

Celedón, A. (2019). Operación piloto: Santiago en tres actos. *Revista 180*, 43:1–12.

Collins, W. J. and Shester, K. L. (2013). Slum Clearance and Urban Renewal in the United States. *American Economic Journal: Applied Economics*, 5.

Dasgupta, B. and Lall, S. V. (2009). Assessing benefits of slum upgrading programs in second-best settings. In *Urban Land markets: Improving Land management for successful urbanization*, chapter 9, pages 225–251. Springer Netherlands.

Deryugina, T. and Molitor, D. (2020). Does When You Die Depend On Where You Live? Evidence From Hurricane Katrina. *American Economic Review*, 110(11):3602–3633.

Deryugina, T. and Molitor, D. (2021). The causal effects of place on health and longevity. *Journal of Economic Perspectives*, 35(4):147–70.

Field, E. (2007). Entitled to work: Urban Property Rights and Land Labor Supply in Peru. *The Quarterly Journal of Economics*, 122(4):1561–1602.

Finkelstein, A., Gentzkow, M., and Williams, H. (2021). Place-based drivers of mortality: Evidence from migration. *American Economic Review*, 111(8):2697–2735.

Franklin, S. (2020). Enabled to work: The impact of government housing on slum dwellers in South Africa. *Journal of Urban Economics*, 118:103265.

Galiani, S., Gertler, P. J., Undurraga, R., Cooper, R., Martinez, S., and Ross, A. (2017). Shelter from the storm: Upgrading housing infrastructure in Latin American slums. *Journal of Urban Economics*, 98.

Gelbach, J. B. (2016). When do covariates matter? and which ones, and how much? *Journal of Labor Economics*, 34(2):509–543.

González, F., Muñoz, P., and Prem, M. (2021). Lost in transition? The persistence of dictatorship mayors. *Journal of Development Economics*, 151:102669.

Haltiwanger, J. C., Kutzbach, M. J., Palloni, G. E., Pollakowski, H., Staiger, M., and Weinberg, D. (2020). The Children of HOPE VI Demolitions: National Evidence on Labor Market Outcomes. Working Paper 28157, National Bureau of Economic Research.

Harari, M. and Wong, M. (2021). Slum Upgrading and Long-run Urban Development: Evidence from Indonesia. *Working Paper*.

Heckman, J., Ichimura, H., Smith, J., and Todd, P. (1998). Characterizing Selection Bias Using Experimental Data. *Econometrica*, 66(5):1017–1098.

Hidalgo, R. (2019). *La Vivienda Social en Chile y la Construcción del Espacio Urbano en el Santiago del siglo XX*. RIL Editores.

Instituto Nacional de Estadísticas (INE) (1970). XIV Censo Nacional de Población y III de Vivienda.

Instituto Nacional de Estadísticas (INE) (1982). XV Censo Nacional de Población y IV de Vivienda.

Kain, J. F. (1968). Housing Segregation, Negro Employment, and Metropolitan Decentralization. *The Quarterly Journal of Economics*, 82(2):175–197.

Kain, J. F. (2004). A Pioneer's Perspective on the Spatial Mismatch Literature. *Urban Studies*, 41(1):7–32.

Labbé, F. J., Llévenes, M., et al. (1986). Efectos redistributivos derivados del proceso de erradicación de poblaciones en el Gran Santiago. *Estudios públicos*, (24).

LaVoice, J. (2023). The Long-Run Implications of Slum Clearance: A Neighborhood Analysis. *Working Paper*.

Lleras-Muney, A., Schwandt, H., and Wherry, L. (2024). Poverty and health. Working Paper 32866, National Bureau of Economic Research.

Marx, B., Stoker, T., and Suri, T. (2013). The Economics of Slums in the Developing World. *Journal of Economic Perspectives*, 27.

Michaels, G., Nigmatulina, D., Rauch, F., Regan, T., Baruah, N., and Dahlstrand, A. (2021). Planning Ahead for Better Neighborhoods: Long-Run Evidence from Tanzania. *Journal of Political Economy*, 129(7):2112–2156.

Ministerio de Vivienda y Urbanismo (MINVU) (1979). Campamentos año 1979: Radicación-erradicación.

Molina, I. (1986). El Programa de Erradicación de Campamentos en la Región Metropolitana de Santiago (1979-1984): Implicancias Socioeconómicas y Espaciales.

Morales, E. and Rojas, S. (1986). Relocalización socio-espacial de la pobreza: Política estatal y presión popular, 1979-1985. *Programa FLACSO*, (280).

Murphy, E. (2015). *For a Proper Home: Housing Rights in the Margins of Urban Chile, 1960-2010.* University of Pittsburgh Press.

Núñez, J., Tocornal, X., and Henríquez, P. (2012). Individual and Residential Surrounding Determinants on the Sense of Security in Neighborhoods of Santiago, Chile. *Revista INVI*, 27(74).

Picarelli, N. (2019). There Is No Free House. *Journal of Urban Economics*, 111:35–52.

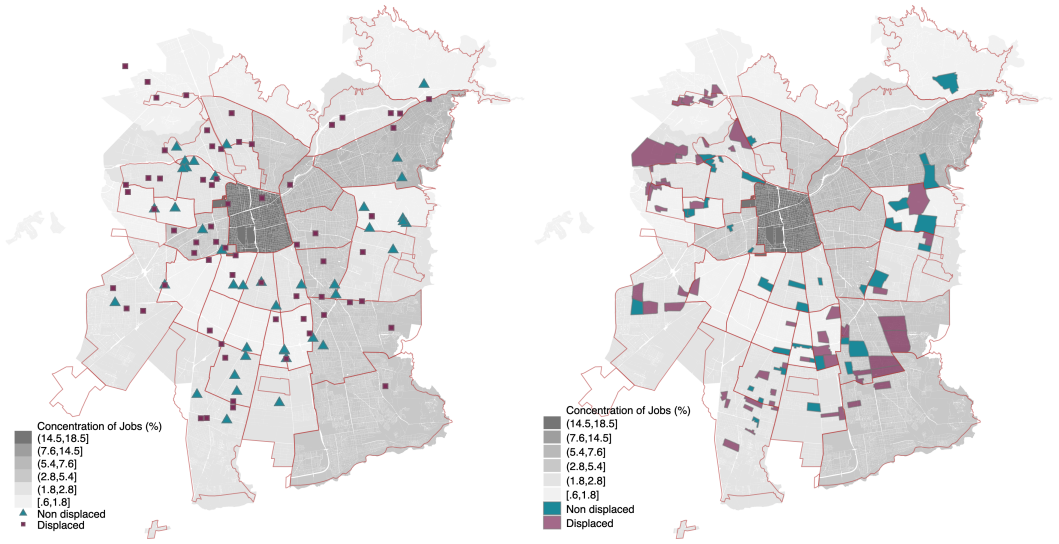
Rodríguez, A. and Icaza, A. M. (1998). Eviction of low-income residents from central santiago de chile. In *Evictions and the right to housing: experience from Canada, Chile, the Dominican Republic, South Africa, and South Korea*, chapter 2. International Development Research Center.

Rosenbaum, P. R. and Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70(1):41–55.

