Immigration and the Role of Slums in Housing Affordability

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ABSTRACT. We study how international immigration interacts with housing supply constraints and the formation of slums in emerging economies. Using comprehensive administrative data covering all formal and informal housing in Chile between 2011 and 2021, and exploiting a shift-share IV strategy, we show that immigration led to large increases in the number of slums, their spatial extent, and the population residing in them. In contrast, evidence from detailed construction-permit data reveals that while immigration also expanded formal housing supply, this occurred exclusively through high-quality units, with no corresponding increase in affordable housing. Exploiting exogenous variation in construction costs induced by terrain ruggedness, we show that slum expansion is significantly larger in municipalities where affordable formal housing supply is most constrained, pointing to substitutability between the two housing sectors. To quantify the general-equilibrium mechanisms underlying these patterns, we calibrate a static spatial model with heterogeneous households and dual formal–informal housing sectors, using causally identified housing supply elasticities in each sector estimated from immigration-induced demand shocks and long-difference changes in rents and housing quantities. Counterfactual simulations show that informal housing acts as an endogenous buffer that absorbs population shocks and limits rent increases. Restricting or eliminating slums without increasing formal supply elasticities can generate sizable welfare losses. Overall, our findings indicate that slums emerge as a second-best but quantitatively important adjustment margin in cities facing large immigration shocks and rigid formal housing markets.

KEYWORDS. Immigration, Affordable Housing, Slums.

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1. Introduction

Amidst a burgeoning global housing crisis propelled by a lack of affordable housing options, 1.6 billion people currently struggle to access adequate housing. In the next decade, nearly 3 billion people, around 40% of the world's population, are projected to lack adequate and affordable housing. This demand will be further intensified by migration inflows, most of which will be concentrated in developing-country cities (UN-Habitat, 2022; United-Nations, 2025). Understanding how immigration interacts with strained housing markets is therefore crucial for assessing its role in shaping the global affordability crisis.

Standard urban theory, from early and new economic geography models to modern quantitative spatial equilibrium models, predicts that newcomers sort across locations according to wage-rent-amenity trade-offs, making the elasticity of housing supply a key determinant of how cities absorb population shocks. Where supply is highly inelastic, rising demand translates into sharply higher rents, pushing some workers out and deterring further immigration. This mechanism lies at the heart of the geography of comparative advantages across cities: only when wages or amenities increase enough to offset higher housing costs will immigration persist; otherwise, unaffordable housing pushes workers toward less productive locations, reducing both their wages and aggregate welfare.[1]

In many developing-country cities, however, standard models' predictions may not hold because a large share of residents rely on informal housing, often in the form of slums. These informal settlements provide an additional adjustment margin that allows low-income households to remain in high-productivity cities and access agglomeration benefits they would otherwise be priced out of. This raises fundamental questions about how informal housing mediates spatial and welfare adjustments in cities under sustained global migration pressures. How does the spatial equilibrium change once workers can sort into an informal housing sector? How steeply would formal sector rents rise under a demand shock if slums were cleared? Can slums, commonly viewed as disadvantaged areas marked by poor housing and negative spatial spillovers, ultimately be welfare-enhancing in cities facing strong demand pressures? These questions are not innocuous: roughly one-sixth of the world's population lives in slums (UN-Habitat, 2022), and both informal housing and immigration are ubiquitous features of developing-country cities.

This paper examines the causal effect of international migration on formal and informal housing supply in developing-country cities and evaluates the role of slums in absorbing population shocks and stabilizing housing markets in general equilibrium. Our context is Chile, where the foreign-born population quadrupled over the last decade, passing from 2% in 2011 to 8% in 2021, driven largely by South–South migration. Although immigrants tend to originate from countries with lower income levels than Chile, they are, on average, more educated than the

[1] For a thorough review of the evolution of early works attempting to model the sorting of individuals across cities and the resulting size distribution and their internal structure, see Fujita et al. (1999), Fujita and Thisse (2002), Baldwin et al. (2003), and Duranton and Puga (2004). For a modern introduction of quantitative spatial equilibrium models, see Redding and Rossi-Hansberg (2017), as well as seminal papers that originated these models, including Lucas and Rossi-Hansberg (2002), Redding and Sturm (2008), Allen and Arkolakis (2014), Ahlfeldt et al. (2015), and Redding (2016), among others. Early works examining the determinants and role of housing supply elasticity on urban dynamics include Glaeser et al. (2006), Glaeser et al. (2008), and Saiz (2010).

native Chilean population: 80 percent have completed high school or more, roughly twice the corresponding share among Chileans.

In parallel to the immigration shock, the number of slums in Chile grew by 50% and the slum population nearly tripled. Because more educated adults are less likely to live in slums, these patterns point to slum growth arising through indirect market adjustment to the immigration shock rather than a direct increase in slum demand from newcomers. This, in turn, motivates building a model that rationalizes the general equilibrium forces through which slums operate and using it to assess what the spatial and welfare equilibrium would look like in their absence. To do so, we extend and calibrate a canonical quantitative spatial model with heterogeneous agents and dual housing sectors (formal and informal) directly to a unique panel dataset on slums and formal housing across Chilean cities.[2,3]

We start by documenting, for the first time, reduced-form evidence on the causal role of immigration on slums formation. Our focus is on urban municipalities, where 99% of migrants arrive and almost 95% of slums are located. The analysis relies on a unique dataset 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 a 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. 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.

We estimate the causal effect of immigration on slums growth 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.[4] The 2SLS estimates imply that, evaluated at the decade's average immigration inflow, immigration increased the number of slums per municipality from 2.5 to 3.5. This one-unit effect mirrors the observed mean increase over 2011–2021, indicating that immigration can fully

[2]Slums in Chile follow the definition stated by UN-Habitat (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.

[3]Chile's trends in terms of immigration and slum formation are 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). For key spatial challenges faced by developing-country cities from the lens of urban economics, including slum formation, see Bryan et al. (2025).

[4]Identifying the causal effect of immigration on slums growth is challenging 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 slums formation. For instance, more economically dynamic municipalities may simultaneously increase immigration, slums, and formal housing, generating an upward bias in our estimates. Likewise, an upward trend in formal housing supply within a specific municipality during a particular year could simultaneously attract immigrants and decrease urban informality, generating a downwards bias in the immigration effect on slum formation.

explain the aggregate growth in slums during this period. On the intensive margin, immigration doubled the baseline slum population, and this is explained by similar increases in both the native and immigrant slum dwellers, suggesting that slum growth arose through indirect market adjustment to the immigration inflows rather than a migrants' preference for residing in slums. The population growth effect is also reflected in a comparable expansion of slum footprints, suggesting a one-to-one relationship between slum population and spatial growth.[5]

As informal housing often develops in response to tight or inelastic formal housing supply, we next study the causal effect of immigration on construction permits required to build formal housing. This includes total number of units approved for each project as well as statistics of number of rooms per unit and a summary index of the quality of construction. We find that immigration had a positive effect on construction projects and construction for high-end residences. However, migrant inflows do not increase the supply of affordable housing units (identified as those below-the-median housing quality), which can be thought of as the type of housing that is more relevant for lower income households at the margin of the formal/informal housing markets. These findings suggest that the immigration-driven demand shock is accommodated by an expansion of high-quality formal housing, with limited supply response in the formal affordable segment. Given the responsiveness of informal housing supply to immigration documented earlier, these result jointly suggest that residual demand for low-cost housing is absorbed by the informal sector, resulting in slum growth.

An indirect test for the formal-informal substitution hypothesis consists of exploiting heterogeneity in housing supply elasticities arising from variation in ruggedness of a municipality's geography, which has previously been used as a plausibly exogenous determinant of housing supply elasticities in the U.S. literature (Gyourko and Saiz, 2006; Burchfield et al., 2006; Saiz, 2010). Reassuringly, 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.[6]

[5] 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 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.

[6] 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,

Until this point, our causally-identified evidence suggests that slums, while providing substandard living conditions, serve as an affordable informal option when formal supply is constrained, suggesting their dynamics are a result of indirect market adjustments. Since slums are generally viewed as economically distressed areas that limit local economic development, governments often respond through slum clearance policies that relocate slum households to formal housing elsewhere in the city. To what extent is this the right approach to slum policy? What would be the counterfactual spatial equilibrium and welfare derived from the immigration shock had slums been cleared or prevented from expanding?

To unpack the role of slums and the general equilibrium forces through which they operate, we next build on the canonical quantitative spatial models of Allen and Arkolakis (2014) and Redding (2016) and extend them along two dimensions. First, we introduce heterogeneous households, distinguishing between high- and low-education workers who choose both where to live and whether to occupy formal or informal (slum) housing. Second, we split the housing market into formal and informal sectors, each with its own congestion externality and sector-specific housing supply elasticity. The model is calibrated to rich data on wages, rents, and populations across Chilean municipalities, and we recover location-specific productivities and amenities using standard inversion techniques from the spatial literature. Because the immigration episode we study is a large, long-run shock observed through two cross-sectional snapshots, our empirical design relies on long differences; accordingly, we adopt a static spatial equilibrium framework that compares pre- and post-shock steady states rather than imposing dynamic adjustment paths that our data cannot convincingly discipline.

Central to our model is the responsiveness of housing supply in each sector. We provide new causal estimates of the formal and informal housing supply elasticities in Chile by exploiting the large, heterogeneous increase in immigration to Chile between 2011 and 2020 as a plausibly exogenous demand shock. Combining a long-difference version of the model's housing supply equation with municipality-level data on rent and housing stock growth, we estimate sector-specific inverse supply elasticities, instrumenting demand shifts with the shift-share measure of immigration shocks. We find a formal housing supply elasticity of about 1.64, which is comparable to estimates for advanced economies, and an informal (slum) supply elasticity of 6.21, which is almost four times as large as the formal sector elasticity. These estimates characterize the relative slopes of the formal and informal supply curves in all subsequent counterfactuals.

Equipped with our well-identified supply elasticities, we use the calibrated model to study how slums shape the adjustment of Chilean municipalities to immigration. In a first experiment, we input the observed decade-long immigration shock, exogenously increasing the total low-education population by 4% and the high-education population by 20%. This experiment isolates the mechanical effect of immigration inflows (of which roughly 80% have at least a high-school diploma) on the skill composition of the population. The model reproduces the intensive growth of slums observed in the data and implies sizable distributional effects: high-education

indicating that immigration's positive effect on slum growth is unlikely to be mediated by either anti-immigrant policies or program-based political capture.

households experience welfare losses driven by higher formal-sector rents and lower wages, while low-education households gain, as stronger labor demand more than offsets rent increases.

Two policy experiments then restrict the informal sector's ability to accommodate the shock. When slum floorspace is locked at its baseline level, slum rents increase sharply while formal rents rise modestly relative to the benchmark shock, leading to additional welfare losses for both groups. When slums are fully removed in the new equilibrium and all households are forced into the formal sector, formal rents jump by about 13%, and welfare losses deepen by up to 11 percentage points relative to the benchmark immigration shock for select household types. Taken together, these experiments highlight slums as a second-best adjustment margin in the presence of inelastic formal housing supply. While slums are commonly viewed as spatial poverty traps (Marx et al., 2013), we find that the adjustment margin they provide mitigates the welfare losses that would arise from sharp increases in formal-sector rents in their absence, underscoring the tension between the severe deprivation they entail and their role in buffering even larger welfare losses.

Our paper is related to recent research using longitudinal data to study the determinants of informal housing, including Henderson et al. (2021) 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.

Taken together, these studies highlight how land-use change, urban policy, and displacement shape slum dynamics. Our paper adds international migration to this set of determinants by providing, to our knowledge, the first causal evidence on its effect on slum growth. More broadly, our findings also speak to the role of incomes versus location preferences in shaping slum formation. The absence of effects of immigration on city-wide incomes, unemployment, and poverty rates suggests that the slum growth we document is unlikely to be driven by income effects. This finding is difficult to reconcile with the view of slums as a poverty trap (Marx et al., 2013). Instead, it is more consistent 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).[7]

Additionally, 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 increases 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.[8] Part of these effects could be driven by discrimination against migrants in rental housing markets (Page, 1995, Ahmed and Hammarstedt, 2008, Bosch et al., 2010, Bo et al., 2006, Ewens et al., 2014, Diaz and Zanoni, 2024). Our paper adds to this literature by showing that the positive effects of immigration on rental prices can have broader consequences. 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 a growing literature that incorporates differentiated formal and informal housing sectors into heterogeneous-agent spatial equilibrium models of cities in developing economies. Prior work has made important progress along these dimensions: Bird and Venables (2020) adapt a static Ahlfeldt et al. (2015) framework with skill heterogeneity and distinct bid-rent curves for formal and informal housing to study how land-tenure systems shape land use in Kampala; Henderson et al. (2021) examine the within-city dynamics of slum formation in Nairobi using a rich monocentric model with sector-specific housing technologies and conversion frictions; Gechter and Tsivanidis (2023) embed skill heterogeneity and differentiated formal–informal construction technologies into a dynamic Ahlfeldt et al. (2015)-style model to analyze local redevelopment shocks in Mumbai. In contrast to these within-city environments, we extend the system-of-cities quantitative spatial framework to a model in which heterogeneous households differentiated by education sort across many urban locations and where formal and informal housing operate as technologically distinct sectors with distinct amenities and crowding

[7] This is in contrast to the early literature on slum formation based on 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. (2021). A related literature study the role of location on earnings and productivity, typically arising from endogenous externalities of population density or human capital. See, for instance, Ciccone and Hall (1996), Glaeser and Maré (2001), Duranton and Puga (2004), Combes et al. (2008), Glaeser and Gottlieb (2009), De la Roca and Puga (2017), Diamond (2016), Dauth et al. (2022), and Card et al. (2024).

[8] 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.

forces. This allows us to quantify the general-equilibrium role of informal housing and how it facilitates economy-wide adjustments to exogenous immigration shocks.

A closely related paper is Cavalcanti-Ferreira et al. (2025), who study the role of slums in Brazil through a three-region OLG model in which slums form and persist because they serve as intergenerational stepping stones for low-educated households but blockades for higher-educated ones. Our paper differs along two key dimensions. First, scope: Cavalcanti-Ferreira et al. (2025) analyze slums in a setting featuring within-country rural-to-urban migration, whereas we examine how slums absorb international (i.e., *between*-country) migration shocks and shape the associated welfare consequences. Second, modeling: we adopt an explicitly spatial framework with heterogeneous locations in which slums are an integral part of the city rather than a separate region. Despite these differences, the papers are complementary. Both reveal that slums play a nuanced economic role, and both show that eliminating slums can generate welfare losses. Cavalcanti-Ferreira et al. (2025) emphasize the role of slums in intergenerational human-capital dynamics; our contribution is to show, in a rich geographic setting, how slums also cushion shocks through the housing-market channel, thereby extending their insight to an environment with spatial heterogeneity and international migration.

Our paper also advances the literature on direct estimates of housing supply elasticities. Prior work has focused primarily on formal housing markets in advanced economies. Saiz (2010) famously uses population-driven demand shocks and cross-sectional variation in geographic land constraints to identify metro-level housing supply elasticities, providing benchmark estimates for U.S. cities. Diamond (2016) similarly estimates a cross-section of location-specific housing supply elasticities in the U.S., incorporating these estimates into a structural spatial model to study the welfare implications of increased spatial sorting. More recently, Baum-Snow and Han (2024) exploit tract-level demand shocks from 2000–2010 to estimate highly granular within-city supply elasticities.

Our setting provides the first opportunity to estimate housing supply elasticities for both formal and informal (slum) sectors in an emerging economy using a unified empirical framework. Our rich data on both the formal and informal housing markets, coupled with a plausibly exogenous immigration shock, allows us to credibly identify sector-specific supply elasticities. We show, first, that formal-sector elasticities are very close to benchmark estimates from developed countries, despite stark institutional differences. Second, we provide the first causal estimate of an informal housing supply elasticity, offering a quantitative benchmark for how slum housing responds to demand shocks. Finally, we embed both elasticities into a quantitative spatial model to assess how differences in formal and informal supply responsiveness shape urban adjustment and welfare under large migration shocks.

The paper is organized as follows. Section 2 describes the data used in this study. Section 3 presents the identification strategy used to estimate the causal effects of immigration on formal and informal housing supply, along with the main results. Section 4 provides causal estimates of formal and informal housing supply elasticities, and calibrate a quantitative spatial model to examine the role of slums in constrained formal housing markets. Section 5 concludes.

2. Data

2.1. Immigration

Chilean legislation provides two principal categories of residence permits for migrants seeking to settle in the country (i.e., non-tourists). First, temporary residence permits, composed primarily of work visas, with less common categories including education and family-reunification visas. Second, permanent residence permits are available to migrants intending to reside in the country indefinitely.

We obtained individual-level administrative data on all first-time residence permits granted by the Chilean Department of State between 2000 and 2021 (Extranjería-Chile, 2021). These records include key demographic information, such as date of birth, nationality, gender, education, and job sector at the time of entry. Among the 3.4 million individual permits in our data, 80 percent were issued after 2010, underscoring the sharp increase in migration in the latter half of the sample period, during which 2.6 million permits were issued (2011–2021). With the exception of Haitians, most migrants originate from Spanish-speaking countries; consequently, language and culture are not major barriers to migrants' integration. Appendix Figures A.I and A.II illustrate the evolution of immigration over the past two decades in aggregate and by origin country.

