Immigration and Slums

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ABSTRACT. South-South international migration is an increasingly important phenomenon, yet we know little about its impact on housing dynamics in developing country cities, where informal housing supply in the form of slums is a key consideration. This paper investigates the causal effect of international immigration on slum formation and growth in Chile, a country that experienced a fourfold increase in immigration in the past decade. To do this, we create a unique panel dataset with information on all slums in Chile as well as the universe of international immigrants and their destination municipalities. Using both a high-frequency within-slum analysis as well as a long-difference shift-share instrumental variable approach at the municipal level, we find a robust positive relationship between international immigration and slum creation and growth. This is evident from observed increments in the number of slums, the population residing in slums (both native and migrant), and the expansion of slum footprints. Notably, international immigration can account for all of the observed slum expansion in the study period. We further provide evidence of the important role that the market for affordable housing plays in mediating the relationship between immigration and slums. The surge in demand for housing, unmet by a concomitant increase in affordable housing supply, resulted in increases in rental prices, which in turn compelled low-income households to seek accommodation in informal slum settlements. Consistent with the housing market mechanism, the effects of immigration on slums are stronger in more rugged municipalities, where we show housing supply elasticities are also lower. Alternative mechanisms such as immigration effects on wages, employment, or poverty rates do not explain these results.

KEYWORDS. Immigration, Affordable Housing, Slums.

JEL CODES. I30, J15, O18, R23, R30.

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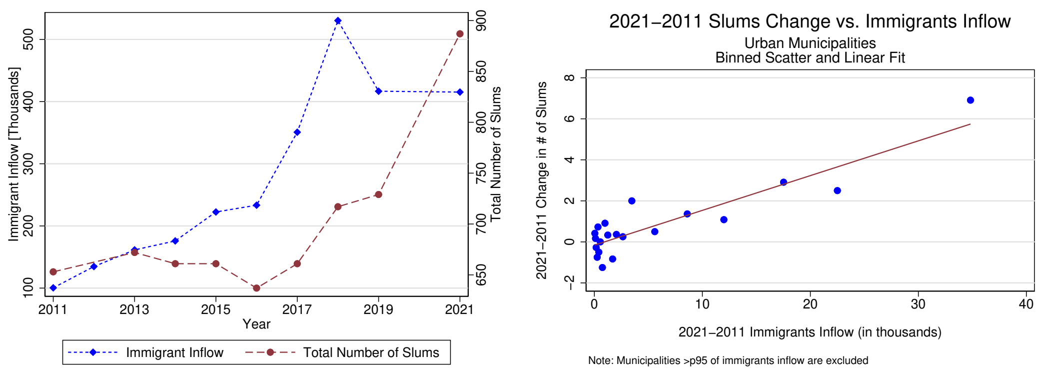
1. Introduction

Amidst a burgeoning global housing crisis propelled by a lack of affordable purchase or rental options, 1.6 billion individuals struggle to access adequate housing, of whom 1 billion live in informal settlements (UN-Habitat (2022)). By 2030, UN-Habitat anticipates that 3 billion individuals, approximately 40% of the global population, will be in need of access to adequate and affordable housing. The interplay of immigration can further accentuate this crisis, as substantial influxes may suddenly escalate demand, compounding the challenge of providing affordable housing in many regions worldwide. The rising trend of South-South international migration highlights a yet unexplored facet of housing dynamics in developing country cities, where informal housing supply in the form of slums is a pivotal concern.

In this paper, we study the causal effect of international immigration on slum formation in Chile, where the foreign-born population quadrupled in the last decade, mostly due to South-South migration. The annual influx rose from around 100,000 migrants in 2011 to more than 400,000 in 2021, with the share of immigrants rising from 2% to 8% of the total population over the same period. In parallel, the expansion of slums has been sizable. Between 2011 and 2021, the total number of slums nationwide increased from around 650 to 900 (with the slum population almost tripling, from 30,000 to more than 80,000). As in most Latin American countries, slum dwellers in Chile live in highly substandard quality housing units. The majority of slum houses are rudimentary units constructed from discarded materials such as cardboard, tin and plastic; have dirt floors and lack connections to basic utilities such as water supply and sewerage systems[1]. As is shown by Figure 1, municipalities with higher immigration inflows show a larger increase in the number of slums.[2]

Figure 1: Immigration and Slums 2011-2021

(a) 2011-2021 Series (b) 2021-2011 Differences



Source: Department of State and MINVU, Chile

[1]Slums in Chile follow the definition stated by UNHabitat (2003), that is, poor neighborhoods where (i) at least 50% of the residents stay under illegal occupation (i.e., either do not have land title or are renting to someone who does not possess land title), and/or (ii) at least 50% of the residents lack access to adequate housing, electricity, drinkable water, and/or improved sanitation.

[2]Chile's trends in terms of immigration and slum formation is hardly unique. As immigration has grown steadily over the last ten years, the population living in slums has increased by 100 million to encompass a total of 1 billion people compared to 2014 (see UN-Habitat (2020), Table 1.4).

We are interested in understanding how changes in immigration inflows causally affect the dynamic of creation, expansion, and closure of slums. Our analysis relies on a unique dataset of immigration comprising the number of residence permits reported by the Chilean Department of State each year throughout the last decade, the residence/destination municipality declared by each immigrant, and their socio-demographic characteristics, including age, gender, and education. We merge this immigration dataset to what we believe is the first long, universal, and high-frequency national panel data on slums, based on censuses collected by a joint effort between the Ministry of Housing (MINVU) and TECHO NGO. This bi-annual panel spanning the period 2011-2021 includes the universe of slums in the Chilean territory, their population (including the native and migrant composition within each slum), and their geo-referenced location, enabling us to observe how slums have developed spatially over time. Our focus is on urban municipalities, where 99% of migrants arrive and almost 95% of slums are located.

Identifying the causal effect of immigration on slum growth is difficult since the distribution of the immigrant population across municipalities and over time may be endogenous to the characteristics of each municipality, which in turn determine slum formation. For instance, more economically dynamic municipalities may simultaneously increase immigration and slums, generating an upward bias in our estimates. Likewise, an upward trend in housing supply within a specific municipality during a particular year could simultaneously attract immigrants and decrease urban informality, generating a downwards bias. We thus estimate causal effects by building a shift-share instrument that combines immigration inflows into countries other than Chile (i.e., an exogenous shifter of migration push factors from origin countries) with the "share" of nationality-specific immigrants located in each municipality in 2010, before the immigration explosion we study began[3].

We find robust evidence that immigration increases slum formation. 2SLS estimates reveal that for every 1,000 immigrants arriving within an urban municipality, the number of slums increased by an average of 0.09 units. To put these numbers in perspective, the average inflow of immigrants per urban municipality is roughly 11,000 in the period 2011-2021, so that on average the number of slums increased by 1 unit per municipality due to immigration. From a mean of 3 slums per municipality in 2011, the latter represents an increase of 1/3 in the total number of slums throughout the country. Moreover, 100% of the 2011-2021 mean change in the number of slums per municipality can be attributed to immigration. On the intensive margin, immigration increased both the native and immigrant population residing in slums, on average doubling the baseline slum population. This is reflected in a comparable expansion of slum footprint, suggesting a one-to-one relationship between slum population and spatial growth.

Goldsmith-Pinkham et al. (2020) show that the validity of Bartik-type instruments like ours rely on exogeneity of the (pre-shock) country shares by municipality. In particular, not violating the excludability assumption requires that the shares do not predict slum formation through channels other than immigration. We show that there are parallel trends in outcomes before the immigration shock began, thereby ensuring that the identification assumption is well met in our

[3]Similar shift-share designs have been used in Bianchi et al. (2012) and Ajzenman et al. (2021).

design, and our results support a causal interpretation. Our results are also robust to different types of residence permits used to build immigration inflows, as well as to adjusting standard errors using Adao et al. (2019)'s correction to account for potential correlation of residuals across municipalities with similar shares and to the use of Anderson and Rubin (1949)'s confidence intervals. Furthermore, both the effect size and statistical inference remain unchanged when grouping municipalities in pairs, triplets or quartets based on the closeness between each other, suggesting our results are robust to variations in internal migration across municipalities. Finally, the evidence is consistent when re-estimate the immigration effects using a high-frequency panel regression model at the slum level.

Turning to mechanisms, we hypothesize that immigration increased slum formation because the rental housing market experienced considerable pressure from immigrant-induced demand. A first piece of evidence comes from survey data on rental prices, where our 2SLS estimates reveal that for every 1,000 immigrants arriving within a municipality, the median monthly rent increased by an average of 0.8% percent. Considering the total inflow of immigrants, approximately 10% of the rent increase throughout the analysis period can be attributed to immigration, a result that is close to the effect size found in Saiz (2003) for the case of the U.S. Consistent with the housing market hypothesis, immigration effects on rental prices are entirely driven by increases in rental rates paid by low-income households, for whom we estimate a larger rent response with respect to immigration. The hypothesis that slums are a result of low-income households being priced out of the formal housing market is also borne out by perceptions among slum dwellers. According to slum census surveys, the most important reason for going to live in a slum is "Unaffordable rents" (31%), as opposed to alternative reasons like "Need for Residential Autonomy" (24%), "Low income" (11%), or "Unemployment" (9%).

We proceed to examine the extent to which immigration effects on rents reflect a formal housing market failure at the low end of the housing market. In particular, we estimate the effects of immigration inflows on construction permits and construction of formal housing in each municipality. We find that immigration does not increase the supply of affordable housing units — the type of housing sought by low income households at the margin of the formal/informal housing markets. In contrast, immigrant inflows do have a small but positive effect on housing permits and construction for high-end residences. These results are consistent with the immigration-induced spike in rental prices we observe for low-income groups. That is, immigration increased the demand for low-cost housing, yet housing supply did not react accordingly, thereby increasing the rents of affordable units and compelling some share of low-income households to instead seek accommodation in informal slum settlements.

A final piece of evidence probing the housing market mechanism relies on exploiting heterogeneity in housing supply elasticites arising from variation in ruggedness of a municipality's geography. This determinant of housing supply elasticity has been well documented in the U.S. literature (Gyourko and Saiz (2006), Burchfield et al. (2006), Saiz (2010)). For the case of Chile, we find that municipalities with higher terrain ruggedness exhibit a smaller increase in affordable housing supply for a given level of immigration, and a concomitant stronger slum proliferation.

Conversely, low-ruggedness municipalities witnessed a stronger expansion of affordable housing as a result of immigration and weaker slum growth. Overall, these results suggest that higher construction costs (and their influence on housing supply and rents) can play a crucial role in moderating the impact of immigration on slum formation.

We examine various alternative explanations for the relationship between immigration and the growth of slums. We find no evidence to suggest that immigration impacts unemployment levels, incomes or poverty rates, indicating that income effects are not a mediating factor. We additionally test for whether the immigration-slum link stems from exclusionary policies deterring migrant households (Feler and Henderson (2011)), or from political capture, where politicians protect immigrant-majority slums for votes, using slum programs as a vote-buying strategy (Keefer and Khemani (2005), Paniagua (2022), Bobonis et al. (2022)). Specifically, we examine the impact of immigration on the share of slums per municipality exposed to slum policy, either housing subsidies or urbanization programs. Our findings suggest that slum policy intensity does not change with varying immigration levels across municipalities, indicating that immigration's positive effect on slum growth is unlikely to be mediated by either anti-immigrant policies or program-based political capture.

Our paper is related to recent research using longitudinal data to study the determinants of informal housing, including Henderson et al. (2020) who trace all formal and slum buildings of Nairobi from aerial photo images for 2003 and 2015, and develop an algorithm that overlays the two cross-sections of polygons to determine which building footprints are unchanged, demolished and/or redeveloped between the two points in time, allowing them to model how changes in land-use affect slums development over time. Michaels et al. (2021) combine high-resolution spatial imagery going back more than 50 years with building-level survey data and georeferenced census data to evaluate the long-run impact of a Sites and Services program on the urban development of Tanzania's poor neighborhoods. Likewise, Harari and Wong (2021) combine administrative data and photographic surveys to follow prices, quantities, and quality of slum territories to evaluate the 1969-1984 KIP slum upgrading program in Jakarta 20 to 30 years later. Gechter and Tsivanidis (2023) estimate local economic spillovers from high-rise developments in early 2000s on slums re-development in Mumbai 15 to 20 years later, for which they follow the spatial evolution of intervened slum areas throughout the period. Rojas-Ampuero and Carrera (2023) examine the displacement effects of a large-scale slum clearance and urban renewal program in Santiago, Chile, during the early 80s, for which they follow displaced and non-displaced slum dwellers 30 to 40 years after the intervention.

Our panel of slums provides a comprehensive means to investigate the micro-dynamics of slum formation across various dimensions, and it exhibits three noteworthy advancements compared to prior endeavors: (i) it encompasses the entire population of slums within a given country; (ii) it features a high frequency of data waves occurring bi-annually, allowing for a time-granular tracking of slums to examine the short- to medium-term evolution of slum growth; and (iii) integrates both the spatial features of slums, which allow us to study the evolution of slums along the extensive margin, and the demographic traits and attributes of the slums, which lets us shed light on the intensive margin of slum development. Our paper leverages this novel dataset to determine the causal effect of immigration-induced population shocks on slum formation, a question that, to the best of our knowledge, no prior research has addressed.

Our paper provides novel evidence on the interaction between immigration and housing markets. Saiz (2003) studies the response of housing markets to immigration shocks in the U.S. after the Mariel boatlift, and find that rents increased from 8% to 11% more in Miami than in the comparison group of cities, with units occupied by low-income Hispanic residents driving most of the effects. Also for the U.S., Saiz (2007) finds that an immigration inflow equal to 1% of a city's population is associated with increases in average rents and housing values of about 1%. Howard (2020) finds that domestic immigration in U.S. cities lowers the local unemployment rate, with the main driving force being the boom in housing markets. In particular, domestic immigration increased house prices and the effect is stronger in cities with inelastic housing supplies. Likewise, Greulich and Raphael (2004), Ottaviano and Peri (2006), Gonzalez and Ortega (2013), and Sanchis-Guarner (2023) find positive effects of immigration on housing costs[4]. We contribute to the existing body of literature by empirically documenting that the positive effects of immigration on rental prices can have a broader impact. Specifically, sudden increases in rental prices faced by low-income households can serve as a catalyst for the growth of slums in developing countries.

We also contribute to our understanding of the role of incomes versus location preferences as determinants of slum formation. Our evidence of zero effects of immigration on city-wide incomes, unemployment, and poverty rates reveals slum growth is unlikely to be associated to income effects. This result goes against the view that slums are a form of poverty trap (Marx et al. (2013)). Alternatively, our evidence is in line with the hypothesis that slums allow the poor to escape subsistence-level poverty (e.g., origin countries of migrants) by taking advantage of the benefits of agglomeration, economies of scale, and networks offered by more developed cities (Glaeser (2011), Celhay and Undurraga (2022))[5].

The paper is organized as follows. Section 2 details the migration and slums data used in this study. Section 3 presents the empirical strategies for estimating the causal effects of immigration on slum formation, and the main results. Then, Section 4 discusses the mechanisms driving the impact of immigration on slums growth, and Section 5 concludes.

[4]Other papers concluding positive effects of migration on housing prices/rents include Akbari and Aydede (2012), Accetturo et al. (2014), Tumen (2016), Alhawarin et al. (2021), Rozo and Sviatschi (2021), Mussa et al. (2017), Busso and Chauvin (2023), Akgündüz et al. (2023). In contrast, Sá (2014) and Depetris-Chauvin and Santos (2018) find either negative or mixed effects of immigration on housing prices/rents.

[5]The literature on slum formation was born under the aegis of the spatial mismatch hypothesis (Kain (1968)), which argues that slums are the product of a geographical poverty trap, i.e., slum dwellers are poor because they are spatially disconnected from job opportunities offered in the inner city. For a thorough review of the spatial mismatch theory, see Gobillon et al. (2007). For partial equilibrium models of slum formation, see Jimenez (1984, 1985), Brueckner and Selod (2009), Brueckner (2013), Cavalcanti et al. (2019), and Henderson et al. (2020).

2. Data

2.1. Immigration

Chilean legislation establishes two main types of residence permits for migrants attempting to settle in the country, i.e., non-tourists: (i) temporary residence permits, composed mostly of work visas (other less-frequent categories are education visas and family reunification visas); and (ii) permanent residence permits for migrants who aim to settle in Chile indefinitely, typically requiring more than two years of temporary residence. Applying for permanent visa is not mandatory, i.e., immigrants with temporary visa can renew it every year. We obtained individual-level data on all temporary and permanent residence permits granted by the Chilean Department of State for the period 2000-2021 (Extranjería-Chile (2021)), which also include migrants' demographic statistics such as date of birth, nationality, gender, education, and job sector at the time of entering the country. Among the 3.4 million individual permits hosted in the data, 89% correspond to temporary residence permits, and 80% were distributed after 2010, for a total inflow of 2.6 million immigrants in the period 2011-2021. Notably, from 2015 onward, the composition of immigrants changed, with Venezuelans and Haitians leading the share of arrivals.[6] Appendix Figures A.I and A.II depict the evolution of immigration over the last 20 years.

