Who Pays and Where?
Local Housing Market Adjustments to Immigration in Spain

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Abstract

We estimate the causal effect of immigration on housing prices using a panel of 699 Spanish municipalities over 2014–2025. Exploiting variation in immigration flows through a shift-share instrument based on historical settlement networks, we find that a one percentage point increase in the immigration rate raises housing prices by 0.73% in the short run, with the effect growing to approximately 2.3% in the long run. The absence of a housing supply response and the lack of native displacement in high-immigration municipalities prevent demand pressure from dissipating, allowing price effects to accumulate over time. Heterogeneity across the degrees of urbanization reveals that the price effect of immigration is substantially larger in non-urban municipalities, driven by native co-location, improvements in local economic conditions, and more binding supply constraints.

Keywords: Housing Prices, Immigration, Local Adjustment, Urban Degree

1. Introduction

Although immigration-induced residential demand can generate upward pressure on local housing prices in the short run (Saiz, 2007; Sanchis-Guarner, 2023; Piyapromdee, 2021), these local distortions may be mitigated or amplified over time depending on the intensity with which alternative adjustment mechanisms operate (Monras, 2020). On the supply side, constraints on housing stock expansion not only raise local prices in their own right, but also amplify the effect of immigration by preventing the demand shock from being absorbed through new construction (Saiz, 2010; González & Ortega, 2013). Beyond supply responses, the spatial mobility of the native population constitutes an equally important equilibrating or amplifying mechanism (Monras, 2020; Borjas, 2006). If natives relocate toward high-immigration areas, joint residential demand pressure is amplified and price effects are larger (Sanchis-Guarner, 2023); if instead they leave those areas, the initial demand pressure is relieved and positive price effects may attenuate or even reverse (Sá, 2015). The magnitude and sign of the effect of immigration on local housing prices therefore depends not only on the size of the demand shock, but on the capacity of local markets to absorb it through these alternative channels.

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This absorption capacity is in turn determined by the structural conditions of local economies. Spatial mobility costs and geographic frictions determine the extent to which native population movements can dissipate local demand distortions (Cadena & Kovak, 2016; Beine & Coulombe, 2018). The capacity of housing supply to respond to demand shocks depends on land availability, zoning regulations, and construction sector capacity, all of which vary systematically across localities according to their size, economic dynamism, and local regulatory environment (Saiz, 2010; García-Montalvo, 2010). This structural heterogeneity is systematically reflected in the urban hierarchy. Recovering it empirically, however, requires operating at the geographic scale at which these mechanisms operate. Studies conducted at the provincial or regional level aggregate localities with highly heterogeneous supply conditions, mobility costs, and labor market dynamics, generating a dilution bias when adjustment channels operate in opposite directions within the same broader geographic unit. Crucially, Monras (2020) and Borjas & Monras (2017) show that native mobility as an adjustment mechanism is more precisely detected at the municipal level, where population flows respond more sharply to the local wage and price differentials induced by immigration. Measuring the effects of immigration at the municipal level is therefore essential for capturing the full local price response to an immigration shock, including which adjustment mechanisms operate, at what intensity, and under what structural conditions.

This paper estimates the causal effect of immigration on housing prices in Spain over the period 2014–2025, using a panel of 699 municipalities. Spain provides an exceptionally relevant setting for this analysis. It ranks among the countries with the largest immigrant populations in the European Union, following the contraction imposed by the 2008–2013 financial crisis, immigration returned to a sharp upward path after 2014, accumulating the largest absolute annual inflows in the EU by 2024 (Eurostat, 2025) and raising the foreign-born share of the population from approximately 12.8% in 2014 to 19.3% in 2025, with Colombia, Morocco and Venezuela representing the largest origin groups by 2025 (INE, 2025). Crucially, this extraordinary expansion in residential demand occurred alongside a period of marked national housing supply restriction, in sharp contrast to the construction boom of the early 2000s. This divergence between strongly expanding demand and a broadly fixed housing stock constitutes a quasi-experimental context that prior studies of immigration and housing prices in Spain have not been able to use, as they operate over a period of rising housing supply and at the provincial level (González & Ortega, 2013; Sanchis-Guarner, 2023), making this the first paper to use municipal-level variation to identify the immigration-price effect. The empirical strategy uses the spatial correlation between annual changes in housing prices and changes in the local immigrant share across municipalities. To isolate the causal effect of immigration from the non-random sorting of immigrants across municipalities, we construct a shift-share instrument based on the settlement networks of immigrants by country of origin recorded in 2005, interacted with national immigrant inflows by country of origin in each period.

In our preferred 2SLS specification, an immigration inflow equal to one percentage point of the municipal population raises the annual housing price growth rate by approximately 0.73 percentage points in the short run, an effect robust to alternative identification strategies, outcome definitions, and sample restrictions. This effect is consistent with the inelasticity of local housing supply, as no significant response is detected in new construction, urban expansion, or residential land use, and with the absence of native population displacement, as natives neither systematically leave nor concentrate in high-immigration municipalities, indicating that spatial redistribution does not operate as an adjustment channel at the municipal level. The effect accumulates monotonically with the time horizon, reaching 2.25 percentage points in the long run, reflecting both the persistence of constrained supply and the progressive assimilation of immigrants toward higher income and expenditure levels.

We also find that these effects vary systematically across the urban hierarchy. While the short-run effect is concentrated in large urban cores, price pressure spreads to and grows larger in intermediate and non-urban municipalities over time, such that a one-percentage-point increase in the immigration rate raises housing prices by approximately 4 percent in the long run in non-urban municipalities. We document two complementary mechanisms behind this pattern. First, housing supply in non-urban municipalities does not respond to the demand shock, so price pressure cannot be absorbed through new construction. Second, immigration raises local economic activity and median income by enough to outweigh higher congestion costs, attracting native population toward high-immigration municipalities and amplifying residential demand pressure over time.

The paper makes three main contributions. First, it is the first to estimate the causal effect of immigration on housing prices in Spain at the municipal level, recovering heterogeneity in supply conditions and adjustment channels that province-level studies necessarily conceal (González & Ortega, 2013; Sanchis-Guarner, 2023). Our preferred estimate of 0.73 percentage points falls below the provincial effects documented for Spain —between 1.0 and 1.6 percentage points during the 2000–2010 boom (González & Ortega, 2013) and approximately 3.3 percentage points over 2001–2012 (Sanchis-Guarner, 2023)— consistent with the absence of native co-location effects in the current period. Second, it documents the full temporal dynamics of the immigration effect on housing prices, contributing to the debate on how local markets absorb residential demand shocks over time. Spatial equilibrium models predict that local price effects dissipate in the long run as housing supply responds and natives relocate (Monras, 2020; Monte et al., 2018; Piyapromdee, 2021). Our results show that when these channels are absent, the demand shock does not dissipate but instead generates local price distortions that grow larger over time. Third, it links demand shock absorption to the structural conditions of local markets, showing that these conditions vary systematically across the urban hierarchy. Our results show that the magnitude and dynamics of the effect depend critically on local supply conditions and on the simultaneous effects of immigration on local economic activity. These economic gains create incentives for natives to locate non-urban municipalities receiving immigrants, amplifying demand pressure rather than relieving it. Unlike prior studies that take co-location as given (Sanchis-Guarner, 2023), this paper shows that this pattern can be explained by the positive effects of immigration on local business creation and income, which are large enough to offset higher congestion costs and attract native population toward high-immigration localities.

The remainder of the paper is organised as follows. Section 2 develops the theoretical framework and derives the empirical hypotheses. Section 3 describes the Spanish immigration context and the data. Section 4 presents the empirical identification strategy. Section 5 reports the main results and the analysis of adjustment channels. Section 6 presents robustness checks. Section 7 documents the heterogeneity of effects across the urban hierarchy. Section 8 concludes.

2. Framework and hypotheses

Although much of the empirical literature on immigration has focused on its consequences for labor markets following an expansion of labor supply (Borjas, 2003; Card, 2001; Peri, 2012), the arrival of immigrants in a local market generates an additional and equally relevant effect on the demand side. Immigrants consume local goods and services, generating an immediate increase in residential demand (Borjas, 2013).[1] Because housing is the canonical non-tradable good, its price is determined locally by the balance between demand and supply: an immigration shock that raises demand will translate directly into higher local housing prices (Sanchis-Guarner, 2023; Piyapromdee, 2021). The extent to which this pressure materialises in prices depends on the capacity of local markets to absorb the demand shock through alternative adjustment mechanisms.

The literature identifies three channels through which local markets can absorb immigration-induced demand pressure on housing prices. First, to the extent that immigration reduces native wages (Borjas, 2003; Dustmann et al., 2013), aggregate housing demand contracts, partially offsetting the price increase. Second, if immigration generates positive productivity externalities or reduces construction costs (Monras, 2020), it may incentivise new residential construction and expand housing supply, partially absorbing the demand shock (González & Ortega, 2013). Third, the spatial mobility of the native population can redistribute demand across markets: if natives leave high-immigration municipalities in response to rising prices or deteriorating labor market conditions, net pressure on local residential demand is reduced (Borjas, 2006; Sá, 2015; Saiz & Wachter, 2011). When none of these channels operates due to persistent housing supply constraints, high mobility costs, or spatial frictions, the increase in residential demand induced by immigration translates directly into higher prices in the short run. This leads to our first hypothesis:

H1: *Immigration exerts upward pressure on housing prices in the short run when local adjustment channels are insufficient to absorb the demand shock.*

The effects of immigration on housing prices are not uniform over time. Three theoretical reasons suggest that the effect accumulates and diverges from the short-run effect. First, if immigration flows are persistent over time and across space, the demand shock accumulates period by period, so that annual differences underestimate the total pressure exerted by immigration on local markets in the medium and long run. Second, the economic assimilation of immigrants improves with length of residence in the host country (Chiswick, 1978; Borjas, 1995): as they narrow their wage gap relative to natives and improve their occupational position, their disposable income grows progressively, cumulatively increasing their housing demand. Third, and most importantly, although standard spatial equilibrium models predict that local demand shocks dissipate as markets converge to a new spatial equilibrium in the long run (Rosen, 1974; Roback, 1982; Monras, 2020; Piyapromdee, 2021; Monte et al., 2018), the speed at which local markets converge depends on the intensity of frictions in the adjustment channels.

[1] This demand effect assumes that immigrant consumption is largely local. To the extent that immigrants remit a substantial share of their income abroad, the effective increase in local residential demand may be attenuated (Olney, 2015).