Although our data capture only authorized immigration, unauthorized entrants constitute a very small share of the migrant population in Chile. Police Agency records indicate that between 2011 and 2020, an estimated average of approximately 4,400 individuals per year entered through unauthorized crossing points. This is equivalent to only 1.7 percent of the mean annual inflow during that period. Several factors help explain the limited scale of unauthorized migration. First, Chile's geography (bounded by the Andes Mountains to the east, the Pacific Ocean to the west, and extremely arid, low-temperature desert to the north) makes irregular entry both costly and infrequent. Second, until 2018, migrants faced few incentives to enter without authorization, as Chilean legislation permitted individuals to arrive as tourists and subsequently apply for a temporary work visa upon securing employment. In addition, permanent residency could be obtained after two years of holding a temporary work visa.[9]

Importantly, the data include the intended municipality of residence at the time of application, a variable that is critical for constructing our shift–share instrument (more in Section 3). This information is collected solely for administrative purposes and does not influence the approval of residence permits. Indeed, during the period of analysis, the Department of State maintained no national or subnational quota policies for immigrants, which reduces any incentive to misreport their intended municipality of residence.

As in most countries, immigration in Chile is overwhelmingly an urban phenomenon: 98.8 percent of inflows are concentrated in urban municipalities. Although immigration increased markedly over the study period, growth rates varied substantially across the country. Table 1 reports descriptive statistics for all urban municipalities (243 in total) and by quartile of

[9] 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.

immigrant growth between 2011 and 2021. On average, municipalities in the top quartile received approximately 38,000 immigrants. This is about ten times the average inflow of municipalities in the third quartile, and between 40 and 200 times the average inflows of municipalities in the bottom half of the distribution. Municipalities receiving larger immigrant inflows tend to have higher per capita income levels, suggesting that migrants' location choices are influenced by the pursuit of greater income opportunities.

Panel I reports average immigrant characteristics for each quartile group at the beginning and end of the sample period, providing snapshots for 2011 and 2021. Approximately half of all immigrants are women, and the average age at entry is 31. Second, despite originating from poorer countries, incoming migrants are more educated than natives: over 80% have at least a high-school degree, compared with only 35% of the Chilean population in 2011. These statistics remain largely stable over the decade.

2.2. Informal Housing Supply

Slums in Chile are defined following UN-Habitat (2003) as neighborhoods in which (i) at least 50% of inhabitants reside under illegal occupation (i.e., lack formal land title or rent from someone who does not hold title), and/or (ii) at least 50% of residents lack access to adequate housing, electricity, potable 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 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 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).[10]

We create a biennial 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.[11] 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.[12] Of the 1,459 territories, 93% are located in urban municipalities, the focus of our study, for a panel size of 1,359$\times$6=8,154 territory-year observations.

We observe the total number of households residing in slums, and in some years the census

[10]Since most slum dwellers cannot afford legal connections, many tap into the public water supply through illegal connections. Others rely on water trucks, typically paying much higher marginal prices than those charged for public provision.

[11]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, it allows the construction of a biennial panel using odd years.

[12]Note that there are no "always-missing" observations; every geographic unit observed in the 2011–2021 period contains a slum in at least one census wave.

also records the nationality of slum residents, allowing us to track the evolution of the immigrant share 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 1 and 2 illustrate examples of slum formation between 2011 and 2021 in terms of population, immigrant share, and area.

The number of slums nationwide increased from 653 in 2011 to 882 in 2021, representing a 35 percent increase. Figure 3 illustrates that municipalities with higher immigration inflows show a larger increase in the number of slums. This is also reflected in Table 1, Panel II, which shows substantial variation in slum growth, with most of it concentrated in municipalities with a high inflow of immigrants. For example, in 2011, municipalities in the upper quartile of immigration inflows had 3.8 times as many slums as those in the lower quartile; by 2021, this ratio had increased to 6.5. This is also reflected in the slum population, which had an average of 124 households per slums in 2011. While low-immigration municipalities exhibited minimal growth in their slum populations, municipalities in the upper immigration quartiles experienced two- to four-fold increases. 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. Finally, the average area occupied by slums also increased, doubling over ten years, with the largest increase concentrated in high-immigration municipalities.

2.3. Formal Housing Supply

In Chile, all formal construction requires approval from municipal housing authorities (Municipal Works Department, DOM), which issue the permits necessary for housing development. The National Institute of Statistics (INE) aggregates these administrative records and reports, for each municipality–year, the universe of approved construction permits. The DOM data include the number of approved projects, the number of housing units authorized per project (ranging from single-unit detached homes to multifamily developments) as well as information on housing characteristics, including the number of rooms per unit and a summary index of construction quality. We complement DOM housing data with national CASEN 2011 and 2020 household-level survey data on rents.

Table 1, Panel III, summarizes the evolution of formal housing markets. Municipalities in the top quartile of immigrant inflows (Q4) issue, on average, twice as many construction permits as municipalities in the bottom quartile (Q1), and authorize roughly three times as many housing units. This higher level of construction activity, however, does not imply that housing needs are being met with formal housing, as Q4 municipalities also experience substantially larger immigration inflows. Using an average immigrant household size of three individuals (MDSF, 2020), the number of housing units built per immigrant household in Q4 municipalities is only 0.32, indicating that formal housing expansion has been insufficient to absorb immigrant housing demand, even before accounting for growth in the native population. Consistent with an imbalance, real housing rents doubled over the decade.

3. The Causal Impact of Immigration on Housing Supply

In this section, we provide new evidence on the causal impact of international immigration on housing outcomes, focusing on both informal housing (slums) and the formal housing sector. After outlining our identification strategy, in Section 3.2 we provide an analysis of how immigration affects the emergence, expansion, and population of slums, which we interpret as changes in informal housing supply. Section 3.3 turns to the formal housing market and analyzes how immigration influences construction activity and the composition of new housing supply in the formal sector. Section 3.4 provides evidence consistent with substitutability between the two housing markets and the rest of the section assesses alternative mechanisms and provides robustness checks.

3.1. Identification Strategy

We are interested in the following long-difference specification for municipal housing outcome changes between 2011 and 2021:

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

where $\Delta Y_{m,2011\text{–}2021}$ denotes the change in either informal or formal housing outcomes in municipality m over the period, measured mainly as the number of households living in slums, the number of slums, the number of formal housing projects and the number of formal housing units permitted. The key regressor, $\Delta \mathit{ImmStock}_{m,2011\text{–}2021}$, captures the change in the immigrant stock in municipality m between 2011 and 2021, constructed as the cumulative sum of annual migrant permits reporting residence in that municipality over the decade.[13]

Note that some municipalities exhibit no informal housing throughout the entire period of analysis, so a log specification would not be well defined for those observations. In such cases, it is common to rely on alternative transformations of the outcome, such as $log(Y + 1)$, which approximates $log(Y)$ for large values of Y while remaining well defined at zero. However, as Chen and Roth (2024) caution, "plus-one" log transformations of zero outcomes do not admit a straightforward interpretation as (approximate) average percentage effects, since $log(Y + 1)$ is sensitive to the units in which Y is measured. Hence, to be on the safe side, equation 1 is specified in levels rather than logs.

Second, estimating equation 1 by OLS is likely to yield biased estimates because immigration inflows are endogenous to municipality-level conditions that also affect slum outcomes. While immigration is partly driven by origin-country supply-push shocks that are common across destinations, immigrants also sort across municipalities based on local demand-pull factors such as housing costs, labor market conditions, amenities, and local policies that enter the error term of

[13] Although our data are available at the annual municipality level, housing supply adjusts slowly over time. We therefore adopt a long-difference specification for the instrumental variables analysis, which is well suited to capturing longer-run responses of both informal and formal housing to immigration inflows. As a robustness check, Appendix Section C presents a biennial frequency specification estimated at the unit level, showing that the timing of immigration shocks and unit dynamics aligns with the patterns implied by the long-difference results.

equation 1. Consequently, cross-municipality variation in immigration may reflect endogenous location choices rather than exogenous shocks. For instance, a positive local economic or housing shock could both attract immigrants and reduce slum growth, biasing OLS estimates of β downward. Similarly, municipality-specific political or policy changes may differentially affect slum dynamics while simultaneously influencing immigrant settlement patterns, generating bias of ambiguous sign. These concerns motivate an instrumental variables strategy that isolates variation in immigration driven by origin-country shocks and pre-determined settlement patterns, which affect slum outcomes only through their impact on immigration inflows.

Our shift–share approach follows Bianchi et al. (2012) and Ajzenman, Domínguez, and Undurraga (2023) and exploits origin-country supply-push shocks as exogenous shifters of immigrant inflows across municipalities. The instrument interacts these origin-specific out-migration shocks with pre-determined settlement shares, measured as the share of immigrants from each origin country residing in municipality m in 2010, the year preceding the rapid acceleration of immigration to Chile.

Specifically, our shift–share instrument predicts immigrant inflows between 2011 and 2021 in each municipality m as follows:

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

where $\theta^{n}_{m,2010}$ denotes the share of immigrants from origin country n among the total immigrant population residing in municipality m in 2010, the pre-shock year.[14] The second component of the instrument summand, $\Delta OutMig^{n}_{2019-2010}$, measures total outmigration from origin country n to destinations *other than Chile* over the 2010–2019 period.[15] The instrument is constructed as the sum, across origin countries, of municipality-level immigrant shares by origin interacted with origin-specific emigration flows to destinations outside Chile. The immigration instrument follows the modern Bartik/shift-share framework: municipalities with larger pre-existing exposure to specific origin groups experience larger predicted inflows when those origin-specific national outflows rise.

Identification relies on the assumption that pre-2011 immigrant settlement patterns across municipalities are orthogonal to municipality-specific shocks to housing outcomes over the 2011–2021 period, except through their effect on subsequent immigration inflows. Under this assumption, variation in predicted immigration generated by origin-country supply-push shocks and historical settlement shares isolates plausibly exogenous variation in local immigrant

[14] Formally, $\theta^{n}_{m,2010} = ImmStock^{n}_{m,2010} / \sum n' ImmStock^{n'}_{m,2010}$, where n' indexes all origin countries. To construct nationality-specific immigrant stocks at the municipality level in 2010, we combine the 2002 Population Census (INE, 2002) with administrative records on country-specific immigration inflows between 2003 and 2010 from Extranjería-Chile (2021).

[15] We use data from the United Nations Population Division (United-Nations, 2021), which report bilateral stocks of international migrants for 232 countries and territories at five- or two-year intervals between 1990 and 2019. Using these data, we construct net emigration flows between 2010 and 2019 for 11 origin countries—Argentina, Bolivia, Brazil, China, Colombia, Ecuador, Haiti, Peru, Spain, the United States, and Venezuela—which together account for 86% of residence permits in 2010 and 95% in 2019. For each origin country n, $OutMig^{n}_{2019-2010}$ is the change in the stock of migrants from country n to countries other than Chile between 2010 and 2019.

populations, purged of municipality-specific demand-pull factors. In other words, conditional on controls, historical settlement patterns affect slum growth and formal housing outcomes only by shaping the distribution of immigration inflows across municipalities.[16]

To assess the plausibility of this identifying assumption, we implement the diagnostic and validity checks proposed by Goldsmith-Pinkham et al. (2020). We find no evidence of differential pre-trends in slum formation or formal housing supply prior to the immigration surge. These findings support the identifying assumption underlying the shift–share instrument and lend credibility to a causal interpretation of our estimates. Appendix Section B provides these checks.

3.2. Effects on Informal Housing Supply

We estimate the causal effect of immigration on informal housing using long-difference (2011–2021) regressions across all urban municipalities in Chile (243 in total). Our empirical strategy exploits plausibly exogenous variation in immigrant inflows by implementing the two-stage least squares (2SLS) instrumental variable design at the municipality level discussed above. Table 2 reports both OLS and IV estimates; throughout this section we focus on the IV results, as OLS estimates are potentially biased by endogenous migrant location choices. As shown, the instrument has a first-stage homoskedastic F-statistic of 11.64, above the conventional threshold for weak instruments.[17]

We begin by examining what we term the intensive margin, focusing on how immigration affects the number of households residing in slums. The second column in Panel A shows that for every 1,000 immigrants arriving in a municipality between 2011 and 2021, the slum population increases by approximately 20 households, corresponding to a 16 percent increase relative to the 2011 mean. Given an average immigrant inflow of roughly 11,000 individuals per municipality over the period, this implies an increase of about 220 slum households attributable to immigration. This magnitude indicates that immigration can account for essentially all of the observed growth in slum households during the decade.

The increase in slum population reflects changes among both native and immigrant households (Columns 4 and 6 of Table 2). For every 1,000 immigrants, the number of native households living in slums rises by about eight, a 7 percent increase relative to the baseline mean. At the same time, immigrant households living in slums increase by roughly twelve, corresponding to a six-fold rise relative to their initial level. These results indicate that the expansion of slum households is not driven exclusively by immigrant self-sorting into informal housing but also by increased participation of native households.

Immigration also leads to a substantial spatial expansion of informal settlements. Aggregating slum areas within each municipality, we find that for every 1,000 immigrants, total slum area

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

[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. Our partial R^2 is 0.02, which is well above the inverse of the number of observations (1/243=0.0041). Instrument strength is further assessed using the effective first-stage F-statistic proposed by Montiel-Olea and Pflueger (2013), which is robust to heteroskedasticity. The effective F-statistic is very similar to the conventional homoskedastic first-stage F-statistic and comfortably exceeds conventional thresholds for weak instruments.

increases by 4,320m^2, implying an average increase of about 47,500m^2 over the decade. This effect nearly doubles the 2011 mean slum area. The close correspondence between household growth and spatial expansion suggests that increases in slum density are accompanied by proportional outward growth, pointing to a roughly one-to-one relationship between demographic and spatial adjustments in informal housing.

We next turn to the extensive margin, examining how immigration affects the number of slums within a municipality. Panel B of Table 2 shows that for every 1,000 immigrants, the number of slums increases by 0.09 units, corresponding to a 4 percent rise relative to the average number of slums per municipality in 2011. Given the average immigrant inflow over the period, this implies an increase of roughly one additional slum per municipality attributable to immigration. Since the observed average change in the number of slums between 2011 and 2021 is also approximately one, immigration can account for essentially all of the net increase in slum counts across urban municipalities.

To understand the mechanisms behind this extensive-margin effect, we decompose changes in the number of slums into creation, persistence, and closure. We measure slum creation as the number of territories transitioning from non-slum to slum status between 2019–2021 relative to 2011–2013. We find that for every 1,000 immigrants, the number of newly created slums increases by 0.09 units, representing a 21 percent increase relative to the baseline rate of slum creation. In contrast, we find no statistically significant effects of immigration on the number of slums that persist over time or on the number of slums that close. Thus, the positive effect of immigration on the stock of slums is driven almost entirely by the formation of new slum territories rather than by changes in the longevity of existing settlements.[18]

Finally, these conclusions are robust to family-wise error rate corrections for multiple hypothesis testing (e.g., Holm, 1979), and this is the case for both intensive and extensive margin outcomes.

3.3. Effects on Formal Housing Supply

We now examine the effect of immigration on the expansion of formal housing supply using annual administrative records on construction permits issued by the Housing Authority Regulator (DOM) at the municipality level between 2011 and 2021. The DOM data capture not only the number of construction permits issued (covering both single-family homes and multi-unit buildings with quality ratings) but also the number and quality of units approved for each project, allowing us to measure formal housing supply at a granular level.

Following our shift-share identification strategy, we estimate the causal effect of the 2011–2021 immigrant inflow per municipality on long-difference changes in formal housing construction. Specifically, we instrument the net immigrant inflow with the supply-push

[18] We verify that these results are not driven by aggregation at the municipality level by re-estimating our specifications using a balanced panel of 1,359 ever-slum territories observed biennially between 2011 and 2021, exploiting two-year changes in immigration at the municipality level (uninstrumented). The slum-level panel estimates yield qualitatively and quantitatively similar results for slum creation, persistence, and closure. Details of this alternative specification are reported in Appendix Section C.

component of immigration growth, constructed as the beginning-of-period immigrant shares interacted with origin-country-specific out-migration shocks, $\Delta \widehat{ImmStock}_{m,2021-2011}$.

Table 3 reports the results. For conciseness, we present only the 2SLS estimates. Column 1 shows that an inflow of 1,000 immigrants into a municipality increases the number of construction permits by approximately 42. Given an average inflow of 11,000 immigrants per municipality over 2011–2021, this implies that immigration accounts for roughly 31 percent of the observed increase in construction permits. Expressed in terms of housing quantities, column 4 indicates that every 1,000 immigrants generate an additional 105 permitted housing units, implying that the average immigrant inflow explains about 55 percent of the increase in formal housing units built during the period.

Disaggregating by housing quality reveals that the expansion in formal housing supply is entirely driven by high-quality construction. Columns 2, and 5 show sizable and statistically significant effects on permits and units associated with high-quality housing, measured both in terms of units and total floors. In contrast, we find no evidence that immigration increases the supply of low-quality formal housing (Columns 3 and 6)[19]. This pattern implies that while immigration induces a substantial formal supply response, that response is concentrated in higher-end housing segments and does not expand the stock of more affordable formal housing. As a result, lower-income households (both immigrant and native) remain exposed to binding affordability constraints, increasing the likelihood of sorting into informal housing.