While the data includes authorized immigration only, unauthorized individuals constitute a tiny proportion of the immigrant population in Chile. According to the Police Agency data, between 2011 and 2020 the annual average number of individuals that entered the country through an unauthorized access point was around 4,400, which represents 1.7% of the mean annual inflow in that period. This is partly due to the natural boundaries of Chilean geography (Andes mountains from the East; Pacific sea from the West; extremely arid and low-temperature desert from the North), which make unauthorized migration so costly and rare. Second, up to 2018, there were few incentives to migrate without authorization since the Chilean legislation allowed immigrants to enter the country as tourists and then apply for a temporary work visa when getting a job. Moreover, immigrants could obtain permanent residency after two years of holding a temporary work visa.[7]

Importantly, the data includes the municipality of residence at the time of application, with this information being critical for building our shift-share instrument (more in Section 3). This information is for internal records only and does not affect the processing of the residence permit. Indeed, at least during the analysis period, the Department of State did not have any policies related to immigrant quotas at national or sub-national levels. Moreover, migrants are informed they are free to move when the permit is processed, suggesting reduced incentives to misreport residence municipality.

[6] With the exception of Haitians, most migrants come from Spanish-speaking countries, thus language is not a barrier for migrants' integration.

[7] In 2018, the government began requiring consular process visas for Haitians and Venezuelans, which made it harder for citizens of these countries to enter Chile legally. See Servicio-Jesuita-Migrante (2020) for additional details.

Table 1: Descriptive Statistics of Urban Municipalities by Quartiles of Immigrant Inflow 2011-2021

	All	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Number of Municipalities	243	61	61	61	60
Total Inflow of Immigrants between 2011 and 2021	2,609,250	11,689	54,202	245,721	2,297,638
Mean Inflow of Immigrants between 2011 and 2021	10,738	192	889	4,028	38,294
Total Change in No. of Slums between 2011 and 2021	229	1	-12	35	205
Mean Change in No. of Slums between 2011 and 2021	0.9	0.0	-0.2	0.6	3.4
Total No. of Construction Permits between 2011 and 2021	395,721	65,790	81,414	107,318	141,199
Total No. of Floors Built between 2011 and 2021	593,216	83,121	104,059	156,182	249,854
Panel I. Immigrants					
A. Immigrants in 2011	Mean	Mean	Mean	Mean	Mean
Municipality Share of Female Imm. (%)	47	39	49	51	51
Municipality Age of Imm.	31	29	33	32	31
Municipality Share of Imm. with High School or more (%)	81	87	84	79	76
B. Immigrants in 2021	Mean	Mean	Mean	Mean	Mean
Municipality Share of Female Imm. (%)	48	48	47	48	50
Municipality Age of Imm.	33	34	33	33	33
Municipality Share of Imm. with High School or more (%)	83	82	83	83	83
Panel II. Incomes and Housing					
A. Incomes and Housing in 2011	Mean	Mean	Mean	Mean	Mean
Municipality Median Per Capita HHs. Income (in US$ 2011)	308	233	273	294	427
Municipality No. of Construction Permits in last 10 years	1,476	909	1,103	1,639	2,268
Municipality No. of Floors Built in last 10 years	2,090	1,012	1,318	2,237	3,822
Municipality Median Unit Rent Prices (in US$ 2011)	173	110	141	188	241
B. Incomes and Housing in 2021	Mean	Mean	Mean	Mean	Mean
Municipality Median Per Capita HHs. Income (in US$ 2011)	461	384	425	439	594
Municipality No. of Construction Permits in last 10 years	1,628	1,079	1,335	1,759	2,353
Municipality No. of Floors Built in last 10 years	2,441	1,363	1,706	2,560	4,164
Municipality Median Unit Rent Prices [*by 2017 (in US$ 2011)]	249	165	211	254	348
Panel III. Slums					
A. Slums in 2011	Mean	Mean	Mean	Mean	Mean
Municipality No. of Slums	2.5	1.3	1.4	2.5	5.0
Municipality No. of Households in Slums	124	56	40	116	287
Municipality No. of Native Households in Slums	122	56	40	116	281
Municipality No. of Immigrant Households in Slums	2	0	0	1	7
Municipality Total Area of Slums (m^2)	27,615	15,569	11,774	31,960	51,548
B. Slums in 2021	Mean	Mean	Mean	Mean	Mean
Municipality No. of Slums	3.5	1.3	1.2	3.1	8.4
Municipality No. of Households in Slums	330	59	48	216	1,009
Municipality No. of Native Households in Slums	219	59	42	182	599
Municipality No. of Immigrant Households in Slums	111	0	5	34	410
Municipality Total Area of Slums (m^2)	62,767	28,183	22,543	84,409	116,822

Notes: Summary statistics of urban municipalities in Chile (243 in total). Quartiles are defined based on the total inflow of immigrants per municipality in the period 2011-2021.

As in most countries, immigration in Chile is fundamentally an urban phenomenon. Indeed, almost all immigration inflows (98.8%) are concentrated in urban municipalities. While immigration rose considerably within our study years, growth rates vary substantially within the country. In Table 1, we show descriptive statistics grouping all urban municipalities (243 in total) according to quartiles of immigrant growth between 2011 and 2021. On average, municipalities in the upper quartile received around 38,000 immigrants, which is about ten times the average inflow received by Q3 counterparts, and between 40 and 200 times the average inflows received by municipalities at the lower end of the distribution of immigrant inflows.

Panel I reports average immigrant characteristics for each quartile group in 2011 and 2021. Roughly half of the immigrants are women, and migrants' average age at entry is 31, both statistics remaining more or less constant over the decade. More than 80% of immigrants that entered the country by 2011 had completed high school education or more, and the levels of education of immigrants entering the country ten years later are somewhat larger.

Panel II describes the dynamics of incomes and housing markets. Municipalities receiving higher influxes of immigrants are typically richer in terms of *per capita* income, and their inhabitants pay on average higher rents. On average, the median rent in Q4 municipalities is more than double that of Q1, and this is the case both in 2011 and ten years later. Likewise, the housing market is more active in these municipalities. The average number of construction permits for buildings in Q4 municipalities is double that of Q1 municipalities, and the number of floors built is triple.[8] However, having a larger number of construction permits in Q4 municipalities does not mean there is an excess of housing supply since they also receive a larger immigration inflow. Indeed, considering an average immigrant household of 3 members (MDSF (2020)), the average number of building floors built per immigrant household is only 0.32 in Q4 municipalities (=249,854/(2,297,638/3)), suggesting formal housing expansion has been completely insufficient to even accommodate housing needs for immigrant families, let alone local resident population growth.

2.2. Slums

Slums in Chile follow the UNHabitat (2003) definition, that is, neighborhoods in which (i) at least 50% of inhabitants reside under illegal occupation (i.e., either do not have land title or are renting to someone who does not possess land title), and/or (ii) at least 50% of the residents lack access to adequate housing, electricity, drinkable water, and/or improved sanitation. As in most Latin American countries, slum dwellers in Chile live in severely substandard housing. The majority of slum houses are rudimentary units constructed from discarded materials such as cardboard, tin and plastic; have dirt floors and lack connections to basic utilities such as water supply and sewerage systems. By 2021, only 7% of slums are connected to formal sewage systems; fewer than 20% have legal connections to electricity, with most slum dwellers using

[8] Construction permits must be granted by the Dirección de Obras Municipales (DOM), a municipal-level regulatory body, before the construction of a new formal building can legally occur. The National Institute of Statistics (INE) reports the number of total construction permits per year authorized in each municipality, as well as statistics of number of floors, number of rooms, and quality of constructions authorized.

makeshift wires or tapping into nearby power lines to satisfy energy needs; and just 7% have permanent connections to the city water system (TECHO (2021)).[9]

According to the Ministry of Housing (MINVU), by 2011 there were 653 slums throughout the country, which increased to 882 in 2021, a sharp 35% increase. As with immigration, slums are also an urban phenomenon, with 93% of slums located in urban municipalities. However, as is shown in Table 1, Panel III, there is substantial variation in slum growth, with most of it concentrated in municipalities with a high inflow of immigrants. For instance, in 2011, municipalities in the upper quartile of immigration inflows had 3.8 times more slums than their counterparts in the lower quartile, yet this ratio increased to 6.5 by 2021. This is also reflected in the slum population, which had an average of 124 households per slums in 2011. While low-immigration municipalities barely increased their slum population, municipalities in the upper quartiles doubled and quadrupled it. The number of foreign-born slum dwellers increased sharply in the same period, going from an average of 2 households per municipality in 2011 to 111 in 2021, and again, the changes are mostly driven by municipalities with higher immigrant inflows. As a result, the average area covered by slums grew too. In ten years, slums doubled their surface, and this is the case across high and low-immigration inflow municipalities.

2.2.1. The Chilean Slums Panel Data

We harmonize a bi-yearly panel of ever-slum territories based on consecutive censuses collected by a joint effort between MINVU and TECHO for the period 2011-2021. This is a six-wave balanced panel comprising a total of 1,459 ever-slum territories, i.e., the universe of territories where at some point in the years 2011, 2013, 2015, 2017, 2019, and 2021, a slum has been formed.[10] Each observation is a territory-year cell where we code a dummy equal to one if a slum exists within that territory in that year and zero if not, with zeros being either territories where a slum has not been formed yet or territories where a slum did exist but eventually closed.[11] Of the 1,459 territories, 93% are located in urban municipalities, the focus of our study, for a panel size of 1,359×6=8,154 territory-year observations.

Whenever a slum exists in the territory, we observe the number of households residing in that slum, and for some years, the censuses also collect the nationality of slum dwellers, allowing us to observe how the share of immigrants evolves within each slum. We further observe the slum's geo-referenced location, thus we can track the spatial evolution of slums over time, e.g., the total area covered by the slum, measured in squared meters. Figures 2 and 3 illustrate examples of slum formation between 2011 and 2021 in terms of population, immigrants share, and area (m^2).

[9] Since most slum dwellers cannot afford to pay for legal connections, they tap into the public water supply through illegal connections. Others access water through water trucks, typically at much higher marginal prices than public supplies.

[10] MINVU and TECHO implemented censuses every year between 2011 and 2021, except in years 2012 and 2020. These two missing years generate gaps that impede us from building a complete yearly panel for the 2011-2021 period. Nevertheless, at least it allows the construction of a bi-yearly panel using odd years, so we use these for the main analysis. Results are robust to using an incomplete yearly panel, i.e., 2011-2021 but without 2012 and 2020 waves.

[11] Note that there are no "always missing" observations, i.e., at any point in 2011-2021 years a slum did exist, actually exists, or will exist in that territory.

Figure 2: El Consuelo Alto Slum

2011: 42 HHs—0% mig.—1,170 m^2. 2021: 250 HHs—32% mig.—10,300 m^2.

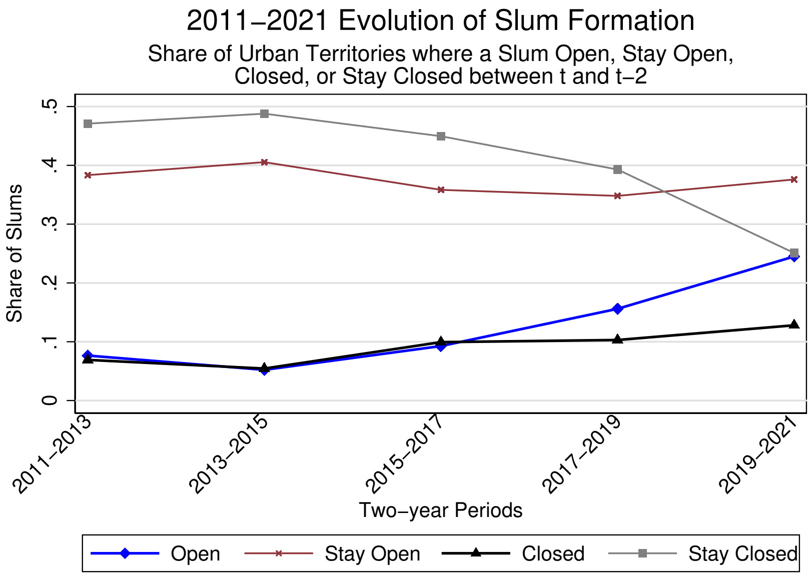
Figure 3: Villa El Esfuerzo Slum

2011: 19 HHs—5.26% mig.—330 m^2. 2021: 535 HHs—88.79% mig.—6,500 m^2.

A high-frequency, biennial characterization of slums dynamics is depicted in Figure 4. For each territory between t and $t-2$ in the panel, we observe whether a slum opened (i.e., the dummy goes from 0 to 1), stayed open (1 to 1), closed (1 to 0), or stayed closed (0 to 0). For instance, between 2011 and 2013, in about 10% of the territories a slum opened, and in about 10% of the territories an existing slum closed. However, between 2019 and 2021, in roughly one-quarter of territories a new slum was created, while the share of territories where a slum closed continued at around 10%. Likewise, the share of territories where a slum stayed open relative to two years before is about 40%, a figure that remains stable over time. In contrast, the share of territories where no slum opened between the two years (i.e., stayed closed) decreased from around 50% in 2011-2013 to about 25% in 2019-2021.

In summary, out of the 653 slums present in 2011, 60% of them shut down before 2021, for an average annual closure rate of 6% and an average lifespan of 24 years. During the same period, 806 new slums opened (i.e., an annual open rate of 12%), but 22% of them closed before 2021. Overall, between 2011 and 2021, the total number of slums increased by 229 units, for an annual slum growth of 3.5%.

Figure 4: Evolution of Slums Formation 2011-2021. *Source*: TECHO-MINVU Panel



3. Estimating the Causal Impact of Immigration on Slum Formation

We examine the causal effect of international immigration on slum dynamics in urban municipalities, where 99% of migrants arrive. Consider a specification for the 2011-2021 growth of slums in a given municipality m taking the form:

$$\Delta Y_{m,2021-2011} = \alpha + \beta \Delta ImmStock_{m,2021-2011} + \epsilon_m \tag{1}$$

where $\Delta ImmStock_{m,2021-2011}$ represents immigrant inflows to municipality *m* between 2011 and 2021, and $\Delta Y_{m,2021-2011}$ the variation in the number of slums per municipality m, that is, we collapse the slums panel at the municipality level and, for each municipality, take the difference between the number of slums in 2021 and 2011[12].

Note that immigration inflows depend on supply-push factors in each origin country (i.e., a common shock to all municipalities) as well as on demand-pull factors, that is, municipality-specific prices and amenities that attract immigrants to live in a given hosting municipality (e.g., rents, wages, transportation, etc.). Since the demand-pull factors could potentially induce endogenous variation of immigration inflows across municipalities, estimating equation 1 through OLS would deliver a biased estimate of β. For instance, a positive economic or housing shock in a particular municipality throughout the 2011-2021 period could simultaneously attract immigrants and decrease slum growth, generating a downwards bias in our estimates. In addition, government turnovers (e.g., changes in mayors, bureaucrats, or policy objectives) could have heterogeneous effects on slum growth across municipalities, which in turn could affect immigrants' location decisions, generating upward or downward biases in our estimates.

To solve this, we follow Bianchi et al. (2012) and Ajzenman et al. (2021) and exploit the supply-push component of immigration by nationality as an orthogonal shifter of the immigrant

[12]Then, for robustness, we also explore a high-frequency model at the slum level. See Section 3.2.4.

population across municipalities, and interact it with the share of immigrants settled in each municipality in 2010 (the year before our initial period of analysis). Specifically, the shift-share instrument predicts the 2011-2021 immigrant inflow in each municipality m as:

$$\Delta \widehat{ImmStock}_{m,2021-2011} = \sum_{n} \theta^{n}_{m,2010} \times \Delta OutMig^{n}_{2019-2010} \tag{2}$$

where $\theta^{n}_{m,2010}$ is the share of immigrants from country of origin n over the total number of immigrants residing in municipality m in 2010, the pre-shock year[13]. On the other side, $OutMig^{n}_{2019-2010}$ represents international migration from source country n to destination countries other than Chile[14].

Importantly, the demand-pull factors in destination countries other than Chile are plausibly exogenous to variation in slum formation across Chilean municipalities, meaning $OutMig^{n}_{2019-2010}$ is by construction orthogonal to demand-pull factors embedded in municipality m. Therefore, the correlation between our endogenous variable $\Delta ImmStock_{m,2021-2011}$ from main equation 1 and our instrument $\Delta \widehat{ImmStock}_{m,2021-2011}$ must be due solely to supply-push factors in origin countries and/or to demand-pull factors from locations outside Chile[15].