On the supply side, geographical constraints and land use regulations reduce the elasticity of housing supply in response to demand shocks, requiring consumers in constrained markets to absorb higher housing costs without relief from new construction (Saiz, 2010; García-Montalvo, 2010). Although immigration inflows may stimulate residential construction, the supply response is typically insufficient to fully absorb the accumulated demand shock (González & Ortega, 2013). On the demand side, the spatial mobility of the native population constitutes the main long-run equilibrating mechanism (Dustmann et al., 2017; Braun & Weber, 2021): if natives displace toward lower-immigration municipalities in response to rising prices or deteriorating labor market conditions, net residential demand in affected markets is reduced. Beine & Coulombe (2018) find that this displacement is more pronounced in the long run, consistent with evidence that local market distortions attenuate as spatial equilibrium is restored in the long run (Borjas & Monras, 2017; Edo, 2020). However, when natives concentrate in the same municipalities as immigrants through *co-location* (Sanchis-Guarner, 2023), demographic redistribution fails to materialise and joint residential demand pressure is further amplified. Building on these arguments, we formulate our second hypothesis:

H2: *Under persistent supply constraints and limited spatial mobility, the price effect of immigration accumulates such that long-run effects exceed short-run estimates.*

The adjustment channels identified above do not operate with equal intensity across municipalities. Local structural conditions determine both the capacity of housing supply to respond to demand shocks and the degree of spatial friction facing the native population when relocating. Municipalities with stricter regulatory constraints or lower productive capacity in the construction sector exhibit structurally lower supply elasticity (Saiz, 2010), so that an identical demand shock generates price effects of differing magnitude. Similarly, relocation costs and spatial frictions vary systematically across municipalities, conditioning the speed at which the native population redistributes in response to immigration shocks (Cadena & Kovak, 2016). The labor market effects of immigration also differ across municipalities, with positive effects on native wages and employment emerging in markets with labor shortages or where immigrants complement rather than compete with native workers (Tomohara, 2022; Moreno-Galbis & Tritah, 2016).

This structural heterogeneity is systematically reflected in the urban hierarchy. While large urban municipalities face the most binding supply constraints, their greater construction capacity allows them to generate new supply in the long run and partially absorb persistent demand shocks (González & Ortega, 2013), smaller municipalities, although less supply-constrained initially, have a more limited capacity to respond through new construction. Crucially, positive immigration effects on native employment and wages stimulate local residential demand directly while also attracting native in-migration, placing compounding pressure on a housing stock with limited capacity to expand, such that the initial local price distortion is not dissipated but reinforced in the long run. These arguments motivate our third hypothesis:

H3: *The price effect of immigration varies systematically across the degree of urbanization, with local supply capacity and labor market conditions determining whether the initial demand pressure dissipates or accumulates in the long run.*

3. Data and Descriptive Evidence

We build a balanced municipal-level panel covering 699 Spanish municipalities with populations above 10,000 as of 2014, spanning the period 2014 to 2025.[2] The main outcome is the municipal average transaction price from the Portal Estadístico del Notariado (PEN), which records notary-certified prices and therefore captures realized transaction values rather than listing or appraisal prices, making it the most direct measure of market-clearing housing prices available at the municipal level in Spain. Robustness outcomes are the average transaction price per square metre (PEN), the appraisal value per square metre from the Ministerio de Transportes y Movilidad Sostenible[3], and a municipal rent price index from INE[4]. The key regressor is the annual net change in the foreign-born population share, constructed from a harmonised series combining the Padrón Municipal (2014–2022) and the Censo Anual de Población (2023–2025), both drawn from INE; this source registers all residents regardless of legal status and allows disaggregation by country of origin. Demand-side controls include the number of Social Security affiliates (TGSS) and a Bartik employment shift-share index; supply-side controls include the number of construction firms (DIRCE, INE), urban land surface area, and the residential and hospitality property shares, the last three from the Dirección General del Catastro. Additional outcome variables include total, service-sector, and construction firm counts (DIRCE, INE) and median disposable income per capita (AEAT, available 2020–2023). Summary statistics for all variables are reported in Table Appendix A.1; full variable definitions and data sources appear in Table Appendix A.2.

Spain has experienced two successive large-scale immigration waves. During the first wave, spanning roughly 1998–2008, the foreign-born population grew from 1.5 million to 5.8 million and was led by EU nationals (INE, Padrón Municipal). The foreign-born share during this decade peaked at 12.9% in 2008. The Great Recession triggered first a stagnation (2008) and then a net out-migration (2012–2014). In our analysis period, which fully captures the second wave (2014–2025), the foreign-born population grew from 5.9 million in 2014 to 9.5 million in 2025, with the share rising from 12.8% to 19.3%. Unlike the first wave, the second is driven predominantly by Latin America. Figure 2 shows that non-EU senders dominated throughout the period, led by Venezuela, Colombia, Peru, and Paraguay, alongside Morocco as the principal African sender. The temporary contraction induced by COVID-19 mobility restrictions was followed by an acceleration in arrivals, consistent with the comparatively rapid recovery of the Spanish labor market relative to sending countries during this period (Banco de España, 2022).[5]

Contemporaneous with the first immigration cycle, Spain's construction sector experienced an unprecedented boom (González & Ortega, 2013). New housing permits increased from 524,181 in 2002 to 865,561 in 2006, a cumulative growth of 65.1% at a compound annual rate of 13.4% (Panel A, Figure 1). Following the onset of the financial crisis in mid-2007, permit issuance collapsed and has never recovered to pre-crisis levels. The second immigration wave unfolded in a housing

[2] Municipalities in País Vasco and Navarra are excluded because the Dirección General del Catastro does not provide harmonised municipal-level data series for territories under the *régimen foral*.

[3] Available for 287 municipalities.

[4] Available for 687 municipalities.

[5] Spain also became one of the principal destinations for refugees displaced by the war in Ukraine, representing a compositionally distinct inflow from the migration that dominates the analysis period.

market with permanently constrained supply capacity, defining the macroeconomic backdrop of our analysis period. New housing permits during 2014–2025 remained far below their early-2000s peak while the foreign-born population surpassed its historical maximum (Panel B, Figure 1), and Spain's housing stock proved insufficient to absorb renewed demographic pressure, as evidenced by the widening gap shown in Appendix Figure Appendix B.3. Combined with a historically unprecedented immigrant shock, an effectively fixed housing supply isolates the price effect of a positive demand shock.

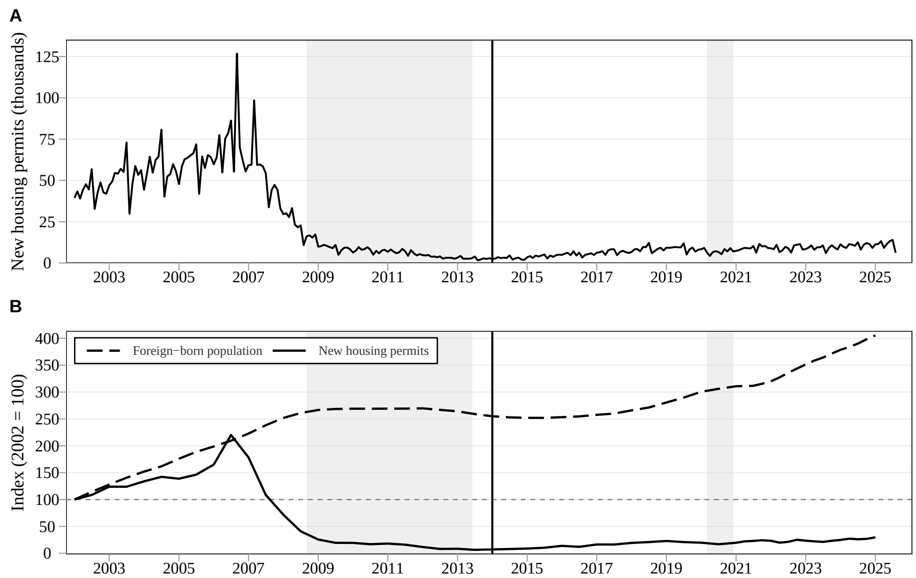

Figure 1: Housing Permits and Immigration Divergence in Spain, 2002–2025.

Notes: Panel A shows monthly new housing permits (thousands). Panel B shows a divergence index (2002 = 100) comparing the foreign-born population and new housing permits. The vertical line marks January 2014, the start of the analysis period. Shaded areas indicate the Global Financial Crisis (September 2008 – June 2013) and the COVID-19 lockdown period (March – December 2020). Housing permit data from the Ministerio de Transportes, Movilidad y Agenda Urbana (MITMA); foreign-born population data from the INE Padrón Continuo de Población (2014–2022) and Censo Anual de Población (2023–2025).

Figure 3 maps the cumulative change in the foreign-born population between 2014 and 2025, confirming that immigration growth is spatially heterogeneous across municipalities.[6] The largest increases cluster around Madrid and Barcelona, along the Mediterranean coast — particularly in the south-eastern corridor of Murcia and Alicante — across the Andalusian south (Cádiz, Sevilla, and Huelva), and in the Canary and Balearic Islands, while interior municipalities exhibit comparatively modest growth.[7] Figure 4 maps the spatial distribution of housing price growth which closely mirrors the geographic concentration of immigration shown above, with the steepest increases recorded in the two main metropolitan areas, along the Andalusian coast, and in the Canary and Balearic Islands, while interior municipalities experienced substantially more modest

[6]Our sample accounts on average for 83.4% of the total immigrant stock in Spain; year-by-year coverage figures are reported in Appendix Figure Appendix B.4.

[7]Only 20 municipalities (2.86% of the total sample) recorded a net decline.

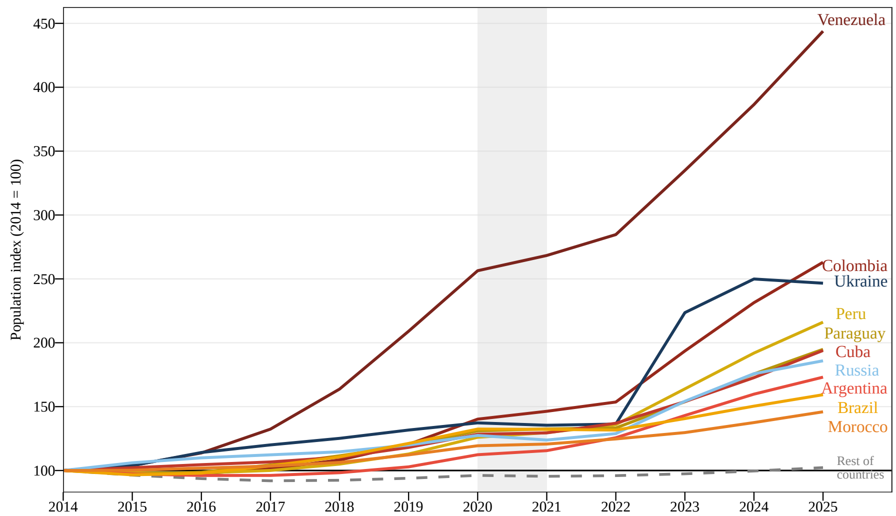

Figure 2: Foreign-Born Population by Country of Origin across Spanish Municipalities Sample, 2014–2025 (index, 2014 = 100).

Notes: The figure displays the ten fastest-growing nationalities over the period. The dashed grey line reports the average index for the remaining nationalities, which includes Italy, China, and other origin countries not individually plotted. Shaded area indicates the COVID-19 pandemic (2020–2021). Source: Padrón Municipal (2014–2022) and Censo Anual de Población (2023–2025) (INE).

growth. Panel A in Table 1 suggests that the evolution of housing prices displays positive spatial correlation with immigration inflows. However, when we account for structural heterogeneity, proxy here by the urbanization degree, Panels B and C in Table 1, suggests that the evolution of housing prices following immigration inflows is not uniform across municipalities but instead varies according the degree of urbanization. Within each urbanization category, high-immigration municipalities exhibit stronger housing price growth across all time horizons, with this differential being the largest among non-urban municipalities.