3.4. Substitutability between Formal and Informal Housing Supply

The immigration-induced expansion of slums documented above is likely mediated by shortages of affordable formal housing. As shown, while immigration substantially increases formal housing supply, these gains are concentrated in high-quality units, with little expansion at the lower end of the market. We therefore hypothesize that when affordable formal housing fails to adjust, part of the immigration-induced demand shock is absorbed by the informal sector. Under this mechanism, municipalities where formal construction is more constrained should experience larger slum responses to immigration.

To test this hypothesis, we exploit exogenous geographic variation in construction costs. This is a standard approach in urban economics. Rugged terrain raises the cost of formal construction through higher expenditures on grading, excavation, and foundations (e.g., Gyourko and Saiz, 2006; Saiz, 2010). In contrast, informal housing relies on low-capital, incremental construction and is unlikely to be directly constrained by terrain. We therefore interpret terrain ruggedness primarily as a shifter of formal-sector supply costs, rather than a direct determinant of slum

[19] The construction quality associated with each project is defined according to the classification established by the General Ordinance on Urban Planning and Construction (OGUC) of the Ministry of Housing and Urbanism (MINVU). Each project is assigned a quality score ranging from 1 to 5, based on 24 indicators that capture structural integrity, construction materials, energy systems, building height and area, and safety features, among others. Scores of 4 or 5 correspond to low-quality construction. Type 4 classifications typically involve low-cost materials (e.g., zinc roofing, fiber cement, galvanized iron, vinyl flooring, or unfinished concrete) and, although basic services such as water, sewerage, and electricity are present, installations are often exposed and living spaces may exhibit deficiencies in ventilation, sunlight, or functionality. Type 5 classifications correspond to the lowest-quality housing, which can lack services, exhibit structural deficiencies, and present minimal finishes.

formation.

We measure ruggedness using high-resolution (30 arc-second) grid-cell data and compute a municipality-level, area-weighted average of the Terrain Ruggedness Index (TRI) following Nunn and Puga (2012). For ease of exposition, we classify municipalities as high-ruggedness or low-ruggedness depending on whether their TRI lies above or below the median, yet the evidence is robust to the use of alternative thresholds. Because ruggedness is time-invariant, we treat it as exogenous and estimate our baseline 2SLS long-difference specification for 2011–2021, interacting immigration inflows with a high-ruggedness indicator and instrumenting both the level and interaction terms using the corresponding shift-share immigration shock and its interaction with ruggedness.[20]

Table 4, Panel A, shows a pattern of immigration leading to smaller expansions of formal housing supply in high-ruggedness municipalities. In column 1, we see that for every 1,000 migrants to a municipality, there are 56 more construction projects permitted in low ruggedness municipalities, whereas point estimate is about half (26 projects) in high ruggedness municipalities. When we consider the number of units permitted, a similar pattern emerges: 124 units for every thousand migrants in low ruggedness municipalities and only 82 in high ruggedness locations. This differential response is driven almost entirely by low-quality housing responses. For every thousand immigrants, low-quality permits increase by about 20 in low-ruggedness municipalities but decline by 15 in high-ruggedness municipalities. These patterns are consistent with developers reducing affordable housing supply when construction costs are high, leading to a more constrained expansion in the formal housing sector when immigration surges.

Panel B shows that higher ruggedness also translates into larger slum responses to migration. Column 1, focusing on the total number of slums, shows that in low ruggedness municipalities the effect of immigration is 0.05 slums per thousand migrants (not significantly different from zero), which contrasts with an increase of 0.13 slums per thousand migrants in high ruggedness municipalities (p-value=0.024). Column 5 showing effects on the total number of households living in slums is stark: low-ruggedness municipalities experience an increase of only 13 additional slum households per 1,000 immigrants, while in high-ruggedness municipalities the response is twice as large, at 27.

Overall, these patterns point to the interconnectedness of the two housing markets and provide evidence consistent with our hypothesis: When formal housing sector construction costs limit the responsiveness of supply, immigration-induced demand spills over into slum formation.

3.5. Robustness Checks

Income Effects. An alternative hypothesis is that slum formation is driven by income effects: if immigrants are too poor or contribute to the economic decline of cities, then slums are expected to multiply. We test for this by evaluating whether changes in immigration affected changes on poverty and extreme poverty rates, as well as on *per capita* income and unemployment rate. We

[20] We note that there is no correlation between immigration inflows and ruggedness, suggesting that migrants do not systematically sort across municipalities based on terrain.

find no evidence of immigration affecting any of these dimensions. See Appendix Section D for details. In addition, we test for whether migrants' levels of education (if had high school diploma or not) had any influence on slum formation, and find no heterogeneous effects. Overall, these results suggest income effects are unlikely to explain the positive effects of immigration on slum growth.

Political Capture. Another potential mechanism behind the immigration-slum link is political capture and policy coordination, wherein politicians safeguard slums inhabited by immigrant majorities to secure votes from this burgeoning electorate, thereby attracting immigrants to slums. However, we observe the intensity of the slum policy does not vary with the level of immigration across municipalities, with slum policy measured by housing subsidies and urbanization programs. Appendix Section E provides detailed evidence on this. The latter suggests the positive effects of immigration on slum growth is unlikely to be mediated by exclusionary policies or program-based political capture.

Subsample Analysis. One concern is that the estimated effect of immigration on slum formation may be mediated by the *Estallido Social* protests that erupted in Chile in 2019, which arguably weakened state capacity to enforce property rights and may have facilitated illegal land occupations. We assess this possibility in Appendix Table A.IV by re-estimating the 2SLS specification using only pre-protest data from 2011–2017. Both extensive and intensive margin effects remain robust when excluding the post-2017 period, suggesting that the estimated immigration effects are unlikely to be driven by the *Estallido* protests.

Temporary versus Permanent Visas. 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, Domínguez, and Undurraga (2023), we test whether the results are robust to using temporary residence permits only. Appendix Table A.I 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 settled permanently in the country.

Inference. In Appendix Table A.I, 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, except for those on formal housing outcomes, for which the estimates become less precise. 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. 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.

Internal Migration and Non-compliance. Third, immigrants may relocate across municipalities after initially declaring their intended residence. Such internal mobility would introduce non-compliance in the "share" component of the instrument, potentially weakening its predictive power. Although we cannot directly observe post-arrival internal migration, this concern should be attenuated if most moves occur across neighboring municipalities, since immigration effects would then persist when these municipalities are treated as a single unit.

To assess this possibility, we randomly aggregate contiguous municipalities into pairs and re-estimate our specifications using these combined units.[21] This procedure yields 108 municipality pairs; 27 municipalities remain unmatched (20 without available partners and 7 with no contiguous urban neighbors). As shown in Appendix Tables A.II and A.III, the estimates are largely unchanged. These results suggest that short-distance internal migration across neighboring municipalities does not materially affect our findings on formal and informal housing supply responses.

4. The Role of Slums in Constrained Formal Housing Markets

Our reduced-form evidence shows that the surge in immigration to Chile led to measurable expansions in slum area and population. In contrast, within the formal housing sector, immigration spurred the construction of high-quality units, but not affordable ones. These patterns suggest that slums, while providing substandard living conditions, serve as an affordable outside option when formal supply is constrained. Moreover, as reported in Table 1, since immigration increased the share of educated individuals (who are arguably less likely to reside in slums) by a larger relative margin than that of their less educated counterparts, then slum expansions appear to be the product of indirect market adjustments to the immigration shock rather than a direct rise in slum demand from newcomers.

We cannot capture these indirect channels using reduced-form estimates alone. To examine how slums shape adjustment in a system of cities exposed to immigration shocks, as well as the general equilibrium forces through which they operate, we extend and calibrate a simple static quantitative spatial model with heterogeneous agents and two housing sectors, formal and informal. We calibrate this model using our detailed data on slums and formal housing across Chilean municipalities. This allows us to perform a series of counterfactual exercises replicating variations of the observed immigration shock to evaluate endogenous outcomes against the baseline equilibrium. The model highlights that in the presence of rigid formal supply, informal housing operates as an endogenous buffer that absorbs population shocks and stabilizes formal housing prices. We find that this endogenous adjustment margin facilitated by slums mitigates potential welfare losses due to sharp increases in formal sector housing rents in their absence.

The motivation for employing a static framework is twofold. First, the immigration shock we

[21] For each urban municipality, we identify its contiguous neighbors and randomly select one (without replacement) to form a pair. Once matched, a municipality cannot be reused. Pairing begins with municipalities that have fewer neighbors to maximize coverage.

study is inherently long-run. Our empirical design, therefore, relies on long differences, making the relevant theoretical object a comparison between a pre-shock and post-shock steady state. A static model is well suited to this setting: it maps changes in fundamentals directly into changes in equilibrium outcomes without requiring assumptions about adjustment paths, expectations, or capital accumulation dynamics that are not identified in the data. Second, a static structure keeps the analysis transparent and tractable. It isolates the general-equilibrium forces through which immigration affects formal and informal housing markets, allows calibration directly to observed steady-state moments, and yields counterfactuals that can be interpreted as long-run equilibrium responses.

4.1. A Quantitative Model of a System of Cities with Slums

4.1.1. Setting

The economy is comprised of M municipalities indexed m, n, or r, which are differentiated by productivity and amenities. The economy is endowed with a geography $\boldsymbol{\tau} = [\tau_{mn}]$, where $\tau_{mn} \geq 1$ denotes the iceberg trade costs à la Armington (1969) associated with shipping goods from m to n and own trade (τ_{mm}) is normalized to unity.

The economy is populated by two types of households, high-educational attainment and low-educational attainment indexed $i \in \{h, \ell\}$, with each type having a fixed population denoted $\overline{L}_i$. Households supply one unit of labor inelastically and make joint discrete choices about where to live and in what type of housing to reside. This joint choice is consistent with the evidence in Section 3.4, which shows that formal and informal housing are substitutes and that margins of adjustment vary in response to immigration-induced changes in relative rents. Households consume a bundle of consumption goods comprised of a differentiated good from each municipality and local housing floorspace. They consume floorspace supplied by the formal sector f or the informal sector s. A type-i household indexed ω, who chooses to live in municipality m in type-$k \in \{s, f\}$ housing, earns a wage w_{im} and has Cobb-Douglas preferences over a bundle of consumption goods C_{im} and housing floorspace H_{imk}:

$$U_{imk}(\omega) = B_{imk} \left(\frac{C_{im}}{\beta}\right)^{\beta} \left(\frac{H_{imk}}{1-\beta}\right)^{1-\beta} \nu_{imk}(\omega), \quad \beta \in (0,1)$$

where

$$B_{imk} = \overline{B}_{imk} L_{mk}^{\eta_k}, \qquad \eta_k < 0$$

$$C_{im} = \left[\sum_n x_{inm}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1$$

$$\nu_{imk}(\omega) \sim \ iid \ F_{imk}(\nu) = F(\nu) = \exp\{-\nu^{-\theta}\}$$

The term B_{imk} is the composite amenity for a type-i household derived from living in type-k housing within municipality m, which is determined by an exogenous component $\overline{B}_{imk}$ and an endogenous component $L_{mk}^{\eta_k}$. The endogenous component is governed by the total number of households of all types residing in m who choose to live in type-k housing, L_{mk}, and η_k. The parameter η_k captures congestion disamenities in type-k housing associated with higher populations. The consumption index, C_{im}, is the usual CES aggregator that takes as input the amount of the good from n consumed by a type-i household residing in municipality m, denoted x_{inm}. Finally, the term $\nu_{imk}(\omega)$ is household ω's idiosyncratic preference shock for living in m in type-k housing, which is distributed Fréchet with shape parameter θ.

Given $\nu_{imk}(\omega)$ is distributed Fréchet, the probability a type-i household lives in type-k housing within municipality m is given by:

$$\pi_{imk} = \frac{(B_{imk} w_{im})^{\theta} \left(P_m^{\beta} R_{mk}^{1-\beta}\right)^{-\theta}}{\sum_n \sum_{l \in \{s,f\}} (B_{inl} w_{in})^{\theta} \left(P_n^{\beta} R_{nl}^{1-\beta}\right)^{-\theta}} \tag{3}$$

where $P_m = \left[\sum_r (p_{rm})^{1-\sigma}\right]^{1/1-\sigma}$ is the CES price index in m, p_{rm} is the price of the good produced in r and sold in m, R_{mk} is the unit price of floorspace of type-k in m, and w_{im} is the wage of type-i worker in m. With this setup, the expected utility (and average ex-post utility) of a type-i worker is:

$$W_i \equiv E_{\nu} \left[\max_{m,k} W_{imk}(\omega)\right] \propto \left[\sum_n \sum_{l \in \{s,f\}} (B_{inl} w_{in})^{\theta} \left(P_n^{\beta} R_{nl}^{1-\beta}\right)^{-\theta}\right]^{\frac{1}{\theta}} \tag{4}$$

A perfectly competitive representative firm in each location produces the differentiated good and uses labor as its sole input. Wages paid to labor depend on the relative importance of a household type in the production process. Total output, Y_m, is produced via the following Cobb-Douglas production function:

$$Y_m = A_m \prod_i L_{im}^{\alpha_i}$$

where $\sum_i \alpha_i = 1$ and $A_m = \overline{A}_m L_m^{\varepsilon}$. The composite term A_m captures exogenous municipality-specific productivity, $\overline{A}_m$, and agglomeration economies external to the firm based on the size of the municipality, $L_m = \sum_i L_{im}$, the extent of which is governed by the parameter ε. The firm in m charges a mill price per unit of output denoted p_m, and the price of the m good in municipality n is denoted $p_{mn} = \tau_{mn} p_m$.

In each municipality, there are two types of housing developers: formal developers (f) and informal developers (s). Developers in both sectors are perfectly competitive. A type $k \in \{s, f\}$ developer produces housing floorspace in municipality m using the following technology:

$$H_{mk} = \overline{a}_{mk} R_{mk}^{\gamma_k} \tag{5}$$

where γ_k is the housing supply elasticity of type-k floorspace and $\overline{a}_{mk}$ is the exogenous productivity of type-k developers in m. The stock of both formal and informal housing is owned by absentee landlords.

4.1.2. Equilibrium

Given exogenous location characteristics $\{\overline{A}_m, \overline{B}_m, \tau_{mn}\}$, household type populations $\{\overline{L}_i\}$, and model parameters $\{\alpha_i, \beta, \gamma_k, \varepsilon, \theta, \eta_k, \sigma\}$, the equilibrium in this model is defined as a vector of endogenous objects $\{L_{imk}, w_{im}, R_{mk}, W_i\}$ satisfying:

1. Goods market clearing: total labor income in m must equal the total expenditure on the good produced in m across all municipalities

$$\sum_i w_{im} L_{im} = \beta \left(\frac{\prod_i w_{im}^{\alpha_i}}{\chi A_m} \right)^{1-\sigma} \sum_n \left(\frac{\tau_{mn}}{P_n} \right)^{1-\sigma} \sum_i w_{in} L_{in}, \quad \forall m \tag{6}$$

2. Labor market clearing: household type (joint) location and housing shares must equal Fréchet choice probabilities

$$\frac{L_{imk}}{\overline{L}_i} = \pi_{imk}, \quad \forall i, m, k \tag{7}$$

3. Housing market clearing: total supply of type-k floorspace in m must equal total demand

$$\bar{a}_{mk} R_{mk}^{\gamma_k} = \frac{(1-\beta) \sum_i w_{im} L_{imk}}{R_{mk}}, \quad \forall m, k \tag{8}$$

where $\chi \equiv \prod_{i=1}^{N} \alpha_i^{\alpha_i}$ measures the Shannon Entropy of factor shares. See Online Appendix Section G.1 for the full derivation of the equilibrium conditions.

4.2. Calibration and Quantification

To perform counterfactual exercises, we causally identify the key housing supply elasticities in the model for both housing sectors. Remaining parameters are calibrated using values from the literature and public data sources. We then employ common inversion techniques in the spatial literature to recover exogenous fundamentals given observed wages, rents, and populations in tandem with calibrated model parameters (see Redding and Rossi-Hansberg, 2017 for details).

4.2.1. Data

We calibrate the model using a sample of urban municipalities in Chile with observed slum rents. Using CASEN survey data, we proceed as follows:

1. We classify respondents holding less than a high school diploma as l-types; all others are h-types;

2. We observe the number of i type households living in k type housing across each municipality, L_{imk};

3. We obtain wages by type, w_{im}, and compute municipality-level medians;

4. We flag dwellings as informal (s) whenever the housing unit's sanitation system is classified as "deficient" or residents live under overcrowded conditions; all remaining units are deemed formal (f);

5. For each municipality m and housing type $k \in \{f, s\}$, we compute median unit rents R_{mk}. Since agents in the model consume floorspace, not discrete units of housing, we convert rents to price per square meter. In the formal sector, we divide unit rents by the average formal housing lot size in m (a proxy for floor area). In the informal sector, we use data from the slum panel and divide the total slum area in each m by the number of slum-dwelling households to proxy for floorspace per slum housing unit in m. Slum prices per square meter are then the CASEN median rent of informal housing divided by this value.[22]

4.2.2. Causal Estimates of Housing Supply Elasticities

Our results from previous sections show that increases in the demand for housing driven by international migration triggered a sizable increase in both formal and informal housing supply. As far as the migration shock affected housing supply only through changes in housing demand (i.e., not through direct or indirect changes in the primitives of housing supply), then we can combine CASEN data on changes in rent prices with data on changes in the stock of formal and informal housing units to trace up each supply curve, causally identifying the housing supply elasticities γ_f and γ_s.