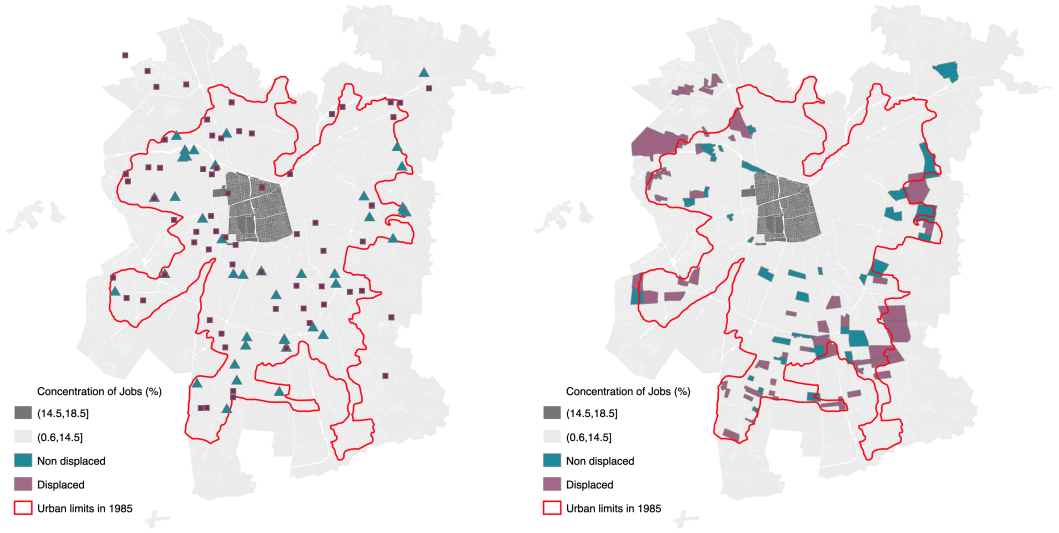
Sullivan, D. and von Wachter, T. (2009). Job displacement and mortality: An analysis using administrative data. *Quarterly Journal of Economics*, 123(3):1265–1306.

Figures and Tables

Figure 1: Eviction policies 1979–1985: Location of families living in slums



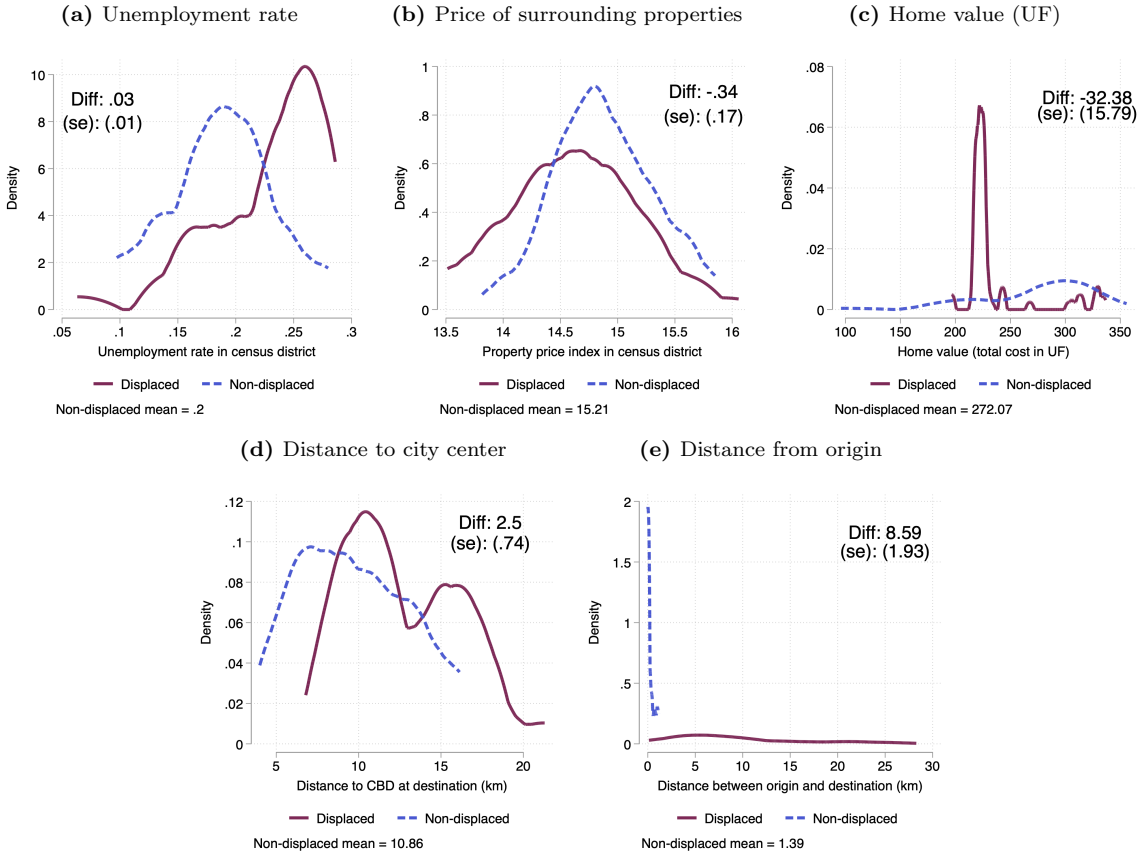
(a) Slum location before 1979 **(b)** Public housing projects after 1985



(c) Slum location before 1979 **(d)** Public housing projects after 1985

Notes: Red lines represent the urban limits of Greater Santiago and grey lines its municipalities. Municipalities are colored in gray scale to depict the concentration of jobs across the city. These figures show the change in the location of families living in slums in 1979 (panels (a) and (c)) and their final destination in 1985 (panels (b) and (d)). Purple squares represent families living in slums that were moved out from their original location to a new neighborhood; blue triangles represent the families in slums that were not evicted but received a housing unit in their original location. The figures also show how the dispersion of the location of these families decreases and how they are relocated to the periphery of the city after the policy. For context, consider that the richest municipalities of Santiago at that time (and today) are the ones located in the northeast of this map and the poorer municipalities are located in the south and northwest of the city, which is exactly where the new public housing projects were built. The data to construct this map come from MINVU (1979), Molina (1986), FLACSO (1982, 1986), and the population censuses of 1982 and 1992.

Figure 2: Density of neighborhood attributes after relocation

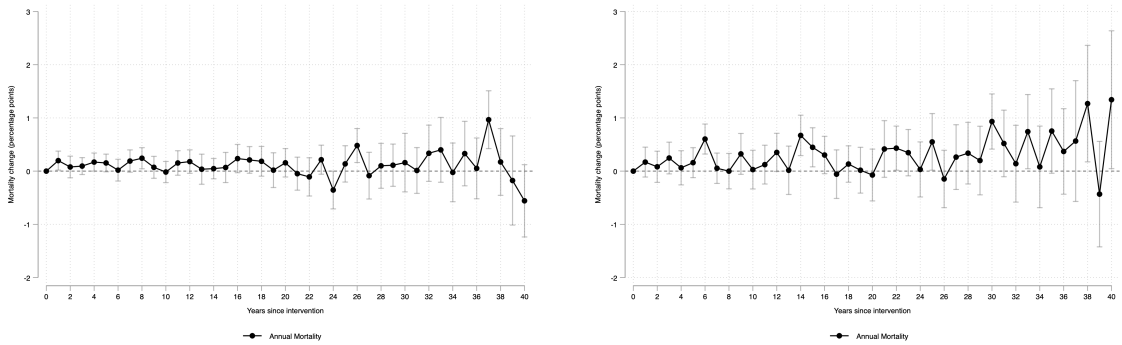


Notes: The figure shows densities by treatment for the average neighborhood attributes for each pair of slum of origin and project of destination in the archival sample (N = 110 unique pairs of slum-project of destination). Each subfigure's footnotes indicate the mean difference between treatments for all households in the sample, conditional on the propensity score (N = 15,613). We compute the average for all households within the common support of the sample regardless of whether a child is present.