Table 1: Descriptive Statistics by Immigration Intensity and urbanization

		Δ log Average Transaction Price					
	Δ Imm. rate	1 yr	2 yrs	3 yrs	4 yrs	2014–2025	N
Panel A: Full Sample							
High Immigration	0.71	4.28	8.33	12.25	16.85	47.12	350
Low Immigration	0.18	2.88	5.38	7.74	10.51	31.67	349
Panel B: Urban Municipalities							
High Immigration	0.68	4.83	9.70	14.43	19.67	53.17	107
Low Immigration	0.22	3.78	7.54	10.97	14.87	41.56	64
Panel C: Non-Urban Municipalities							
High Immigration	0.72	4.04	7.73	11.29	15.62	44.46	243
Low Immigration	0.17	2.68	4.90	7.02	9.53	29.45	285

Notes: All values are population-weighted means. Δ Imm. rate is the long-run change in the foreign-born population share (2014-2025). Price columns report the mean cumulative Δ log average transaction price over the indicated window length. High (low) immigration municipalities are those above (below) the sample median of the long-run change in the immigration rate. Urban classification follows the EUROSTAT degree-of-urbanization typology. N denotes the number of municipalities.

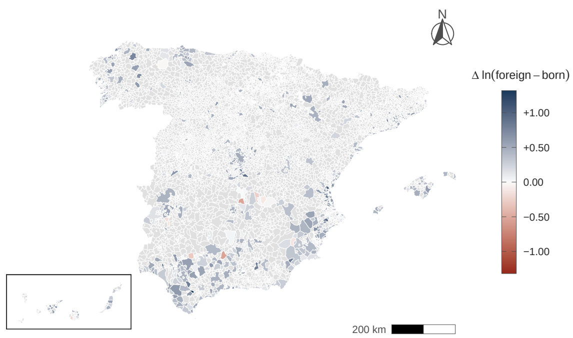

Figure 3: Change in foreign-born population share across Spanish municipalities, 2014–2025.

Notes: Choropleth map of the change in foreign-born population share (percentage points) between 2014 and 2025 for $N = 699$ sample municipalities. Source: Padrón Municipal (INE, 2014–2022) and Censo Anual de Población (INE, 2023–2025).

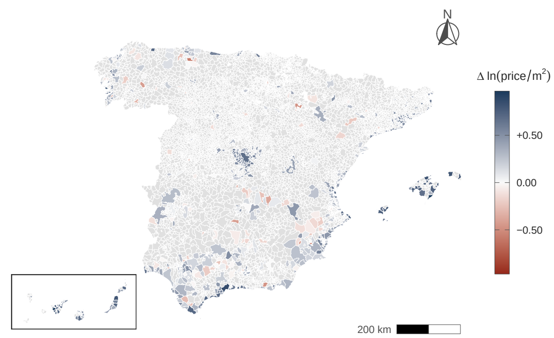

Figure 4: Housing price growth across Spanish municipalities, 2014–2025.

Notes: Choropleth map of municipal-level housing price growth between 2014 and 2025, measured as $\Delta \ln(\text{price}/m^2)$. Source: Portal Estadístico del Notariado.

4. Empirical Strategy

4.1. Regression specifications

Like much of the empirical literature on immigration and housing markets, this paper exploits spatial variation in the intensity of immigration flows across local markets to identify their effect on housing prices (Dustmann et al., 2016; Monras, 2020; Accetturo et al., 2014; Mocetti & Porello, 2010). We follow the annual differences approach at the municipal level of Saiz (2007) and Sá (2015), relating housing price growth to the intensity of the local immigration shock over the period 2014–2025. The baseline specification is:

$$\Delta \log P_{c,t} \;=\; \alpha + \beta \, \frac{\Delta \mathrm{M}_{c,t}}{Pop_{c,t-1}} + \phi \Delta X^{D}_{c,t} + \Phi \Delta X^{H}_{c,t} + \lambda_t + \lambda_r + (\lambda_t \cdot \lambda_r) + \epsilon_{c,t} \tag{1}$$

where $\Delta \log P_{c,t}$ is the annual change in the log average transaction price in municipality c in the year t, and $\frac{\Delta \mathrm{M}_{c,t}}{Pop_{c,t-1}}$ is the change in the stock of foreign-born residents between $t-1$ and t, normalized by total municipal population in the prior period. The normalization by $Pop_{c,t-1}$ serves two purposes. First, it standardizes the shock by local market size, preventing scale effects from inducing a spurious correlation between absolute flows and price changes (Card, 2001; Peri & Sparber, 2011). Second, by fixing the reference population prior to the shock, it mitigates the endogeneity that would arise from a contemporaneous denominator, which would introduce a mechanical correlation between the measured shock and the dependent variable through native displacement or co-location (Borjas & Monras, 2017; Sanchis-Guarner, 2023).[8] Under this design, β captures the semi-elasticity of housing prices with respect to a one-percentage-point increase in the net immigration rate, reflecting the direct pressure of the demand shock on prices to the extent

[8] When we fix the denominator at the 2014 municipal population throughout all annual differences, the 2SLS coefficients are virtually identical to those from the preferred specification.

that housing supply, local wages, and demographic composition do not adjust instantaneously.[9]

To absorb observable sources of heterogeneity, specification (1) includes two vectors of municipal-level time-varying controls. The vector $\Delta X^D_{c,t}$, captures demand-side conditions through two complementary variables. The first is the log change in the number of workers affiliated to the social security system, which controls for local employment cycles that generate demand pressure on housing markets beyond the immigration shock. The second is a Bartik employment demand index, $B_{c,t} = \sum_s \lambda_{c,s,2011} \cdot \Delta \log E_{s,t}$,[10] constructed by interacting 2011 Census industry shares with national sectoral employment growth. This index captures exogenous shifts in local labor demand driven by national industry trends, providing a clean control for local demand dynamics orthogonal to the immigration shock (Bartik, 1991).

The vector $\Delta X^H_{c,t}$ captures supply-side housing conditions through four variables. The log change in the number of construction firms proxies for the local capacity to expand housing supply in response to demand shocks. The log change in residential land area and the log change in total urban area jointly capture adjustments in the availability of buildable land, a key determinant of medium-run housing supply elasticity (Saiz, 2010). Finally, the log change in the share of properties classified for tourist use captures the reallocation of the existing housing stock toward short-term rental and tourist accommodation, which compresses the supply available for residential use and independently generates upward price pressure in municipalities with high tourist exposure.

The specification further includes year fixed effects λ_t, which absorb national macroeconomic cycles, monetary policy shifts, and aggregate regulatory changes. Province fixed effects λ_r control for time-invariant unobservable factors generating persistent differences in price trends across provinces. Province-specific linear time trends $(\lambda_t \cdot \lambda_r)$ control for gradual and heterogeneous dynamics in housing prices at the provincial level that would otherwise confound the within-province variation used for identification. Finally, standard errors are clustered at the municipal level to account for serial correlation in the error term within municipalities over time.

4.2. Identification and Assumptions

4.2.1. Endogeneity of Immigrant Shocks

OLS estimation of β is unlikely to recover a consistent estimate: unobserved local shocks may simultaneously attract immigrants and generate independent upward pressure on housing prices, such that $\mathbb{E}[\Delta M_{c,t} \cdot \epsilon_{c,t}] \neq 0$ even after conditioning on the full set of controls and fixed effects in specification 1. Immigrants concentrate in labor markets with more favourable conditions and in municipalities with inelastic supply (Albert & Monras, 2022; Cadena & Kovak, 2016; Card & Peri, 2016), biasing $\widehat{\beta}$ upward, while sorting into low-cost elastic markets would attenuate the

[9] In Section 7.1 we test whether native mobility, labor market effects, and housing supply responses can account for the estimated short- and long-run effects.

[10] In this expression, $\lambda_{c,s,2011}$ denotes the share of municipality c's employed workforce in sector s as recorded in the 2011 Population Census, and $\Delta \log E_{s,t}$ is the national log-change in employment in sector s between $t-1$ and t.

estimate downward. To address this, we construct a shift-share instrument following Card (2001), exploiting the well-documented tendency of new immigrants to settle in municipalities where immigrants from the same country of origin are already established (Bartel, 1989; Munshi, 2003; Borjas, 1995). This clustering behaviour implies that the historical geographic distribution of immigrants by country of origin is a strong predictor of subsequent inflows, independently of contemporaneous local economic conditions.

Using data from the 2005 *Padrón Municipal*, we compute the historical distribution of immigrants across the 699 municipalities by country of origin τ as:

$$\theta^{(\tau)}_{c,2005} = \frac{M^{\tau}_{c,2005}}{\sum_c M^{\tau}_{c,2005}} \tag{2}$$

where $M^{\tau}_{c,2005}$ is the stock of immigrants from country of origin τ registered in municipality c in 2005. The share $\theta^{\tau}_{c,2005}$ captures the fraction of all immigrants from country τ settled in municipality c at the base year, reflecting the historical geographic concentration of each origin group driven by early settlement decisions, ethnic networks, and local labor market specialisation.[11] We then assign aggregate national inflows by country of origin to each municipality and sum across origins to obtain the shift-share predictor:

$$\Delta\widehat{M}_{c,t} = \sum_{\tau} \theta^{(\tau)}_{c,2005} \cdot \Delta M^{\tau}_{t} \tag{3}$$

where ΔM^{τ}_{t} is the national-level change in the stock of immigrants from country τ between $t-1$ and t. This predictor allocates aggregate national inflows across municipalities according to their pre-determined settlement shares, so that its variation reflects the interaction of historical network patterns with origin-country-specific push factors rather than local pull conditions.[12]

Since the lagged municipal population $Pop_{c,t-1}$ includes native residents who do not distribute randomly across municipalities (Card & Peri, 2016), the denominator is itself potentially endogenous. To address this, we construct a predicted native population for each period using an analogous procedure:

$$\widehat{N}_{c,t} = \frac{N_{c,2005}}{\sum_c N_{c,2005}} \cdot \Delta N_t \tag{4}$$

where $N_{c,2005}$ is the native population in municipality c in 2005 and ΔN_t is the national-level change in the native population in period t. The first-stage regression then takes the form:

$$\frac{\Delta M_{c,t}}{Pop_{c,t-1}} = \alpha + \pi \frac{\Delta\widehat{M}_{c,t}}{\widehat{Pop}_{c,t-1}} + \phi \Delta X^{D}_{c,t} + \Phi \Delta X^{H}_{c,t} + \lambda_t + \lambda_r + (\lambda_t \cdot \lambda_r) + \varepsilon_{c,t} \tag{5}$$

[11] The instrument is constructed using the 28 origin countries that account for the largest immigrant stocks in Spain over the sample period. Table Appendix B.2 in the Appendix lists the full set of countries included.