We derive estimating equations from the functional form of housing production in the model, and use CASEN data for the years 2011 and 2020 for estimation. Though the model is static, we interpret both 2011 and 2020 as steady state equilibria and estimate inverse housing supply elasticities via a long-difference form of the model. Implicitly, this approach assumes a time-invariant γ_k and a multiplicative technology term with a common k-specific trend and an idiosyncratic market component. The long differences absorb levels, common drift, and the influences of transient shocks. Our parameter of interest is identified through the plausibly exogenous immigration shock exploited above.

Concretely, taking the log-difference of equation 5 between 2011 and 2020 after further parameterizing $\overline{a}_{mkt} = a_{mkt}a_{kt}$, where a_{mkt} captures the location-specific technological component for producing k housing at time t and a_{kt} captures the common (i.e., country-wide) component, yields:

$$\Delta \ln H_{mk,2020-2011} = \Delta \ln a_{k,2020-2011} + \gamma_k \Delta \ln R_{mk,2020-2011} + \Delta \ln a_{mk,2020-2011}$$

[22]This implicitly assume that slums are one story. For observations where data are missing, we impute missing values for slum area and units using a municipality's most similar neighbor in terms of slum population.

The model-implied specification to estimate the inverse housing supply elasticity for the 2011-2020 rents growth in housing sector k is then

$$\Delta \ln R_{mk,2020-2011} = \widetilde{\alpha} + \widetilde{\beta}_k \Delta \ln H_{mk,2020-2011} + \widetilde{\epsilon}_{mk,2020-2011} \quad (9)$$

where $\widetilde{\alpha} \equiv -(1/\gamma_k)\, \Delta \ln a_{k,2020-2011}$, $\widetilde{\beta}_k \equiv 1/\gamma_k$, and $\widetilde{\epsilon}_{mk,2020-2011} \equiv -(1/\gamma_k)\, \Delta \ln a_{mk,2020-2011}$. Note that this functional form has a mapping to the empirical specifications utilized by other authors, such as Saiz (2010) and Diamond (2016).[23]

Since log-differences are numerically fragile in the presence of small baseline values, which are common in our data, we recover housing supply elasticities using a level-difference specification that serves as a first-order (local) approximation to the model-implied estimating equation. This approach is consistent with our empirical strategy in earlier sections. Specifically, for small changes we have

$$\Delta \ln R_{mf,2020-2011} \approx \frac{\Delta R_{mf,2020-2011}}{\overline{R}_{mf,2011}}, \qquad \Delta \ln H_{mf,2020-2011} \approx \frac{\Delta H_{mf,2020-2011}}{\overline{H}_{mf,2011}}$$

where $\overline{R}_{mf,2011}$ and $\overline{H}_{mf,2011}$ denote baseline (2011) averages. Substituting these approximations into equation 9 yields the level-difference analog

$$\Delta R_{mf,2020-2011} \approx \alpha + \beta_k \Delta H_{mf,2020-2011} + \epsilon_{mk,2020-2011} \quad (10)$$

where $\alpha = \widetilde{\alpha}\, \overline{R}_{mf,2011}$, $\beta_k = \widetilde{\beta}_k \left(\overline{R}_{mf,2011}/\overline{H}_{mf,2011}\right)$, and $\epsilon_{mk,2020-2011}$ is the error term.

It follows that the housing supply elasticity implied by the model can be recovered from the estimated level-difference coefficient as

$$\gamma_k \;\approx\; \frac{1}{\beta_k} \left(\frac{\overline{R}_{mf,2011}}{\overline{H}_{mf,2011}} \right)$$

which we interpret as the elasticity evaluated at baseline means.

For the formal housing sector $\Delta R_{mf,2020-2011}$ is the 2020-2011 levels difference in the median rent price of formal housing and $\Delta H_{mf,2020-2011}$ represents formal housing demand levels difference in municipality m between 2011 and 2020, that is, for each municipality, we take the difference between the accumulated number of units built between 2020 and 2011.

Identification. We obtain a causal estimate of the supply inverse-elasticity parameter β_f for formal housing by instrumenting housing demand changes by the supply-push component of 2011-2020 immigration growth per municipality, weighted by the beginning-of-period share of immigrants. We assume our shift-share instrument is relevant for formal housing demand

[23] Glaeser and Gyourko (2025) argue that structurally identifying long-run housing supply elasticities in the US (and, implicitly, other advanced economies) is complicated because demand shocks coupled with shifts in neighborhood composition can endogenously alter local permitting and regulation, flattening observed supply responses over time. Such feedback mechanisms may be less pronounced in middle-income countries like Chile, where housing markets and local regulatory institutions are less mature.

changes but excludable from formal housing supply factors determining rent prices, and provide evidence supporting this assumption (more on this below). Otherwise, immigration-driven price changes would also reflect changes in the supply of formal housing, thereby impeding a causal identification of the elasticity.[24]

Note that a similar equation can be estimated for levels differences in informal housing rents $\Delta R_{ms,2020-2011}$, with $\Delta H_{ms,2020-2011}$ proxied by the number of households residing in slums, and the identification conditions for recovering a causal estimate of the inverse-elasticity parameter follows the very same logic. To avoid using the same shift-share instrument for two different endogenous variables, we instrument changes in the demand for formal housing by the supply-push component of 2011-2020 growth of high-education immigrants per municipality (completed high school or more), weighted by the beginning-of-period share of high-education immigrants. In contrast, we instrument changes in the demand for informal housing by exploiting the exogenous growth of the remaining low-education immigrants. 2SLS models are estimated separately for each housing type.

Data on slum rents are unfortunately very limited and typically come from unofficial and non-representative sources, which are not directly comparable to the representative formal rent data available from CASEN. These data, however, provide reliable household-level information on housing quality (such as access to basic services and overcrowding) which are commonly used as proxies to distinguish formal from informal housing (UN-Habitat, 2003). We therefore construct three alternative definitions of formal and informal housing based on CASEN data, each generating mutually exclusive categories:

(i) a binary indicator of whether the housing unit's sanitation system is classified as "deficient" (informal) or "acceptable" (formal);

(ii) a binary indicator of whether residents live under overcrowded (informal) or non-overcrowded (formal) conditions; and

(iii) a composite indicator identifying a unit as informal if it meets either (i), (ii), or both criteria.

Each definition produces a clear dichotomy, i.e., housing units are either formal or informal. Having multiple definitions is not merely for accommodation but allows us to assess the robustness of our results and ensure they are not driven by ad hoc classification choices.

[24] Saiz (2010) estimates the housing supply elasticity across metro areas in the U.S. by regressing changes in rent prices (adjusted by construction costs) on changes in population between 1970 and 2000 as a proxy of changes in housing demand, and instrumenting housing demand by a shift-share instrument. A potential drawback of this strategy is that individuals have different tastes for housing, and thus the number of housing units demanded may not be well reflected in the total population. We attempt to overcome this measurement error problem by using the effective number of units built as a proxy of the formal housing units demanded. Of course, measurement errors may persist if there is vacancy in built floors. However, this is unlikely in our context as Chile is a country where formal housing deficit has been large and persistent during the last decades, oscillating from 675,000 units in 1996 to 575,000 in 2020 (CECT, 2024).

Internal Validity. A first internal validity test consists of showing that the differential exposure to the 2011-2020 common immigration shock does not lead to differential changes in rents, i.e., the 2010 "share" component does not predict rental price changes through channels other than immigration-driven housing demand. As is shown in Appendix Figure B.II, we find there are parallel trends on rental prices before the immigration shock began, and this is the case for both formal and informal housing types.

We also examine the extent to which immigration inflows affected equilibrium employment and wages in the housing construction labor market. According to CASEN 2020, only 7% of workers in the construction sector are migrants. Also, the share of migrants declaring that their field of job specialization is construction is 8%, which is small and similar to that of locals (6%).[25] We use 2011 and 2020 CASEN data to estimate the causal effect of immigration on 2020-2011 changes in the share of workers in the construction sector by using $\Delta \widehat{ImmStock}_{m,2020-2011}$ as an instrument of the 2011-2020 net immigrant inflow per municipality. As is shown in Appendix Table F.I, we find no effects of immigration on the construction industry's labor supply, and this is the case for all workers as well as for subgroups of native and migrant workers. We then replicate the exercise but for changes in mean wages in the construction sector as the outcome, and again, null effects are observed. Overall, this result suggests that immigration inflows are orthogonal to changes in labor inputs of housing supply, which in turn imply our shift-share instrument is excludable, i.e., it affects rents through no other alternative channel than changes in formal housing demand.[26]

Results. Table 5 presents 2SLS estimates of equation 10. Regressions are run on the cross-section of 2011-2020 within-municipality differences considering the full set of urban municipalities in Chile for which CASEN data on rent prices was available in both rounds, 222 in total. Regression columns (1)-(3) estimate the housing supply elasticity in the formal housing market, with each regression using a different definition of formal housing. This is calculated as the inverse of the elasticity coefficient multiplied by the ratio of mean changes in housing demanded (independent variable) over mean changes in median rents (dependent variable). Estimates reveal that immigration-driven changes in housing demand generated statistically significant increases in formal rent prices, with the results being robust across different definitions, for a housing supply elasticity that ranges between 1.64, our preferred estimate, and 1.73. This is within the range of elasticity estimates provided by Glaeser et al. (2008), not far from the 1.54 estimated by Saiz (2010) for the case of the U.S. and close to the 1.86 estimated by Combes et al. (2021) and Baum-Snow and Duranton (2025) for the case of France.[27]

[25] We identify jobs in the construction industry as CASEN categories associated with building construction, civil engineering construction (e.g., heavy civil or heavy construction), and specialized construction activities like electrical, plumbing, and heating work.

[26] The absence of a construction industry in the informal housing sector implies that most slum dwellings are self-constructed by slum dwellers. Housing expansion in these areas thus occurs outside market-based labor demand for construction, relying largely on household and community labor inputs.

[27] Our main estimates of housing supply elasticity are defined at the housing-unit level. As a robustness check, we re-estimate the same specification using per-square-meter measures, rescaling changes in median rents and housing quantities by median housing size in 2011, the only year for which housing-size data are available. The

Next, regression columns (4)-(6) replicate the analysis for the alternative definitions of informal housing. The sample size is naturally lower and varies across regression models since not all municipalities had informal housing units in the CASEN survey sampling. Yet the results are, again, quite robust across the board. Our estimates suggest the informal housing supply elasticity ranges between 5.37 and 6.65, with this being 6.21 under our preferred composite measure of informal housing in the last column.[28]

4.2.3. Additional Parameters

We set the output elasticity of high-education workers, α_h, to 0.7 to match their observed share of the total wage bill, implying $\alpha_\ell = 1 - \alpha_h = 0.3$ for low-education workers. The housing expenditure share, $1 - \beta$, is set to 0.18 following the value for Chile reported by the OECD.[29] The agglomeration elasticity in production, ε, and the congestion elasticity in formal housing, η_f, are set to 0.1 and -0.3, respectively, consistent with Allen and Arkolakis (2014). The elasticity of substitution across traded goods, σ, is set to 5, following Redding and Rossi-Hansberg (2017), and the Fréchet dispersion parameter, θ, is set to 3, as in Redding (2016). Following how Faber and Gaubert (2019) calibrate intranational trade costs in Mexico, iceberg trade costs between municipalities are defined as $\tau_{mn} = (d_{mn}/d_{\text{min}})^{1/\sigma}$, where d_{mn} is the great-circle distance between municipality centroids and $d_{\text{min}} = \min_{i \neq j} d_{ij}$ is the minimum observed non-own distance. Own distance is normalized such that $d_{mm} = d_{\text{min}}$, implying own trade costs are normalized to unity. Finally, we set the congestion elasticity in slum housing, $\eta_s = -0.35$, implying slightly stronger crowding disamenities in slums relative to formal housing. Although this choice is somewhat ad hoc, it aligns with the notion that slums experience greater overcrowding. We assess the sensitivity of the predicted outcomes of the counterfactual exercises to this parameter in Online Appendix Section G.3 and find the results are robust to alternative values of η_s, as plotted in Appendix Figure A.V.

4.2.4. Recovering Exogenous Fundamentals

Given parameters $\{\alpha_i, \beta, \gamma_k, \varepsilon, \theta, \eta_k, \sigma\}$, adapting the inversion technique from Redding (2016), we recover the location-specific exogenous components of amenities, firm productivity, and

resulting estimates are somewhat smaller, ranging from 1.12 to 1.32. Although these per-square-meter estimates are not far from our baseline estimates, they are likely downward biased due to classical measurement error, since changes in housing quantities are rescaled using only 2011 median housing size, which may differ from median housing size in 2020 (in the absence of later housing-size data, we must assume that median housing size is constant over time). Consistent with this, the instrument is also weaker in these specifications (F-stat=9.23), likely because measurement error in changes in housing size adds noise to the endogenous variable, thereby reducing its predictability.

[28] The CASEN measures of informal housing we use are based on the housing conditions of surveyed households rather than on neighborhood-level characteristics, which may introduce exclusion errors. In particular, some households classified as living in informal housing may reside in poor or peri-informal neighborhoods rather than in slums. To address this concern, we replicate the analysis restricting the sample to municipalities that, according to slum censuses, contain slums in both 2011 and 2020. The results are qualitatively similar; under the composite definition in column 6, we estimate an inverse supply elasticity of 5.36.

[29] See https://www.oecd.org/content/dam/oecd/en/data/datasets/affordable-housing-database/hc1-1-housing-related-expenditure-of-households.pdf.

housing developer productivity using observed data on populations, wages, and rents. We map the spatial distribution of productivities and amenities across Chile in Appendix Figures A.III and A.IV, respectively. We describe the recovery strategy in detail in Online Appendix Section G.2.

4.3. Policy Counterfactuals

We conduct three counterfactual experiments using the calibrated model to quantify the role of slums in the economy's adjustment to an immigration influx. In each simulation, we shock the baseline economy with the observed population change in Chile between 2011 and 2020 by exogenously increasing the population of high-education households ($\overline{L}_h$) by 20% and low-education households ($\overline{L}_\ell$) by 4%.[30] Table 6 reports municipality-average percentage changes in key endogenous outcomes—wages (w_h, w_ℓ), rents in the formal and informal sectors (R_f, R_s), slum population (L_s), slum floorspace (H_s), and welfare (W_h, W_ℓ)—relative to the baseline equilibrium.

In the first exercise (column 1 of Table 6), we examine the model's response to the immigration shock in isolation. Given the skill composition of the inflow, the model predicts a 7.25% welfare decline for h-types and a 7.14% welfare gain for ℓ-types. Column 1 highlights the core mechanism of the model: the immigration shock raises rents in both housing sectors, reflecting increased housing demand, while generating asymmetric welfare effects across skill groups. The welfare loss among h-types arises primarily from higher rents in the formal sector combined with lower wages due to shock-induced abundance of highly skilled workforce. For ℓ-types, the rise in wages dominates the rent increase, yielding net positive welfare gains. Moreover, consistent with the empirical evidence, the model predicts slum growth at the intensive margin, with the mean number of households residing in slums increasing 10.73% and the area of floorspace occupied by slums increasing 14.66%.

This first analysis suggests that the Chilean immigration shock led to higher housing costs, an expansion of informal housing, and increased wages for the low-skilled group of workers. Weighting by population share, the immigration shock was welfare improving and pro-poor. The model predictions can be compared to the OLS results in the first column and seventh column of Table 2, Panel A, respectively. The predicted changes lie within the estimated 95% confidence intervals, suggesting the model captures observed empirical adjustment mechanisms.[31]

Next, we extend beyond the observed immigration shock by imposing counterfactual restric-

[30] These changes correspond to the 2011–2020 shift in educational composition when immigration is treated as the sole population shock. In 2011, 35.2% of the population held a high-school degree or more; adding the full immigration inflow raises this share to 43%, implying a roughly 20% increase. Over the same period, the share without a high-school degree rises from 64.7% to 67%, corresponding to a roughly 4% increase.

[31] Both the model's predicted changes and the OLS estimates capture the aggregate effects of endogenous general-equilibrium adjustments to immigration shocks. Accordingly, the counterfactual results in Table A.VII are most directly comparable to the OLS estimates. The OLS coefficients imply that an additional 1,000 immigrants between 2011 and 2021 increase the number of slum households by 6.08 and total slum area by 1,428 m^2. At the mean inflow of 11,000 immigrants, this corresponds to a 53.9% increase in slum households (95% CI: [–21.7%, 129.6%]) and a 56.8% increase in slum area (95% CI: [–17.4%, 131.1%]). Slum floorspace maps directly to slum area in this setting, as slums do not build vertically.

tions on the informal housing sector. In the second exercise (column 2 of Table 6), we apply the same immigration shock but hold the stock of slum floorspace fixed at its baseline level, rendering informal housing supply perfectly inelastic. This counterfactual corresponds to a slum-lock policy under which existing slums at baseline are allowed to persist but cannot expand, nor can new settlements emerge.