Figure 3: Annual mortality of adults since year of treatment

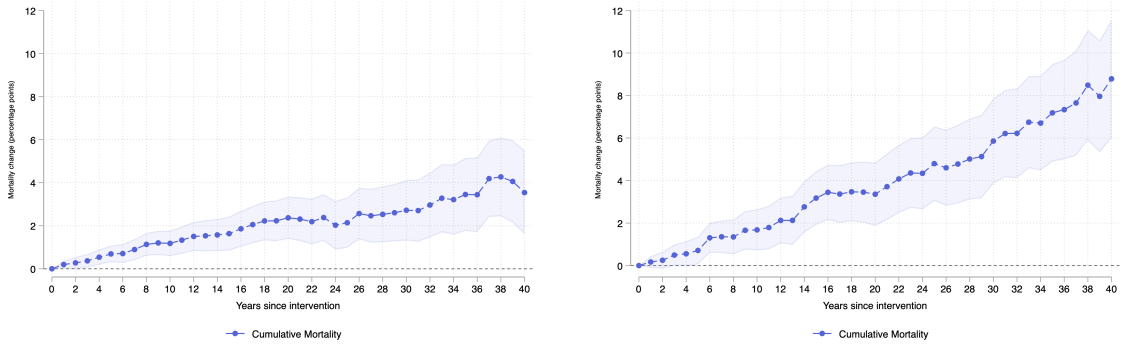
A. Effect by year

(a) Women **(b)** Men



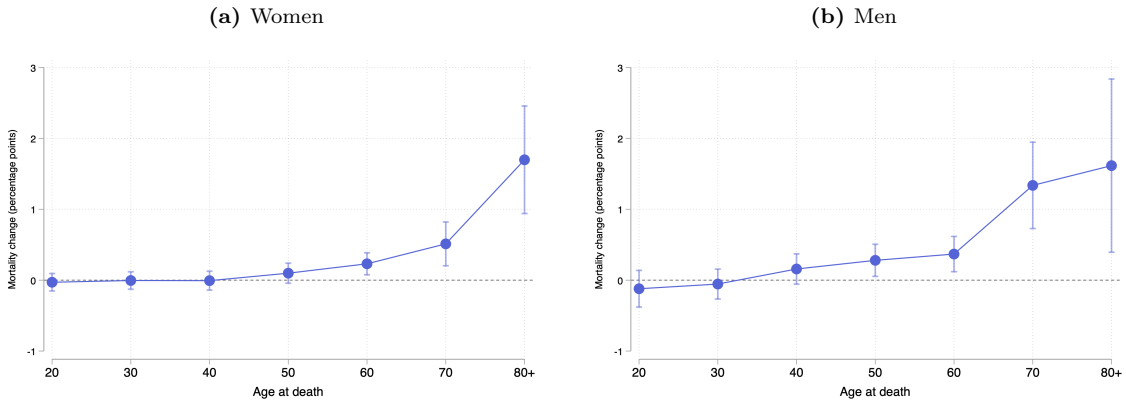
B. Cumulative effect by year

(c) Women **(d)** Men



Notes: Estimates in percentage points. This figure plots the coefficients β_τ and their 95% confidence intervals from regression $Died_{it} = \sum_{\tau=0}^{40} \beta_\tau 1(t=\tau) \cdot Displaced_{s\{i\}} + X_i'\theta + \psi_o + \hat{p}(X_s) + \psi_o \times \hat{p}(X_s + \gamma_t + \gamma_a + \varepsilon_{it}$. Panels (a) and (c) estimates the displacement effect on annual and cumulative mortality of women, and panels (b) and (d) do the same for men.

Figure 4: Displacement effect on mortality of adults by age at measurement



Notes: The figure plots the estimates and their 95% confidence intervals equivalent to column (4) in Table 3 stratified by age at death.

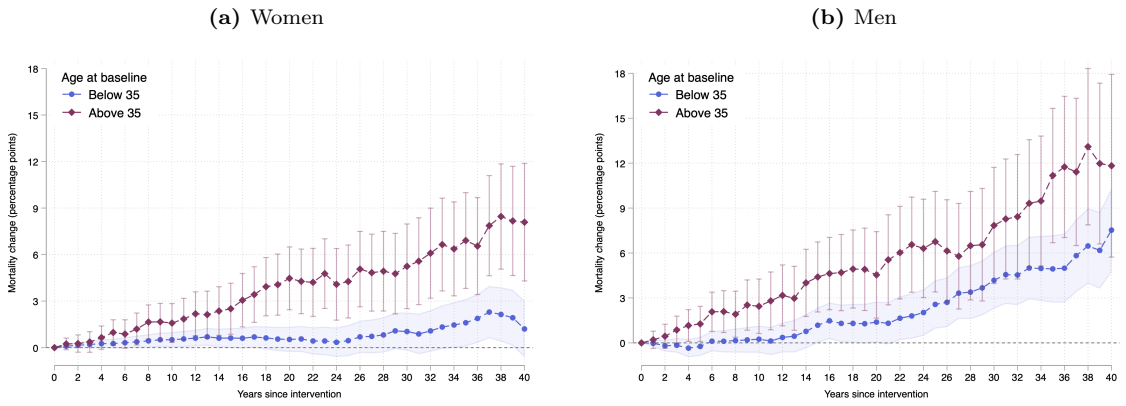
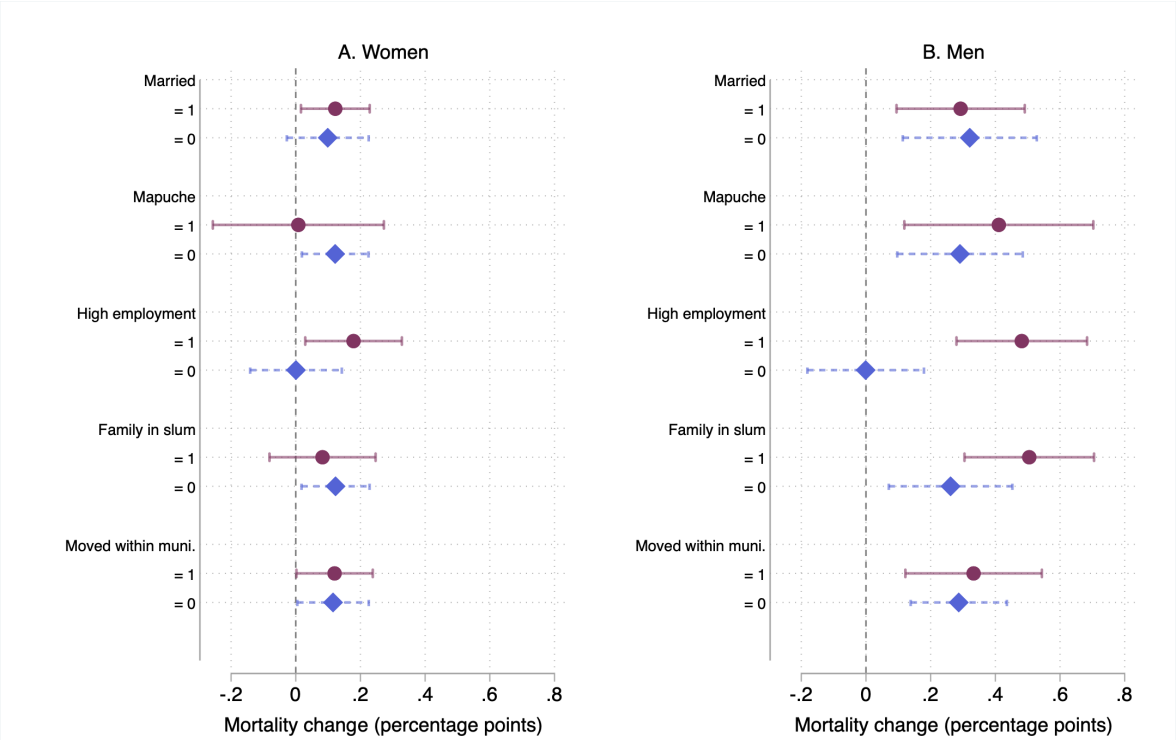


Figure 6: Displacement effects by demographic groups at baseline

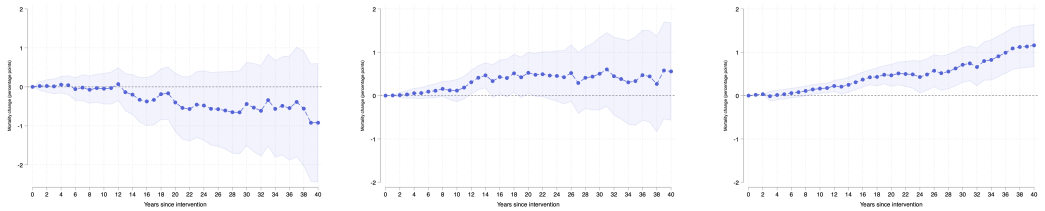


Notes: The figure plots the estimates and their 95% confidence intervals equivalent to column (4) in Table 3 stratified by demographic groups at baseline.