[12] Although historical settlement shares mitigate concerns about demand-pull sorting, the national inflows ΔM^{τ}_{t} could still reflect destination-specific attraction factors. As a robustness check, Section 7.3 replicates the main results instrumenting national inflows with supply-push factors from origin countries.

where $\widehat{Pop}_{c,t-1} = \widehat{M}_{c,t-1} + \widehat{N}_{c,t-1}$ is the predicted total municipal population in the prior period, combining predicted native and immigrant populations to avoid mechanical correlation between the denominator and contemporaneous local conditions.

Table 2 reports the first-stage estimates. The shift-share predictor is a strong and stable predictor of actual immigrant flows across all specifications. In Panel A, the first-stage coefficient indicating that a one-percentage-point increase in the predicted immigration rate translates into a 0.60 to 0.75 percentage-point increase in the actual immigration rate, confirming that municipalities with denser historical settlement networks for origin countries experiencing larger national inflows received significantly larger local immigrant flows. Kleibergen-Paap F-statistics comfortably exceed the conventional weak-instrument threshold of 10 across all columns (Stock & Yogo, 2005). Panel B replicates the analysis using the 2014–2025 long difference and confirms that the instrument retains its strength, with KP F-statistics well above conventional thresholds throughout.[13]

Table 2: First-Stage Regressions

	Dependent Variable: $\Delta\text{Immigration}_{c,t}$			
	(1)	(2)	(3)	(4)
	Panel A. Short-Run (Annual Differences)			
$\Delta\widehat{Immigration}_{c,t}$	0.603***	0.604***	0.599***	0.752***
	(0.057)	(0.058)	(0.057)	(0.052)
KP F-stat	111.9	109.6	109.0	208.6
R-Squared	0.584	0.585	0.587	0.671
Clusters	699	699	699	699
Observations	7,689	7,689	7,689	7,689
	Panel B. Long-Run (Long Difference 2014–2025)			
$\Delta\widehat{Immigration}^{14-25}_{c,t}$	0.505***	0.499***	0.470***	0.605***
	(0.142)	(0.145)	(0.145)	(0.069)
KP F-stat	47.5	42.9	39.6	77.7
R-Squared	0.337	0.349	0.377	0.623
Clusters	46	46	46	46
Observations	699	699	699	699
Year FE	Yes	Yes	Yes	Yes
Housing Supply Controls	No	Yes	Yes	Yes
Demand Controls	No	No	Yes	Yes
Province FE	No	No	No	Yes
Province × Trend	No	No	No	Yes

Notes: The dependent variable is the change in the immigration rate. Panel A uses annual first differences over 2014–2025, with standard errors clustered at the municipal level. Panel B uses the single long difference 2014–2025 with standard errors clustered at the province level. The excluded instrument $\Delta\widehat{Immigration}_{c,t}$ is the shift-share predictor constructed using 2005 settlement shares interacted with national-level immigrant inflows by origin country. Columns (1)–(4) add controls sequentially: year fixed effects only; adding housing supply controls; adding local demand controls; and adding province fixed effects together with province-specific linear trends. The Kleibergen-Paap (KP) F-statistic tests for weak identification of the excluded instrument. All specifications are weighted by 2014 municipal population. $^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$.

[13] Standard errors in Panel A are clustered at the municipal level. In Panel B, where identification relies on a single long difference, clustering is at the province level to account for spatial correlation across municipalities within the same province.

The validity of the instrument requires that both components satisfy the exclusion restriction (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022; Jaeger et al., 2018). The historical settlement shares $\theta^{\tau}_{c,2005}$ must predict immigrant flows exclusively through the network mechanism, and not through persistent local demand conditions, housing supply constraints, or pre-existing price trends. This assumption is supported by the temporal distance between the base year and the estimation period, as the shares are drawn from 2005, nearly a decade before the marked acceleration in immigration flows after 2014, which substantially reduces the likelihood that they capture contemporaneous local economic conditions. The national inflows ΔM^{τ}_{t}, in turn, must be independent of contemporaneous economic conditions in receiving municipalities. This assumption is plausible given that, as Figure 2 documents, the countries accounting for the largest immigration growth in Spain over 2014–2025 were predominantly those experiencing exogenous political, economic, and humanitarian crises, whose emigration decisions were driven by origin-country conditions. Nevertheless, to the extent that aggregate Spanish labor market conditions or immigration policy may have jointly influenced both national inflows and local housing markets, we complement the baseline instrument with supply-push factors from origin countries as an additional robustness check (Section 7.3).

To assess instrument validity more directly, we implement a falsification test in the spirit of Goldsmith-Pinkham et al. (2020), adapted to a setting where pre-period transaction price data are unavailable. The test exploits the temporal structure of the sample as follows. We split the estimation period into two subperiods, 2014–2020 and 2020–2025, and construct an alternative shift-share predictor using the same 2005 settlement shares interacted with national inflows observed during the second subperiod. We then regress changes in housing prices and other key local outcomes during the first subperiod on this forward-looking predictor. Since future national inflows cannot causally affect past local price dynamics, any statistically significant relationship between the second-subperiod predictor and first-subperiod outcomes would indicate that the instrument is correlated with persistent local structural conditions that independently drive housing market dynamics across both subperiods, violating the exclusion restriction. Table Appendix B.1 reports the results. None of the estimated coefficients is statistically significant at conventional levels across any of the seven outcome variables considered, consistent with the assumption that the instrument captures exogenous variation in immigrant flows rather than persistent structural conditions in local markets.

4.2.2. Omitted Spillovers Shocks

A second threat to causal identification arises from the spatial interdependence between local housing markets. The literature documents that internal migration acts as an equilibrating mechanism that absorbs initial disparities in wages, employment, and housing prices generated by local shocks (Monte et al., 2018; Dustmann et al., 2017; Cadena & Kovak, 2016; Albert & Monras, 2022), and that migration responses to local shocks are bilateral location decisions that depend on conditions in both the own market and alternative destinations (Borusyak et al., 2022). The degree of local price adjustment therefore depends not only on the municipality's own shock but also on the intensity of the shock in neighbouring markets, since the latter determines the scope for equilibrating mobility to take place. When immigration shocks and local price responses are spatially correlated, this interdependence constitutes a direct violation of SUTVA (Angrist et al.,

1996) and generates an omitted variable bias in specification 1 when the own shock is correlated with shocks in neighbouring municipalities (Borusyak et al., 2022).

To address this, we construct a spatial attraction variable that captures the housing demand pressure transmitted from neighbouring municipalities. We define the exogenous spatial pull of municipality c in year t as:

$$\text{Pull}^{\text{exog}}_{c,t} = \frac{\sum_{j \neq c} \frac{A_j}{d^2_{cj}} \Delta \widehat{M}_{j,t}}{\sum_{j \neq c} \frac{A_j}{d^2_{cj}}} \tag{6}$$

where $\Delta \widehat{M}_{j,t}$ are the immigrant flows predicted by the shift-share instrument in municipality j, d_{cj} is the geodesic distance in kilometres between the centroids of municipalities c and j, and A_j is the area of municipality j in square kilometres. The inverse-square distance kernel assigns greater weight to nearby municipalities, while the area term corrects for the mechanical tendency of larger municipalities to receive more immigrants. The denominator normalizes the index so that $\text{Pull}^{\text{exog}}_{c,t}$ is interpretable as a weighted average rather than a weighted sum, ensuring comparability across municipalities that differ in geographic isolation or neighbourhood density.

The construction of $\text{Pull}^{\text{exog}}_{c,t}$ improves on two related approaches in the literature in ways that are directly relevant for identification. Saiz & Wachter (2011) propagate historical immigrant shares to approximate geographic attractiveness, but their weights reflect past settlement patterns that may themselves be correlated with local economic conditions. Kim et al. (2025) weight neighbouring shocks by observed bilateral migration flows, introducing endogeneity through the weights. Our approach addresses both concerns: we propagate exogenous immigrant flows predicted by the shift-share instrument, which are orthogonal to unobserved local shocks in neighbouring municipalities, and weight them purely by geography, so that the resulting variable is determined solely by pre-determined settlement networks, national inflows by country of origin, and geographic distance.[14]

Including $\text{Pull}^{\text{exog}}_{c,t}$ as an additional control in specification 1 corrects for this omitted variable bias under the assumption that the geographic weights adequately capture the spatial transmission of demand pressure, allowing β to be interpreted as the causal effect of the own immigration shock on housing prices holding constant the demand pressure transmitted from neighbouring municipalities.

[14] Figure Appendix B.2 documents the relationship between the exogenous spatial pull and the local immigration shock, both residualised with respect to the full set of fixed effects and controls. The negative slope indicates that, conditional on provincial trends and observed local conditions, municipalities receiving above-average immigration inflows tend to be located in areas where neighbouring municipalities receive below-average inflows, reflecting a spatial distribution of immigration within provinces whereby the concentration of immigrants in one municipality comes partly at the expense of neighbouring ones.

5. Results

5.1. Immigration and Housing Prices

Table 3 presents the main results. Panel A reports OLS estimates. Panel B reports 2SLS estimates in which the change in the immigration rate is instrumented with the shift-share predictor described in Section 4.2.1. Panel C extends the preferred 2SLS specification with exogenous controls for spatial spillovers from neighbouring municipalities, as described in Section 4.2.2. Across all three panels, the four columns add controls sequentially: year fixed effects only (column 1); housing supply controls (column 2); local labor-market demand controls (column 3); and province fixed effects together with province-specific linear trends (column 4). The coefficient in column (4) is identified from within-province deviations of municipal immigration inflows from their province-specific linear trend, using only municipalities that receive more immigration than their provincial trajectory predicts and where prices simultaneously rise by more than that trajectory would imply. All specifications are weighted by the 2014 municipal population and standard errors are clustered at the municipal level.

The OLS estimates in Panel A are positive and statistically significant across all specifications, implying that an immigration inflow equal to one percentage point of the municipal population is associated with an increase in the annual housing price growth rate of between 0.52 and 1.16 percentage points, with the estimate declining monotonically as the specification becomes more saturated. Across all specifications in Panel B, the 2SLS estimates are positive and exceed their OLS counterparts, indicating that the net endogeneity bias is downward and that immigrants disproportionately concentrate in municipalities where price growth is relatively contained (González & Ortega, 2013; Sanchis-Guarner, 2023). The 2SLS coefficients decline as controls and fixed effects are added, with the sharpest reduction following the inclusion of province fixed effects and linear trends, suggesting that a substantial share of the raw immigration-price correlation reflects province-level macroeconomic dynamics rather than idiosyncratic local variation.

Panel C further probes the robustness of the baseline estimates by controlling for immigration-driven demand spillovers from geographically proximate municipalities.[15] Comparing Panels B and C reveals that accounting for spatial spillovers modestly attenuates the main immigration coefficient, from 0.840 to 0.727 in the fully saturated model, confirming that the baseline 2SLS estimate absorbs a small component of spatially correlated variation that is not attributable to the municipality's direct immigration shock. In our preferred specification, which combines the shift-share instrument, province-level fixed effects and trends, and the spatial pull control (column 4 of Panel C), an immigration inflow equal to one percentage point of the municipal population raises the annual housing price growth rate by approximately 0.73 percentage points, indicating that the demand pressure induced by immigration is not offset by any alternative local adjustment mechanism and translates directly into higher housing prices.