Relative to the immigration shock in isolation, slum rents increase sharply — by an additional 12.17 percentage points — while formal rents rise more modestly, by an additional 0.2 percentage points. This pattern is intuitive: restricting the informal housing response forces the adjustment to occur through prices rather than quantities in the informal sector. Wage effects remain broadly similar to the baseline counterfactual, but the absence of an informal housing margin substantially worsens welfare outcomes. Aggregate welfare for high-skilled (h) workers declines by a further 5.1 percentage points relative to the initial counterfactual, and low-skilled (ℓ) workers experience welfare losses relative to baseline, with welfare falling by 1.63 percent. This exercise underscores the buffering role of the informal housing sector in limiting housing price increases following an immigration shock. In the absence of a slum response, welfare is predicted to decline for both types of workers.

In the third exercise (column 3 of Table 6), we consider a policy that removes the informal sector entirely, both the existing slums at baseline as well as the new slums that would be formed, a slum clearance policy that forces all households to occupy formal housing. In this case, formal rents rise sharply by 13.39% from the baseline equilibrium, generating welfare losses of 8.69% for ℓ-types and amplifying h-type welfare losses to 18.38%, 11 percentage points worse than in the immigration-only counterfactual.

Taken together, these results suggest that slums act, in some capacity, as a "second-best" adjustment margin when formal housing supply is inelastic. By providing an elastic, low-cost housing option, slums absorb part of the immigration-induced housing demand pressure, moderating rent increases in the formal sector and mitigating welfare losses. We interpret this as evidence that restricting or eliminating slums without concomitant increases in the elasticity of formal housing supply can generate large welfare costs. This evidence is consistent with slums alleviating inefficiencies caused by rigid formal housing markets.[32]

Since welfare losses stem primarily from the rigidity of formal housing supply, increasing the responsiveness of the formal sector can substitute for the cushioning role played by slums. To illustrate this, we take each of the three immigration-shock counterfactuals and impose an additional perturbation: we vary the formal housing supply elasticity γ_f in the counterfactual equilibrium, holding the baseline equilibrium (where $\gamma_f = 1.64$) fixed throughout. In other words, the baseline is never re-solved with a different γ_f; instead, we ask whether shifting γ_f exogenously after the immigration shock offsets the resulting welfare losses.

Figure 4 plots the percent change in welfare for h-type households under this two-step

[32] As a robustness check, we re-calibrate the model and repeat all counterfactual exercises using per-square-meter housing supply elasticities, obtained by re-estimating columns (3) and (6) of Table 5 after rescaling prices and quantities by median housing size from CASEN 2011. This yields $\gamma_f = 1.32$ and $\gamma_s = 7.16$. All qualitative conclusions from Table 6 hold, and welfare losses are larger in magnitude for both household groups across all counterfactuals.

experiment. For each immigration-shock counterfactual, we solve for each counterfactual equilibrium over a dense grid of exogenously imposed values of the formal housing supply elasticity γ_f. This allows us to trace how welfare responds as the formal supply curve is progressively flattened in the new equilibrium. A roughly 25% increase in γ_f (i.e., augmenting it from 1.64 to 2.05) eliminates welfare losses in the first counterfactual; a 45% increase is required under the slum lock-in policy; and a 70% increase suffices even when slums are entirely eliminated. Although these are large interventions, they show that slums primarily act as a buffer against an inelastic formal sector: once formal supply is sufficiently elastic, the cushioning role of slums largely disappears.[33]

Finally, we extend these exercises to a reversed-skill immigration shock (raising $\overline{L}_\ell$ by 20% and $\overline{L}_h$ by 4%) in Appendix Table A.VII. Despite the reversed wage effects, the qualitative role of slums remains: they mitigate welfare losses for the group facing downward wage pressure by tempering rent increases in the formal sector. Appendix Figure A.V further shows that these welfare effects are robust to alternative values of the slum congestion parameter η_s.

5. Conclusion

Standard urban theory predicts that when housing supply is highly inelastic, rising demand translates into sharply higher rents, rendering housing unaffordable and pushing workers toward less productive locations, thereby reducing both wages and aggregate welfare. In many developing-country cities, however, this prediction is altered by the presence of a large informal housing sector, which provides an additional margin of adjustment that allows low-income households to remain in high-productivity locations, reshaping spatial sorting and welfare. In the face of large migration inflows, understanding the role of slums in absorbing population shocks and stabilizing housing markets in general equilibrium is therefore essential.

Leveraging a unique panel dataset that includes all formal and informal housing records in Chile over more than a decade, we provide causal evidence that international migration boosted the demand for housing, yet the supply of formal housing did not respond sufficiently, thereby increasing slum formation and growth. Notably, international immigration can account for all of the observed slum expansion in the study period. To unpack the role of slums and the general equilibrium forces through which they operate, we built a quantitative spatial model that allows high- and low-education workers to choose both where to live and whether to occupy formal or informal (slum) housing, with each sector possessing its own congestion externality and sector-specific housing supply elasticity. The model is calibrated to rich data on wages, rents, and populations across Chilean municipalities, as well as on causally-estimated sector-specific inverse supply elasticities. The model reproduces the intensive growth of slums observed in the data and implies sizable distributional effects: high-education households experience welfare losses driven by higher formal-sector rents and lower wages, while low-education households gain, as stronger labor demand more than offsets rent increases.

[33] Given the skill composition of the immigration shock, any intervention that raises h-type welfare also raises ℓ-type welfare.

Popular housing policies in developing-country cities include slum growth control and slum clearance. A policy experiment that restricts the informal sector's ability to accommodate the immigration shock shows that slum rents increase sharply while formal rents rise modestly relative to the benchmark shock, leading to additional welfare losses for both groups. When slums are fully removed in the new equilibrium and all households are forced into the formal sector, formal rents jump by about 13%, and welfare losses deepen by up to 11 percentage points relative to the benchmark immigration shock for select household types. Taken together, these experiments highlight slums as a second-best adjustment margin in the presence of inelastic formal housing supply. While slums are commonly viewed as places of disadvantage, we conclude that the adjustment margin they provide mitigates the welfare losses that would arise from sharp increases in formal-sector rents in their absence, underscoring the tension between the severe deprivation they entail and their role in buffering even larger welfare losses.

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Figures and Tables

Figure 1: El Consuelo Alto Slum, Coquimbo Region

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

Figure 2: Villa El Esfuerzo Slum, Antofagasta Region

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

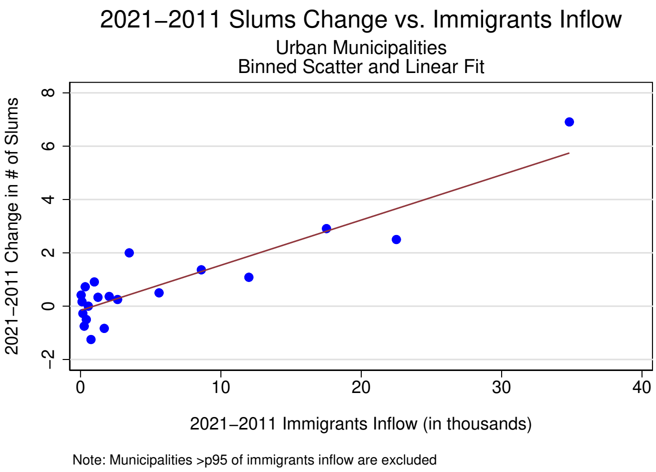


Figure 3: Immigration and Slums 2011-2021. Municipalities grouped in ventiles according to 2011-2021 immigrants inflow. *Source*: Department of State and MINVU, Chile

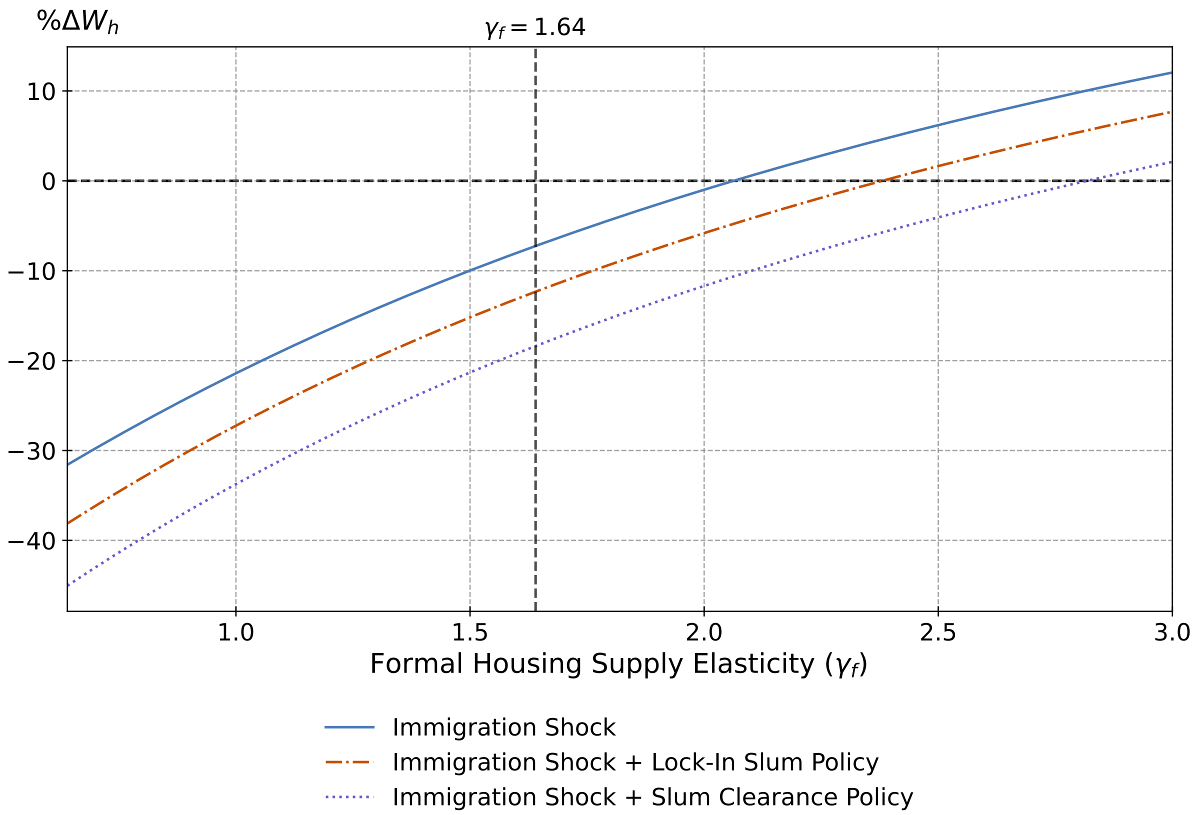


Figure 4: High-Skill Welfare Response to Immigration Shock under Varying Formal Housing Elasticity

Notes: This figure plots the percent change in welfare for high-education households ($\%\Delta W_h$) under the three counterfactual scenarios as the formal housing supply elasticity (γ_f) exogenously deviates from baseline in the new counterfactual equilibrium. The dashed vertical line marks the baseline equilibrium calibrated value (γ_f = 1.64).

Table 1: Descriptive Statistics: Urban Municipalities by 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 btw. 2011 and 2021	2,609,250	11,689	54,202	245,721	2,297,638
Mean Inflow of Immigrants btw. 2011 and 2021	10,738	192	889	4,028	38,294
Median Per Capita HHs. Income in 2011 (in US$ 2011)	308	233	273	294	427
Median Per Capita HHs. Income in 2021 (in US$ 2011)	461	384	425	439	594
Share of Pop. w/ High School or more in 2011 (%)	35	28	31	37	44
Mean Change of Pop. w/ High School or more btw. 2011 and 2020 (%)	11	10	12	11	11
Total Change in No. of Slums btw. 2011 and 2021	229	1	-12	35	205
Mean Change in No. of Slums btw. 2011 and 2021	0.9	0.0	-0.2	0.6	3.4
Total No. of Construction Permits btw. 2011 and 2021	395,721	65,790	81,414	107,318	141,199
Total No. of Units Built between 2011 and 2021	593,216	83,121	104,059	156,182	249,854
Panel I. Immigrants	All	Quartile 1	Quartile 2	Quartile 3	Quartile 4
A. Immigrants in 2011	Mean	Mean	Mean	Mean	Mean
Share of Female Imm. (%)	47	39	49	51	51
Age of Imm.	31	29	33	32	31
Share of Imm. w/ High School or more (%)	81	87	84	79	76
B. Immigrants in 2021	Mean	Mean	Mean	Mean	Mean
Share of Female Imm. (%)	48	48	47	48	50
Age of Imm.	33	34	33	33	33
Share of Imm. w/ High School or more (%)	83	82	83	83	83
Panel II. Informal Housing	All	Quartile 1	Quartile 2	Quartile 3	Quartile 4
A. Slums in 2011	Mean	Mean	Mean	Mean	Mean
No. of Slums	2.5	1.3	1.4	2.5	5.0
No. of Households in Slums	124	56	40	116	287
No. of Native Households in Slums	122	56	40	116	281
No. of Immigrant Households in Slums	2	0	0	1	7
Slum Area (m^2)	27,615	15,569	11,774	31,960	51,548
B. Slums in 2021	Mean	Mean	Mean	Mean	Mean
No. of Slums	3.5	1.3	1.2	3.1	8.4
No. of Households in Slums	330	59	48	216	1,009
No. of Native Households in Slums	219	59	42	182	599
No. of Immigrant Households in Slums	111	0	5	34	410
Slum area (m^2)	62,767	28,183	22,543	84,409	116,822
Panel III. Formal Housing	All	Quartile 1	Quartile 2	Quartile 3	Quartile 4
A. Formal Housing in 2011	Mean	Mean	Mean	Mean	Mean
No. of Construction Permits in last 10 years	1,476	909	1,103	1,639	2,268
No. of Units Built in last 10 years	2,090	1,012	1,318	2,237	3,822
Median Unit Rent Prices (in US$ 2011)	173	110	141	188	241
B. Formal Housing in 2021	Mean	Mean	Mean	Mean	Mean
No. of Construction Permits in last 10 years	1,628	1,079	1,335	1,759	2,353
No. of Units Built in last 10 years	2,441	1,363	1,706	2,560	4,164
Median Unit Rent Prices 2020 (in US$ 2011)	360	264	308	370	489

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.

Table 2: The Causal Effect of Immigration on Informal Housing Supply

	Panel A: 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

	Panel B: 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

Notes: Table reports OLS and 2SLS long-difference estimates for 2011–2021 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.V 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 outcomes as well as for Panel B, Changes in Stock, the Baseline Mean DV reports the mean of the outcome at 2011. For Panel B outcomes under the heading Changes in Slums Dynamics, the Baseline Mean DV reports the mean variation of the outcome between 2011 and 2013. *10%, **5%, ***1%.

Table 3: The Causal Effects of Immigration on Formal Housing Supply

	Construction Permits			Units		
	Δ_{2011}^{2021} Total # Permits All	Δ_{2011}^{2021} Total # Permits High Quality	Δ_{2011}^{2021} Total # Permits Low Quality	Δ_{2011}^{2021} Total # Units All	Δ_{2011}^{2021} Total # Units High Quality	Δ_{2011}^{2021} Total # Units 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 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: Table reports 2SLS long-difference estimates for 2011–2021 across 243 urban municipalities. See Appendix Table A.V for outcome definitions. $\Delta ImmStock_{m,2021-2011}$ 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). 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 4: Substitution Between Formal and Informal Housing: Evidence from Formal Housing Construction Cost Shifters

	Panel A: Formal Housing Supply					
	Construction Permits			Units		
	Δ_{2011}^{2021} Total # Permits All	Δ_{2011}^{2021} Total # Permits High Quality	Δ_{2011}^{2021} Total # Permits Low Quality	Δ_{2011}^{2021} Total # Units All	Δ_{2011}^{2021} Total # Units High Quality	Δ_{2011}^{2021} Total # Units 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: Informal Housing Supply					
	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.V 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%.

Table 5: Housing Supply Elasticity: 2SLS Estimation of Rents on Housing Demand.