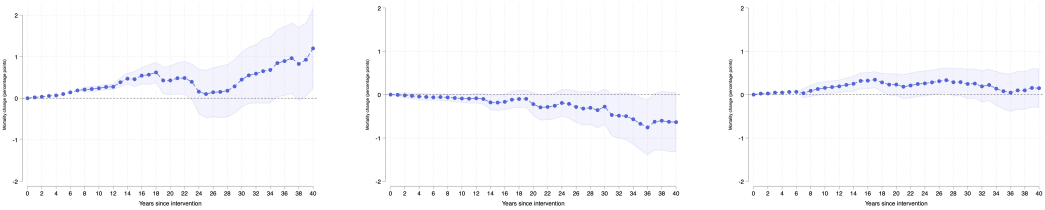
Figure 7: Displacement effect on cumulative mortality by causes of death

A. Women

(a) Cancer **(b)** Cardiovascular disease **(c)** Diabetes

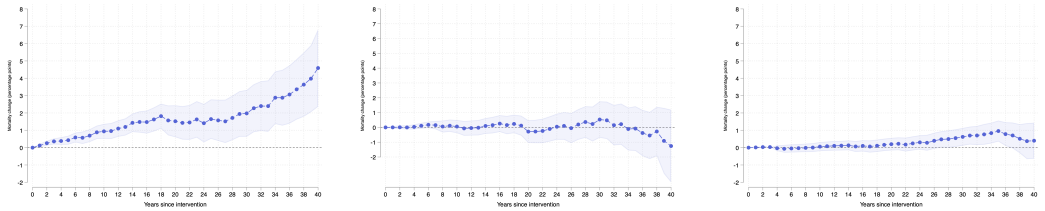


(d) High blood pressure **(e)** Tobacco related **(f)** External cause

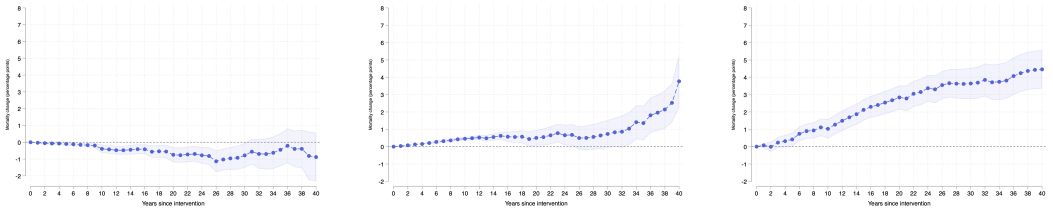


B. Men

(g) Cancer **(h)** Cardiovascular disease **(i)** Diabetes



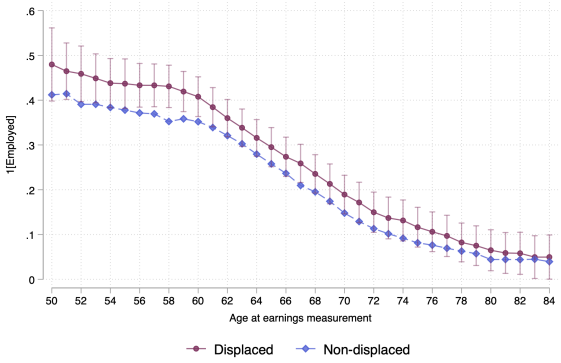
(j) High blood pressure **(k)** Tobacco related **(l)** External cause



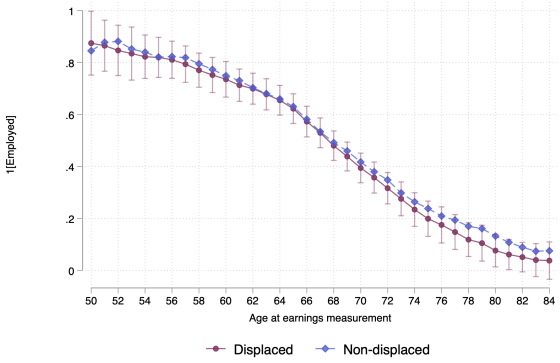
Notes: The figure plots the cumulative displacement estimates and their 95% confidence intervals equivalent to panel B in Figure **??** by cause of death.

Figure 8: Displacement effects on labor market outcomes by age at earnings measurement

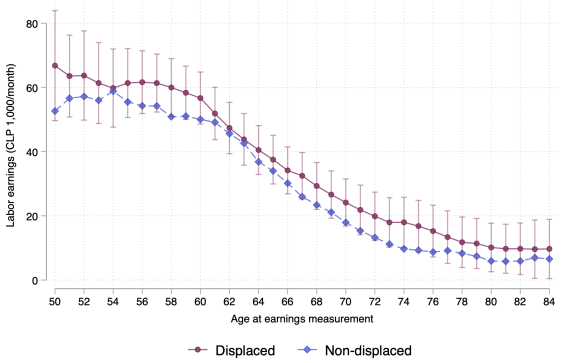
(a) Women's employment trajectories



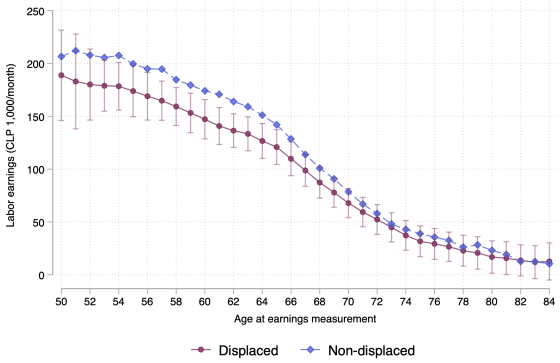
(b) Men's employment trajectories



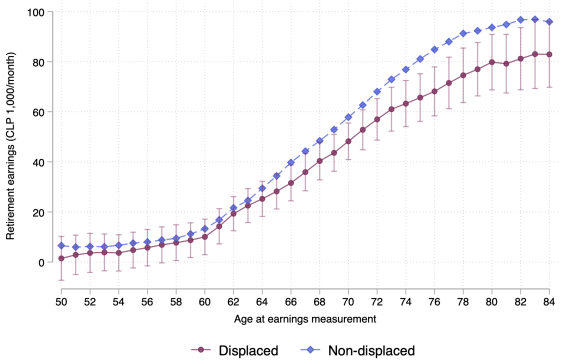
(c) Women's earnings trajectories (CLP$1,000/month)



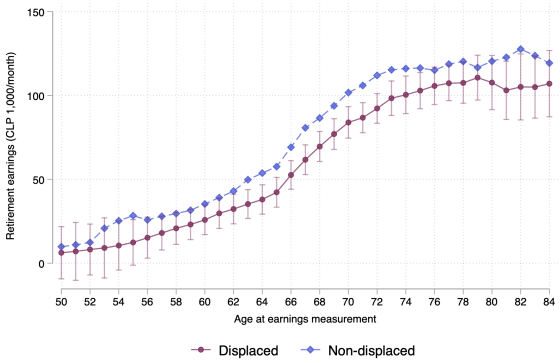
(d) Men's earnings trajectories (CLP$1,000/month)



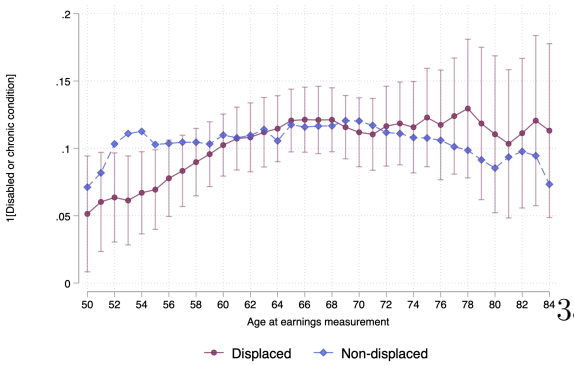
(e) Women's retirement earnings trajectories