[15] Panel A of Table Appendix B.3 treats spatial spillovers as an endogenous regressor; Panel B instruments them with the exogenous spatial pull predictor. Baseline estimates are robust to both treatments.

Table 3: Immigration and Housing Prices

	Dependent Variable: $\Delta \log$ Average Transaction Price			
	(1)	(2)	(3)	(4)
	Panel A. OLS			
ΔImmigration	1.159***	1.129***	1.057***	0.522***
	(0.217)	(0.216)	(0.206)	(0.137)
R-Squared	0.123	0.129	0.133	0.182
	Panel B. 2SLS			
ΔImmigration	2.169***	2.142***	2.061***	0.840***
	(0.438)	(0.423)	(0.407)	(0.259)
KP F-stat	111.9	109.6	109.0	208.6
R-Squared	0.117	0.123	0.127	0.182
	Panel C. 2SLS + Spatial Exogenous Spillover			
ΔImmigration	2.144***	2.116***	2.041***	0.727***
	(0.426)	(0.413)	(0.400)	(0.265)
ΔSpatial Pull	-0.060***	-0.062***	-0.054***	-0.067***
	(0.023)	(0.021)	(0.020)	(0.016)
KP F-stat	116.2	114.1	112.7	212.8
R-Squared	0.118	0.124	0.128	0.183
Year FE	Yes	Yes	Yes	Yes
Housing Supply Controls	No	Yes	Yes	Yes
Demand Controls	No	No	Yes	Yes
Province FE	No	No	No	Yes
Province × Trend	No	No	No	Yes
Clusters	699	699	699	699
Observations	7,689	7,689	7,689	7,689

Notes: Each column reports a separate regression. The dependent variable throughout is the change in log average transaction price. Panel A reports OLS estimates. Panel B reports 2SLS estimates in which ΔImmigration is instrumented with the shift-share predictor $\Delta \widehat{Immigration}_{c,t}$. Panel C adds a spatially exogenous spillover instrument for ΔSpatial Pull to the 2SLS specification. Columns (1)–(4) add controls sequentially: year fixed effects only; adding housing supply controls; adding local demand controls; and adding province fixed effects together with province-specific linear trends. All specifications are weighted by 2014 municipal population. Standard errors are clustered at the municipal level and reported in parentheses. The Kleibergen-Paap (KP) F-statistic tests for weak identification of the excluded instrument.*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The preferred estimate is consistent in magnitude with the effects documented in the existing literature, which range from approximately 0.7 percent for rental prices across US states (Monras, 2020) to 0.6–1.5 for rents and transaction prices at the MSA level in the United States (Saiz, 2007), 1.0–1.6 percent at the province level in Spain during the 2000–2010 boom period (González & Ortega, 2013), and approximately 2.7 percent for single-family homes in Switzerland (Degen & Fischer, 2017). Differences in the magnitude of estimated effects across studies reflect three sources of variation. First, our estimates rely on realized transaction prices signed before a notary rather than appraised values or subjective owner estimates, providing a more direct measure of actual market clearing prices. Second, we are the first to exploit municipal-level variation in Spain, a finer geographic scale than the province-level studies of González & Ortega (2013) and Sanchis-Guarner (2023), which aggregate across municipalities with heterogeneous immigration intensity and housing market conditions. Third, and most importantly, differences in the capacity of local markets to absorb immigration-induced demand through alternative adjustment channels drive systematic variation in estimated price effects across contexts. The substantially larger effects found by Sanchis-Guarner (2023) are driven in part by the co-location of natives with immigrants, which amplifies joint demand pressure beyond the direct immigration effect, while the negative effects documented by Sá (2015) for England and Wales reflect strong native displacement that relieves local demand pressure and dominates the direct effect in that context.

5.2. Local Adjustment Dynamics

As Hypothesis 2 establishes, the effect of immigration on housing prices need not be uniform over time (Edo, 2023). The literature generally finds that short-run local effects tend to dissipate as markets converge toward a new spatial equilibrium through capital reallocation or population mobility (Edo, 2020; Jaeger et al., 2018; Monras, 2020; Piyapromdee, 2021). However, when these channels operate slowly or are constrained by structural frictions, the initial demand shock is not rapidly absorbed and its effect on prices may persist and intensify over longer horizons. To examine this possibility, we extend the baseline specification to multi-period differences, estimating the following equation:

$$\Delta^h \log P_{c,t} = \alpha + \beta^h \frac{\Delta^h \mathrm{M}_{c,t}}{Pop_{c,t-h}} + \phi \Delta^h X^D_{c,t} + \Phi \Delta^h X^H_{c,t} + \lambda_t + \lambda_r + (\lambda_t \cdot \lambda_r) + \epsilon_{c,t} \tag{7}$$

where $h \in \{2, 3, 4\}$ denotes the length of the differencing window in years, and the long difference corresponds to the single 2014–2025 change. The dependent variable is the h-period change in log average transaction price, and $\Delta^h \mathrm{M}_{c,t}$ is instrumented with the corresponding h-period shift-share predictor.[16].

Table 4 reports the 2SLS results. Columns (1)-(3) include province fixed effects and province-specific linear trends; column (4) includes province fixed effects only. Standard errors are clustered at the municipal level in columns (1)-(3) and at the province level in column (4). Panel A shows that the effect of immigration on housing prices grows monotonically with the length of the differencing window. An immigration inflow equal to one percentage point of the municipal population is associated with a 1.3 percent rise in housing prices over a two-year horizon, growing to 2.2 percent over four years and reaching 2.4 percent in the long difference. This monotonic accumulation is consistent with Hypothesis 2: the price response to immigration does not reflect a transitory adjustment that dissipates as markets equilibrate but rather strengthens persistently over time, reflecting both the cumulative intensity of the immigration shock and the absence of sufficiently strong local adjustment mechanisms to absorb the accumulated demand pressure. Panel B adds a spatially exogenous pull control constructed over the same time window h. The immigration coefficients remain positive, significant, and monotonically increasing across all horizons, with estimates only marginally below those in Panel A, confirming the robustness of the dynamic pattern to the correction for spatial spillovers.

Two complementary factors may account for this pattern. First, the immigration demand shock

[16] Taking longer differences is a standard approach in the immigration literature to capture dynamic adjustments (Edo, 2023; Monras, 2020)

is cumulative, as new flows add to the pre-existing immigrant stock and both the size and duration of residential demand pressure grow with the time horizon. Second, economic assimilation amplifies this effect, as immigrants accumulate labor market experience and their wages and housing expenditure rise progressively (Borjas, 2015; Brücker et al., 2021), further intensifying residential demand in the long run. This pattern is well documented across a broad range of host economies and is consistent with the assimilation profiles observed for immigrants residing in Spain, as shown in Appendix Figure Appendix B.1, which plots mean log wages (Panel A) and mean log imputed rent (Panel B) by years of residence.[17]

Table 4: Immigration and Housing Prices: Dynamic Differences

	Dependent Variable: Δ^h log Average Transaction Price			
	$h = 2$	$h = 3$	$h = 4$	Long Diff.
	(1)	(2)	(3)	(4)
	Panel A. 2SLS			
Δ^hImmigration	1.335***	1.852***	2.185***	2.444***
	(0.277)	(0.331)	(0.414)	(0.796)
KP F-stat	200.9	201.8	178.6	74.7
R-Squared	0.332	0.399	0.444	0.627
	Panel B. 2SLS + Spatial Exogenous Pull			
Δ^hImmigration	1.242***	1.799***	2.137***	2.246***
	(0.276)	(0.328)	(0.409)	(0.790)
Δ^hSpatial Pull$^{\text{exog}}$	-0.051***	-0.029**	-0.024	-0.066***
	(0.014)	(0.014)	(0.015)	(0.021)
KP F-stat	204.5	204.6	181.0	75.9
R-Squared	0.334	0.400	0.446	0.642
Province FE	Yes	Yes	Yes	Yes
Province × Trend	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes
Clusters	699	699	699	46
Observations	6,990	6,291	5,592	699

Notes: The dependent variable is the h-period change in log average transaction price, where $h \in \{2, 3, 4\}$ denotes overlapping differences and the long difference corresponds to the single 2014–2025 change. Δ^hImmigration is instrumented with the corresponding h-period shift-share predictor. Panel B adds the spatially exogenous pull control Δ^hSpatial Pull$^{\text{exog}}$, constructed using predicted immigrant flows as spatial weights. Columns (1)–(3) include province fixed effects and province-specific linear trends; column (4) includes province fixed effects only. All specifications include demand and housing supply controls and are weighted by 2014 municipal population. Standard errors in columns (1)–(3) are clustered at the municipal level; column (4) clusters at the province level.* $p < 0.10$,** $p < 0.05$, $^{***}p < 0.01$.

5.3. Native Mobility and Local Adjustment Channels

The results in Section 5.1 document a positive and significant effect of immigration on housing prices that intensifies in the long run. What adjustment mechanisms explain the rise in prices in high-immigration municipalities, and why are these effects more pronounced over longer horizons?

[17] This analysis draws on microdata from the European Statistics on Income and Living Conditions (EU-SILC) for immigrants residing in Spain over the period 2021–2023.

Does a reallocation of the native population redistribute demand pressure across space, or does an endogenous housing supply response attenuate it over time? Understanding which adjustment mechanisms underlie this pattern is relevant for two reasons. First, any endogenous response of housing supply or native population displacement conditions the estimated price effects both in the short and in the long run, as established in Hypotheses Hypothesis 1 and Hypothesis 2 (Saiz, 2007; Monras, 2020; Piyapromdee, 2021). Second, if immigration induces supply expansion or native outmigration, the coefficients estimated in Section 5.1 would be downward biased, constituting an additional identification concern that would lead to an underestimate of the direct effect of immigration on local housing prices (Borjas & Monras, 2017; Card & Peri, 2016).

The native population response can be assessed through two empirical strategies. The first uses internal migration flows across areas of varying immigration intensity to directly identify the extensive margin of geographic displacement (Borjas, 2006; Card, 2001; Dustmann et al., 2017). The second exploits the spatial correlation between native and immigrant population stocks across local labor markets to test whether immigration systematically reshapes the local demographic composition (Card, 2007; Monras, 2020). We follow Peri & Sparber (2011) and estimate the effect of the immigration shock on the net change in native population at the municipal level using the following equation:

$$\frac{\Delta N_{c,t}}{Pop_{c,t-1}} = \alpha + \beta \frac{\Delta \mathrm{M}_{c,t}}{Pop_{c,t-1}} + \phi \Delta X^{D}_{c,t} + \Phi \Delta X^{H}_{c,t} + \lambda_t + \lambda_r + (\lambda_t \cdot \lambda_r) + \epsilon_{c,t} \tag{8}$$

where $\Delta N_{c,t}$ denotes the change in the number of registered native residents in municipality c between periods t and $t-1$, normalised by total population at the beginning of the period, $Pop_{c,t-1}$. A negative and significant estimate of $\hat{\beta}$ would indicate native displacement (Borjas, 2006), whereas a positive or statistically insignificant coefficient would be consistent with co-location or an absence of migratory response (Sanchis-Guarner, 2023; Peri & Sparber, 2011). Panel A of Table 5 shows that immigration has no significant effect on native population growth across any time horizon. Native residents neither systematically leave nor concentrate in high-immigration municipalities in response to the immigration shock, ruling out both native displacement and co-location as operative adjustment channels at the municipal level. The positive price effects documented in Section 5.1 therefore reflect a setting in which neither native displacement nor co-location operates at the municipal level, in contrast to Sanchis-Guarner (2023), where co-location amplifies joint demand pressure generating larger price effects, and Sá (2015), where strong native displacement produces negative price effects.