	Formal Housing			Informal Housing		
	Δ_{2011}^{2020} Median Rent Formal Sanit.	Δ_{2011}^{2020} Median Rent Not Overcrowd	Δ_{2011}^{2020} Median Rent Formal Sanit. + Not Overcrowd	Δ_{2011}^{2020} Median Rent Inform. Sanit.	Δ_{2011}^{2020} Median Rent Overcrowd	Δ_{2011}^{2020} Median Rent Inform. Sanit. + Overcrowd
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_{2011}^{2020} Total # Floors Built	0.047**	0.051**	0.049**			
	(0.021)	(0.023)	(0.021)			
	[0.021]	[0.025]	[0.020]			
Δ_{2011}^{2020} Total # HHs in Slums				0.129*	0.159**	0.151**
				(0.077)	(0.079)	(0.072)
				[0.093]	[0.046]	[0.037]
Observations	222	222	222	140	182	204
Mean Dep. Var. 2011	176.12	180.43	174.36	137.12	134.43	134.21
Mean Indep. Var. 2011	2168.49	2168.49	2168.49	159.73	157.46	143.11
Estimated Elasticity:						
γ_f	1.73	1.63	1.64			
γ_s				6.65	5.37	6.21
F-statistic (First Stage)	10.879	10.879	10.879	11.119	8.988	10.406

Notes: Results of IV estimates on the cross-section of 2020-2011 differences across urban municipalities for which data on rent prices is available in both CASEN 2011 and CASEN 2020. The dependent variable is changes in median rent prices by municipality between 2011 and 2020. Regression columns (1)-(3) consider only rents from formal housing market, while regression columns (4)-(6) consider only rents from informal housing markets. Top 10 peri-rural municipalities are excluded from the analysis. Formal housing is defined upon three alternative definitions based on CASEN 2011 and 2020 data: (i) if housing unit has formal sanitation system (column 1); (ii) if housing unit is not overcrowded (column 2); (iii) if housing unit has formal sanitation system and is not overcrowded (column 3). Likewise, informal housing is defined upon three alternative definitions: (i) if housing unit has informal sanitation system (column 4); (ii) if housing unit is overcrowded (column 5); (iii) if housing unit has informal sanitation system and is overcrowded (column 6). Rent prices for formal housing is available in both CASEN 2011 and CASEN 2020 for all urban municipalities under analysis, yet this is not the case for informal housing, thus sample sizes differ across formal and informal housing markets. Δ_{2011}^{2020} Total # Floors Built is the change in formal housing demand between 2011 and 2020 (MINVU data). Δ_{2011}^{2020} Total # HHs in Slums is the change in informal housing demand between 2011 and 2020 (MINVU-TECHO panel). The instrument used for demand shocks of formal housing is $\Delta \widehat{ImmStock_{m,2020-2011}}_{,HighEduc}$, the supply-push component of 2011-2020 high-education immigration growth per municipality weighted by the beginning-of-period share of immigrants with high levels of education (completed high school or more). The instrument used for demand shocks of informal housing is $\Delta \widehat{ImmStock_{m,2020-2011}}_{,LowEduc}$, the supply-push component of 2011-2020 low-education immigration growth per municipality weighted by the beginning-of-period share of immigrants with low levels of education (completed high school or less). Estimated Elasticity (at means) is calculated as the inverse of the elasticity coefficient multiplied by the ratio of mean changes in housing demanded (independent variable) over mean changes in median rents (dependent variable). γ_f is the estimated elasticity of formal housing supply. γ_s is the estimated elasticity of informal housing supply. Kleibergen-Paap F-statistic is computed for first stage regressions. Robust standard errors in parentheses. *Sign. at 10%, **Sign. at 5%, ***Sign. at 1%.

Table 6: Counterfactual Experiments.

	(1) Immigration Shock	(2) Immigration Shock + Lock-In Slum Policy	(3) Immigration Shock + Slum Clearance Policy
$\%\Delta w_\ell$	11.76	11.75	11.53
	(0.12)	(0.10)	(2.70)
$\%\Delta w_h$	-3.18	-3.19	-3.62
	(0.09)	(0.09)	(1.25)
$\%\Delta R_f$	5.82	6.02	13.39
	(0.08)	(0.09)	(0.92)
$\%\Delta R_s$	2.23	14.40	
	(0.12)	(0.81)	
$\%\Delta L_s$	10.73	8.13	
	(1.23)	(1.31)	
$\%\Delta H_s$	14.66		
	(0.84)		
$\%\Delta W_\ell$	7.14	-1.63	-8.69
$\%\Delta W_h$	-7.25	-12.33	-18.38

Notes: Table presents municipality average percent changes (and standard deviations in parenthesis) in endogenous outcomes due to counterfactual policy changes relative to the baseline equilibrium. There are three counterfactual scenarios: Immigration Shock only (column 1); Immigration Shock + Fixed Lock-In Slum Policy (column 2); Immigration Shock + Slum Clearance Policy (column 3). Endogenous outcomes include group wages w_i for $i \in \{h, \ell\}$, rent per unit of floorspace by housing type R_k for $k \in \{f, s\}$, total population living in slums L_s, slum floorspace H_s, and welfare W_i for $i \in \{h, \ell\}$. Given Fréchet taste shocks, group specific welfare W_i is common across locations. In the "Immigration Shock" exercise (column 1), we exogenously increase the low-education population $\overline{L}_\ell$ by 4% and high-education population $\overline{L}_h$ by 20% to simulate the *observed* increase in immigrants between 2011 and 2020. In the "Immigration Shock + Fixed Lock-In Slum Policy" exercise (column 2), we again shock $\overline{L}_\ell$ and $\overline{L}_h$ by the *observed* changes, but also restrict the stock of housing floorspace in slums to the baseline level (hence there is no percent change in H_s). In the "Immigration Shock + Slum Clearance Policy" exercise (column 3), we again replicate the *observed* immigration shock, but remove the slum market from all municipalities, forcing all households to occupy formal housing.

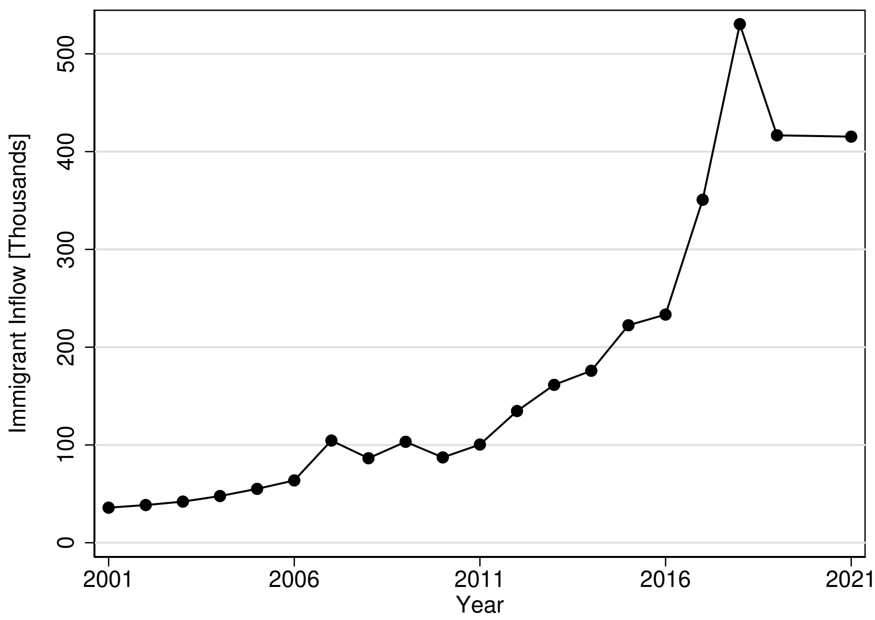
ONLINE APPENDIX

Structure of the Online Appendix

This appendix provides supplemental material for the paper. Appendix A presents additional figures and tables referenced in the main text. Appendix B validates the immigration shift-share instrument by decomposing the Bartik estimator into nationality-specific components and testing for pre-2011 differential trends. Appendix C examines whether the main panel results hold at the slum-territory level using two-year difference models of slum creation, persistence, closure, and growth. Appendix D tests whether immigration affected poverty, incomes, or unemployment to evaluate income-based mechanisms of slum growth. Appendix E assesses whether selective slum policies, such as upgrading programs, housing subsidies, or politically motivated interventions, mediate the relationship between immigration and slum formation. Appendix F provides additional evidence on whether immigration induced changes in the construction sector. Finally, Appendix G derives the model's equilibrium conditions, details the inversion procedure used to recover exogenous fundamentals, and studies the sensitivity of counterfactual outcomes to the slum congestion parameter η_s.

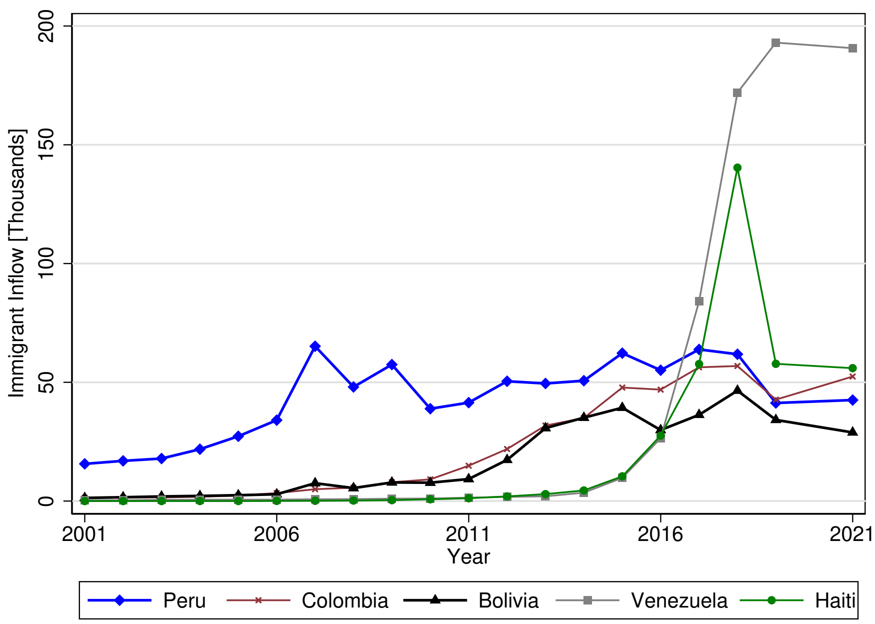
A. Additional Figures and Tables

Figure A.I: Immigrant inflows: 2001-2021



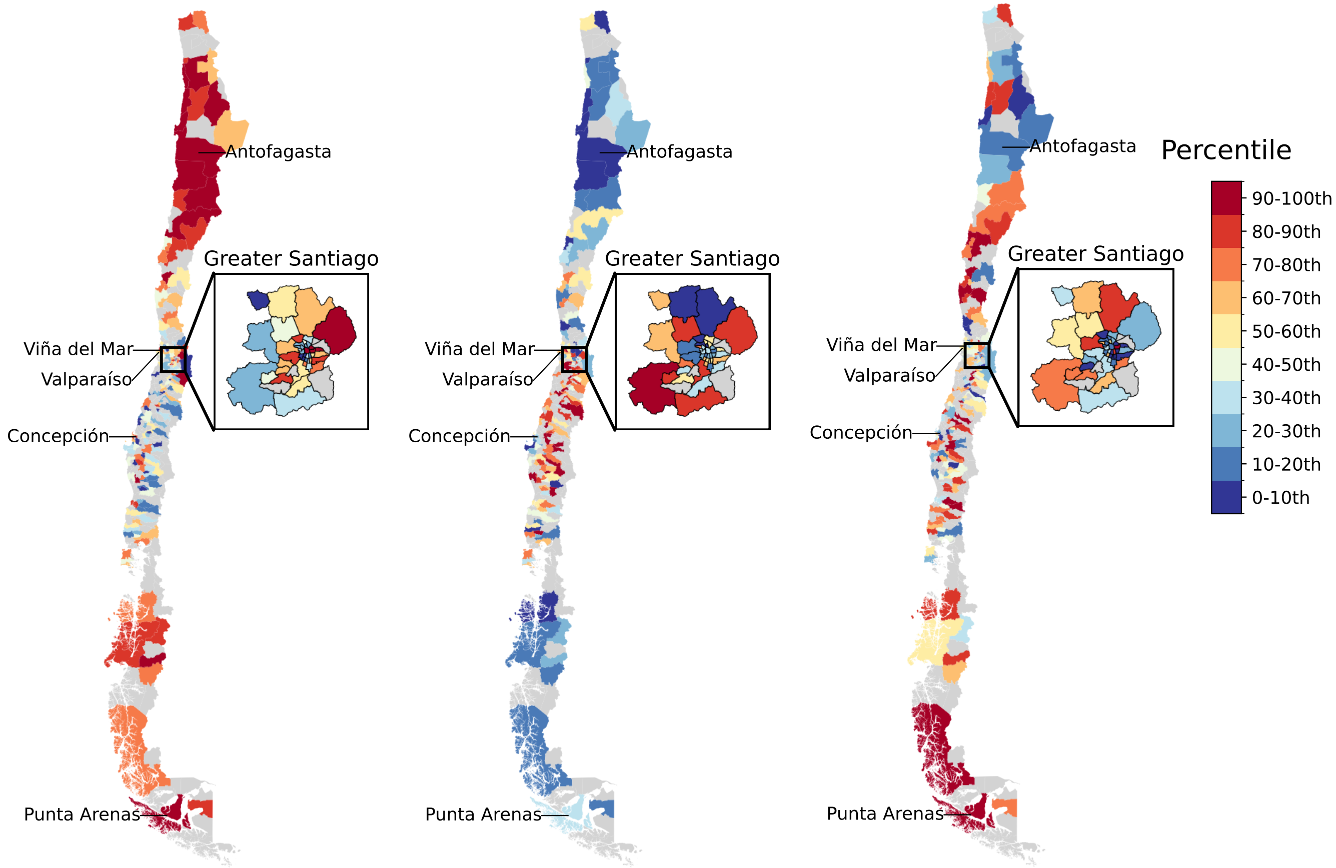
Source: Department of State, Chile. Based on authors' calculations.

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



Source: Department of State, Chile. Based on authors' calculations.

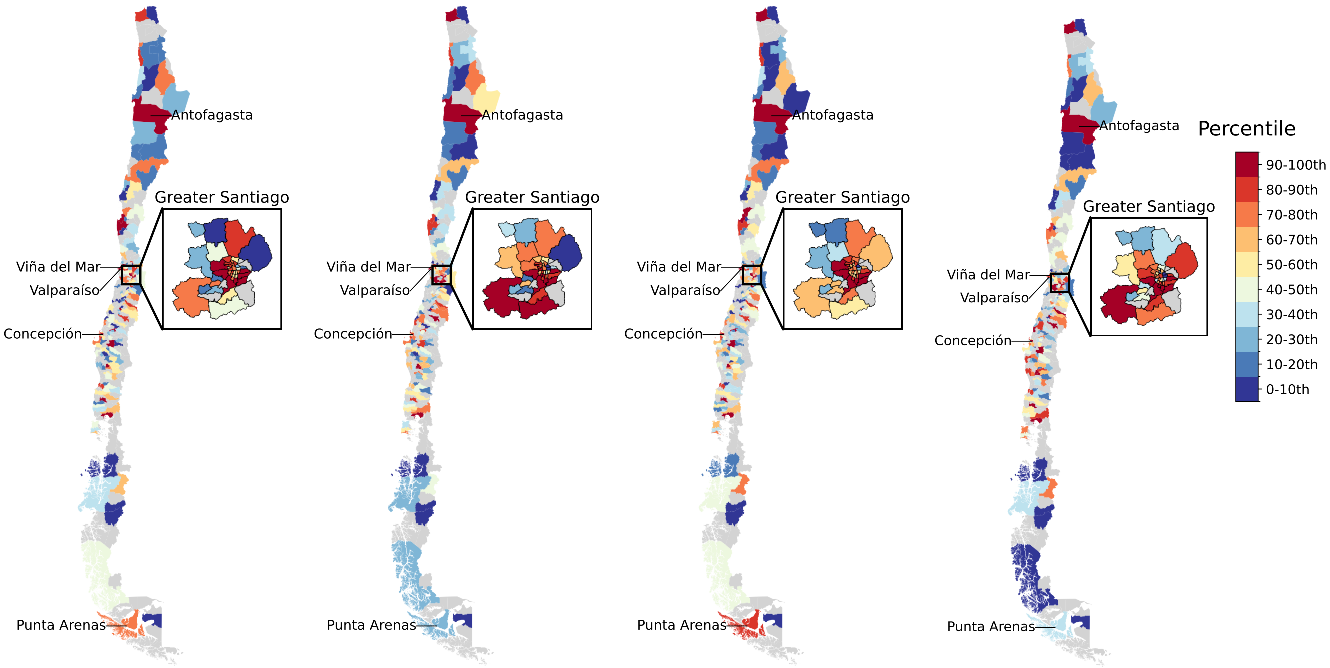
Figure A.III: Spatial Distribution of Exogenous Productivity



(a) $\overline{A}$ (b) $\overline{a}_f$ (c) $\overline{a}_s$

Notes: Each panel displays the spatial distribution of exogenous firm productivity values ($\overline{A}$) and housing developer productivity values by sector ($\overline{a}_f$, $\overline{a}_s$) across Chilean municipalities, expressed in percentile ranks. Warm colors denote municipalities in higher percentiles (more productive), while cool colors denote those in lower percentiles. Darker shades correspond to percentile extremes (top and bottom deciles). Gran Santiago refers to the Greater Santiago Metropolitan Area. We recover these exogenous fundamentals by inverting the model's equilibrium conditions following the standard procedures, as described in Redding and Rossi-Hansberg (2017). Given model parameters, trade costs, and observed wages, rents, and populations, we solve the system implied by the goods-market equilibrium to obtain the vector of productivities A_m that rationalize observed wages and population shares; the exogenous component $\overline{A}_m$ follows after removing the agglomeration term and normalizing by the geometric mean. Housing developer productivities $\overline{a}_{mk}$ are obtained as residuals directly from the housing supply equation using data on wages, rents, and housing-type populations, without fixed-point iteration. All recovered fundamentals are normalized by their geometric means. See Online Appendix Section G.2 for details.