We thus estimate the causal effect of immigration on slum formation by using the supply-push component of 2011-2021 immigration growth per municipality weighted by the beginning-of-period share of immigrants, $\Delta \widehat{ImmStock}_{m,2021-2011}$, as an instrument of the 2011-2021 net immigrant inflow per municipality in main equation 1. 2SLS regressions are run on a cross-section of 2011-2021 within-municipality differences considering the full set of urban municipalities in Chile (243 in total)[16].

Results. Table 2 reports our main shift-share results. We report both the OLS (equation 1) and 2SLS estimates. The OLS coefficients resemble the naive estimator and are generally smaller, likely downwards biased (more on this in Section 4).

[13]That is, $\theta^{n}_{m,2010} = ImmStock^{n}_{m,2010} / \sum_{n'} ImmStock^{n'}_{m,2010}$, where n' represents nationalities other than Chilean. To calculate the stock of nationality-specific immigrants per municipality in 2010, we take 2002 Census data (INE (2002)) on country-specific baseline population per municipality and add to it the 2003-2010 country-specific immigration inflows to each municipality from Extranjería-Chile (2021) data.

[14]To this end, we use U.N. Population Division migration data (United-Nations (2021)) reporting the bilateral stocks of international migrants for 232 countries and areas of the world. For most countries, information is available from at least 1990 to 2019 at a five- and two-year frequency, depending on the period (e.g., 1990, 1995, 2000, 2005, 2010, 2015, 2017, and 2019). Although the data coverage is limited to the most relevant origin-destination countries, we were able to build the 2010-2019 net immigrant inflow $\Delta ImmStock^{n}_{2019-2010}$ for 11 countries (Argentina, Bolivia, Brazil, China, Colombia, Ecuador, Haiti, Peru, Spain, USA, and Venezuela), which collectively represent 86% and 95% of residence permits in 2010 and 2019, respectively. For example, for the case of Peru, we first calculate the stock of Peruvians $ImmStock^{P.E.}_{2019}$ in the remaining ten countries in 2019 and 2010 so that Peru (PE) $\Delta ImmStock^{PE}_{2019,2010} = ImmStock^{PE}_{2019} - ImmStock^{PE}_{2010}$. We then replicate this exercise for each of the ten additional countries in the list.

[15]For a review of studies using Bartik-like instrument to identify immigration effects, see Jaeger et al. (2018).

[16]The statistical inference of our results is robust to using the net immigrant inflow divided by the national population in 2011 as the endogenous variable, i.e., they remain the same regardless of whether we measure the immigration shock in levels or in percentage relative to the baseline national population.

Table 2: Long Difference 2021-2011 2SLS Estimation. 243 Urban Municipalities

	Panel A: Extensive Margin Effects							
	Changes in Stocks		Changes in Slums Dynamics					
	Δ_{2011}^{2021} Total # Slums		$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Opened		$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Stayed Open		$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Closed	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\Delta ImmStock_{m,2021-2011}$	0.04	0.09**	0.01	0.09***	0.02	-0.00	0.00	0.01
(× 1,000)	(0.03)	(0.04)	(0.01)	(0.03)	(0.02)	(0.02)	(0.00)	(0.01)
	[0.186]	[0.030]	[0.131]	[0.004]	[0.296]	[0.846]	[0.222]	[0.530]
Observations	243	243	243	243	243	243	243	243
Baseline Mean DV	2.53	2.53	0.43	0.43	2.14	2.14	0.39	0.39
	First Stage Regression							
$\Delta Imm\widehat{Stock}_{m,2021-2011}$		0.25***		0.25***		0.25***		0.25***
		(0.07)		(0.07)		(0.07)		(0.07)
F-statistic		11.64		11.64		11.64		11.64
Partial R^2		0.02		0.02		0.02		0.02
	Panel B: Intensive Margin Effects							
	Δ_{2011}^{2021} Total # HHs in Slums		Δ_{2011}^{2021} Total # Native HHs in Slums		Δ_{2011}^{2021} Total # Imm. HHs in Slums		Δ_{2011}^{2021} Total Area of Slums (m^2)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\Delta ImmStock_{m,2021-2011}$	6.08	19.50***	1.85	7.94**	4.23	11.56**	1,428	4,320**
(× 1,000)	(4.35)	(7.47)	(1.29)	(3.66)	(3.24)	(4.55)	(951)	(1,934)
	[0.164]	[0.009]	[0.153]	[0.030]	[0.194]	[0.011]	[0.135]	[0.026]
Observations	243	243	243	243	243	243	243	243
Baseline Mean DV	124	124	122	122	2	2	27,615	27,615
	First Stage Regression							
$\Delta Imm\widehat{Stock}_{m,2021-2011}$		0.25***		0.25***		0.25***		0.25***
		(0.07)		(0.07)		(0.07)		(0.07)
F-statistic		11.64		11.64		11.64		11.64
Partial R^2		0.02		0.02		0.02		0.02

Notes: Results of OLS and IV estimates on the cross section of 2021-2011 differences across 243 urban municipalities. If no slum existed in the municipality during the analysis period, a zero is coded in the outcome. See Appendix Table A.VIII for outcome definitions. Changes in Total Area of Slums is winsorized at 99^{th} perc. $\Delta ImmStock_{m,2021-2011}$ is the immigrant inflow (in thousands) in municipality m between 2011 and 2021; $\Delta Imm\widehat{Stock}_{m,2021-2011}$ is the instrument (equation 2). OLS columns report the naive estimates of regressing the cross section of differences across municipalities on immigration inflow (equation 1), i.e., without instrumenting for $\Delta Imm\widehat{Stock}_{m,2021-2011}$. 2SLS coefficients are reported under the heading IV. Robust standard errors in parenthesis. p-values in brackets. For Panel A, Changes in Stock, and Panel B outcomes, the Baseline Mean DV reports the mean of the outcome at 2011. For Panel A, Changes in Slums Dynamics, the Baseline Mean DV reports the mean variation of the outcome between 2011 and 2013. *Sign. at 10%, **Sign. at 5%, ***Sign. at 1%.

Extensive Margin Effects. 2SLS estimates reveal that for every 1,000 immigrants arriving within a municipality during the last decade, the number of slums increased by 0.09 of a unit, which represents a 4% increase relative to the average number of slums per municipality in 2011, the initial period of analysis (see Panel A, Changes in Stocks). Our instrument is relatively strong (F=11.64)[17].

To put this result in perspective, the average inflow of immigrants per municipality is around 11,000 in the period 2011-2021. Hence, for an effect size of 0.09 slums for every 1,000 immigrants, the number of slums per municipality increased in (11,000/1,000)$\times$0.09 =1 unit due to immigration, on average. For a mean of 3 slums per municipality in 2011, this represents an increase of one third in the total number of slums throughout urban municipalities in the country. Notably, between 2011 and 2021, municipalities show an average change of 1 slum. Therefore, international immigration can account for all of the observed slum expansion in the study period. The OLS coefficients are generally smaller, likely downwards biased due to omitted factors including endogenous migration responses which are expected to correlate positively with immigration but negatively with slum formation (more on this in Section 4).

Second, we examine changes in the dynamics of slum formation (see Panel A, under the heading "Changes in Slums Dynamics"). In order to measure changes in creation of new slums, we count the number of territories per municipality that passed from non-slum (i.e., closed) to slum (i.e., open) between 2019 and 2021 (the last two years of our slums panel) and differentiate it with respect to that number between 2011 and 2013 (first two years). We find that for every 1,000 immigrants arriving within a municipality, the number of opened (new) slums increased by 0.09 of a unit, which represents a 21 percent increase relative to the average number of new slums per municipality created in 2011-2013, the initial period of analysis. We then replicate the same measure but for the number of territories where a slum persisted open in 2019-2021 relative to 2011-2013, and find that it did not change with immigration. Also, we find no effects on the dynamics of the number of territories where a slum passed from open to closed. Therefore, the main driver behind the positive effect of immigration on slums is the creation of new slums and not the longevity of existing ones[18].

Intensive Margin Effects. See Table 2, Panel B. First, within each slum, we count the total number of households, and then sum up across slums for each municipality. We do this for 2021 and 2011 and take the within-municipality difference. We find that for every

[17] Nelson and Startz (1990) suggest that an instrument is likely to be weak if the bias-corrected partial R^2 falls short of the inverse of the sample size. We find no statistical support for this in our sample, which reinforces the internal validity of our results. Our partial R^2 is 0.02, which is well above the inverse of the number of observations (1/243=0.0041).

[18] Overall, our results are robust to Holm (1979)'s FWER correction for multiple hypotheses. We have four extensive margin indicators of slum formation (total number of slums; opened; stayed open; closed), that is, four associated null hypotheses. We proceed by ordering p-values from smallest to largest: $\hat{p}_{n,(1)} \leq \hat{p}_{n,(2)} \leq \hat{p}_{n,(3)} \leq \hat{p}_{n,(4)}$ with their corresponding null hypotheses labeled accordingly, i.e., $H(1), H(2), H(3), H(4)$. Then, we reject $H(s)$ if and only if $\hat{p}_{n,(j)} \leq \frac{\alpha}{S-j+1}$ for $j = 1, .., 4$. Holm's method starts with testing the most significant hypothesis by comparing its p-value to α/S, as in the Bonferroni method. If the hypothesis is rejected, then we move on to the second most significant hypothesis by comparing its p-value to $\alpha/(S-1)$, and so on, until the list of hypotheses is completed. We compute Holm (1979)'s FWER correction at the 10% level of statistical significance, i.e., for our most significant hypothesis the corrected p-value is 0.1/4=0.025; for the second most significant hypothesis the corrected p-value is 0.1/3=0.033; and so on.

1,000 immigrants arriving within a municipality between 2011 and 2021, the slums population increased by 20 households or 16 percent relative to the 2011 mean, on average. Taking the whole immigration inflow throughout the period, the slum population per municipality increased by (11,000/1,000)$\times$20=220 households due to immigration. Moreover, in the span of a decade, the average number of slum households per municipality increased from 124 to 330. Hence, the immigration effect on slum population explains the whole slum population growth throughout this period.

Importantly, the effects of immigration on slum population growth is observed in both natives and migrant sub-populations. While native slum dwellers increased by an average of 8 households for every 1,000 immigrant inflow (a 7 percent change relative to the baseline mean), immigrant slum households increased by 12 (a six-folds increase). Finally, the immigration effects on slum population expanded the surface of slums. Within each municipality, we sum up the area of each slum to obtain the total area covered by slums. Taking the 2021-2011 within-municipality difference, we find that for every 1,000 immigrant arrivals, aggregate slums area increased by 4.3 km^2, or 47.5 km^2 in ten years, on average. This almost doubles the 2011 mean surface. In terms of the order of magnitude, this is similar to the immigration effect on population growth, meaning that population and spatial growth of slums follow a one-to-one relationship.

3.1. Internal Validity

Goldsmith-Pinkham et al. (2020) show that the Bartik-type 2SLS estimator is numerically equivalent to a generalized method of moments (GMM) estimator. In particular, they build on Rotemberg (1983) to decompose the Bartik 2SLS estimator into a weighted sum of the just-identified instrumental variable estimators that use each entity-specific share as a separate instrument. That is, the local shares play the role of instruments, and the growth shocks play the role of a weighting matrix that "shifts" the "share" effects. The statistical implication of this result is that the exogeneity condition (and thus the consistency of the estimator) should be interpreted in terms of the shares.[19]

Thus, the internal validity of our shift-share instrument relies on that the differential exposure to the 2011-2021 common immigration shock does not lead to differential changes in slum formation, i.e., the 2010 "share" component does not predict slum formation through channels other than immigration. Similar to a difference-in-differences design, the immigration effects found in the 2011-2021 period should not be driven by changes that occurred in the period prior to the analysis, e.g., endogenous mechanisms affecting both the composition of immigrants within municipalities and slum formation.[20]

In order to assess the plausibility of this assumption, we follow Goldsmith-Pinkham et al. (2020)'s proposed steps. First, for each country-specific instrument, we calculate the Rotemberg

[19] In contrast, Borusyak et al. (2022) emphasize that the consistency of the estimator can also be derived from the shocks and provide a numerical equivalence result to support this interpretation.

[20] As remarked by Peri (2016), the concern that past and persistent area-specific trends may affect the past inflow of immigrants (and in turn the local economic performance) was first formulated in Borjas et al. (1997) as they cautioned against the risks of the area approach in assessing labor market effects of immigrants.

weights (R.W), which indicate the level of influence that each country-specific exposure has on the overall Bartik-2SLS estimate. The R.W. reflect the variation in the data that the estimator is using, and thus which nationality-share effects are worth testing, i.e., what types of deviations from the identifying assumption are likely to be important. As is shown in Appendix Table A.I, Sub-Panel II, Peru has by far the highest weight ($\hat{\alpha}^n$ =1.206), followed by Bolivia (0.174), Venezuela (0.167), Haiti (0.035), and China (0.026).[21]

Second, we test for pre-existing differential trends in the outcomes across municipalities with different shares of immigrants (and hence, with different exposures to the post-2011 shock). As in parallel trends tests, we plot the reduced form effect of each nationality-share against our outcomes for the pre-periods. In particular, we take advantage of slum census data on the total number of slums per municipality (extensive margin) and the total number of households residing in slums per municipality (intensive margin) for the years 2005, 2007, and 2011.[22] We regress the outcome of interest against the nationality-shares in each year interacted with each year's fixed effect, controlling for municipality fixed effects and year fixed effects. In each case, we collapse the data at the municipality-year level to have exactly the same structure as the 2SLS models. We then convert the growth rates to levels and index them to 0 in 2005.

Figure A.III presents the results. We show separate graphical analyses for the top R.W. (Peru), the mean of the top 5 R.W., and the mean of the full set of countries. Parallel trends assumption seems to be met as we generally find no evidence of statistically significant pre-trends. The differences in the shares of Peruvian immigrants across municipalities do not predict higher slum formation in pre-shock years, and this is the case for both extensive and intensive margin outcomes. Peru is relevant in terms of its R.W.; hence it is not surprising that the aggregate instrument closely resembles that of Peru. In all, we never reject the joint test for the null hypothesis of no pre-trends. This evidence supports our identification assumption that the pre-shock shares do not predict outcomes through channels other than the post-2011 immigration shock, reinforcing the internal validity of our design.

3.2. Robustness

3.2.1. Temporary versus Permanent Residence Permits

Throughout the analysis period, 10% of permits issued were for permanent residence. Migrants who apply for this type of visa typically have a formal job and can demonstrate economic self-sufficiency, and thus are unlikely to live in slums. Following Ajzenman et al. (2021), we test whether the results are robust to using temporary residence permits only. Appendix Table

[21] Sub-Panel I in the same table reports a correlation matrix to understand the level of correlation between the weights ($\hat{\alpha}^n$), the immigration shocks (g_k), the just-identified coefficient estimates ($\hat{\beta}_n$), the first-stage F-statistics (F_n), and the variance of the origin country shares across municipalities ($Var(\theta^n_{2010})$). For instance, the immigration shocks (g_k) are weakly correlated with the sensitivity-to-misspecification elasticities ($\hat{\alpha}^n$), thus the "shifts" provide a poor guide to understanding what variation in the data drives the estimates. In contrast, the $\hat{\alpha}^n$s are quite related to $Var(\theta^n_{2010})$, meaning the variation in the origin country shares across municipalities likely works as a key moderator of the estimates.

[22] Unfortunately, pre-period census data do not collect information on other intensive margin outcomes like migrants share per slum or slums area, thus we are not able to implement the parallel pre-trends test for those outcomes.

A.II show the results. As for comparison, Column (1) shows the 2SLS estimates considering all permits (i.e., main results from Table 2), while column (2) replicates the exercise but only considering temporary residence permits. As is shown by column (2), all the results hold. Moreover, coefficients tend to be larger in magnitude, suggesting most of the immigration effect on slum formation is driven by migrants who have not yet established formally in the country.

3.2.2. Shift-share Standard Errors Correction

In Appendix Table A.II, column (3), we replicate the main specification but adjust the standard errors using Adao et al. (2019)'s correction to account for a potential correlation of residuals across municipalities with similar shares. The statistical significance of most of the results survives this stringent test. We further complement this analysis by showing the results of our 2SLS model including Anderson and Rubin (1949)'s confidence intervals. This is potentially important if the correlation between our instrument and the endogenous regressor is weak, since in such case the normal approximation of the t-statistic performs poorly (Nelson and Startz (1990)). As a result, the conventional test of significance on the parameter of the instrumented variable has an incorrect size, and the Wald-type confidence interval has low coverage probability. As is shown by column (4), all the results are robust to Anderson-Rubin confidence intervals.