To assess whether municipalities with higher immigration inflows exhibited positive housing supply responses, we estimate specification 1 replacing the outcome variable with alternative proxies for housing supply changes. Panels B through E show no significant housing supply response across any of the proxies considered. Immigration does not significantly affect urban area expansion (Panel B), residential land share (Panel C), the number of construction firms (Panel D), or hospitality land use share (Panel E). The absence of a supply response is consistent with the land availability and regulatory constraints that characterise local housing markets (Saiz, 2010; González & Ortega, 2013), and with the pattern of price effects estimated in Section 5.1, whereby the inability of housing supply to respond to the demand shock allows the resulting pressure to translate persistently into higher prices and to intensify in the long run.

Table 5: Immigration and Alternative Outcomes: Testing for Adjustment Channels

	Dependent Variable: Δ^h Outcome				
	Short Diff.	$h=2$	$h=3$	$h=4$	Long Diff.
	(1)	(2)	(3)	(4)	(5)
	Panel A. Native Population Growth				
Δ^hImmigration	0.036	0.030	0.027	0.012	-0.020
	(0.063)	(0.070)	(0.084)	(0.109)	(0.140)
KP F-stat	212.2	204.1	204.4	181.7	74.6
	Panel B. Urban Area				
Δ^hImmigration	-0.215	-0.288	-0.233	-0.321	0.471
	(0.189)	(0.190)	(0.210)	(0.274)	(0.614)
KP F-stat	212.7	204.2	204.5	180.7	74.6
	Panel C. Residential Land Share				
Δ^hImmigration	0.020	0.027	0.037	0.045	0.045
	(0.023)	(0.025)	(0.030)	(0.037)	(0.068)
KP F-stat	212.7	204.0	204.3	180.8	83.4
	Panel D. Construction Firms				
Δ^hImmigration	-0.301	-0.076	-0.337	-0.415	-0.436
	(0.385)	(0.354)	(0.417)	(0.470)	(1.198)
KP F-stat	214.9	206.6	206.6	182.1	78.1
	Panel E. Hospitality land use share				
Δ^hImmigration	0.319	0.651	0.860	0.662	1.63
	(0.976)	(0.907)	(0.935)	(1.077)	(2.389)
KP F-stat	212.7	204.7	205.0	181.3	67.8
	Panel F. Affiliated workers				
Δ^hImmigration	0.048	0.108	0.171	0.205	0.579
	(0.180)	(0.180)	(0.195)	(0.236)	(0.428)
KP F-stat	212.3	198.8	199.3	176.5	96.3
	Panel G. Total Firms				
Δ^hImmigration	0.399***	0.538***	0.688***	0.884***	1.212***
	(0.111)	(0.098)	(0.105)	(0.122)	(0.149)
KP F-stat	212.7	204.5	204.6	181.0	75.9
	Panel H. Services Firms				
Δ^hImmigration	0.081	0.166	0.271*	0.399**	0.351
	(0.149)	(0.137)	(0.144)	(0.163)	(0.289)
KP F-stat	212.7	204.5	204.6	181.0	75.9
	Panel I. Median Income				
Δ^hImmigration	0.469***	1.378***	—	—	1.473***
	(0.128)	(0.025)	—	—	(0.433)
KP F-stat	126.1	129.4	—	—	49.7
Clusters	699	699	699	699	46
Observations	7,689	6,990	6,291	5,592	699

Notes: All specifications include the full set of controls. Columns (1)–(4) cluster standard errors at the municipal level; column (5) clusters at the province level. Standard errors in parentheses.*$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

If housing costs rise and supply does not adjust, why do native residents not relocate to lower-immigration municipalities? One possibility is that spatial mobility costs may be sufficiently high to discourage relocation, or high-immigration municipalities may be geographically proximate to one another, restricting the set of available alternatives. Second, immigration may generate positive local externalities in terms of employment and economic activity that, in spatial equilibrium (Monras, 2020; Monte et al., 2018), compensate residents for higher housing costs and discourage out-migration. Panel F shows no significant effect on affiliated workers across any time horizon, while immigration has a positive and significant effect on total firm creation across all time horizons (Panel G), with effects increasing monotonically from the short to the long run, indicating that immigration stimulates local economic activity primarily through business creation. Effects on service-sector firms (Panel H) are positive but reach significance only at intermediate horizons. Panel I documents a positive and significant effect on median income, both in the short run and in the long difference. These income and economic activity gains not only compensate native residents for higher housing costs in utility terms, discouraging out-migration, but also reflect an increase in local aggregate spending capacity that sustains residential demand over time, even in the absence of native in-migration. Taken together, these results are consistent with a spatial equilibrium in which the economic gains generated by immigration offset higher housing costs, sustaining residential demand and discouraging native out-migration

6. Heterogeneous Effects

6.1. Immigration and Urbanization

The baseline estimates establish that immigration exerts a persistent positive effect on housing prices (Hypothesis 1) that accumulates over time in the absence of supply and native population responses (Hypothesis 2). Hypothesis 3 predicts that the price response is heterogeneous across degrees of urbanization. The magnitude and dynamics of the price effect depend on local supply capacity and labor market conditions. Supply capacity is shaped by physical geography and regulatory constraints (Saiz, 2010; Hilber & Vermeulen, 2016), whereas labor market conditions vary with municipality size, density, and distance to major metropolitan cores.

We test whether the heterogeneity predicted by Hypothesis 3 materialises using the EUROSTAT degree of urbanization. This classification divides municipalities into cities, towns and suburbs, or rural areas based on the share of residents in high-density population clusters.[18] Table 6 reports the estimates and total marginal effects by group and horizon are shown in Figure 5. It is worth noting that here identification rests on within-category variation in immigration flows, so the estimates capture the causal effect of an immigration shock within each urban type. In the very short run (Column 1, Table 6), both urban and non-urban municipalities show comparable price responses; however, by $h = 4$ (Column 4), non-urban municipalities with higher immigration intensity experience a price increase 1.7 percentage points higher than urban municipalities that also receive the shock, rising to 3.1 in the long-difference setup. Altogether, the non-urban total

[18] In the analysis, towns and suburbs and rural areas are grouped into a single non-urban category, so that estimates compare cities against all remaining municipalities. Full details regarding the classification are provided in Appendix Appendix C.

marginal effect (4.080%) stands in sharp contrast to their urban counterparts, whose long-run price response is no longer statistically significant (Figure 5). The price response to immigration-induced demand varies systematically with both the degree of urbanization and the time horizon. The widening gap across horizons indicates that local markets differ not only in the strength of their response to a demand shock, but in the speed at which adjustment occurs and the extent to which it does.

Table 6: Immigration and Housing Prices: Heterogeneity by Urban Status

	Dependent Variable: Δ^h log Average Transaction Price				
	$h = 1$ (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)	Long Diff. (5)
Δ^hImmigration *(Urban)*	0.547*	0.887***	1.263***	1.270***	0.993
	(0.290)	(0.280)	(0.329)	(0.414)	(0.714)
Δ^hImmigration $\times$ Non-Urban	0.200	0.563**	0.970***	1.674***	3.087***
	(0.281)	(0.261)	(0.275)	(0.348)	(0.533)
KP F-stat	131.2	116.1	112.1	94.1	17.7
SW-F: Δ^hImm.	218.1	200.4	184.2	148.3	75.4
SW-F: Δ^hImm. $\times$ Non-Urban	338.2	296.9	252.2	205.3	23.5
Province FE	Yes	Yes	Yes	Yes	Yes
Province $\times$ Trend	Yes	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes
Clusters	699	699	699	699	46
Observations	7,689	6,990	6,291	5,592	699

Notes: Each column reports a 2SLS regression for a different time horizon h using the preferred specification (province fixed effects, province-specific linear trends, full demand and supply controls, and spatially exogenous pull). Δ^hImmigration is instrumented with the shift-share predictor $\widehat{M}^h$ and Δ^hImmigration $\times$ Non-Urban with $\widehat{M}^h \times$ Non-Urban. All interaction terms are instrumented with the corresponding interaction of the shift-share predictor. All specifications are weighted by 2014 municipal population. Standard errors are clustered at the municipal level in columns (1)–(4) (699 clusters) and at the province level in column (5) (46 clusters), and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

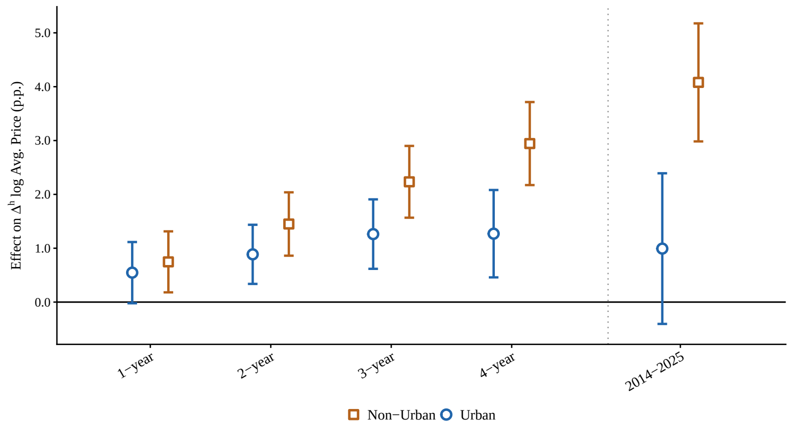

Figure 5: Dynamic Causal Effects of Immigration on Housing Prices by Degree of Urbanization.

Notes: Each point reports the 2SLS estimate of the total marginal effect of a 1 pp increase in the net immigration rate on the h-period log change in average transaction prices (in pp), computed as the linear combination of the baseline coefficient and the relevant interaction term. Error bars denote 95% confidence intervals. See Table Appendix C.4 for full specification details.

To explain the heterogeneous price response by degree of urbanization, we examine whether local adjustment channels operate differently across urban categories. Figure 5 presents the total marginal effect of immigration on local adjustment outcomes by urban classification and table **??** reports the full estimates. The native population response provides a first indication. Within non-urban municipalities, immigration shocks generate a significantly larger native in-migration response than within urban municipalities, where the within-group effect is not significant at any horizon (Panel A in Figure 6). An additional immigrant in a non-urban municipality attracts approximately five native residents in the long run (Column 5 in Figure **??**). Immigration shocks thus activate a native internal mobility channel that is substantially stronger in non-urban markets, compounding local housing demand pressure and helping account for the larger and more persistent price effects documented above.