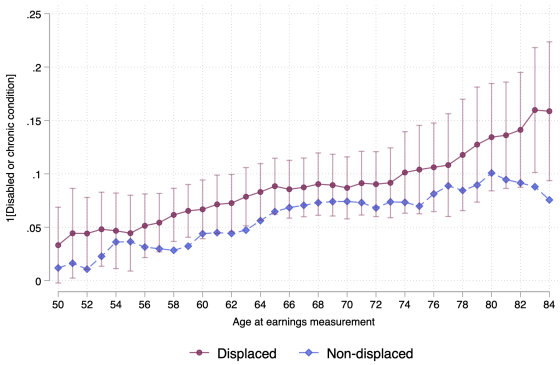
(f) Men's retirement earnings trajectories



(g) Women's probability of a disability



(h) Men's probability of a disability



Notes: The figure shows regressions for individuals that are matched to the RSH data between 2007 and 2019. Panels plot the predicted trajectories for displaced and non-displaced individuals between ages 50 and 84 from the regression $y_{it} = \sum_{\tau=50}^{84} \beta_\tau Displaced * 1[Age = \tau] + \sum_{\tau=50}^{84} \delta_\tau 1[Age] + \psi_o + \hat{p}(X_s) + \hat{p}(X_s) \times \psi_o + X'_{it}\gamma + u_{it}$. Figures include

Table 1: Slum characteristics before intervention

	Displaced mean (1)	Non-displaced mean (2)	Difference (3)	Difference within municipality (4)
Panel A. Slum attributes				
Families/hectare	81.96	68.42	13.55	9.47
			(11.02)	(12.67)
Military name	0.11	0.17	-0.06	-0.04
			(0.05)	(0.05)
Elevation (mas)	581.51	582.00	-0.49	-14.43***
			(12.34)	(4.80)
Slope (degrees)	3.07	2.55	0.52**	0.26
			(0.26)	(0.24)
Close to river/canal (<100 m)	0.06	0.03	0.04	0.01
			(0.03)	(0.03)
Flooding risk	0.09	0.02	0.07**	0.03
			(0.03)	(0.02)
Distance to CBD	9.93	10.39	-0.47	-0.41
			(0.61)	(0.39)
Panel B. Census district attributes				
Population's schooling	7.89	7.09	0.80***	0.32*
			(0.25)	(0.19)
Unemployment rate	0.18	0.21	-0.02***	-0.01*
			(0.01)	(0.01)
Number of schools	3.96	4.54	-0.58	-0.40
			(0.46)	(0.39)
Log surrounding prices	14.80	14.72	0.08*	0.03
			(0.04)	(0.02)
Number of slums	92	130	222	222
Number of municipalities	14	14	14	14

Notes: The table shows summary statistics for non-displaced (redeveloped) and displaced (relocated) slums in Morales and Rojas (1986)'s sample with non-missing attributes or locations. Slum locations and characteristics are constructed from Benavides et al. (1982), Morales and Rojas (1986), MINVU (1979), newspapers, and the Population Census of 1982. Elevation, slope, and flooding risk data are obtained from Geoportal. Prices, unemployment, number of schools, and population's schooling are measured at the census district level where a slum was located. Column (3) reports the simple difference in each attribute between displaced and non-displaced slums, and column (4) shows the difference between groups within municipalities of origin. Robust standard errors are in parentheses. 10%*, 5%**, 1%***.

Table 2: Comparing displaced and non-displaced adults at baseline (year of intervention)

	All adults			Women			Men		
	Displaced mean	Non-displaced mean	Difference	Displaced mean	Non-displaced mean	Difference	Displaced mean	Non-displaced mean	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	0.536	0.535	-0.006**						
			(0.003)						
Age	34.726	35.492	-0.406	34.196	34.970	-0.377	35.339	36.094	-0.462
			(1.135)			(1.109)			(1.181)
Female HH	0.353	0.333	-0.045	0.410	0.376	-0.037	0.287	0.283	-0.053
			(0.047)			(0.048)			(0.047)
Married	0.782	0.821	-0.016	0.751	0.793	-0.014	0.819	0.853	-0.019**
			(0.011)			(0.014)			(0.009)
Cohabit	0.149	0.134	0.008	0.143	0.130	0.008	0.157	0.138	0.008
			(0.007)			(0.007)			(0.009)
Mapuche	0.058	0.046	0.009**	0.058	0.040	0.007	0.058	0.051	0.012**
			(0.004)			(0.006)			(0.006)
# children	2.349	2.264	0.165	2.361	2.279	0.154	2.334	2.247	0.178
			(0.116)			(0.106)			(0.128)
No children	0.136	0.144	-0.018	0.136	0.141	-0.013	0.135	0.147	-0.025*
			(0.012)			(0.012)			(0.013)
Youngest child	6.188	6.397	-0.318	6.443	6.638	-0.263	5.894	6.118	-0.371
			(0.525)			(0.535)			(0.525)
Oldest child	11.102	11.180	0.119	11.427	11.488	0.135	10.726	10.823	0.113
			(0.790)			(0.754)			(0.844)
Years of educ[a]	6.700	7.124	-0.156	6.431	6.819	-0.093	7.068	7.530	-0.230
			(0.168)			(0.189)			(0.176)
Formal employment (1975-1980)									
by slum [b]	0.311	0.351	-0.008	0.100	0.130	-0.016	0.547	0.593	-0.002
			(0.013)			(0.014)			(0.019)
			(0.026)			(0.026)			(0.027)
Child mortality (last 5 years)[c]									
# Children died < 28 days	0.005	0.007	0.000	0.004	0.006	-0.001	0.005	0.008	0.001
			(0.001)			(0.002)			(0.002)
# Children died < 1y	0.016	0.017	0.006	0.016	0.016	0.006*	0.017	0.018	0.005
			(0.004)			(0.003)			(0.005)
Adults	18,347	8,917	27,264	9,837	4,772	14,609	8,510	4,145	12,655
Slums	52	39	90	52	39	90	52	39	90
Municipalities		14			14			14	

Column (1) reports means for displaced adults at baseline and column (2) for non-displaced adults. Column (3) reports the difference between groups, adjusted by the probability of slum clearance ($\hat{p}_s \times \psi_o$) in the full sample of families found in the archival sample and in the common support of the propensity score. Columns (4)–(6) repeat the exercise for women, and columns (7)–(9) repeat the exercise for men. Standard errors are clustered by slum of origin in parentheses. 10%*, 5%**, 1%***. [a]Years of schooling is observed in the sample of individuals found in the RSH and is conditional on an individual being alive after the year 2007. [b]Formal employment is measured at the slum level using historical data from the Superintendence of Pensions. [c]Child mortality measures whether an individual in the sample had a child born alive who died in the first year or less, in the five years before treatment.

Table 3: Annual mortality of adults (percentage points)

	1[Died after intervention]			
	(1)	(2)	(3)	(4)
Displaced	0.111*	0.214***	0.217***	0.200***
	(0.067)	(0.063)	(0.064)	(0.069)
Adj. R^2	0.003	0.015	0.014	0.015
Non-displaced mean	0.670	0.670	0.670	0.670
Percent effect (%)	16.6	31.9	32.4	29.9
Observations	974,559	974,559	974,559	974,559
Individuals	27,264	27,264	27,264	27,264
Municipality of origin FE	✓	✓	✓	✓
Baseline controls		✓	✓	✓
Slum controls			✓	
$\psi_o \times p(X_s)$				✓

Notes: Outcome is annual mortality in t conditional on surviving in $t-1$. Coefficients multiplied by 100 to represent percentage points. All regressions include calendar year fixed effects, and year of treatment. Standard errors are clustered by slum of origin in parentheses (90 clusters). Baseline controls include the following: female, woman is head of household, married, age fixed effects, number of children per couple, Mapuche last name dummy, formal employment, and year-of-intervention fixed effects. Slum characteristics include families per hectare, military name, closeness to rivers/canals, slope, risk of flooding, average schooling and unemployment by census district, number of schools per census district, and distance to the CBD. The row labeled as "Percent effect" stands for percentage variation with respect to the non-displaced mean. The non-displaced mean in column (4) is computed conditional on $\hat{p}_s$. 10%*, 5%**, 1%***.