3.2.3. Internal Migration

Finally, migrants could have moved across municipalities over time, and end up residing in a different municipality relative to the intended one declared in the frontier. The latter would generate non-compliance in the "share" component of the instrument, thus affecting the predictive power of the instrument. Unfortunately, we do not observe the share of immigrants that stayed in the origin municipality, and thus cannot measure internal migration. Still, if internal migration occur mostly across limiting municipalities, then one would expect the immigration effects remain the same after treating limiting municipalities as part of the same unit. We study this possibility by randomly creating pairs of limiting municipalities and evaluating immigration effects over this paired, smaller sample of geographical units[23]. We obtain 108 pairs of limiting municipalities, with 20 limiting municipalities with no available pairs. There are also 7 municipalities that do not limit with any other municipality. Hence, out of 243 urban municipalities, we keep 108 pairs and left out of the analysis the resting 27 single municipalities. We then flexibilize the grouping process and add the chance of randomly form triples, quartets and quintents, thereby allowing migrants to move to more than one municipality, and obtained 92 pairs, 14 triplets, and 2 quintets. As is shown in Appendix Tables A.III and A.IV, all the results are robust to allowing for internal migration, either using pairs or higher-order groups. This suggests that internal migration, if existed, played no major role in the effects of immigration on slum formation.

[23]In particular, for each urban municipality, we first identify the set of limiting municipalities. Second, for each municipality, we randomly select (without replacement) a limiting municipality. Once a given municipality is selected as a pair, it cannot be used as a pair of a different municipality. The selection of pairs start from municipalities with less contiguous municipalities and advances to those with more of them, such that we maximize the number of pairs.

3.2.4. Two-year Difference Panel Regression Model

We further check whether the 2SLS results holds when instead of using municipality-level data we use slum-level data. To do so, we merge our bi-yearly panel of 1,359 ever-slum territories with the municipality-year panel of immigration stocks to build a territory-level, balanced panel for the years 2011, 2013, 2015, 2017, 2019, and 2021. The 1,359 territories are distributed across 180 urban municipalities[24]. The stock of immigrants variable counts the cumulative temporary and permanent residence permits granted per municipality per year. We take the two-year differences in immigration stocks per municipality to examine how municipality-level changes in immigration inflows affect the two-year dynamics of creation, persistence, and closure of slums. Estimating a within-difference model implies reducing the panel in one wave, and thus the total number of observations is 1,359×5=6,795.

Our primary outcomes of interest are at the extensive margin. We first define a dummy for whether between $t-2$ and t years, the territory ends up being a slum in t or not, i.e., the two-year difference is equal to 1 if either the slum was created between $t-2$ and t or existed in $t-2$ and continued open in t; and zero otherwise. This is for testing the effects of changes in immigration on the probability change that a slum exists in the territory. We then define three dummies to separately study the role of immigration on the opening, persistence, and closure dynamics of slums: a dummy for whether the territory passed from not being a slum in $t-2$ to be a slum in t (opening); a dummy for whether the territory remains as a slum between $t-2$ and t (persistence); and a dummy for whether the territory passed from being a slum in $t-2$ to not being a slum in t (closure)[25]. Finally, we also look at the intensive margin, that is changes in the characteristics of the territory conditional on it being a slum. Specifically, we examine the two-year changes in the number of total households residing in the slum (all, locals, immigrants), as well as the two-year change in the total area covered by the slum, measured in squared meters (m^2). In all, if a territory is not a slum in a given year, we compute a zero in that territory for that year[26].

We estimate a two-year difference panel regression model of the form:

$$\Delta Y_{smt,t-2} = \beta \Delta ImmStock_{mt,t-2} + \eta_t + \epsilon_{smt} \tag{3}$$

where $\Delta Y_{smt,t-2}$ are the two-year differences in the outcome of interest within a territory s located in municipality m. $\Delta ImmStock_{mt,t-2}$ takes the difference in the stock of immigrants in municipality *m* between years t and $t-2$, i.e., the net immigrant inflow (in thousands)[27]; η_t are year fixed effects capturing year-specific shocks across municipalities; and ϵ_{smt} is the error term,

[24] There are 63 out of 243 urban municipalities in Chile where no slums were observed in the 2011-2021 study period.

[25] We omit the dummy for whether the territory remained not being a slum between $t-2$ and t since it is just the complement of the other three dummies.

[26] We only observe the number of immigrants vs. natives in the slum for the years 2011, 2019, and 2021; hence the sample size is substantially smaller in those regressions. Similarly with slum area, which is only observed for the years 2011, 2017, 2019, and 2021.

[27] An alternative definition is to divide the net immigrant inflow by the population in 2011 (baseline year), such that we measure the change in the immigrant share on the change in slum formation. Our results hold under this alternative definition.

which is likely serially correlated. Note that within-territory differences absorb both territory and municipality time-invariant characteristics, thus including either territory or municipality fixed effects is unnecessary. Our parameter of interest is β, which represents the average effect of increasing the migrant inflow per municipality by 1,000 inhabitants. Slums within the same municipality can be subject to common shocks, thus we report standard errors clustered at the municipality level, accounting for serial and spatial correlation within municipalities.

Appendix Table A.VI, Panel A, shows that for every 1,000 immigrants arriving within a municipality in the previous two years, the probability that the ever been slum territory is a slum increases in 0.90 *pp*., on average. This is either because the territory was a slum at $t-2$ and continue being a slum at t or because the slum was formed between $t-2$ and t. The immigration effect represents a 1.6 percentage increase relative to the share of territories that are slums by 2013, the end of the first difference period (2011-2013). This result is reflected in the slum formation dynamics. For every 1,000 immigrants arriving within a municipality, the probability that a slum opened in the territory during the last two years increased by 0.25 *pp*., and the probability that an existing slum persist open increased by 0.65 *pp*., on average, for increases of 3.2% and 1.7% relative to the 2011-2013 baseline mean change, respectively. Likewise, slums closure also plays a role, with an effect size on the order of 1.8 percentage reduction relative to the 2011-2013 mean change. Overall, the statistical inference of our results is robust to multiple hypothesis testing in that the rejection decision of the null hypothesis remains unchanged after adjusting for Holm (1979)'s Family-Wise Error Rates (FWER).

On the intensive margin (Panel B), we find that for every 1,000 immigrants arriving within a municipality, the slum population increases by 0.52 households, on average, which represent a 2.3 percentage increase relative to 2011-2013 mean variations. This is reflected in both the native and immigrant populations residing in slums, yet we only reject the null hypothesis of no effect for the case of natives. Lastly, immigration also expanded slum area: for every 1,000 immigrant inflow within a municipality, the slum area increased, on average, by 165 squared meters, equivalent to a 2.8 percentage change increase relative to the 2011-2017 mean change. Again, the results survive Holm (1979)'s FWER corrections for multiple hypothesis testing.

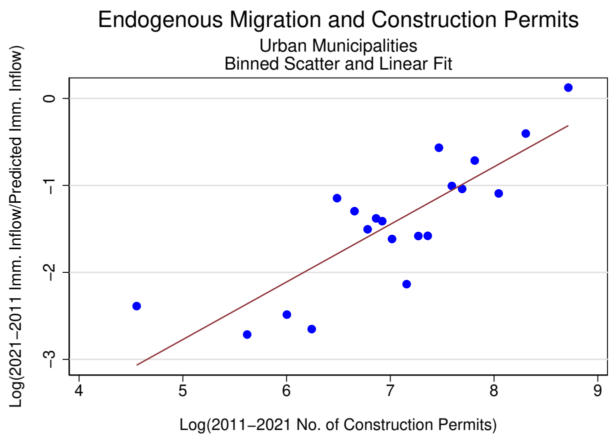
Importantly, these findings should be approached with caution. Using the within-difference panel regression model to identify the causal effect of immigration on slum formation may fail if the distribution of the immigrant population across municipalities and over time correlates with time-variant, unobservable factors affecting slum formation. Still, the direction of the coefficients are aligned with those derived from 2SLS estimates, lending support to the positive impact of immigration on slums growth.

4. Mechanisms

Consider the 2011-2021 growth of slums in a given municipality takes the form of our OLS model in equation 1, that is, $\Delta Y_{m,2021-2011} = \alpha + \beta_{OLS} \Delta ImmStock_{m,2021-2011} + \Delta \epsilon_{m,2021-2011}$. Our results from previous sections indicate β_{OLS} is downwards biased, possibly due to omitted variable bias. A natural candidate is the variation in housing supply trends across municipalities, such that $\Delta\epsilon_{m,2021-2011} = \gamma\Delta HS_{m,2021-2011} + \Delta\mu_{m,2021-2011}$. If so, then $\beta_{OLS} = \beta + \gamma Cov(\Delta ImmStock_{m,2021-2011}, \Delta HS_{m,2021-2011})/Var(ImmStock_{m,2021-2011})$. Under the assumption that $\gamma < 0$ (i.e., increased housing reduces slums growth), then β^{OLS} will be downward biased only if $Cov(\Delta ImmStock_{m,2021-2011}, \Delta HS_{m,2021-2011}) > 0$, that is, if immigrants have an endogenous taste for municipalities whose housing supply show higher growth trends.

We explore this possibility in Figure 5, which shows a binscatter plot of the endogenous portion of 2021-2011 immigration inflow against the 2021-2011 log change in the number of housing permits per municipality, for which we use annual records of construction permits delivered by the Housing Authority Regulator (DOM) in each municipality throughout this period[28]. Indeed, we observe a straight positive correlation between endogenous migration and housing supply trends, which indicates migrants do have an intrinsic taste for municipalities showing better prospects in the availability of housing, and thus $Cov(\Delta ImmStock_{m,2021-2011}, \Delta HS_{m,2021-2011}) > 0$.

Figure 5: Endogenous Migration and Construction Permits.



This result suggests that increased housing has to reduce slums growth ($\gamma < 0$) in order for β_{OLS} to be downwards biased. We estimate γ by including 2021-2011 changes in housing supply as a covariate in equation 1. Note, however, that in such a regression γ could pick up the effect of unobservable factors embedded in $\Delta\mu_{m,2021-2011}$ that simultaneously correlate with both $\Delta ImmStock_{m,2021-2011}$ and $\Delta HS_{m,2021-2011}$. Hence, instead of $\Delta ImmStock_{m,2021-2011}$ we use the instrument-based predicted immigrant inflow, which is by definition exogenous to $\Delta\mu_{m,2021-2011}$. We find that, on average, a 1% increase in the supply of construction permits reduces the number of slums per municipality in 0.15 units. The latter proves that $\gamma < 0$, and thus β_{OLS} is downwards biased likely due to an omitted variable bias originated in housing supply factors.

More generally, these results suggest that the positive effects of immigration on slums could be mediated by the limited capacity of housing markets to effectively accommodate sudden population increases, and a consequent upward surge in rental prices. Unless housing supply responds sufficiently quickly, a sharp immigrant influx can thus lead the demand for housing to

[28]Endogenous migration can be estimated as the log ratio of the change in total immigrant inflow over the change in the exogenous, instrument-based predicted immigrant inflow.

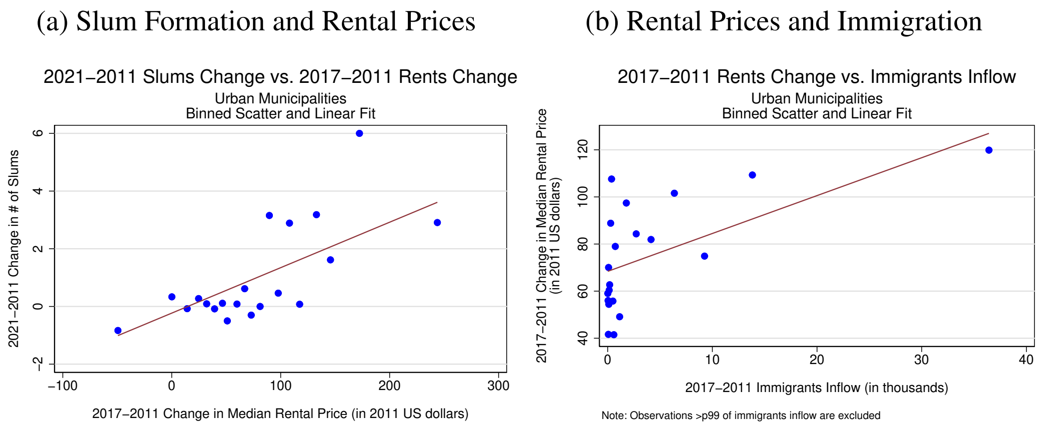
be supplied informally by slums. We provide evidence for this housing market mechanism in what follows.

4.1. Housing Shortage, Rental Prices, and the Role of Construction Costs

As part of the Slum Census conducted by MINVU in 2019, a household-level survey was conducted to inspect the slum dwellers' most important reasons to come to live to a slum. The top reason reported by the interviewees is "Unaffordable rents" (31%), as opposed to alternative reasons like "Need for Residential Autonomy" (24%), "Low income" (11%), or "Unemployment" (9%)[29]. This is consistent with a large increase in rental prices observed in Chile's housing market during the immigration surge period. According to CASEN (2011-2017) survey data, between 2011 and 2017, median rent prices per municipality increased by US$76, on average, or about 25% of the median *per capita* income in 2011[30].

Figure 6, Panel (a) shows a positive correlation between the 2021-2011 change in the number of slums per municipality (Y-axis) and the 2017-2011 change in the median rental price (X-axis). A US$100 increase in the median rent price is associated with two additional slums per municipality, on average. Likewise, a 10,000 increase in the immigrant inflow implies a US$17 increase in the rental price, on average (Panel (b)), suggesting the increased number of slums due to immigration could be mediated by increased rental prices.

Figure 6: Slums, Rental Prices, and Immigration. *Source*: CASEN Survey, INE, MINVU, and Dept. of State



The increased rents may in part stems from a housing shortage. Indeed, between 2011 and 2021, 2.6 million of migrant individuals entered the country, yet only about 600,000 housing units were built in the same period. Considering an average immigrant household size of 3 members (MDSF (2020)), the number of new housing units per incoming migrant household is 0.69.

[29] Lower in the list, 7% reported "Family Conflicts and Violence", 7% reported "Networks in the Slum", and the resting 11% reported other reasons.

[30] CASEN (2011-2017) is a series of cross-section household surveys that are representative at the municipality level and collect standard questions related to demographics, income, education, and housing. Considering the analysis period, the CASEN survey was conducted in 2011, 2013, 2015, 2017, and 2020. However, the 2020 version did not collect data on rental prices; hence the largest difference we can take for the analysis period is 2017-2011.

Moreover, according to CASEN 2017, 74% of households with immigrant heads lived in rental units in 2017, and compared to native-rented units, immigrant-rented units were more likely to be classified as of low quality in terms of habitability (32% vs. 19%), overcrowding (22% vs. 7%), and access to basic services (11% vs. 4%), meaning immigrants are disproportionately likely to demand lower-cost, affordable housing. Such a demand for affordable housing is also greater among poor households (those who cannot afford higher rents), thereby increasing the chance they are compelled to seek accommodation in informal slum settlements.

4.1.1. The Causal Effect of Immigration on Rental Prices

The positive association between immigration and rental prices is full of potential confounders. A prominent example is amenities: municipalities offering better public services may increase immigrant inflows and at the same time rental prices, thereby overestimating the effect of immigration on rental prices.

We explore the causal effect of changes in immigration on rental price changes at the municipality level, for which we take the 2017-2011 within-municipality difference in the median rental price reported by the household heads in CASEN (2011-2017) surveys. Importantly, people may have misperceptions about rental prices, in which case changes in rental prices may not alter location decisions. Hence, as robustness, we replicate the same measures but on perceptions of rental prices[31]. Finally, we examine high-quality and affordable housing markets separately. To do so, we create the same measures but only consider the reported prices of household heads whose total *per capita* income is above the median of the national *per capita* income (high-income) or below the median (low-income).

For identification, we use the same 2SLS approach employed in previous sections, but for 2017-2011 differences, the largest series offered by CASEN on rental price data. In particular, we define our shift-share instrument as the predicted immigrant inflow in each municipality as:

$$\Delta \widehat{ImmStock_{m}}_{,2017-2011} = \sum_{n} \theta^{n}_{m,2010} \times \Delta ImmStock^{n}_{2015-2010} \tag{4}$$

, with $\theta^{n}_{m,2010}$ the share component. The shift component, $\Delta ImmStock^{n}_{2015-2010}$, is the net immigrant inflows of nationality *n* in destination countries other than Chile during 2010-2015. As in immigration-slums 2SLS regressions, this is built through the U.N. Population Division migration data (United-Nations (2021)), which considers the same 11 countries. We thus estimate the causal effect of immigration on rental prices by using $\Delta \widehat{ImmStock_{m}}_{,2017-2011}$ (the supply-push component of 2011-2017 immigration growth per municipality weighted by the beginning-of-period share of immigrants) as an instrument of the 2011-2017 net immigrant inflow per municipality. All regressions are run on a cross-section of 2011-2017 within-municipality differences considering urban municipalities surveyed by CASEN (223 in total).