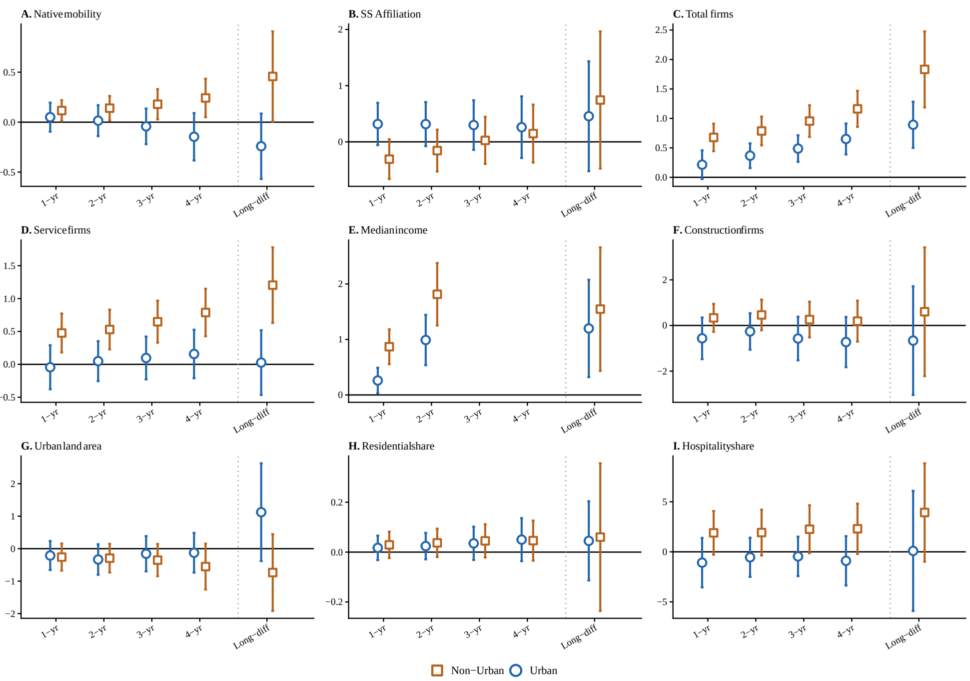

Figure 6: By urban degree

Figure 7: The effect of immigration on other outcomes of interest by degree of urbanization

Notes: Figure reports 2SLS estimates of the effect of a one-unit increase in the net immigration flow, normalized by base-year population, on the indicated outcome. Rolling-window horizons span 1–4 years; the rightmost point corresponds to the long-difference specification (2014–2025 for all outcomes except median disposable income, available for 2020–2023 only). All specifications include province fixed effects, province-specific linear trends, year fixed effects, and the baseline controls, weighted by 2014 population. Standard errors are clustered at the municipal level in rolling-window specifications and at the province level in the long-difference specification. Bars denote 95% confidence intervals.

The immigration shock activates local economic activity predominantly in non-urban municipalities. The number of firms grows across all horizons in both urban categories, but the effect is larger in non-urban municipalities (Panel C, Figure 6). Growth in service-sector firms is significant only in non-urban municipalities, while the corresponding urban within-group responses are non significant throughout (Panel D, Figure 6). Median income (Panel E) rises significantly in both urban and non-urban municipalities, with the non-urban effect substantially larger at short horizons and converging to comparable levels in the long run (Panel E, Table **??**).[19]

However, as in the full sample estimates, supply side outcomes shows no significant response across urban degrees. The differential effects (Table **??**) reveal that construction firms grow more in high-immigration non-urban municipalities relative to urban ones at short horizons, with this gap dissipating over time, yet residential property shares remain unchanged, available urban land

[19]Social Security affiliation is not significant at any horizon within either urban category (Panel B, Figure 6), though the interaction term is significantly negative for non-urban municipalities at short horizons (Panel B, Table **??**), indicating that employment growth in formal labor markets is relatively weaker in non-urban municipalities and that local economic expansion operates instead through growth in the number of firms.

turns significantly negative in non-urban municipalities in the long run, and the hospitality share differential is significantly positive for non-urban municipalities. This could suggest that building activity may be directed toward hospitality and tourism uses rather than residential housing. The absence of a supply response implies that immigration-induced demand cannot be absorbed through new construction and translates directly into price growth (Saiz, 2010; Hilber & Vermeulen, 2016).

7. Robustness Checks

7.1. Alternative Housing Outcomes

One concern that may arise regarding the main results is that average transaction prices combine changes in local prices with changes in the composition of the transacted housing mix. In this sense, Panel A in Table 7 replicates the preferred specification using the log change in transaction price per square meter (Portal Estadístico del Notariado), addressing this concern by controlling for changes in size. Estimates closely track the baseline results throughout all the time windows (Columns 1 to 5). The short-run (Column 1) gap relative to average transaction prices (0.43% vs. 0.72%) narrows progressively and virtually closes by the long difference (2.02% vs. 2.49%).

Panel B reports estimates for the rent price index, where rent estimates are positive and significant across horizons but attenuated relative to transaction prices, with a long-run effect of 0.41%, likely reflecting the staggered adjustment of existing tenancy contracts under Spanish rental regulation, consistent with Sanchis-Guarner (2023).[20] Panel C reports appraisal values per square meter, where estimates grow monotonically from 0.37% at $h = 1$ to 2.03% over the full sample period, almost identical to the baseline and close to the average-price benchmark.

[20]Sanchis-Guarner (2023) finds rent effects approximately four times smaller than transaction price effects in a comparable Spanish setting.

Table 7: Immigration and Housing Prices: Alternative Outcomes

	Short Diff. (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)	Long Diff. (5)
	Panel A. Δ^h log *Square-meter Transaction Price*				
Δ^hImmigration	0.428*	0.770***	1.206***	1.417***	2.020***
	(0.244)	(0.245)	(0.290)	(0.340)	(0.580)
KP F-stat	212.8	204.5	204.6	181.0	75.9
Clusters	699	699	699	699	46
Observations	7,689	6,990	6,291	5,592	699
	Panel B. Δ^h log *Rent Price Index*				
Δ^hImmigration	0.140**	0.150**	0.116	0.112	0.409***
	(0.058)	(0.067)	(0.074)	(0.080)	(0.125)
KP F-stat	284.3	211.4	137.8	108.0	57.0
Clusters	687	687	687	687	46
Observations	6,183	5,496	4,809	4,122	687
	Panel C. Δ^h log *Average Appraisal Value per* m^2				
Δ^hImmigration	0.369**	0.723***	0.929***	0.955***	2.034***
	(0.174)	(0.195)	(0.231)	(0.254)	(0.470)
KP F-stat	154.9	147.0	143.9	128.1	62.4
Clusters	287	287	287	287	46
Observations	3,025	2,738	2,451	2,164	265
Province FE	Yes	Yes	Yes	Yes	Yes
Province × Trend	Yes	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate 2SLS regression for a different time horizon h. The long difference in Panels A and C covers 2014–2025; in Panel B it covers 2014–2023, the last year for which the rent price index is available. Panel A uses the full sample of 699 municipalities. Panel B covers 687 municipalities for which the rent price index is available. Panel C covers only 287 municipalities since the data is only available for municipalities bigger than 25,000 inhabitants. All specifications include province fixed effects, province-specific linear trends (except the long difference), demand and supply controls, and are weighted by 2014 municipal population. Columns (1)–(4) cluster standard errors at the municipal level; column (5) clusters at the province level (46 clusters). * $p < 0.10$,** $p < 0.05$, ***$p < 0.01$.

7.2. Correlated Random-Effects (CRE) Model

Differencing eliminates time-invariant municipal heterogeneity and province-specific linear trends absorb common provincial dynamics, but systematic differences in mean levels of local supply and demand conditions may persist across municipalities and remain correlated with both immigration intensity and housing prices. As a robustness check, we follow Mundlak (1978) and Lin & Wooldridge (2019) and add municipality-level time averages of all time-varying controls (supply, demand, the spatial pull control, and the immigration rate) to each specification. Lin & Wooldridge (2019) and Yang (2022) show that, in the linear instrumental variables case, this correction exactly reproduces the FE-2SLS estimator.

Results are reported in Table 8. The Mundlak joint test rejects the null of zero Mundlak terms across all specifications, confirming that the standard random effects assumption is violated and that the CRE correction is warranted. First-stage KP F-statistics remain well above conventional thresholds. The short-run estimate loses statistical significance, but coefficients for $h \in \{2, 3, 4\}$ are consistent in magnitude and significance with the baseline, indicating that the correction for unobserved heterogeneity does not alter the main findings. These results confirm the robustness of the baseline estimates to systematic differences in mean conditions across municipalities.

Table 8: Immigration and Housing Prices: CRE Correction

	Dependent Variable: Δ^h log Average Transaction Price			
	Short Diff. (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)
Δ^hImmigration	0.599	1.250***	2.347***	3.457***
	(0.379)	(0.381)	(0.566)	(0.977)
KP F-stat	109.8	91.2	76.2	56.2
Mundlak joint test (χ^2)	22.29	49.29	79.75	100.33
Province FE	Yes	Yes	Yes	Yes
Province $\times$ Trend	Yes	Yes	Yes	Yes
Demand Controls	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes
Clusters	699	699	699	699
Observations	7,689	6,990	6,291	5,592

Notes: The dependent variable is the h-period change in log average transaction price. Δ^hImmigration is instrumented with the corresponding h-period shift-share predictor. All specifications include province fixed effects, province-specific linear trends, demand and housing supply controls, and are weighted by 2014 municipal population. The Mundlak joint test reports the χ^2 statistic from a test of joint significance of all Mundlak terms. Standard errors are clustered at the municipal level. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

7.3. Gravity IV

Although the baseline shift-share instrument passes exogeneity placebo tests, its exogeneity rests on two assumptions: that historical settlement shares are sufficiently predetermined, and that national-level immigration shocks are orthogonal to contemporaneous local demand conditions. The latter assumption may be compromised if municipality-specific demand-pull factors drive national immigrant stocks, since the observed shifts aggregate changes across all municipalities. As an additional robustness check, we replace the observed national shifts with predicted shifts constructed from origin-country supply-push characteristics, isolating the component of immigration that is clearly orthogonal to local housing market conditions (Sanchis-Guarner, 2023; ?; Saiz, 2007).

To this end, we estimate the following equation on a panel of origin countries over 2005-2025:

$$\widehat{\Delta M}_t^{\tau} = \beta \ln \mathrm{GDP}_{t-1}^{\tau} + \sum_t \gamma_t \cdot \Delta \mathrm{Out}^{\tau} + \delta_\tau + \gamma_t + \varepsilon_t^{\tau} \tag{9}$$

where $\ln \mathrm{GDP}_{t-1}^{\tau}$ captures lagged origin-country macroeconomic conditions, which determine the propensity to emigrate. $\Delta \mathrm{Out}^{\tau}$ is the change in the stock of emigrants from country k to destinations other than Spain.[21] This latter variable serves as a time-invariant measure of structural

[21] Data on emigration stocks come from United Nations, Department of Economic and Social Affairs, Population

supply-push pressure, interacted with year fixed effects γ_t to allow its effect to vary freely over time. Origin-country fixed effects δ_τ absorb persistent characteristics of each migrant group that shape their propensity to emigrate to Spain. The fitted values $\widehat{\Delta M}_t^\tau$ replace the observed national shifts in the baseline shift-share construction (Equation 3), ensuring that the shift component is driven exclusively by origin-country supply-push fundamentals.