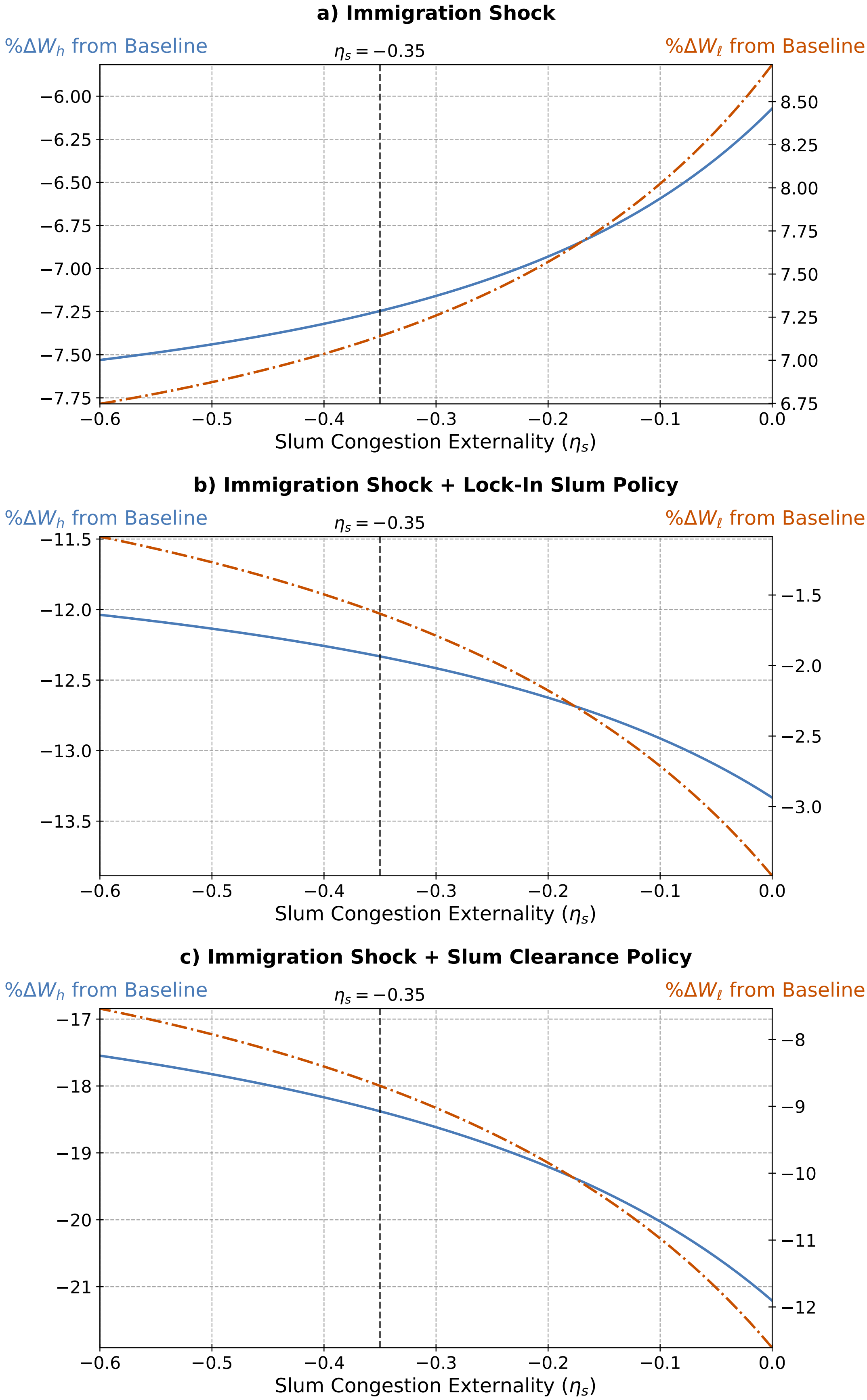
Figure A.IV: Spatial Distribution of Exogenous Amenities



(a) $\overline{B}_{hf}$ (b) $\overline{B}_{hs}$ (c) $\overline{B}_{\ell f}$ (d) $\overline{B}_{\ell s}$

Notes: Each panel displays the spatial distribution of exogenous amenity values ($\overline{B}_{hf}$, $\overline{B}_{hs}$, $\overline{B}_{\ell f}$, $\overline{B}_{\ell s}$) across Chilean municipalities, expressed in percentile ranks within each skill–housing-type group. Warm colors denote municipalities in higher percentiles (more desirable amenities), while cool colors denote those in lower percentiles. Darker shades correspond to percentile extremes (top and bottom deciles). Gran Santiago refers to the Greater Santiago Metropolitan Area. We recover these exogenous fundamentals by inverting the model's equilibrium conditions, following the standard procedures as described in Redding and Rossi-Hansberg (2017). Given model parameters, trade costs, and observed wages, rents, and populations, after recovering the vector of exogenous firm productivities, we use the estimated price indices to invert the residential location conditions to retrieve the composite amenities B_{imk} and back out their exogenous counterparts $\overline{B}_{imk}$ from observed household type-housing sector population. See Online Appendix Section G.2 for details.

Figure A.V: Counterfactual Welfare Change Sensitivity



Notes: The figure reports welfare changes for h-type (left y-axis, $\%\Delta W_h$) and ℓ-type (right y-axis, $\%\Delta W_\ell$) households under each counterfactual as we vary the slum congestion externality parameter η_s over a dense grid from -0.6 to 0. For each value of η_s, the model is re-calibrated holding all other parameters fixed, and both the baseline and counterfactual equilibria are recomputed. The plotted welfare changes therefore reflect how sensitive each counterfactual is to alternative congestion externalities. See Online Appendix Section G.3 for details.

Table A.I: 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]
Δ_{2011}^{2021} Total # Permits	42.53**	60.30***	42.53	42.53***
	(17.06)	(22.92)	(129.48)	(12.13; 86.44)
	[0.013]	[0.009]	[0.484]	[0.008]
Δ_{2011}^{2021} Total # Units	104.99***	145.05***	104.99	104.99***
	(28.31)	(37.70)	(241.19)	(56.78; 180.10)
	[0.000]	[0.000]	[0.368]	[0.000]
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.V 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.II: Long Diff. 2021-2011 2SLS Estimation. Informal Housing Supply. 108 Urban Mun. Pairs

	Panel A: 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*
(× 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

	Panel B: 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
(× 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

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.V 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 outcomes as well as for Panel B, Changes in Stock, the Baseline Mean DV reports the mean of the outcome at 2011. For Panel B outcomes under the heading 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.III: Long Diff. 2021-2011 2SLS Estimation. Formal Housing Supply. 108 Urban Mun. Pairs

	Construction Permits			Units		
	Δ_{2011}^{2021} Total # Permits All	Δ_{2011}^{2021} Total # Permits High Quality	Δ_{2011}^{2021} Total # Permits Low Quality	Δ_{2011}^{2021} Total # Units All	Δ_{2011}^{2021} Total # Units High Quality	Δ_{2011}^{2021} Total # Units Low Quality
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2021-2011}$	28.77	38.01***	-9.23	89.96***	90.21***	-0.25
(× 1,000)	(17.56)	(10.57)	(12.87)	(30.10)	(20.08)	(19.15)
	[0.101]	[0.000]	[0.473]	[0.003]	[0.000]	[0.990]
Observations	108	108	108	108	108	108
Baseline Mean $\text{DV}_{2001-2011}$	3,222	1,303	1,918	4,885	2,308	2,576
	First Stage Regression					
$\Delta \widehat{ImmStock}_{m,2021-2011}$	0.76***	0.76***	0.76***	0.76***	0.76***	0.76***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
F-statistic	14.67	14.67	14.67	14.67	14.67	14.67

Notes: IV estimates of the effects of immigration on the cross section of 2021-2011 total housing supply 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.V for outcome definitions. $\Delta ImmStock_{m,2021-2011}$ is the immigrant inflow (in thousands) in pair of municipalities m between 2011 and 2021; $\Delta \widehat{ImmStock}_{m,2021-2011}$ is the instrument (equation 2). 2SLS coefficients are reported under the heading IV. 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 outcome. Robust standard errors in parenthesis. p-values in brackets. * Sign. 10%, ** Sign. 5%, *** Sign. 1%.

Table A.IV: 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					
$\Delta \widehat{ImmStock_m}_{,2017-2011}$		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; $\Delta \widehat{ImmStock_m}_{,2017-2011}$ is the instrument (equation 2). OLS columns report the naive estimates of regressing the cross section of differences across municipalities on immigration inflow, without instrumenting for $\Delta \widehat{ImmStock_m}_{,2017-2011}$ (equation 1). 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. *Sig. at 10%, **Sig. at 5%, ***Sig. at 1%.

Table A.V: Definition of Variables

Variable	Definition
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.
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).

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

Variable	Definition
Δ_{2011}^{2021} Total # of 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 # Units	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} Median Rent	Calculated at the municipality level for a total of 222 urban municipalities. Data Sources are CASEN 2011 and CASEN 2020 household level surveys. We take the median rent (in $US dollars of 2011) of each municipality for 2020 and for 2011, and compute the within-municipality difference.

Table A.VII: All Policy Counterfactuals

	(1) h-biased Immigration Shock	(2) h-biased Immigration Shock + Lock-In Slum Policy	(3) h-biased Immigration Shock + Slum Clearance Policy	(4) ℓ-biased Immigration Shock	(5) ℓ-biased Immigration Shock + Lock-In Slum Policy	(6) ℓ-biased Immigration Shock + Slum Clearance Policy
$\%\Delta w_\ell$	11.76	11.75	11.53	-8.47	-8.47	-8.67
	(0.12)	(0.10)	(2.70)	(0.10)	(0.11)	(2.25)
$\%\Delta w_h$	-3.18	-3.19	-3.62	5.65	5.64	5.17
	(0.09)	(0.09)	(1.25)	(0.09)	(0.10)	(1.36)
$\%\Delta R_f$	5.82	6.02	13.39	3.66	3.76	10.93
	(0.08)	(0.09)	(0.92)	(0.08)	(0.07)	(0.92)
$\%\Delta R_s$	2.23	14.40		1.18	7.44	
	(0.12)	(0.81)		(0.12)	(0.74)	
$\%\Delta L_s$	10.73	8.13		13.15	11.73	
	(1.23)	(1.31)		(1.21)	(1.37)	
$\%\Delta H_s$	14.66			7.57		
	(0.84)			(0.77)		
$\%\Delta W_\ell$	7.14	-1.63	-8.69	-12.28	-19.26	-25.16
$\%\Delta W_h$	-7.25	-12.33	-18.38	1.32	-4.08	-10.82

Notes: Table presents municipality average percent changes changes (and standard deviations in parenthesis) in endogenous outcomes due to counterfactual policy changes relative to the baseline equilibrium. Endogenous outcomes include group wages w_i for $i \in \{h, \ell\}$, rent per unit of floorspace by housing type R_k for $k \in \{f, s\}$, total population living in slums L_s, slum floorspace H_s, and welfare W_i. Given Fréchet taste shocks, group specific welfare W_i is common across locations. In the "h-biased Immigration Shock" exercise, we exogenously increase the low-education population $\overline{L}_\ell$ by 4% and high-education population $\overline{L}_h$ by 20% to simulate the observed increase in immigrants between 2011 and 2020. In the "h-biased Immigration Shock + Fixed Lock-In Slum Policy" exercise, we again shock $\overline{L}_\ell$ and $\overline{L}_h$ by the observed changes, but also restrict the stock of housing floorspace in slums to the baseline level (hence there is no percent change in H_s). In the "h-biased Immigration Shock + Slum Clearance Policy" exercise, we again replicate the observed immigration shock, but remove the slum market from all municipalities, forcing all households to occupy formal housing. The ℓ-based exercises are identical to the h-biased exercises with the exception that $\overline{L}_\ell$ increases by 20% and $\overline{L}_h$ by 4%, swaping the immigration intensity of both types to what was observed.

B. Shift-Share Instrument: Internal Validity Test

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.[34]

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.[35]

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 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 B.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).[36]

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.[37] We

[34]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.

[35]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.

[36]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*(θ^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*(θ^n_{2010}), meaning the variation in the origin country shares across municipalities likely works as a key moderator of the estimates.

[37]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.

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.

Appendix Figure B.I 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. Similar results are observed for the total number of construction permits per municipality. 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.

Table B.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

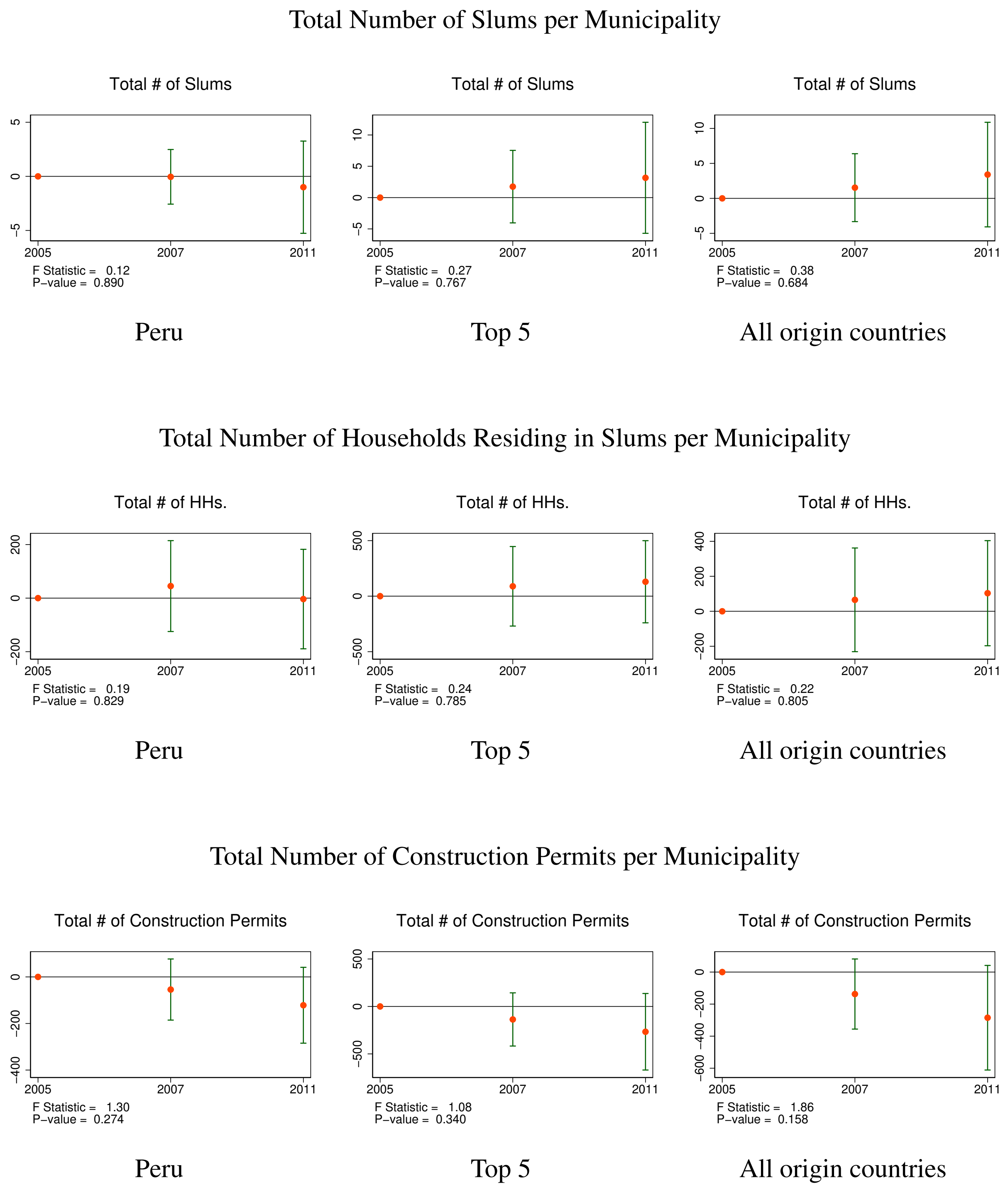
	$\hat{\alpha}^n$	g_k	$\hat{\beta}_n$	F_n	Var(θ^n_{2010})
$\hat{\alpha}^n$	1				
g_k	0.070	1			
$\hat{\beta}_n$	-0.030	0.070	1		
F_n	0.037	-0.232	-0.469	1	
Var(θ^n_{2010})	0.434	-0.223	-0.097	0.268	1

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.