[31] Specifically, CASEN surveys ask "What is the estimated rent fee in this sector for housing units similar to yours?".

Table 3: 2SLS Estimation. Differences in Rent Prices and Housing Supply

	Panel A: Rent Prices					
	Median Changes in Rent Prices			Median Changes in Perception of Rent Prices		
	Δ_{2011}^{2017} Median Rent All HHs	Δ_{2011}^{2017} Median Rent High Inc. HHs	Δ_{2011}^{2017} Median Rent Low Inc. HHs	Δ_{2011}^{2017} Median Rent Perc. All HHs	Δ_{2011}^{2017} Median Rent Perc. High Inc. HHs	Δ_{2011}^{2017} Median Rent Perc. Low Inc. HHs
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2017-2011}$	1.40**	0.43	1.65**	2.60***	1.37*	1.91***
(× 1,000)	(0.71)	(1.51)	(0.78)	(0.84)	(0.79)	(0.69)
	[0.048]	[0.774]	[0.034]	[0.002]	[0.083]	[0.005]
Observations	223	223	223	223	223	223
Baseline Mean DV_{2011}	173	198	146	189	214	172
	First Stage Regression					
$\Delta Imm\widehat{Stock}_{m,2017-2011}$	0.62***	0.62***	0.62***	0.62***	0.62***	0.62***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
F-statistic	11.39	11.39	11.39	11.39	11.39	11.39
	Panel B: Housing Supply					
	Construction Permits			Floors to be Built		
	Δ_{2011}^{2021} Total # Permits All	Δ_{2011}^{2021} Total # Permits High Quality	Δ_{2011}^{2021} Total # Permits Low Quality	Δ_{2011}^{2021} Total # Floors Built All	Δ_{2011}^{2021} Total # Floors Built High Quality	Δ_{2011}^{2021} Total # Floors Built Low Quality
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2021-2011}$	42.53**	38.75***	3.78	104.99***	88.59***	16.40
(× 1,000)	(17.06)	(9.80)	(11.64)	(28.31)	(18.15)	(17.14)
	[0.013]	[0.000]	[0.745]	[0.000]	[0.000]	[0.339]
Observations	243	243	243	243	243	243
Baseline Mean $\text{DV}_{2001-2011}$	1,476	651	825	2,090	1,106	985
	First Stage Regression					
$\Delta Imm\widehat{Stock}_{m,2021-2011}$	0.25***	0.25***	0.23***	0.25***	0.25***	0.23***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
F-statistic	11.64	11.64	11.56	11.64	11.64	11.56

Notes: Panel A shows results of IV estimates on the cross section of 2017-2011 rent prices differences across 223 (urban) municipalities. See Appendix Table A.IX for outcome definitions. All outcomes are in 2011 $US dollars. $\Delta ImmStock_{m,2017-2011}$ is the immigrant inflow (in thousands) in municipality m between 2011 and 2017; $\Delta Imm\widehat{Stock}_{m,2017-2011}$ is the instrument (equation 4). High (Low) Income refers to within-municipality medians for households above (below) the national median income. Municipalities with only high or only low income households are excluded from analysis. Baseline Mean DV reports the mean of the outcome at 2011. Panel B shows results of IV estimates on the cross section of 2021-2011 total housing supply differences across 243 (urban) municipalities. $\Delta ImmStock_{m,2021-2011}$ is the immigrant inflow (in thousands) in municipality m between 2011 and 2021; $\Delta Imm\widehat{Stock}_{m,2021-2011}$ is the instrument. High and Low Quality of housing is defined by the Urbanism and Construction Quality Regulator (OGUC) from the Ministry of Housing and Urbanism (MINVU). Baseline Mean DV reports the mean variation in the outcome for the period 2001-2011. Robust standard errors in parenthesis. *p*-values in brackets. * Sign. 10%, ** Sign. 5%, *** Sign. 1%.

Table 3 provides the results. For every 1,000 immigrants arriving within a municipality, the median monthly rent fee increased, on average, by US$1.40. Considering an average inflow of 5,720 immigrants per municipality during 2011-2017, we have that (5,720/1,000)$\times$(1.40/173)$\approx$4.6 percent of the rent increase is attributed to immigration. More importantly, the immigration effects on rental prices are wholly driven by increases in the rental fees paid by low-income households, i.e., affordable housing rents, which increased by US$1.65 for every 1,000 immigrants, on average, or US$9.44 if consider total immigration in the 2011-2017 period. This is equivalent to 12.6 percent of the average rent increase in the 2011-2017 period (US$75), and 5.5 percent of the average incomes of low-income households in 2011, the baseline year. Finally, all the results are robust to the use of changes in perception of rent prices as the primary outcome, suggesting that misperceptions about rental prices is not an issue here. Finally, for robustness, we replicated the analysis on slum formation but for the period for which we have rent data, i.e., 2011-2017. As is shown in Appendix Table A.V, the effects of immigration on slum formation remain the similar. In both extensive and intensive margin outcome, we still find positive and statistically significant results, which reinforces higher rents as a mechanism underlying slum formation.

Note that the coefficient of immigration on rents reflects general equilibrium changes, and it does not allows us to distinguish the effect of increased housing demand (through immigration) from possible diminished demand (via native out-migration). For example, natives might relocate from areas populated by immigrants to sidestep competition in local employment markets. Analogous reasoning applies to housing market competition; for instance, immigrants might prioritize local amenities and networks tailored to them over the cost of housing rents, unlike natives. Consequently, immigration inflows could spur net out-migration of natives due to rising housing costs triggered by a shock to housing demand. Saiz (2007) posits that a positive equilibrium effect of immigration on rents should be anticipated if natives do not exhibit infinite sensitivity to changes in housing costs and are not displaced “one for one” in the labor market. Our findings align with this hypothesis.

4.1.2. Immigration and Affordable Housing Shortage

We now turn to examine the extent to which the immigration effects on rents reflect a housing shortage. We estimate the effects of immigration on the annual records of construction permits delivered by the Housing Authority Regulator (DOM) in each municipality for the 2011-2021 period. DOM data encompasses not only the aggregate number of units slated for construction (such as houses and buildings) but also the total number of floors approved for each unit, enabling us to monitor housing supply at a granular level. Table 3, Panel B, provides the results. 2SLS estimates reveal that for every 1,000 immigrants arriving within a municipality, the total number of construction permits increased by 42, on average. Considering an average inflow of 11,000 immigrants per municipality during 2011-2017, we have that (11,000/1,000)$\times$(42/1,476)$\approx$31 percent of the construction permits increase is attributed to immigration. Likewise, immigration explains about 55 percent of the increase in the number of floors built.

However, the immigration effects on housing supply are fully driven by increases in construction permits of high quality, with this result being robust across the number of construction permits associated to units as well as to floors[32]. In contrast, immigration did not increase the supply of low quality housing units, i.e., affordable housing[33]. This is in line with the immigration-induced spike in rental prices we observe for low income groups in Panel A. That is, immigration increased the demand for affordable housing, yet the supply of low-quality housing units did not react accordingly, thereby increasing the rents of affordable housing. Overall, the latter reinforces the hypothesis that the positive effects of immigration on slum formation is mediated by a housing shortage of reasonably-priced units.

4.1.3. The Role of Construction Costs

A final piece of evidence probing the housing market mechanism relies on exploiting heterogeneity in housing supply elasticites arising from variation in a municipality's geography, which can determine variation in construction costs. For instance, ruggedness or unevenness of the terrain implies investment in grading, excavation, retaining walls, and specialized foundations (Burchfield et al. (2006)). Waterlogged or marshy lands might require soil stabilization or pilings, which can also add to costs (Gyourko and Saiz (2006)). In fact, Saiz (2010) show that most U.S. metropolitan areas regarded as supply-inelastic are severely land-constrained by the presence of mountainous formations, which generate a deterrent effect on housing development[34]. Thus, we should expect municipalities with higher terrain ruggedness exhibit a smaller increase in affordable housing supply for a given level of immigration, and thus a concomitant stronger slum proliferation.

We examine this hypothesis by using data on terrain ruggedness for individual cells on a 30 arc-seconds grid across the surface of urban municipalities. Within each municipality, we follow Nunn and Puga (2012) and compute a weighted average of the Terrain Ruggedness Index (TRI) of each cell, using as weights the values of the area of each cell[35]. The measure captures small-scale terrain irregularities, thus averaging across cells within each municipality allows us

[32]The quality of construction associated to each permit is defined based on the criteria established by the Urbanism and Construction Quality Regulator (OGUC) from the Ministry of Housing and Urbanism (MINVU). Each construction has a 1-5 score that combines 24 indicators including structure integrity, energy system, altitude, area, type of construction materials, and safety features, among others. Constructions with scores 4 or 5 are considered of low quality. For instance, type 4 quality classification are for constructions that typically include economical type materials, such as zinc roofing, fibrocement, galvanized iron, vinyl flooring, polished concrete, non-durable wooden planks, vinyl or similar materials in terms of cost. While basic sanitary facilities are complete (sewerage, drinking water, electricity), some installations are visible, and some spaces may have deficiencies in sunlight, ventilation, or functionality. Likewise, type 5 quality classification includes basic housing that typically lack basic services. They may also have some structural defects, and their finishes and installations are minimal and of low quality and/or poorly installed or made of waste materials.

[33]If we consider the 2011-2017 variation in housing supply (such that we make the series comparable to that of rent prices), the effect of immigration on low-quality housing supply is even negative. For total number of low-quality permits, the 2SLS estimate (and standard deviation) is -15.80** (6.73), while for total number of low quality floors, this is -15.78* (8.89).

[34]For instance, by 2000, 47% of the land area within 50 *km* of Los Angeles' geographic center was considered as steep-slope block groups (i.e., their slope was above 15%), yet less than 4% of the population lived in them.

[35]The Terrain Ruggedness Index, initially formulated by Riley and Elliot (1999), was designed to measure the topographic variation in wildlife habitats, which offer hiding places for prey and lookout spots.

to proxy for the heterogeneity of average housing costs across municipalities.

We are interested on testing whether differences on ruggedness across municipalities can moderate the effect of immigration on housing supply. For ease of exposition, we classify municipalities as of high or low-rugged depending on whether their Weighted Average TRI is above (high) or below (low) the median. We thus estimate our 2SLS model of 2021-2011 differences on housing supply on immigration inflow but adding an interaction between immigration inflow and the dummy of high ruggedness, using as instrumental variables both the shift-share instrument and the interaction between the shift-share and the high ruggedness dummy. Note that endogenous migration cannot alter ruggedness since this is fixed over time. Then, the identification assumption is that ruggedness moderates the effect of immigration on housing supply only through its effect on construction costs, and not through other channels. A simple correlation test between endogenous migration and ruggedness shows no relationship between the two variables, suggesting migrants' location preferences are not mediated by ruggedness. In other words, amenities in municipalities with steeper slopes do not appear to be more attractive than those found in flatter municipalities[36].

Table 4, Panel A, shows the results. We observe a diminished impact of immigration on housing supply in municipalities with a high degree of ruggedness, assessed both through the lens of construction permits issued and the extent of floors constructed. The overall difference in effect size is predominantly accounted for by the contrasting impact of immigration on the provision of low-quality housing units. For every 1,000 immigrants arriving within a low-rugged municipality (β_1), the average number of low-quality construction permits increased by $20\times11=220$. Conversely, in a highly rugged municipality ($\beta_1 + \beta_2$), this figure declined by $15\times11=165$, for a statistically significant difference of $35\times11=385$ permits or 47% of the baseline number of permits per municipality in 2011. Similarly, for the case of number of floors, the order of magnitude of the differential effect is 51% of the baseline mean. A hypothesis is that developers maximize profits by constructing buildings involving the highest possible quality (and thereby prices) subject to the lowest construction costs. Hence, with escalating construction costs, high-quality units garner more profitability compared to their low-quality counterparts.

As expected, the limited supply of affordable housing in highly rugged municipalities translated into a large and significant effect of immigration on slums, especially due to the larger number of slums that remained open (Panel B). Conversely, in low-rugged municipalities, the expansion of low-quality housing driven by immigration served to curb the proliferation of slums. The evidence is consistent across both the extensive (number of slums) and intensive margins (slum population and slum area). Overall, the effect of immigration is significantly more pronounced in municipalities with higher degrees of ruggedness, revealing that higher construction costs (and their influence on affordable housing supply) can play a crucial role in moderating the impact of immigration on slum formation.

[36] We first obtain the residuals of regressing 2021-2011 changes in housing supply against migration inflows in a cross-section of 243 urban municipalities, and then regress the residuals against the ruggedness dummy. The coefficient and its associated standard error are -2.536 (4.055), with a p-value of 0.532 for the null hypothesis of no differences.

Table 4: Ruggedness: Long Difference 2021-2011 2SLS Estimation. 243 Urban Municipalities

	Panel A: Housing Supply					
	Construction Permits			Floors to be Built		
	Δ_{2011}^{2021} Total # Permits All	Δ_{2011}^{2021} Total # Permits High Quality	Δ_{2011}^{2021} Total # Permits Low Quality	Δ_{2011}^{2021} Total # Floors Built All	Δ_{2011}^{2021} Total # Floors Built High Quality	Δ_{2011}^{2021} Total # Floors Built Low Quality
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2021-2011}$	56.16**	35.77***	20.40	124.22***	86.26***	37.96
(× 1,000) (β_1)	(24.52)	(13.17)	(15.28)	(43.01)	(26.19)	(23.22)
	[0.022]	[0.007]	[0.182]	[0.004]	[0.001]	[0.102]
$\Delta ImmStock_{m,2021-2011}$	-29.33	6.42	-35.75**	-41.36	5.01	-46.38**
∗ *High Weighted Avg. TRI*	(23.75)	(14.17)	(14.01)	(42.91)	(28.34)	(20.49)
(× 1,000) (β_2)	[0.217]	[0.651]	[0.011]	[0.335]	[0.860]	[0.024]
$\beta_1 + \beta_2$	26.83	42.18***	-15.35	82.85***	91.27***	-8.42
	(16.71)	(10.47)	(12.42)	(26.03)	(18.51)	(16.96)
	[0.108]	[0.000]	[0.216]	[0.001]	[0.000]	[0.620]
	Panel B: Slum Formation					
	Extensive Margin Effects				Intensive Margin Effects	
	Changes in Stocks	Changes in Slums Dynamics				
	Δ_{2011}^{2021} Total # Slums	$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Opened	$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Stayed Open	$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Closed	Δ_{2011}^{2021} Total # HHs in Slums	Δ_{2011}^{2021} Total Area of Slums (m^2)
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2021-2011}$	0.05	0.09**	-0.04	0.01	13.21*	1,916
(× 1,000) (β_1)	(0.04)	(0.04)	(0.03)	(0.02)	(6.94)	(1,776)
	[0.239]	[0.033]	[0.109]	[0.383]	[0.057]	[0.281]
$\Delta ImmStock_{m,2021-2011}$	0.08	0.00	0.08**	-0.02	13.53	5,172**
∗ *High Weighted Avg. TRI*	(0.06)	(0.05)	(0.04)	(0.02)	(11.53)	(2,557)
(× 1,000) (β_2)	[0.164]	[0.968]	[0.043]	[0.338]	[0.241]	[0.043]
$\beta_1 + \beta_2$	0.13**	0.09***	0.04	-0.00	26.74**	7,088**
	(0.06)	(0.04)	(0.04)	(0.01)	(11.44)	(2,741)
	[0.024]	[0.009]	[0.304]	[0.932]	[0.019]	[0.010]
	First Stage Regression					
F-statistic	13.11	13.11	13.11	13.11	13.11	13.11
Partial R^2	0.14	0.14	0.14	0.14	0.14	0.14

Notes: Results of IV estimates on the cross section of 2021-2011 differences across 243 (urban) municipalities. In Panel B, if no slum existed in the municipality during the analysis period, a zero is coded in the outcome. See Appendix Tables A.VIII and A.IX for outcome definitions. High and Low Quality of housing is defined by the Urbanism and Construction Quality Regulator (OGUC). Changes in Total Area of Slums is winsorized at 99^{th} perc. $\Delta ImmStock_{m,2021-2011}$ is the immigrant inflow (in thousands) in municipality m between 2011 and 2021; $\Delta ImmStock_{m,2021-2011}$ ∗ *High Weighted Avg. TRI* is the immigrant inflow (in thousands) interacted with a dummy that takes the value of one for urban municipalities with weighted average terrain ruggedness index (TRI) above the median, and zero otherwise. First stage regression shows the F-Statistic and the partial R^2 of the first stage for the endogenous variable interacted by the high ruggedness dummy. Robust standard errors in parenthesis. *p*-values in brackets. *Sign. at 10%, **Sign. at 5%, ***Sign. at 1%.