Table 4: Annual mortality of adults by sex (percentage points)

	Women		Men	
	1[Died after intervention]		1[Died after intervention]	
	(1)	(2)	(3)	(4)
Displaced	0.107	0.148**	0.147	0.297***
	(0.083)	(0.059)	(0.135)	(0.096)
Adj. R^2	0.004	0.014	0.005	0.016
Non-displaced mean	0.557	0.557	0.789	0.789
Percent effect (%)	19.2	26.6	18.6	37.6
Observations	537,037	537,037	437,522	437,522
Individuals	14,609	14,609	12,655	12,655
$\psi_o \times p(X_s)$	✓	✓	✓	✓
Baseline controls		✓		✓

Notes: Outcome is annual mortality in t conditional on surviving in $t-1$. Coefficients multiplied by 100 to represent percentage points. All regressions include calendar year fixed effects, and year of treatment. Standard errors are clustered by slum of origin in parentheses (90 clusters). Baseline controls include the following: female, woman is head of household, married, age fixed effects, number of children per couple, Mapuche last name dummy, formal employment, and year-of-intervention fixed effects. The row labeled as "Percent effect" stands for percentage variation with respect to the non-displaced mean. The non-displaced mean in column (4) is computed conditional on $\hat{p}_s$. 10%*, 5%**, 1%***.

Table 5: Displacement effect and characteristics of destination locations at time of treatment

	Women			Men		
	1[Died after intervention]			1[Died after intervention]		
	Base	Full	Decomp.	Base	Full	Decomp.
	(1)	(2)	(3)	(4)	(5)	(6)
Displaced	0.148**	0.076		0.297***	-0.031	
	(0.059)	(0.083)		(0.069)	(0.061)	
Slum Network		-0.022	-0.164= 2.4%		-0.157	-0.163=8.6%
		(0.070)			(0.131)	
Distance from origin		0.006	9.766=39.6%		0.011*	9.890=36.6%
		(0.004)			(0.007)	
ΔDistance to CBD		-0.003	3.605=-7.3%		-0.001	3.713=-1.3%
		(0.006)			(0.011)	
Δ Unemployment		-0.005	3.535=-11.9%		0.011**	3.597=13.3%
		(0.004)			(0.006)	
Δ PCH centers/hh		0.004	-0.0686=-0.2%		-0.025	-0.137=1.2%
		(0.028)			(0.033)	
Adj. R^2	0.014	0.014		0.016	0.016	
Non-displaced mean	0.557	0.557		0.789	0.789	
Observations	537,037	537,037		437,522	437,522	

Notes: Outcome is annual mortality in t conditional on surviving in $t-1$. Coefficients multiplied by 100 to represent percentage points. Regressions equivalent to column (4) in Table 3. Columns (3) and (6) report the decomposition of the displacement effect using the method proposed by Gelbach (2016). These columns report auxiliary regressions of each determinant of displacement, and the corresponding share they represent of the average displacement effect in column (1) and (4). All regressions include calendar year fixed effects, and year of treatment. Standard errors are clustered by slum of origin in parentheses (90 clusters). Baseline controls include the following: female, woman is head of household, married, age fixed effects, number of children per couple, Mapuche last name dummy, formal employment, and year-of-intervention fixed effects. The row labeled as "Percent effect" stands for percentage variation with respect to the non-displaced mean. The non-displaced mean in column (4) is computed conditional on $\hat{p}_s$. 10%*, 5%**, 1%***.

Table 6: Displacement effect on adults' labor market outcomes between 2007 and 2019

	(1)	(2)	(3)	(4)	(5)
Outcome	1[Employed]	Total income	Labor income	Retirement income	Domestic service
Panel A. All Adults					
Displaced	0.032*	-10.389**	0.102	-10.052***	0.020***
	(0.017)	(4.279)	(3.537)	(3.383)	(0.006)
Non-displaced mean	0.386	130.129	71.313	52.654	0.045
Adj. R^2	0.129	0.175	0.154	0.040	0.039
Individuals	21,536	21,536	21,536	21,536	21,536
Panel B. Women					
Displaced	0.061***	-1.404	8.587**	-8.293**	0.037***
	(0.020)	(4.961)	(3.786)	(3.893)	(0.011)
Non-displaced mean	0.275	83.466	38.233	37.434	0.069
Adj. R^2	0.020	0.040	0.041	0.021	0.012
Individuals	12,385	12,385	12,385	12,385	12,385
Panel C. Men					
Displaced	-0.014	-24.977***	-14.629**	-11.709**	-0.002
	(0.026)	(6.761)	(5.961)	(4.516)	(0.002)
Non-displaced mean	0.536	192.762	115.976	72.840	0.011
Adj. R^2	0.041	0.067	0.065	0.054	0.231
Individuals	9,151	9,151	9,151	9,151	9,151

Notes: Regressions equivalent to column (4) in Table 3 for the sample of adults matched to the RSH data. Standard errors clustered by slum of origin. 10%*, 5%**, 1%***. Controls include: woman is head of household, married, age fixed effects, number of children per couple, Mapuche last name dummy, formal employment, and year-of-intervention fixed effects.

Table 7: Heads of household's long-term location between 2017 and 2019

	Probability of living in			Distance	Poverty index
	assigned municipality	assigned neighborhood	municipality of origin	from assigned neighborhood	in current neighborhood
	(1)	(2)	(3)	(4)	(5)
Displaced	0.030	-0.186	-0.162	1.719	0.033***
	(0.126)	(0.134)	(0.129)	(1.651)	(0.009)
Non-displaced mean	0.599	0.536	0.599	4.260	0.509
Percent effect	**5.0**	**-34.7**	**-27.0**	**40.4**	**6.5**
Observations	10,392	10,392	10,392	8,952	10,392

Notes: This table shows inverse propensity score weighted estimates. We cannot estimate equation (1) due to a small sample, and dummies are not identified. Regressions for head of households parents that are matched to the RSH, and report non-missing schooling. Standard errors clustered by slum of origin in parenthesis. 10%*, 5%**, 1%***.

Table 8: Differences in poverty rates by neighborhoods between 2017 and 2019

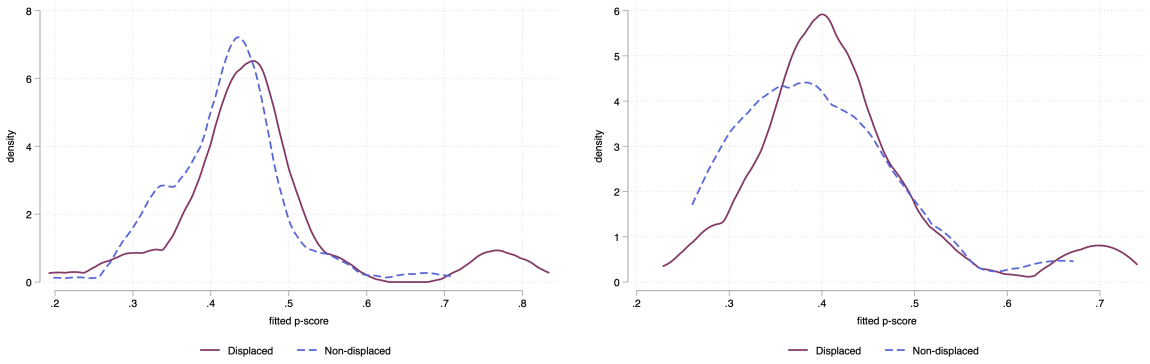
	(1)	(2)	(3)	(4)	(5)	(6)
Relocation neighborhood	0.076***	0.062***	0.072***	0.062***	0.034	0.029
	(0.016)	(0.013)	(0.016)	(0.013)	(0.022)	(0.032)
Redeveloped neighborhood	0.041**	0.058***	0.037**	0.058***		
	(0.017)	(0.018)	(0.017)	(0.018)		
All other neighs mean	0.493	0.486	0.497	0.485	0.541	0.548
Adj. R^2	0.002	0.100	0.002	0.081	0.024	0.540
Observations	22,406	22,406	18,747	18,747	582	582
Projects	4,293	4,293	3,630	3,630	97	97
Municipality FE		✓		✓		✓

Notes: Regressions for neighborhoods in Great Santiago. Clustered standard errors by municipality.