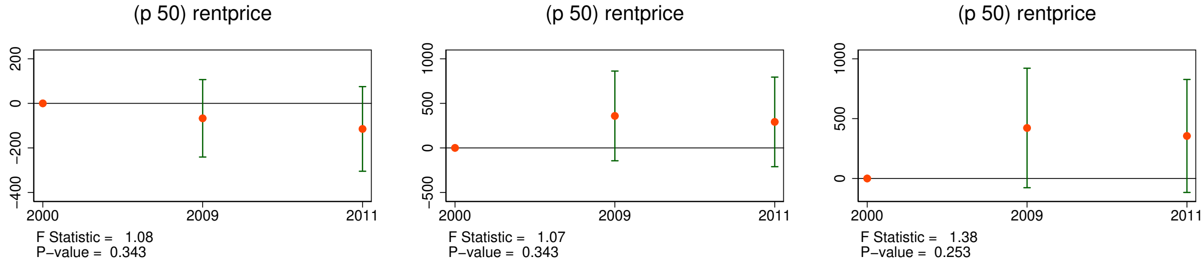
Figure B.I: Internal Validity Check for Estimating 2SLS Effects of Immigration on Informal and Formal Housing Supply: Pre-trends for high Rotemberg weight countries and all together



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.

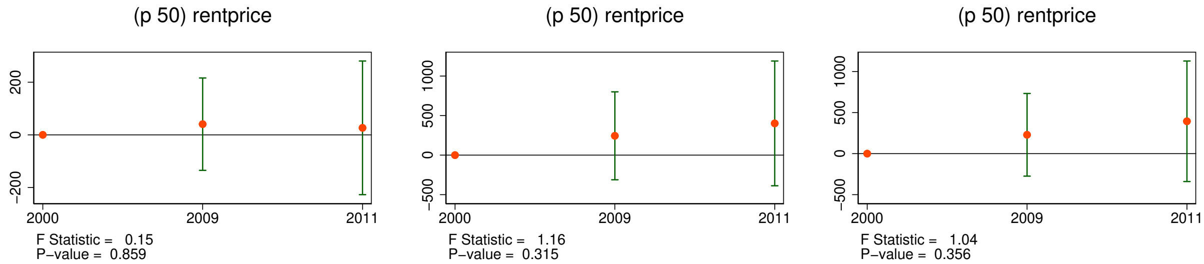
Figure B.II: Internal Validity Check for Estimating (Inverse) Housing Supply Elasticities in Formal and Informal Housing Sectors: Pre-trends for high Rotemberg weight countries and all together

Median Rent Price per Municipality – Formal Housing



Peru | Top 5 | All origin countries

Median Rent Price per Municipality – Informal Housing



Peru | Top 5 | All origin countries

Note: Unit of analysis is the urban municipality. We classify housing units as formal or informal based on whether they have formal access to sanitation. Median rent prices for each housing type are computed using CASEN surveys for 2000, 2009, and 2011 —years in which both rent and housing-type questions are defined consistently across surveys, thereby ensuring comparability over time. 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 2000, our baseline year. We convert the growth rates to levels and index the levels in 2000 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.

C. Results from 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 biennial 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[38]. 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)[39]. 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[40].

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

$$\Delta Y_{smt,t-2} = \beta \Delta ImmStock_{mt,t-2} + \eta_t + \epsilon_{smt} \tag{11}$$

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)[41]; η_t are year fixed effects capturing year-specific shocks across municipalities; and ϵ_{smt} is the error term,

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

[39] 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.

[40] 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.

[41] 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.

Column (1) in Appendix Table C.I, Panel A, shows that for every 1,000 immigrants arriving within a municipality in the previous two years, the probability that the slum is open 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.

Table C.I: 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 11). 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). 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.

D. Immigration and Slum Formation: The Role of 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). That is, if immigrants are too poor or contribute to the economic decline of cities, then slums are expected to multiply[42].

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[43]. 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 D.I, 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).

[42]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. (2021).

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

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

	Panel A: Poverty					
	Changes in Poverty Rate (CASEN)			Changes in Extreme Pov. Rate (CASEN)		
	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					
$\Delta Imm\widehat{Stock}_{m,2020-2011}$	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 (CASEN)			Changes in Unemployment Rate (CASEN)		
	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					
$\Delta Imm\widehat{Stock}_{m,2020-2011}$	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 urban municipalities. 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; $\Delta Imm\widehat{Stock}_{m,2020-2011}$ is the instrument. Robust standard errors in parenthesis. *p*-values in brackets. * Sign. at 10%, ** Sign. at 5%, *** Sign. at 1%.

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"[44].

The absence of detectable effects of immigration on municipality-wide income, unemployment, and poverty suggests that slum growth in our setting is unlikely to be explained by a deterioration in average local economic conditions. Rather, the evidence points to a housing-market adjustment mechanism: immigration raises demand for access to urban location, and when affordable formal supply is constrained, informal housing expands. This interpretation is more in line with accounts that view slums as enabling poor households to access the benefits of agglomeration and urban opportunity (Glaeser, 2011, Celhay and Undurraga, 2022) than with views of slums as poverty traps (Marx et al., 2013). We stress, however, that this conclusion is only suggestive, as our data do not allow us to observe household-level sorting into slums or the extent to which higher rents reduce real housing consumption among marginal households.

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 D.II, the immigration effect on slum formation is generally larger for the case of migrants with high school diploma relative to the case of all migrantsThus, 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, but this is instead due to an indirect housing-market adjustment (see Section 4).

[44]We are not the first in testing the immigration effects on labor outcomes in Chile. Using data from the National Institute of Statistics (INE), Ajzenman, Domínguez, and Undurraga (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.

Table D.II: 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. 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).

E. Immigration and Slum Formation: The Role of Selective Slum Policy

Immigration could trigger slum growth because political capture and policy coordination, wherein politicians safeguard slums inhabited by immigrant majorities to secure votes from this burgeoning electorate, thereby attracting immigrants to slums. 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 (Gertler et al., 2025). 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[45].

We use 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 these slum policies. Table E.I shows the results. We observe the intensity of the slum policy does not vary with the level of immigration across municipalities, this being the case for both housing subsidies and urbanization programs. The 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.

[45] 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.

Table E.I: 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. $\Delta ImmStock_{m,2020-2011}$ 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%.

F. Immigration and Labor Supply in Construction Sector

Table F.I: 2SLS Estimation. Differences in Labor Supply in Construction Sector.

	Δ_{2011}^{2020} Labor Share in Construction (%)			Δ_{2011}^{2020} Mean Wage in Construction (in 2011 $US dollars)		
	All Workers	Native Workers	Immigrant Workers	All Workers	Native Workers	Immigrant Workers
	IV	IV	IV	IV	IV	IV
$\Delta ImmStock_{m,2020-2011}$	-0.03	-0.04	-0.06	3.89	6.28	-5.58
(× 1,000)	(0.04)	(0.04)	(0.20)	(8.91)	(10.18)	(21.08)
	[0.513]	[0.385]	[0.647]	[0.641]	[0.531]	[0.742]
Observations	222	222	222	222	222	222
Baseline Mean DV	0.07	0.07	0.05	858	861	244
	First Stage Regression					
$\Delta \widehat{ImmStock}_{m,2020-2011}$	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
F-statistic	16.89	16.89	16.89	16.89	16.89	16.89

Notes: Results of IV estimates on the cross section of 2020-2011 differences across urban municipalities for which data on rent prices is available in both CASEN 2011 and CASEN 2020 (222 in total). Top 10 peri-rural municipalities are excluded from the analysis. Labor share outcomes are expressed in percentage (%). Mean Wage is in 2011 $US dollars. 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%.

G. Model

G.1. Deriving Equilibrium Conditions

Households A type-i household indexed ω has utility from consuming type-k housing in city m is given by:

$$U_{imk}(\omega) = B_{imk}\left(\frac{C_{im}}{\beta}\right)^{\beta}\left(\frac{H_{imk}}{1-\beta}\right)^{1-\beta}\nu_{imk}(\omega), \quad \beta \in (0,1)$$

where

$$\begin{aligned} B_{imk} &= \overline{B}_{imk}L_{mk}^{\eta_k} \\ C_{im} &= \left[\sum_{n=1}^{M} x_{inm}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1 \\ \nu_{imk}(\omega) &\sim \ iid \ F_{imk}(\nu) = F(\nu) = \exp\{-\nu^{-\theta}\} \end{aligned}$$

Beginning with the lower tier CES consumption index, Marshallian demands for each differentiated good are:

$$\begin{aligned} x_{inm} &= \left(\frac{p_{nm}}{P_m}\right)^{-\sigma}\frac{\beta w_{im}}{P_m} \\ P_m &= \left[\sum_{r=1}^{M}(p_{rm})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \end{aligned}$$

where $p_{nm} = \tau_{nm}p_n$, p_n is the mill price of the good produced in n, and P_m is the usual CES price index for consumption in m. Total expenditure in m on goods from n is expressed as:

$$X_{nm} = \sum_{i=1}^{N} p_{nm}x_{inm} = \beta\left(\frac{p_{nm}}{P_m}\right)^{1-\sigma}\sum_{i=1}^{N} w_{im}L_{im} \tag{12}$$

where L_{im} is the total number of type-i households residing in m.

The Cobb-Douglas upper-tier implies total Marshallian demands for consumption and housing are:

$$\begin{aligned} C_{im} &= \beta\frac{w_{im}}{P_m} \\ H_{imk}^{D} &= (1-\beta)\frac{w_{im}}{R_{mk}} \end{aligned} \tag{13}$$

where R_{mk} is the price per square unit of type-k floorspace in m, implying household ω has indirect utility

$$W_{imk} = \frac{B_{imk}w_{im}}{P_m^{\beta}R_{mk}^{1-\beta}}\nu_{imk}(\omega)$$

Given $\nu_{imk}(\omega)$ is Fréchet, the probability a type-i household lives in type-k housing within municipality m is given by:

$$\pi_{imk} = \frac{(B_{imk}w_{im})^{\theta}\left(P_m^{\beta}R_{mk}^{1-\beta}\right)^{-\theta}}{\sum_{n=1}^{M}\sum_{l\in\{s,f\}}(B_{inl}w_{in})^{\theta}\left(P_n^{\beta}R_{nl}^{1-\beta}\right)^{-\theta}}$$

and expected utility (and average ex-post utility) of a type-i worker is

$$E_{\nu}\left[\max_{m,k} W_{imk}(\omega)\right] \propto \left[\sum_{n=1}^{N}\sum_{l\in\{s,f\}}(B_{inl}w_{in})^{\theta}\left(P_n^{\beta}R_{nl}^{1-\beta}\right)^{-\theta}\right]^{\frac{1}{\theta}}$$

Firms The total output of the representative firm in city m, Y_m, is produced via the following Cobb-Douglas production function:

$$Y_m = A_m \prod_{i=1}^{N} L_{im}^{\alpha_i}, \quad \sum_{i=1}^{N}\alpha_i = 1$$

where

$$A_m = \overline{A}_m L_m^{\varepsilon}$$

Perfect competition implies the mill price of the good from m is:

$$p_m = \frac{\prod_{i=1}^{N} w_{im}^{\alpha_i}}{\chi A_m} \tag{14}$$

where $\chi \equiv \prod_{i=1}^{N}\alpha_i^{\alpha_i}$ measures (a monotone transformation of) the Shannon entropy of factor shares.

Housing Developers Perfectly competitive type $k \in \{s, f\}$ developers produce type-k housing floorspace in municipality m using the following technology:

$$H_{mk}^{S} = \overline{a}_{mk} R_{mk}^{\gamma_k} \tag{15}$$

Equilibrium The equilibrium in this model is characterized by three market clearing conditions: goods market clearing, labor market clearing, and housing market clearing. In equilibrium, the goods market clears when the value of the supply of goods equals total goods expenditure. Since firms are perfectly competitive, the value of supply is the total amount paid to factors (i.e., the total wage bill, $\sum_i w_{im}L_{im}$). Following from equation 12, total expenditure from all locations on the good from m satisfies:

$$X_m = \sum_n \beta \left(\frac{p_{mn}}{P_n}\right)^{1-\sigma} \sum_i w_{in} L_{in}$$

Substituting for p_{mm} using equation 14 and equating X_m to the wage bill yields the goods market clearing condition

$$\sum_i w_{im} L_{im} = \beta \left(\frac{\prod_i w_{im}^{\alpha_i}}{\chi A_m}\right)^{1-\sigma} \sum_n \left(\frac{\tau_{mn}}{P_n}\right)^{1-\sigma} \sum_{i=1}^{N} w_{in} L_{in}$$

which must hold for all m.

Labor market clearing requires $\overline{L}_i = \sum_m \sum_k L_{imk}$ for both types of households i. Since taste shocks are distributed Fréchet, it must be in equilibrium that population shares equal the choice probabilities for each household type:

$$\frac{L_{imk}}{\overline{L}_i} = \frac{(B_{imk} w_{im})^{\theta} \left(P_m^{\beta} R_{mk}^{1-\beta}\right)^{-\theta}}{\sum_{n=1}^{M} \sum_{l \in \{s,f\}} (B_{inl} w_{in})^{\theta} \left(P_n^{\beta} R_{nl}^{1-\beta}\right)^{-\theta}}$$

which must hold for all i, m, and k jointly.

Housing market clearing requires total demand for housing in m must equal supply. Equating equations 15 and 13, housing market clearing requires

$$\bar{a}_{mk} R_{mk}^{\gamma_k} = \frac{(1-\beta) \sum_i w_{im} L_{imk}}{R_{mk}}$$

for both housing markets k in all cities m.

G.2. Recovering Exogenous Fundamentals

Given exogenous parameters $\{\alpha_i, \beta, \gamma_k, \varepsilon, \theta, \eta_k, \sigma\}$, estimated bilateral trade costs shipping from m to n, τ_{mn}, as well as data on wages, rents, and populations, we can invert the equilibrium conditions to write location characteristics as functions of observables:

$$A_m = \frac{\prod_{i=1}^{N} w_{im}^{\alpha_i}}{\chi} \left(\frac{\beta \sum_{n=1}^{M} \left(\frac{\tau_{mn}}{P_n}\right)^{1-\sigma} \sum_{i=1}^{N} w_{in} L_{in}}{\sum_{i=1}^{N} w_{im} L_{im}}\right)^{\frac{1}{1-\sigma}}, \quad \forall m \tag{16}$$

$$B_{imk} = \left[\sum_{n=1}^{M} \sum_{l \in \{s,f\}} \left(\frac{B_{inl} w_{in}}{P_n^{\beta} R_{nl}^{1-\beta}}\right)^{\theta} \frac{L_{imk}}{\overline{L}_i}\right]^{\frac{1}{\theta}} \frac{P_m^{\beta} R_{mk}^{1-\beta}}{w_{im}}, \quad \forall i, m, k \tag{17}$$

$$\bar{a}_{mk} = \frac{(1-\beta) \sum_{i=1}^{N} w_{im} L_{imk}}{R_{mk}^{1+\gamma_k}}, \quad \forall m, k \tag{18}$$

We proceed as follows. From the system of M equations implied by equation 16, we solve for the vector of composite productivities $\widehat{\mathbf{A}} = [\widehat{A}_1, \ldots, \widehat{A}_M]^T$ that jointly satisfy the system via a fixed point algorithm. We recover the estimate exogenous component for each m, $\widehat{\overline{A}}_m$, using observed populations and the agglomeration force:

$$\widehat{\overline{A}}_m = L_m^{-\varepsilon} \widehat{A}_m$$

where L_m is the total number of households living (and working) in m. Given that the recovered values are unique up to scale, we normalize the productivities by their geometric mean.

Substituting the elements of $\widehat{\mathbf{A}}$ into equation 14 yields estimated mill prices, which in turn are substituted into the CES price index for each m to derive an estimated value for $\widehat{\mathbf{P}} = \mathbf{P}(\widehat{\mathbf{A}}) = [P_1(\widehat{A}_1), \ldots, P_M(\widehat{A}_M)]^T$. Similar to above, for each i, using the system of $M \times 2$ equations implied by equation 17 and the estimated price indices, we solve for the vector of composite amenities $\widehat{\mathbf{B}_i} = [\widehat{B}_{i1f}, \widehat{B}_{i1s}, \ldots, \widehat{B}_{iMf}, \widehat{B}_{iMs}]^T$ that jointly satisfy the system via a fixed point algorithm. Again, we recover the exogenous component $\widehat{\overline{B}}_{imk}$ using observed populations by housing type and the congestion force:

$$\widehat{\overline{B}}_{imk} = L_{mk}^{-\eta_k} \widehat{B}_{imk}$$

Finally, we normalize the $M \times 2$ vector of recovered amenities for worker type group by its geometric mean.

Given the set up of the model, housing developer productivities are a function of observed wages, rents, and population, independent of the estimated values for productivities and amenities. The vector of formal and informal housing developers productivity follow immediately from equation 18 after substituting data without the need for fixed point iteration. As with goods productivity and amenities, we normalize each vector of housing developer productivites by their respective geometric mean. We map the spatial distribution of these exogenous fundamentals across Chile in Appendix Figures A.III and A.IV.

G.3. Slum Congestion Externality Sensitivity

We assess the robustness of our counterfactuals to the specification of the slum congestion externality parameter η_s by re-estimating the baseline and counterfactual equilibria over a dense grid of values from -0.6 to 0. For each value in this grid, we recalibrate the model while holding all other parameters fixed, recompute the baseline equilibrium implied by those fundamentals, and then resolve each policy counterfactual. Welfare changes for h-type and ℓ-type households are computed relative to the baseline associated with the same η_s. Appendix Figure A.V displays the resulting welfare profiles. While the magnitude of welfare changes varies slightly with η_s, the patterns are stable and do not alter the qualitative conclusions drawn under our preferred calibration $\eta_s =$ -0.35.