4.2. Income Effects

The theories of slum formation are divergent. On the one side, slums allow the poor to escape subsistence-level rural poverty by taking advantage of the benefits of agglomeration, economies of scale, and networks offered by large cities, meaning cities are not making people poor but instead attracting poor people (Glaeser (2011)). Accordingly, slums would emerge because the poor are willing to live in substandard housing and hostile geographical environments if doing so also enables them to be close to employment opportunities (Celhay and Undurraga (2022)). Alternatively, slums are argued to be a form of poverty trap, a product of the interaction of market and policy failures that hinder capital accumulation for those living in slums (Marx et al. (2013)). Accordingly, if immigrants are too poor or contribute to the economic decline of cities, then slums are expected to multiply[37].

We inform this debate by directly testing whether changes in immigration affected changes on poverty and extreme poverty rates, for which we use 2011-2020 variations measured from CASEN data in 238 urban municipalities[38]. We follow the definitions established by the Ministry of Social Development in Chile, which fix poverty and extreme poverty lines based on *per capita* income measures reflecting the value of goods and services needed to satisfy essential needs. The value of the lines are updated over years to reflect changes in the prices of goods and services, such that we can accurately track how rates evolve in the 2011-2020 period. By 2011, municipality-level poverty was 13.8%, on average, which decreased to 10.8% by 2020. In contrast, extreme poverty rate increased from 3.1% to 4.2% in the same period.

For analysis, we calculate the 2020-2011 difference in poverty and extreme poverty rates at the municipality level and regress it against the 2011-2020 immigration shock while using our shift-share instrument. Table 5, Panel A, shows the results. We find no statistically significant effect of immigration on either poverty or extreme poverty rates. Indeed, the IV effects are shown to be null for both native and migrant populations, although the instrument for estimating the IV model on migrants subsample seems to be weak (F=3.24).

Then, in Panel B, we replicate the same exercise but for *per capita* incomes and unemployment rate, also measured from CASEN surveys. We find immigration did not change population incomes, but if anything, it increased natives' *per capita* income by 1.3% relative to 2011 mean. Second, we find immigration did not lead to changes in unemployment rate. This is consistent with the subjective reports of slum dwellers when asked about the reasons to live in slums. According to the 2019 MINVU survey, only 11 percent reported "Low Incomes" as the top reason to come to live in a slum, and just 9 percent argued reasons associated to "Unemployment".

[37]The literature on slum formation was born under the aegis of the spatial mismatch hypothesis (Kain (1968)), which argues that slums are the product of a geographical poverty trap, i.e., slum dwellers are poor because they are spatially disconnected from job opportunities offered in the inner city. For a thorough review of the spatial mismatch theory, see Gobillon et al. (2007). For partial equilibrium models of slum formation, see Jimenez (1984, 1985), Brueckner and Selod (2009), Brueckner (2013), Marx et al. (2013), Cavalcanti et al. (2019), and Henderson et al. (2020).

[38]Unfortunately, CASEN survey was not implemented in 2021, thus we cannot include that year in the series.

Table 5: 2SLS Estimation. Differences in Poverty Rate, Incomes, and Unemployment.

	Panel A: Poverty					
	Changes in Poverty Rate			Changes in Extreme Pov. Rate		
	Δ_{2011}^{2020} Poverty Rate All	Δ_{2011}^{2020} Poverty Rate Natives	Δ_{2011}^{2020} Poverty Rate Immigrants	Δ_{2011}^{2020} Ext. Pov. Rate All	Δ_{2011}^{2020} Ext. Pov. Rate Natives	Δ_{2011}^{2020} Ext. Pov. Rate Immigrants
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2020-2011}$	0.02	-0.03	0.33	-0.02	-0.04	0.28
(× 1,000)	(0.10)	(0.10)	(0.75)	(0.05)	(0.05)	(0.25)
	[0.809]	[0.766]	[0.660]	[0.683]	[0.407]	[0.253]
Observations	238	238	110	238	238	110
Baseline Mean DV	0.14	0.14	0.10	0.03	0.03	0.03
	First Stage Regression					
$\Delta \widehat{ImmStock}_{m,2020-2011}$	0.23***	0.23***	0.23*	0.23***	0.23***	0.23*
	(0.07)	(0.07)	(0.13)	(0.07)	(0.07)	(0.13)
F-statistic	11.26	11.26	3.24	11.26	11.26	3.24
	Panel B: Per Capita Household Income and Unemployment					
	Changes in Per Capita Household Income			Changes in Unemployment Rate		
	Δ_{2011}^{2020} Median *per cap.* Income All	Δ_{2011}^{2020} Median *per cap.* Income Natives	Δ_{2011}^{2020} Median *per cap.* Income Immigrants	Δ_{2011}^{2020} Unemp. Rate All	Δ_{2011}^{2020} Unemp. Rate Natives	Δ_{2011}^{2020} Unemp. Rate Immigrants
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2020-2011}$	2.85	3.96*	-3.70	0.01	0.03	-0.39
(× 1,000)	(2.01)	(2.05)	(78.2)	(0.09)	(0.09)	(0.71)
	[0.156]	[0.053]	[0.962]	[0.930]	[0.775]	[0.587]
Observations	238	238	110	238	238	98
Baseline Mean DV	308	307	1,104	0.04	0.04	0.03
	First Stage Regression					
$\Delta \widehat{ImmStock}_{m,2020-2011}$	0.23***	0.23***	0.23*	0.23***	0.23***	0.16
	(0.07)	(0.07)	(0.13)	(0.07)	(0.07)	(0.14)
F-statistic	11.26	11.26	3.24	11.26	11.26	1.44

Notes: Results of IV estimates on the cross section of 2020-2011 differences across 238 (urban) municipalities. See Appendix Table A.IX for outcome definitions. Poverty rate and unemployment rate are expressed in percentage (%). Per Capita Household Income is in 2011 $US dollars. There are municipalities where no immigrant head of households was interviewed, thus the number of observations for immigrant outcomes is lower. The variable $\Delta ImmStock_{m,2020-2011}$ is the immigrant inflow (in thousands) in municipality m between 2011 and 2020; $\Delta \widehat{ImmStock}_{m,2020-2011}$ is the instrument. Robust standard errors in parenthesis. p-values in brackets. * Sign. at 10%, ** Sign. at 5%, *** Sign. at 1%.

Overall, these results suggest income effects (and thus poverty trap hypothesis) are unlikely to explain the positive effects of immigration on slum growth[39].

[39]We are not the first in testing the immigration effects on labor outcomes in Chile. Using data from the National

We finally test for whether migrants' levels of education had any influence on slum formation. We compare the 2SLS coefficient estimates we obtain when considering as the endogenous variable all inflows versus only migrants with high school diploma. For high school migrants, we use the same shift component to build the instrument, but the share component, $\theta^n_{m,2010}$, is computed considering only migrants with a high school diploma. As is shown in Appendix Table A.VII, the immigration effect on slum formation is generally larger for the case of migrants with high school diploma relative to the case of all migrants[40]. As far as education is a good predictor of incomes, this result reinforces our hypothesis that income effects do not drive the causal effect of immigration on slum formation.

4.3. Selective Slum Policy

Immigration could have trigger slum growth because political capture and policy coordination, wherein politicians safeguard slums inhabited by immigrant majorities to secure votes from this burgeoning electorate. For instance, slum upgrading programs could work as a vote buying strategy implemented in coordination with slum dwellers, thereby promoting slum formation (Keefer and Khemani (2005), Paniagua (2022), Bobonis et al. (2022)). Likewise, slums may grow if government develop a pro-slum agenda that increases the demand for slum housing (Alves (2023)). Alternatively, immigration could promote slum growth due to government-enforced exclusionary measures that under-service slums in municipalities with high influxes of migrants, making slums in those municipalities to persist more over time (Feler and Henderson (2011)).

Slums policy in Chile combines slum-level urbanization programs with household-level housing subsidies. Urbanization programs are oriented to transform existing slums into formal neighborhoods, including street paving, electricity, water, and sewage connection, all of which mechanically reduce the incidence of slums. In contrast, household-level housing subsidies, especially the DS49 program, are oriented to move slum dwellers to formal housing through the provision of own house in housing projects built by a public-private partnership between the government and real estate companies[41]. We obtain 2011-2020 yearly data on the share of slums per municipality that were intervened with either housing subsidies or urbanization programs, and examine how 2020-2011 immigration changes affected the 2020-2011 change in the share of slums per municipality exposed to any of these slum policies. Table 6 shows the results. We observe the intensity of the slum policy does not vary with the level of immigration

Institute of Statistics (INE), Ajzenman et al. (2022) find no effects of immigration on either employment levels and unemployment rates, but find positive effects on unemployment-related concerns, thus revealing a (mis)perception of the true effect of immigration on labor market outcomes. More generally, most researchers and policymakers agree in that high-skilled immigration lead to positive net outcomes for the native population, yet there is less agreement regarding the impact of immigration for low-skill jobs (Card (1990), Borjas (2003), Ottaviano and Peri (2012), Lewis and Peri (2015), Dustmann et al. (2016b), Dustmann et al. (2016a), Blau et al. (2017), Biavaschi et al. (2018), Imbert and Papp (2020), Bahar et al. (2021), Clemens and Lewis (2022), Imbert and Ulyssea (2023)). This is in part due to that estimates vary substantially depending on the assumptions used to identify causal effects.

[40] We further test for the case of migrants with no high school diploma, but the F-test is too low (F=0.78) and thus coefficients are likely misleading due to weak instrument.

[41] DS49 subsidies have an average value of USD $15,000 per household (in dollars of 2008), and beneficiaries must complement the subsidy with roughly USD $800 per household to obtain it. New owners are not allowed to rent or sell their property, but they can bequeath it to their children.

across municipalities, this being the case for both housing subsidies and urbanization programs. These results suggest that the positive effects of immigration on slum growth is not mediated by exclusionary policies or program-based political capture.

Other political capture actions like money transfers or social interventions, for which we do not have data, may have also played a role on the impact of immigration on slum formation. Nevertheless, our empirical findings refute the notion that immigration impedes slum eradication as we find no effects of immigration on either the sustainability of existing slums or on slum closure (Table 2, Panel A). Instead, our evidence reveal that the impact of immigration on slum proliferation stems from the creation of new slums. Hence, for the political capture hypothesis to be credible politicians would have had to incentivize the creation of new slums in high immigration-inflow municipalities, a scenario that seems less likely.

Table 6: 2SLS Estimation. 2020-2011 Differences in Slums Policy. 243 Urban Municipalities

	Δ_{2011}^{2020} Total % of Slums Receiving Housing Subs.	Δ_{2011}^{2020} Total % of Slums Receiving Urban. Progr.	Δ_{2011}^{2020} Total % of Slums Receiving Housing Subs. or Urban. Progr.	Δ_{2011}^{2020} Total % of Slums Receiving Housing Subs. and Urban. Prog.
	IV	IV	IV	IV
$\Delta ImmStock_{m,2020-2011}$	0.29	0.04	0.00	0.33
(× 1,000)	(0.46)	(0.45)	(0.46)	(0.43)
	[0.531]	[0.927]	[0.998]	[0.442]
Observations	243	243	243	243
Mean DV_{2011}	28.14	1.61	28.70	1.05
	First Stage Regression			
$\Delta Imm\widehat{Stock}_{m,2020-2011}$	0.23***	0.23***	0.23***	0.23***
	(0.07)	(0.07)	(0.07)	(0.07)
F-statistic	11.58	11.58	11.58	11.58

Notes: Results of IV estimates on the cross section of 2020-2011 differences across 243 (urban) municipalities. See Appendix Table A.IX for outcome definitions. $\Delta ImmStock_{m,2020-2011}$ is the immigrant inflow (in thousands) in municipality m between 2011 and 2020; $\Delta Imm\widehat{Stock}_{m,2020-2011}$ is the instrument. Robust standard errors in parenthesis. p-values in brackets. * Sign. at 10%, ** Sign. at 5%, *** Sign. at 1%.

5. Conclusion

In the face of a growing global housing shortage driven by limited affordable buying and renting opportunities, UN-Habitat estimates that by the end of the decade, about 3 billion people, or roughly 40% of the world's population, will require access to suitable and reasonably-priced housing. The surge in South-South migration can intensify this issue. Large migrant inflows can boost housing demand, further complicating the task of ensuring affordable housing in many areas globally. However, the influence of international immigration on housing dynamics in developing cities is yet to be fully understood, particularly regarding the crucial role of slums as an informal housing option.

This paper investigates the causal effect of international immigration on slum formation and growth in Chile, a country that experienced a fourfold increase in immigration in the past decade. To do this, we create a unique panel dataset with information on all slums in Chile as well as the universe of international immigrants and their destination municipalities. Using both a high-frequency within-slum analysis as well as a long-difference shift-share instrumental variable approach at the municipal level, we first provide robust evidence on the positive relationship between international immigration and slum creation and growth. This is evident from observed increments in the number of slums, the population residing in slums (both native and migrant), and the expansion of slum footprints. Notably, international immigration can account for all of the observed slum expansion in the study period.

We further provide evidence of the important role that the market for affordable housing plays in mediating the relationship between immigration and slums. The surge in demand for housing, unmet by a concomitant increase in affordable housing supply, resulted in increases in rental prices, which in turn compelled low-income households to seek accommodation in informal slum settlements. Consistent with the housing market mechanism, the effects of immigration on slums are stronger in more rugged municipalities, where we show housing supply elasticities are also lower.

Taken together, our results suggest that having vivid housing markets that successfully absorb population explosions derived from immigration is a first order concern to tackle slum formation in developing cities. Either regulating the rental market (e.g., rent control) or providing low income households and migrants with rental subsidies that avoid them to chose moving to a slum seem natural policy solutions in this context. Governments might also provide public housing to slum dwellers (Franklin (2020)). However, public housing programs are typically expensive, and planning ahead the necessary housing supply is challenging due to the unpredictable dynamics of slum development. Moreover, public housing may not be a sustainable solution if their locations do not match with the location preferences of beneficiaries (Barnhardt et al. (2017)). An interesting alternative is the implementation of urban revitalization programs designed to gradually transform slums into formal neighborhoods. For instance, Michaels et al. (2021) demonstrate that a sites and services program in Tanzania, which offers slum dwellers formal residential plots with basic amenities (water, electricity, roads) and allows them to construct their own homes on these plots for a nominal fee, yielded significant long-term improvements in housing quality. A key advantage is that these types of programs are significantly less expensive than constructing public housing, making them more financially feasible for developing cities.

Nonetheless, a challenge is that numerous migrants might remain outside the purview of social security and government structures, a situation that hinders them from benefiting from official government initiatives. Moreover, many living in slums are undocumented migrants, making it harder for the government to integrate them into the social safety net. Additionally, given the transient nature of migrants who may not stay long in the host country, the allure of formal housing diminishes. This could be due to various reasons, such as the temporary nature of their stay, the complexities of the application process, costs, or other barriers. These factors make it challenging to implement housing policies designed to lessen the impact of international immigration on the creation of slums.