Appendix and Supplementary Material

A Additional Figures and Tables

Figure A.1: Distribution of the probability of slum clearance versus redevelopment



(a) Full sample of urban slums **(b)** Urban slums in Archives

Notes: This figure plots the fitted values of a logit regression using the estimates of column (3) in Table 1, by treatment in the FLACSO sample. Figure (b) plots the densities of the predicted propensity score in the sample of slums in Archives.

Figure A.2: Kaplan-Meier survival functions by year after treatment

(a) Women **(b)** Men

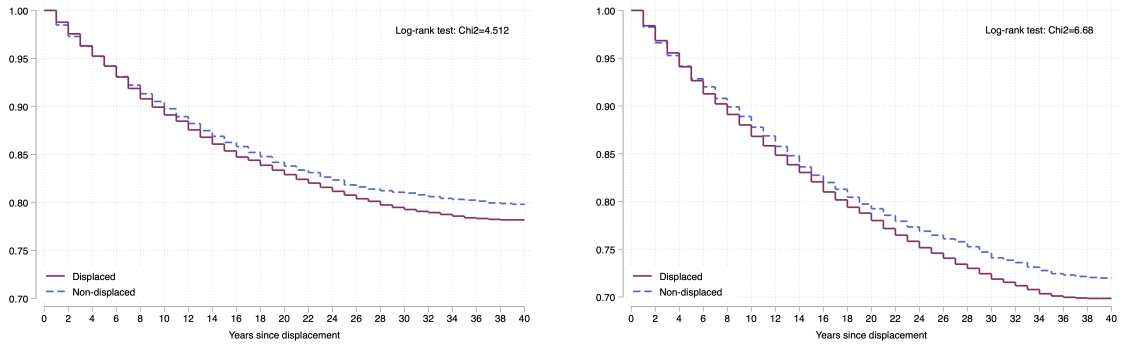
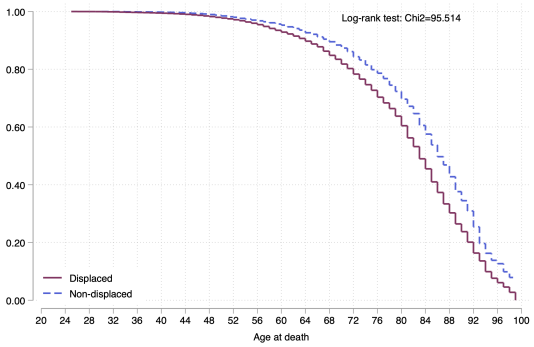


Figure A.3: Kaplan-Meier survival functions by age at death

(a) Women



(b) Men

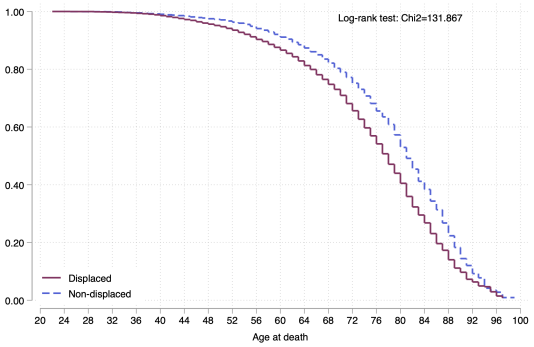


Table A.1: Main causes of death Chilean population (DEIS)

Cause of death	2001		2018	
	Males (%)	Females (%)	Males (%)	Females (%)
Cancer	22.46	25.32	25.90	25.70
Lung cancer	3.24	1.89	3.73	2.78
Stomach cancer	4.56	2.78	3.91	2.05
Breast cancer	0.01	2.89	0.01	3.14
Colorectal cancer	1.00	1.46	2.07	2.29
Pancreatic cancer	0.77	1.11	1.30	1.61
Prostatic cancer	3.10	0.00	4.00	0.00
Gynecologic cancer	0.0	3.65	0.00	3.10
Bile duct cancer	1.26	3.84	1.26	2.66
Cardiovascular disease	15.03	15.91	14.18	13.07
Diabetes	3.27	4.50	2.94	3.30
High blood pressure	2.77	4.64	4.73	7.45
External cause	8.81	2.12	6.92	2.45
Alcohol related	4.50	0.78	2.25	0.41
Tobacco related	4.09	2.80	5.20	4.34

Table A.2: Causes in Death Certificates (DC) and Admin. Data (DEIS)

Cause of death	Women		Men	
	DEIS (%)	DC (%)	DEIS (%)	DC (%)
Cancer	31.40	25.70	28.05	24.40
Lung cancer	3.52	4.37	5.57	6.50
Stomach cancer	3.66	2.98	5.18	4.31
Breast cancer	2.84	2.33	0.02	0.02
Colorectal cancer	2.30	1.10	1.71	0.94
Pancreatic cancer	1.67	1.63	1.26	1.27
Prostatic cancer	0.0	0.02	3.12	2.75
Gynecologic cancer	3.97	2.90	0.00	0.0
Bile duct cancer	4.43	3.82	1.47	1.13
Cardiovascular disease	15.12	15.74	15.64	16.62
Diabetes	5.84	0.82 (4.20)	4.90	0.53 (3.18)
High blood pressure	5.62	0.36 (11.69)	4.63	0.30 (9.73)
External cause	2.38	1.49	4.93	5.25
Alcohol related	2.87	1.51	5.69	4.84
Tobacco related	6.67	5.71	8.37	8.88
Undetermined	0.84	1.26	0.86	1.87
Not classified	-	0.3	-	0.4

Table A.3: Variations to the propensity score method

	Outcome: 1[Died after intervention]					
	(1)	(2)	(3)	(4)	(5)	(6)
	Base					
Displaced	0.200***	0.240***	0.198***	0.205***	0.258***	0.233***
	(0.069)	(0.065)	(0.058)	(0.056)	(0.075)	(0.049)
Adj. R^2	0.015	0.015	0.015	0.015	0.015	
P-score method	Common sup.	Inv. weight	$p_1 < p < p_{99}$	$p_5 < p < p_{95}$	$p_{10} < p < p_{90}$	Origin FE
Non-displaced mean	0.775	0.775	0.775	0.775	0.775	0.775
Observations	974,479	974,479	959,305	906,781	807,712	950,038
# Slums	92	92	89	81	72	90

Table A.4: Assignment location attributes and displaced families' characteristics at baseline