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A. Online Appendix

Figure A.I: Immigrant inflows: 2001-2021

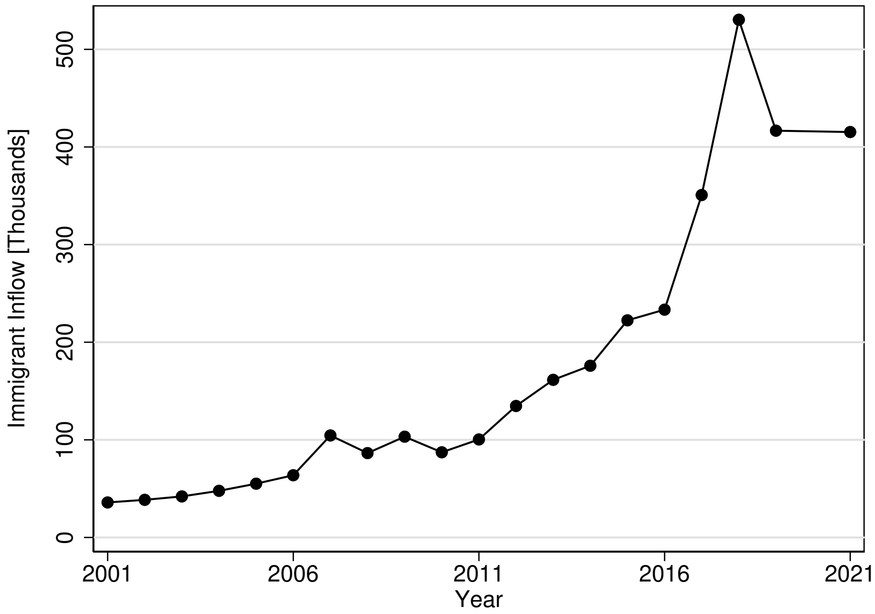


Figure A.II: Immigrant inflows by country of origin: 2001-2021

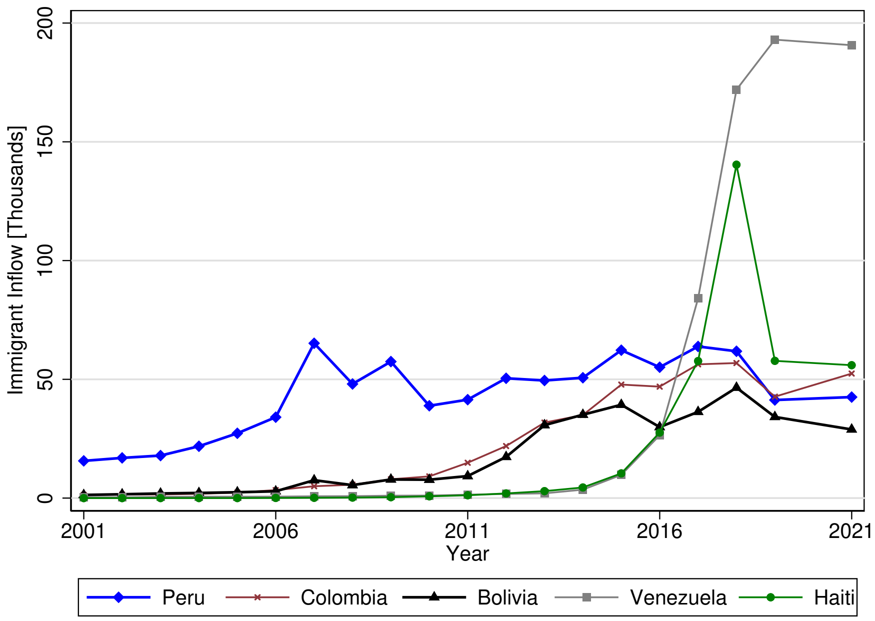


Table A.I: Summary of Rotemberg Weights

Panel A: Total # of Slums Per Municipality

Sub-Panel I: Correlations

	$\hat{\alpha}^n$	g_k	$\hat{\beta}_n$	F_n	Var(θ^n_{2010})
$\hat{\alpha}^n$	1				
g_k	0.070	1			
$\hat{\beta}_n$	-0.023	-0.282	1		
F_n	0.037	-0.232	-0.365	1	
Var(θ^n_{2010})	0.434	-0.223	0.093	0.268	1

Sub-Panel II: Top 5 Rotemberg Weigth Origin Countries

	$\hat{\alpha}^n$	g_k	$\hat{\beta}_n$
Peru	1.206	46,172	0.040
Bolivia	0.174	88,360	0.512
Venezula	0.167	1,708,485	-0.030
Haiti	0.035	178,735	0.014
China	0.026	33,753	0.060

Panel B: Total # of HHs. in Slums Per Municipality

Sub-Panel I: Correlations

	$\hat{\alpha}^n$	g_k	$\hat{\beta}_n$	F_n	Var(θ^n_{2010})
$\hat{\alpha}^n$	1				
g_k	0.070	1			
$\hat{\beta}_n$	-0.030	0.070	1		
F_n	0.037	-0.232	-0.469	1	
Var(θ^n_{2010})	0.434	-0.223	-0.097	0.268	1

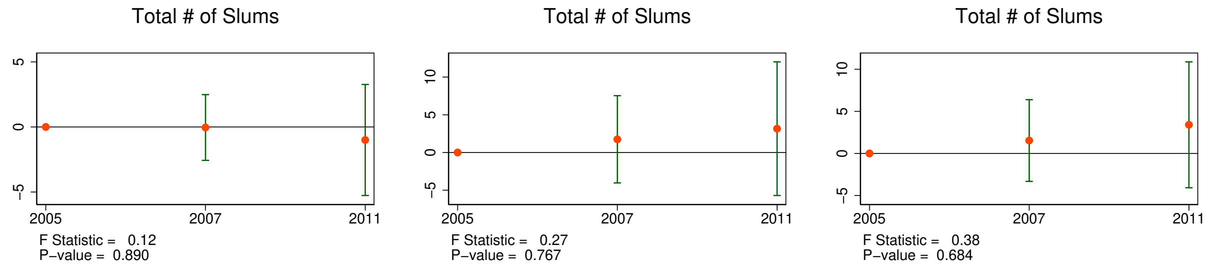
Sub-Panel II: Top 5 Rotemberg Weigth Origin Countries

	$\hat{\alpha}^n$	g_k	$\hat{\beta}_n$
Peru	1.206	46,172	8.646
Bolivia	0.174	88,360	69.894
Venezula	0.167	1,708,485	28.217
Haiti	0.035	178,735	6.146
China	0.026	33,753	11.479

Notes: This table reports statistics about the Rotemberg weights for the case of Total Number of Slums per Municipality (Panel A) and Total Number of Households residing in Slums per Municipality (Panel B). Sub-Panel I: Correlations reports correlations between the weights ($\hat{\alpha}^n$), the number of immigrants from 2011 to 2021 (immigration shock g_k), the just-identified coefficient estimates ($\hat{\beta}_n$), the first-stage F-statistics (F_n), and the variation in the origin country shares across municipalities (Var(θ^n_{2010})). Sub-Panel II: Top 5 Rotemberg Weigth Origin Countries report the top five origin countries according to the Rotemberg weights.

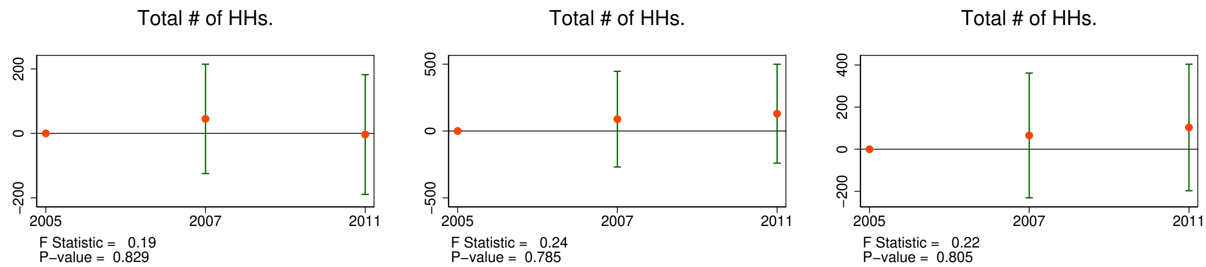
Figure A.III: Pre-trends for high Rotemberg weight countries and all together

Extensive Margin: Total Number of Slums per Municipality



Peru | Top 5 | All origin countries

Intensive Margin: Total Number of Households Residing in Slums per Municipality



Peru | Top 5 | All origin countries

Note: Unit of analysis are urban municipalities. We regress the outcome of interest against the nationality shares in each year interacted with year fixed effects, controlling for municipality fixed effects and year fixed effects. Point estimates reflect the differential effect of nationality-specific shares relative to 2005, our baseline year. We convert the growth rates to levels and index the levels in 2005 to 0. F-statistic and p-value of the joint hypothesis of null differences is reported below each sub-figure. The top 5 Rotemberg weight countries are Peru, Bolivia, Venezuela, Haiti, and China.

Table A.II: Robustness: Long Difference 2021-2011 2SLS Estimation. 243 Urban Municipalities

Dependent Variable	All Residence Permits (1)	Temporary Residence Permits (2)	Adao et al. (2019) Correction (3)	Anderson-Rubin 95% C.I. (4)
Δ_{2011}^{2021} Total # Slums	0.09**	0.11**	0.09*	0.09**
	(0.04)	(0.05)	(0.09)	(0.01; 0.19)
	[0.030]	[0.033]	[0.097]	[0.024]
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Opened	0.09***	0.12***	0.09	0.09***
	(0.03)	(0.04)	(0.13)	(0.04; 0.18)
	[0.004]	[0.004]	[0.156]	[0.001]
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Stayed Open	-0.00	-0.01	-0.00	-0.00
	(0.02)	(0.03)	(0.17)	(-0.06; 0.04)
	[0.846]	[0.790]	[0.951]	[0.844]
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Closed	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.05)	(-0.02; 0.03)
	[0.530]	[0.545]	[0.728]	[0.529]
Δ_{2011}^{2021} Total # HHs in Slums	19.50***	26.04***	19.50**	19.50***
	(7.47)	(9.51)	(12.26)	(6.18; 38.74)
	[0.009]	[0.006]	[0.041]	[0.005]
Δ_{2011}^{2021} Total # Native HHs in Slums	7.94**	11.22**	7.94	7.94**
	(3.66)	(4.89)	(9.83)	(1.43; 17.06)
	[0.030]	[0.022]	[0.159]	[0.021]
Δ_{2011}^{2021} Total # Imm. HHs in Slums	11.56**	14.81***	11.56**	11.56***
	(4.55)	(5.74)	(8.33)	(3.46; 22.90)
	[0.011]	[0.010]	[0.043]	[0.008]
Δ_{2011}^{2021} Total Area of Slums (m^2)	4,320**	5,779**	4,320	4,320**
	(1,935)	(2,485)	(6,472)	(719; 8,993)
	[0.026]	[0.020]	[0.209]	[0.023]
Observations	243	243	243	243
F-Statistic	11.64	11.49	n.a.	11.64
Part. R^2	0.02	0.02	n.a.	0.02

Notes: Results of the IV estimates on the cross section of 2021-2011 differences across 243 (urban) municipalities. See Appendix Table A.VIII for outcome definitions. If no slum existed in the municipality during the analysis period, a zero is coded in the outcome. Changes in Total Area of Slums are winsorized at 99^{th} perc. Column (1) regressions consider all immigrant inflows, regardless of the type of permit. Column (2) considers only migrants that entered the country with a temporary visa. Robust standard errors are presented in parentheses and p-values in brackets. Regressions in column (3) show All Permits coefficient but adjusting the standard errors using Adao et al. (2019). Regressions in column (4) show All Permits coefficient but including Anderson and Rubin (1949)'s confidence interval and its associated p-value. * Sign. at 10%, ** Sign. at 5%, *** Sign. at 1%.

Table A.III: Long Difference 2021-2011 2SLS Estimation. 108 Urban Municipalities Pairs

	Panel A: Extensive Margin Effects							
	Changes in Stocks		Changes in Slums Dynamics					
	Δ_{2011}^{2021} Total # Slums		$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Opened		$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Stayed Open		$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Closed	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\Delta ImmStock_{m,2021-2011}$	0.03	0.08*	0.02	0.09***	0.01	-0.00	0.00	0.02
($\times$ 1,000)	(0.03)	(0.05)	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.03)
	[0.204]	[0.066]	[0.160]	[0.006]	[0.359]	[0.924]	[0.458]	[0.379]
Observations	108	108	108	108	108	108	108	108
Baseline Mean DV	5.27	5.27	0.94	0.94	4.50	4.50	0.77	0.77
	First Stage Regression							
$\Delta Imm\widehat{Stock}_{m,2021-2011}$		0.76***		0.76***		0.76***		0.76***
		(0.20)		(0.20)		(0.20)		(0.20)
F-statistic		14.67		14.67		14.67		14.67
Partial R^2		0.04		0.04		0.04		0.04
	Panel B: Intensive Margin Effects							
	Δ_{2011}^{2021} Total # HHs in Slums		Δ_{2011}^{2021} Total # Native HHs in Slums		Δ_{2011}^{2021} Total # Imm. HHs in Slums		Δ_{2011}^{2021} Total Area of Slums (m^2)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\Delta ImmStock_{m,2021-2011}$	6.14	19.93**	1.90	7.81*	4.24	12.12**	1,744	4,636*
($\times$ 1,000)	(4.62)	(8.72)	(1.50)	(4.14)	(3.31)	(5.21)	(1,255)	(2,603)
	[0.187]	[0.022]	[0.208]	[0.059]	[0.203]	[0.020]	[0.168]	[0.075]
Observations	108	108	108	108	108	108	108	108
Baseline Mean DV	263	263	259	259	4	4	56,934	56,934
	First Stage Regression							
$\Delta Imm\widehat{Stock}_{m,2021-2011}$		0.76***		0.76***		0.76***		0.76***
		(0.20)		(0.20)		(0.20)		(0.20)
F-statistic		14.67		14.67		14.67		14.67
Partial R^2		0.04		0.04		0.04		0.04

Notes: Results of OLS and IV estimates on the cross section of 2021-2011 differences across 108 pairs of urban municipalities. If no slum existed in the pair of municipalities during the analysis period, a zero is coded in the outcome. See Appendix Table A.VIII for outcome definitions. Changes in Total Area of Slums is winsorized at 99^{th} perc. $\Delta ImmStock_{m,2021-2011}$ is the immigrant inflow (in thousands) in pair of municipalities m between 2011 and 2021; $\Delta Imm\widehat{Stock}_{m,2021-2011}$ is the instrument (equation 2). OLS columns report the naive estimates of regressing the cross section of differences across municipality pairs on immigration inflow (equation 1), i.e., without instrumenting for $\Delta Imm\widehat{Stock}_{m,2021-2011}$. 2SLS coefficients are reported under the heading IV. Robust standard errors in parenthesis. *p*-values in brackets. For Panel A, Changes in Stock, and Panel B outcomes, the Baseline Mean DV reports the mean of the outcome at 2011. For Panel A, Changes in Slums Dynamics, the Baseline Mean DV reports the mean variation of the outcome between 2011 and 2013. *Sign. at 10%, **Sign. at 5%, ***Sign. at 1%.

Table A.IV: Long Difference 2021-2011 2SLS Estimation. 108 Urban Municipalities Groups

	Panel A: Extensive Margin Effects							
	Changes in Stocks		Changes in Slums Dynamics					
	Δ_{2011}^{2021} Total # Slums		$\Delta_{2011}^{2013}-\Delta_{2019}^{2021}$ Total # Slums Opened		$\Delta_{2011}^{2013}-\Delta_{2019}^{2021}$ Total # Slums Stayed Open		$\Delta_{2011}^{2013}-\Delta_{2019}^{2021}$ Total # Slums Closed	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\Delta ImmStock_{m,2021-2011}$	0.03	0.08*	0.02	0.09***	0.01	-0.00	0.00	0.01
(× 1,000)	(0.02)	(0.05)	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.02)
	[0.210]	[0.065]	[0.150]	[0.005]	[0.432]	[0.910]	[0.521]	[0.513]
Observations	108	108	108	108	108	108	108	108
Baseline Mean DV	5.66	5.66	0.96	0.96	4.81	4.81	0.85	0.85
	First Stage Regression							
$\Delta Imm\widehat{Stock}_{m,2021-2011}$		0.76***		0.76***		0.76***		0.76***
		(0.20)		(0.20)		(0.20)		(0.20)
F-statistic		14.76		14.76		14.76		14.76
Partial R^2		0.04		0.04		0.04		0.04
	Panel B: Intensive Margin Effects							
	Δ_{2011}^{2021} Total # HHs in Slums		Δ_{2011}^{2021} Total # Native HHs in Slums		Δ_{2011}^{2021} Total # Imm. HHs in Slums		Δ_{2011}^{2021} Total Area of Slums (m^2)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\Delta ImmStock_{m,2021-2011}$	5.96	19.58**	1.75	7.84*	4.21	11.74**	1,712	4,641*
(× 1,000)	(4.41)	(8.59)	(1.40)	(4.10)	(3.21)	(5.10)	(1,205)	(2,572)
	[0.179]	[0.023]	[0.214]	[0.056]	[0.193]	[0.021]	[0.158]	[0.071]
Observations	108	108	108	108	108	108	108	108
Baseline Mean DV	279	279	274	274	4	4	62,953	62,953
	First Stage Regression							
$\Delta Imm\widehat{Stock}_{m,2021-2011}$		0.76***		0.76***		0.76***		0.76***
		(0.20)		(0.20)		(0.20)		(0.20)
F-statistic		14.76		14.76		14.76		14.76
Partial R^2		0.04		0.04		0.04		0.04

Notes: Results of OLS and IV estimates on the cross section of 2021-2011 differences across 92 pairs, 14 triplets, and 2 quintets urban municipalities. If no slum existed in the group of municipalities during the analysis period, a zero is coded in the outcome. See Appendix Table A.VIII for outcome definitions. Changes in Total Area of Slums is winsorized at 99^{th} perc. $\Delta ImmStock_{m,2021-2011}$ is the immigrant inflow (in thousands) in groups of municipalities m between 2011 and 2021; $\Delta Imm\widehat{Stock}_{m,2021-2011}$ is the instrument (equation 2). OLS columns report the naive estimates of regressing the cross section of differences across municipality groups on immigration inflow (equation 1), i.e., without instrumenting for $\Delta Imm\widehat{Stock}_{m,2021-2011}$. 2SLS coefficients are reported under the heading IV. Robust standard errors in parenthesis. p-values in brackets. For Panel A, Changes in Stock, and Panel B outcomes, the Baseline Mean DV reports the mean of the outcome at 2011. For Panel A, Changes in Slums Dynamics, the Baseline Mean DV reports the mean variation of the outcome between 2011 and 2013. *Sign. at 10%, **Sign. at 5%, ***Sign. at 1%.

Table A.V: Long Difference 2017-2011 2SLS Estimation. 243 Urban Municipalities

	Δ_{2011}^{2017} Total # Slums		Δ_{2011}^{2017} Total # HHs in Slums		Δ_{2011}^{2017} Total Area of Slums (m^2)	
	OLS	IV	OLS	IV	OLS	IV
$\Delta ImmStock_{m,2017-2011}$	0.05	0.15**	7.14	17.99**	1,066	2,810**
(× 1,000)	(0.04)	(0.07)	(6.18)	(3.99)	(743)	(1,312)
	[0.283]	[0.025]	[0.249]	[0.015]	[0.153]	[0.032]
Observations	243	243	243	243	243	243
Baseline Mean DV	2.53	2.53	124	124	27,615	27,615
	First Stage Regression					
$\Delta Imm\widehat{Stock}_{m,2017-2011}$		0.42***		0.42***		0.42***
		(0.13)		(0.13)		(0.13)
F-statistic		10.82		10.82		10.82
Partial R^2		0.06		0.06		0.06

Notes: Results of OLS and IV estimates on the cross section of 2017-2011 differences across 243 urban municipalities. If no slum existed in the municipality during the analysis period, a zero is coded in the outcome. Changes in Total Area of Slums is winsorized at 99^{th} perc. $\Delta ImmStock_{m,2017-2011}$ is the immigrant inflow (in thousands) in municipality m between 2011 and 2017; $\Delta Imm\widehat{Stock}_{m,2017-2011}$ is the instrument. OLS columns report the naive estimates of regressing the cross section of differences across municipalities on immigration inflow, without instrumenting for $\Delta Imm\widehat{Stock}_{m,2017-2011}$. 2SLS coefficients are reported under the heading IV. Robust standard errors in parenthesis. p-values in brackets. The Baseline Mean DV reports the mean of the outcome at 2011. *Sign. at 10%, **Sign. at 5%, ***Sign. at 1%.

Table A.VI: Two-Year Difference Panel Regression Model of Immigration Inflows and Slum Formation

	Panel A: Extensive Margin Outcomes			
	Changes in Stocks	Changes in Slums Dynamics		
	$\Delta_2 = 1$ if Slum is Open in t	$\Delta_2 = 1$ if Slum Opened between $t-2$ and t	$\Delta_2 = 1$ if Slum Stayed Open between $t-2$ and t	$\Delta_2 = 1$ if Slum Closed between $t-2$ and t
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
$\Delta ImmStock_{mt,t-2}$	0.0090***	0.0025***	0.0065***	-0.0013***
($\times$ 1,000)	(0.0015)	(0.0004)	(0.0014)	(0.0003)
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	6,795	6,795	6,795	6,795
R-squared	0.431	0.156	0.302	0.089
Baseline Mean DV	0.5475	0.0765	0.3834	0.0692
Two-year Diff. Panel	Full Panel	Full Panel	Full Panel	Full Panel

	Panel B: Intensive Margin Outcomes			
	Δ_2 # HHs in Slum between $t-2$ and t	Δ_2 # Native HHs in Slum between $t-2$ and t	Δ_2 # Imm. HHs in Slum between $t-2$ and t	Δ_2 Area of Slum (m^2) between $t-2$ and t
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
$\Delta ImmStock_{mt,t-2}$	0.5243***	1.5967*	1.0952	165.034**
($\times$ 1,000)	(0.0753)	(0.9574)	(1.0474)	(81.033)
	[0.000]	[0.097]	[0.297]	[0.043]
Observations	6,779	1,205	1,205	2,718
R-squared	0.014	0.016	0.003	0.010
Baseline Mean DV	22.2090	21.8919	0.3171	5,165
Two-year Diff. Panel	Full Panel	2011-19-21	2011-19-21	2011-17-19-21

Notes: Results of a first-difference panel regression model at the ever been slum territory level in urban municipalities (equation 3). The dependent variable is the two-year difference of the outcome in a slum territory, with the panel including years 2011, 2013, 2015, 2017, 2019, and 2021, for a total of 5 observations (two-year differences) per slum territory ($1,359 \times 5 = 6,795$ observations in total). See Appendix Table A.X for outcome definitions. The variable $\Delta ImmStock_{mt,t-2}$ is the immigrant inflow (in thousands) in municipality m between years t and $t-2$. All regressions include year fixed effects. Outcomes in Panel A regressions are observed in all panel years. Baseline Mean DV reports the mean of each outcome across territory-years observations for the first difference (2013-2011). In Panel B, if a slum is closed in a given year, we compute a zero in that territory for that year. Outcome in regression columns (1) is observed in all panel years. Outcomes in regression columns (2) and (3) are only observed for panel years 2011, 2019, and 2021. Outcome in regression column (4) is only observed for panel years 2011, 2017, 2019, and 2021. Changes in area of slum are winsorized at 99^{th} percentile. Standard errors clustered at the municipality level are reported in parenthesis. p-values in brackets. * Sign. at 10%, ** Sign. at 5%, *** Sign. at 1%. Multiple-hypothesis testing: Holm (1979)'s FWER correction at the 10% level of significance. The families of extensive (Panel A) and intensive margin outcomes (Panel B) have 4 outcomes each, such that the most significant coefficient among them is rejected if its p-value<0.1/4=0.025; the second most significant coefficient is rejected if its p-value<0.1/3=0.033; the third if its p-value<0.1/2=0.05; and the fourth if its p-value<0.1/1=0.1.

Table A.VII: Immigration Effects by Immigrants Levels of Education: Long Difference 2021-2011 2SLS Estimation. 243 Urban Municipalities

Dependent Variable	Residence Permits All (1)	Residence Permits High School or more (2)	p-val. $\beta_{All} = \beta_{HS}$ (3)
Δ_{2011}^{2021} Total # Slums	0.09**	0.12*	0.331
	(0.04)	(0.07)	
	[0.030]	[0.066]	
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Opened	0.09***	0.18***	0.010
	(0.03)	(0.06)	
	[0.004]	[0.004]	
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Stayed Open	-0.00	-0.04	0.144
	(0.02)	(0.04)	
	[0.846]	[0.300]	
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Closed	0.01	0.01	0.917
	(0.01)	(0.03)	
	[0.530]	[0.856]	
Δ_{2011}^{2021} Total # HHs in Slums	19.50***	32.04**	0.098
	(7.47)	(13.13)	
	[0.009]	[0.015]	
Δ_{2011}^{2021} Total # Native HHs in Slums	7.94**	11.21	0.492
	(3.66)	(7.01)	
	[0.030]	[0.110]	
Δ_{2011}^{2021} Total # Imm. HHs in Slums	11.56**	20.83**	0.062
	(4.55)	(8.70)	
	[0.011]	[0.017]	
Δ_{2011}^{2021} Total Area of Slums (m^2)	4,320**	7,067**	0.098
	(1,934)	(3,080)	
	[0.026]	[0.022]	
Observations	243	243	
F-Statistic	11.64	14.46	
Part. R^2	0.02	0.03	

Notes: Results of the IV estimates on the cross section of 2021-2011 differences across 243 (urban) municipalities. See Appendix Table A.VIII for outcome definitions. If no slum existed in the municipality during the analysis period, a zero is coded in the outcome. Changes in Total Area of Slums is winsorized at 99^{th} perc. Regressions in column (1) consider all immigrant inflows, regardless of their level of education. Regressions in column (2) consider only migrants with high school diploma or more. Robust standard errors are presented in parentheses and p-values in brackets. *Sign. at 10%, **Sign. at 5%, ***Sign. at 1%. Column (3) provides the p-value of testing the null hypothesis of no difference between the coefficients across regression models in columns (1) and (2).

Table A.VIII: Definition of Variables

Panel A. Municipality Level Outcomes	
Name	Definition
Δ_{2011}^{2021} Total # Slums	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2021 slums censuses. We count the number of open slums per municipality for 2021 and for 2011, and take the within-municipality difference. If no slum existed in the municipality during the analysis period, a zero is coded.
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Opened	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2013, 2019, and 2021 slums censuses. We count the number of ever been slum territories per municipality where a slum opened between 2019 and 2021 (i.e., it was closed in 2019 but open in 2021) and differentiate it with respect to the number of ever been slum territories where a slum opened between 2011 and 2013 (i.e., it was closed in 2011 but open in 2013).
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Stayed Open	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2013, 2019, and 2021 slums censuses. We count the number of ever been slum territories per municipality where a slum remained open between 2019 and 2021 (i.e., it was open in 2019 and remained open in 2021) and differentiate it with respect to the number of ever been slum territories where a slum remained open between 2011 and 2013 (i.e., it was open in 2011 and remained open in 2013).
$\Delta_{2011}^{2013} - \Delta_{2019}^{2021}$ Total # Slums Closed	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2013, 2019, and 2021 slums censuses. We count the number of ever been slum territories per municipality where a slum closed between 2019 and 2021 (i.e., it was open in 2019 but close in 2021) and differentiate it with respect to the number of ever been slum territories where a slum closed between 2011 and 2013 (i.e., it was open in 2011 but close in 2013).
Δ_{2011}^{2021} Total # HHs in Slums	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2021 slums censuses. We count the total number of households residing in slums for 2021 and 2011, and take the within-municipality difference. If no slum existed in the municipality during the analysis period, a zero is coded.
Δ_{2011}^{2021} Total # Native HHs in Slums	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2021 slums censuses. We count the total number of native households residing in slums for 2021 and 2011, and take the within-municipality difference. If no slum existed in the municipality during the analysis period, a zero is coded.
Δ_{2011}^{2021} Total # Imm. HHs in Slums	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2021 slums censuses. We count the total number of immigrant households residing in slums for 2021 and 2011, and take the within-municipality difference. If no slum existed in the municipality during the analysis period, a zero is coded.
Δ_{2011}^{2021} Total Area of Slums (m^2)	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU 2011 and TECHO 2021 slums censuses. We sum up the area of each slum (in m^2) to obtain the total area covered by slums. We do this for 2021 and 2011 and take the within-municipality difference. If no slum existed in the municipality during the analysis period, a zero is coded.

Table A.IX: Definition of Variables (cont.)

Panel A. Municipality Level Outcomes (cont.)	
Name	Definition
Δ_{2011}^{2017} Median Rent	Calculated at the municipality level for a total of 223 urban municipalities. Data Sources are CASEN 2011 and CASEN 2017 household level surveys. We take the median rent (in $US dollars of 2011) of each municipality for 2017 and for 2011, and compute the within-municipality difference.
Δ_{2011}^{2017} Median Rent Perc. (Perception)	Calculated at the municipality level for a total of 223 urban municipalities. Data Sources are CASEN 2011 and CASEN 2017 household level surveys. We take the median rent perception of each municipality for 2017 and for 2011, and compute the within-municipality difference. Perception of rents are derived from the following question: "What is the estimated rent fee in this sector for housing units similar to yours?"
Δ_{2011}^{2021} Total # of construction permits	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are INE 2002-2021 construction permits datasets. We compute the difference between the accumulated stock of construction permits up to 2021 and the the accumulated stock of construction permits up to 2011.
Δ_{2011}^{2021} Total # of floors built	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are INE 2002-2021 construction permits datasets. According to the number of floors approved to be built associated to each construction permit, we compute the difference between the accumulated stock of floors built up to 2021 and the accumulated stock of floors built up to 2011.
Δ_{2011}^{2020} Poverty Rate	Calculated at the municipality level for a total of 238 urban municipalities. Data Sources are CASEN 2011 and CASEN 2020 household level surveys. We compute the poverty rate of each municipality for 2020 and for 2011, and compute the within-municipality difference.
Δ_{2011}^{2020} Ext. Poverty Rate	Calculated at the municipality level for a total of 238 urban municipalities. Data Sources are CASEN 2011 and CASEN 2020 household level surveys. We compute the extreme poverty rate of each municipality for 2020 and for 2011, and compute the within-municipality difference.
Δ_{2011}^{2020} Median *per capita* Income	Calculated at the municipality level for a total of 238 urban municipalities. Data Sources are CASEN 2011 and CASEN 2020 household level surveys. We compute the median per capita household income (in 2011 $US dollars) of each municipality for 2020 and for 2011, and compute the within-municipality difference.
Δ_{2011}^{2020} Unemployment Rate	Calculated at the municipality level for a total of 238 urban municipalities. Data Sources are CASEN 2011 and CASEN 2020 household level surveys. We compute the unemployment rate of each municipality for 2020 and for 2011, and compute the within-municipality difference.
Δ_{2020}^{2011} Total % of Slums Receiving Housing Subsidies	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU records on slums that have been intervened with housing subsidies. We compute the difference between the share of slums per municipality where MINVU delivered housing subsidies in 2020 and the share of slums per municipality where MINVU delivered housing subsidies in 2011.
Δ_{2020}^{2011} Total % of Slums Receiving Urbanization Programs	Calculated at the municipality level for a total of 243 urban municipalities. Data Sources are MINVU records on slums that have been intervened with Urbanization Programs. We compute the difference between the share of slums per municipality where MINVU implemented urbanization programs in 2020 and the share of slums per municipality where MINVU implemented urbanization programs in 2011.

Table A.X: Definition of Variables (cont.)

Panel B. Slum Level Outcomes	
Name	Definition
$\Delta_2 = 1$ if Slum is open in t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2011 and 2019 slums censuses, and TECHO 2013, 2015, 2017, and 2021 slums censuses. We define a dummy that equals one if the territory is a slum in t (i.e., the slum is open) and zero otherwise. That is, the dummy takes a value of 1 either if the territory was a slum in $t-2$ and continue being a slum in t, or if it was formed between $t-2$ and t. Then, the dummy takes the value of 0 either if the territory was not a slum in $t-2$ and continue not being a slum in t, or if it was a slum in $t-2$ but it closed between $t-2$ and t.
$\Delta_2 = 1$ if Slum Opened between $t-2$ and t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2011 and 2019 slums censuses, and TECHO 2013, 2015, 2017, and 2021 slums censuses. We define a dummy that equals one if the slum opened in that territory between $t-2$ and t (i.e., the slum was closed in $t-2$ but open in t) and zero otherwise.
$\Delta_2 = 1$ if Slum Stayed Open between $t-2$ and t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2011 and 2019 slums censuses, and TECHO 2013, 2015, 2017, and 2021 slums censuses. We define a dummy that equals one if the slum stay opened in that territory between $t-2$ and t (i.e., the slum was open in $t-2$ and remains open in t) and zero otherwise.
$\Delta_2 = 1$ if Slum Closed between $t-2$ and t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2011 and 2019 slums censuses, and TECHO 2013, 2015, 2017, and 2021 slums censuses. We define a dummy that equals one if the slum closed in that territory between $t-2$ and t (i.e., the slum was open in $t-2$ but close in t) and zero otherwise.
Δ_2 # HHs in Slum between $t-2$ and t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2011 and 2019 slums censuses, and TECHO 2013, 2015, 2017, and 2021 slums censuses. We compute the difference in the number of households residing in the slum between $t-2$ and t. If the slum is closed, the number of households residing in the slum is coded as zero.
Δ_2 # Native HHs in Slum between $t-2$ and t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2019 and TECHO 2021 slums censuses. We compute the difference in the number of native households residing in the slum between $t-2$ and t. If the slum is closed, the number of native households residing in the slum is coded as zero.
Δ_2 # Imm. HHs in Slum between $t-2$ and t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2019 and TECHO 2021 slums censuses. We compute the difference in the number of immigrant households residing in the slum between $t-2$ and t. If the slum is closed, the number of immigrant households residing in the slum is coded as zero.
Δ_2 Area of Slum (m^2) between $t-2$ and t	Calculated at the territory level for a total of 1,359 ever been slum territories in urban municipalities. Data Sources are MINVU 2019 and TECHO 2017 and 2021 slums censuses. We compute the difference in the total area covered by the slum (in m^2) between $t-2$ and t. If the slum is closed, the total area covered by the slum is coded as zero.