Attributes at destination	Home value (UF) (1)	Distance from origin (2)	Adult pop. schooling (3)	# schools/ 1,000 students (4)	Log property prices (5)	Distance to CBD (6)	Primary care centers (7)	Unemployment rate (8)
Female HH	-1.544	0.030	-0.002	0.066	0.023	0.130	0.003	0.008
	(1.591)	(0.108)	(0.001)	(0.050)	(0.016)	(0.105)	(0.002)	(0.006)
# Children	0.180	-0.003	-0.000	-0.009	0.006	-0.018	-0.000	0.002
	(0.225)	(0.022)	(0.000)	(0.007)	(0.005)	(0.022)	(0.000)	(0.002)
Married HH	0.855*	-0.104*	0.001	0.010	-0.007	-0.107***	-0.001	-0.002
	(0.452)	(0.055)	(0.001)	(0.021)	(0.009)	(0.038)	(0.001)	(0.004)
HH age	0.128	-0.015**	0.000	-0.002	-0.002	-0.015*	-0.000	-0.001
	(0.120)	(0.007)	(0.000)	(0.005)	(0.001)	(0.008)	(0.000)	(0.001)
Mapuche HH	1.831	-0.131	0.000	-0.048	-0.022	-0.121	-0.003	-0.004
	(1.452)	(0.087)	(0.001)	(0.051)	(0.014)	(0.101)	(0.002)	(0.004)
HH schooling > 6	0.671	0.015	-0.000	-0.014	-0.012	-0.060	-0.000	-0.006
	(0.460)	(0.047)	(0.001)	(0.015)	(0.011)	(0.046)	(0.001)	(0.004)
HH schooling > 12	-1.466	0.213*	-0.002	0.090	-0.000	0.183	0.004	-0.002
	(1.972)	(0.110)	(0.001)	(0.067)	(0.006)	(0.128)	(0.003)	(0.003)
HH schooling unknown	0.292	-0.082*	0.000	-0.063*	0.008	-0.063	-0.002	0.004
	(1.019)	(0.068)	(0.001)	(0.033)	(0.009)	(0.076)	(0.002)	(0.003)
Adjusted R^2	0.750	0.923	0.718	0.499	0.699	0.750	0.784	0.619
Observations				8,435				
P-value of F-test of joint significance of education dummies								
Attribute in Δ	0.018	0.246	0.208	0.170	0.417	0.180	0.445	0.295
P-value of F-test of joint significance of households' characteristics								
Attribute in Δ	0.210	0.009	0.319	0.116	0.258	0.131	0.570	0.201
Municipality of origin FE	✓	✓	✓	✓	✓	✓	✓	✓
Year of intervention FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors clustered by slum of origin. 10%*, 5%**, 1%***. Attributes in columns (3) to (8)are measured at the census district level in 1982; schools, hospitals and subway are measured in 1985.

Table A.5: Displacement effect on the probability of selling home by 2019

		Conditional on selling		
	Home ever sold	Log(Price)	Year sold	# years after treatment
	(1)	(2)	(3)	(4)
Displaced	-0.042	-0.335	0.156	-0.050
	(0.031)	(0.305)	(4.830)	(4.879)
Adj. R^2	0.070	0.337	0.286	0.307
Non-displaced mean	0.118	9.453	2008.5	25.609
Percent effect	**-35.6**	**-3.5**	**0.008**	**-0.2**
Observations	1,845	197	197	197
Municipality of origin FE	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓

Notes: Inverse propensity score estimates in a sample of 20% of families in archives who received a home in a municipality located in the Northern areas of Greater Santiago. Number of slums of origin is 35, and number of municipalities of origin is 12. Baseline controls include: female headed household, number of children in family, married head of household, head of household's age, Mapuche head of household, head of household year of birth fixed effect, and year of intervention fixed effects. Robust standard errors in parenthesis. 10%*, 5%**, 1%***.

Table A.6: Displacement and social capital in the long run

Outcome	Chose neighborhood (1)	Conflictive neighbors (2)	Insecure neighborhood (3)	No trust in neighbors (4)	Trust own child with neighbor (5)	Divided neighborhood (6)
Displaced	-0.037	0.101	-0.099	0.046	-0.100**	0.209***
	(0.047)	(0.277)	(0.637)	(0.032)	(0.050)	(0.048)
R^2	0.160	0.062	0.071	0.111	0.161	0.224
Fragmentation Index	-0.027	0.877**	-0.442	0.083	-0.070	0.284***
	(0.060)	(0.420)	(0.975)	(0.051)	(0.067)	(0.069)
R^2	0.142	0.068	0.065	0.108	0.154	0.230
Non-displaced mean	0.780	1.586	1.652	0.116	0.341	0.296
Observations	1,184	1,184	1,184	1,184	1,184	1,184
# neighborhoods	43	43	43	43	43	43

Notes: Results of equation (1) on individuals' perceptions about their neighborhoods in 2012. Data come from Núñez et al. (2012). Each individual in this dataset is matched with a neighborhood in our sample, using current address. Standard errors clustered by municipality of residence in parenthesis. 10%*, 5%**, 1%***.

B Eviction Policies

Table B.1: Characteristics of each version of the program

Intervention	**Location**	Property right	Type of dwelling	Public services	Cost for family
Non-displaced (1/3) (urban renewal)	**Same**	Yes	Starting kit (*) or apartment	Yes	25% paid in 15 years
Displaced (2/3) (evicted)	**New (periphery)**	Yes	Apartment or house	Yes	25% paid in 15 years

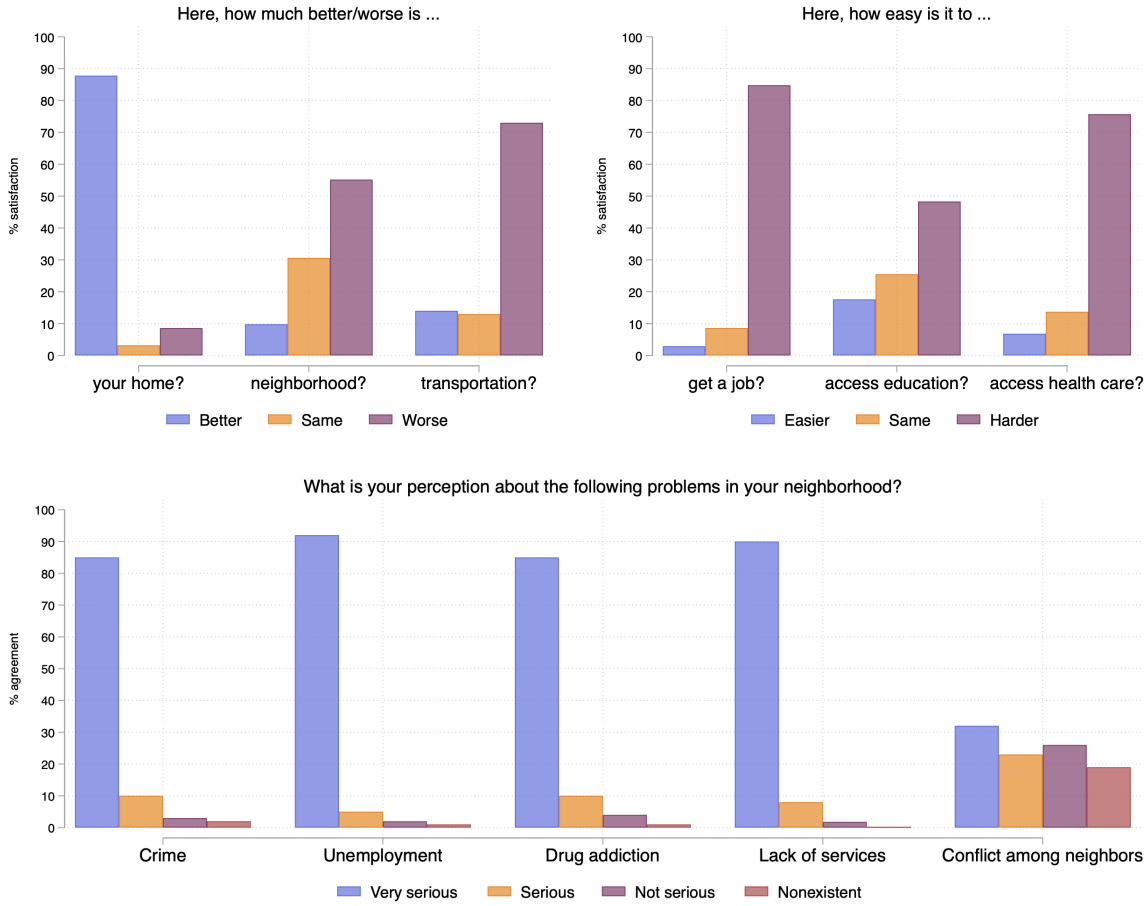
(*) A starting kit includes a living room, a bathroom, and a kitchen.

Figure B.1: Example of a slum and new neighborhoods

Notes: Examples of neighborhoods from Hidalgo (2019).

B.1 Evaluation of evictions program in 1987

Figure B.2: Summary of evaluation of the Program for Urban Marginality (Aldunate et al., 1987)



Notes: Summary of results found by Aldunate et al. (1987). The authors interviewed 592 displaced slum dwellers that were relocated into four new neighborhoods.