Results are reported in Table 9. First-stage coefficients are stable and strongly significant across all horizons. Second-stage estimates are positive and significant, and quantitatively close to the baseline estimates across all horizons, including the long difference. The close correspondence between both sets of estimates confirms the robustness of the main results to potential endogeneity in the observed national shifts.

Table 9: Immigration and Housing Prices: Gravity IV Robustness

	Dependent Variable: Δ^h log Average Transaction Price				
	$h = 1$	$h = 2$	$h = 3$	$h = 4$	Long Diff.
	(1)	(2)	(3)	(4)	(5)
Δ^hImmigration	0.699*	1.196***	1.696***	1.995***	2.938**
	(0.379)	(0.366)	(0.382)	(0.468)	(1.153)
First-Stage Gravity IV	0.644***	0.645***	0.645***	0.628***	0.520***
	(0.054)	(0.054)	(0.050)	(0.051)	(0.101)
KP F-stat	144.1	142.4	165.2	152.3	26.4
Province FE	Yes	Yes	Yes	Yes	Yes
Province × Trend	Yes	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes
Clusters	699	699	699	699	46
Observations	7,689	6,990	6,291	5,592	699

Notes: The dependent variable is the h-period change in log average transaction price. Δ^hImmigration is instrumented with a gravity-based predictor of immigrant flows constructed from origin-country supply-push components replacing the observed national shifts in the baseline shift-share instrument (see Equation 9). Columns (1)-(4) include province fixed effects and province-specific linear trends; column (5) includes province fixed effects only. All specifications include demand and housing supply controls, the spatially exogenous pull variable, and are weighted by 2014 municipal population. Standard errors in columns (1)-(4) are clustered at the municipal level; column (5) clusters at the province level. * $p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

7.4. Other Robustness

7.4.1. Excluiding Large Cities

A natural concern is that results are driven by a small number of large urban agglomerations, most notably Madrid and Barcelona, which concentrate a disproportionate share of recent immigration flows and have experienced particularly sharp housing price increases over the sample period. Panels A–C of Table 10 address this concern by progressively excluding the largest municipalities by 2014 population (top 5, 10, and 20, respectively). Coefficients are positive, statistically significant, and quantitatively close to the baseline across all horizons, confirming that the results are not

Division (2024).

driven by the dynamics of large cities.

7.4.2. Unweighted Regressions

The baseline specification weights each municipality by its 2014 population, giving greater weight to larger municipalities and, consequently, to those with higher immigration concentration and larger price variation. Panel D of Table 10 replicates the baseline assigning equal weight to each municipality. Coefficients remain positive and significant across all horizons with magnitudes in line with the baseline, confirming that population weighting does not drive the results.

Table 10: Immigration and Housing Prices: Additional Robustness

	Dependent Variable: Δ^h log Average Transaction Price				
	$h = 1$	$h = 2$	$h = 3$	$h = 4$	Long Diff.
	(1)	(2)	(3)	(4)	(5)
Panel A. Excluding top-5 municipalities by 2014 population					
Δ^hImmigration	0.750**	1.255***	1.748***	2.202***	2.442***
	(0.294)	(0.290)	(0.327)	(0.405)	(0.663)
KP F-stat	151.6	147.3	154.6	155.3	56.8
Panel B. Excluding top-10 municipalities by 2014 population					
Δ^hImmigration	0.845***	1.336***	1.789***	2.278***	2.498***
	(0.276)	(0.294)	(0.340)	(0.425)	(0.715)
KP F-stat	148.8	142.9	149.7	151.0	57.8
Panel C. Excluding top-20 municipalities by 2014 population					
Δ^hImmigration	0.694**	1.240***	1.769***	2.315***	2.768***
	(0.282)	(0.297)	(0.344)	(0.433)	(0.675)
KP F-stat	137.0	132.0	141.4	143.8	52.2
Panel D. Unweighted regressions					
Δ^hImmigration	0.889***	1.525***	1.989***	2.662***	3.347***
	(0.286)	(0.305)	(0.319)	(0.374)	(0.808)
KP F-stat	171.6	166.8	191.0	171.5	41.4
Panel E. Fixed 2014 denominator for immigration rate					
Δ^hImmigration	0.724***	1.213***	1.755***	2.089***	2.246***
	(0.253)	(0.263)	(0.311)	(0.391)	(0.790)
KP F-stat	211.6	206.4	203.9	170.0	75.8
Province FE	Yes	Yes	Yes	Yes	Yes
Province × Trend	Yes	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the h-period change in log average transaction price. Δ^hImmigration is instrumented with the corresponding h-period shift-share predictor. Panels A–C progressively exclude the largest municipalities by 2014 population (top 5, 10, and 20, respectively). Panel D assigns equal weight to each municipality regardless of size. Panel E fixes the population denominator at its 2014 value throughout, so that changes in the immigration rate reflect exclusively changes in the immigrant stock. All specifications include province fixed effects, province-specific linear trends (except the long difference), demand and housing supply controls, the spatially exogenous pull variable, and are weighted by 2014 municipal population (except Panel D). Standard errors in columns (1)–(4) are clustered at the municipal level; column (5) clusters at the province level.* $p < 0.10$, **$p < 0.05$, *** $p < 0.01$.

7.4.3. Fixed Native Population Changes

If immigration shocks simultaneously displace native residents, the population denominator falls endogenously in response to the shock being identified, mechanically inflating the measured immigration rate and biasing the estimated price effect upward. Although Section 5.3 finds no evidence of native displacement, bilateral internal migration flows at the municipal and annual level are unavailable, precluding a precise assessment of its magnitude. While the baseline uses lagged population as the denominator, this continues to vary endogenously period by period. Panel E of Table 10 addresses this by fixing the denominator at its 2014 value throughout, so that changes in the immigration rate reflect exclusively changes in the immigrant stock. Coefficients are positive, significant, and quantitatively close to the baseline across all horizons.

8. Conclusion

The decade 2014 – 2025 in Spain was characterized by historically high immigration inflows and a structurally constrained housing supply. We exploit this setting to provide causal evidence on the local housing market consequences of immigration. While previous literature in Spain relies on provincial data, we build a municipal-level panel using actual average transaction prices to better capture heterogeneous demand pressures and adjustment channels. To address the endogenous sorting of immigrants, we implement a shift-share instrument based on historical settlement networks and introduce an exogenous spatial pull variable to control for local demand spillovers from neighboring municipalities.

We find that an immigration inflow equal to one percentage point of the municipal population increases the annual housing price growth rate by 0.73 percentage points in the short run. Our dynamic estimates show that this initial price effect, instead of dissipating over time, accumulates monotonically, reaching 2.25 percentage points in the long difference (2014–2025). These results are robust to alternative housing price measures (price per square meter, appraisal value per square meter, and rent price index), an alternative gravity-based instrument purged of demand-pull factors, progressive exclusions of large urban agglomerations, and a correlated random-effects correction. This persistence reflects the inability of local adjustment channels to absorb the residential demand shock. On the supply side, we find no significant response in new construction, urban expansion, or residential land use, indicating that housing supply is structurally constrained. On the demand side, we find no evidence of native displacement, which implies that immigration-induced demand pressure is not relieved through native outflows in high-immigration municipalities.

Aggregate estimates, however, mask substantial heterogeneity in how local markets absorb the demand shock across the urban hierarchy. The price effect of immigration is substantially larger in non-urban municipalities than in urban ones, particularly in the long run, accumulating approximately 4 percentage points over 2014–2025. This pattern is explained by native co-location in high-immigration non-urban municipalities, where immigration-driven gains in local economic activity and median income attract native in-migration, and by greater constraints on housing supply in the long run.

The results show that internal mobility does not necessarily dissipate localized shocks in residential demand over time. When structural constraints on housing supply are restrictive and demographic flows generate positive local economic externalities, spatial reallocation can instead amplify local market distortions. The degree of urbanization plays a central role in this process, as non-urban municipalities, where supply constraints are most binding and native co-location effects are strongest, accumulate the largest and most persistent price pressures. From a policy perspective, this implies that addressing housing affordability requires targeting land-use regulations and supply rigidities across all municipalities, and especially in non-urban areas where demand pressures are most persistent. Native population redistribution unaccompanied by supply expansion in receiving municipalities compounds rather than relieves affordability pressures precisely where residential demand is accumulating.

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Appendix

Appendix A. Descriptive Statistics and Data Sources

Table Appendix A.1: Descriptive Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Panel A: Dependent variables					
Δ log avg. transaction price	7,689	0.0448	0.0798	−0.7367	1.0373
Δ native population (share)	7,689	−0.0014	0.0064	−0.1654	0.0552
Panel B: Key regressor and instruments					
Δ immigration rate	7,689	0.0054	0.0082	−0.0849	0.0765
Bartik instrument	7,689	0.0053	0.0074	−0.0413	0.0603
Spatial pull (exogenous)	7,689	0.0156	0.0418	−0.2497	1.0955
Spatial pull (endogenous)	7,689	0.0139	0.0312	−0.1343	0.5245
Panel C: Baseline controls					
Sectoral Bartik (industry)	8,388	0.0219	0.0168	−0.0350	0.0497
Δ log construction firms	7,689	−0.0049	0.0616	−0.3903	0.2578
Δ log urban land area	7,689	−0.0066	0.0688	−1.3713	1.5099
Δ residential land share	7,689	−0.0014	0.0042	−0.1998	0.0638
Δ hospitality land share	7,689	0.0186	0.1666	−1.6420	3.0810
Δ log total social security affiliates	7,689	0.0271	0.0310	−0.3902	0.3412
Panel D: Mechanism variables					
Δ log total firms	7,689	0.0060	0.0318	−0.3050	0.1129
Δ log service-sector firms	7,689	0.0232	0.0345	−0.2257	0.1949
Δ log median disposable income (IRPF)^a	2,796	0.0247	0.0280	−0.4224	0.4630
Panel E: Robustness variables					
Δ log price per m^2	7,689	0.0469	0.0843	−0.7801	1.1987

Notes: All statistics are weighted by 2014 municipal population. The effective population weight totals 374,158,356 for the main sample ($N = 699$ municipalities, 11 years) and 408,172,756 for the sectoral Bartik control, which is available for the full panel prior to sample restrictions. The unit of observation is the municipality-year. All variables in log-changes or changes in shares are expressed as year-on-year first differences. The spatial pull variables capture predicted immigrant pressure from neighbouring municipalities, weighted by area and inverse distance squared, normalised by predicted municipal population. ^{a} Δ log median disposable income (IRPF) is available for 2020–2023 only.

Table Appendix A.2: Variables and Data Sources

Variable	**Description**	**Period**	**Source**
Panel A: Outcome variables			
Δ log(avg. price)	Log-change in average transaction price per municipality	2014–2025	Portal Estadístico del Notariado
Δ log(price/m^2)	Log-change in average price per square metre	2014–2025	Portal Estadístico del Notariado
Δ log(transactions)	Log-change in number of housing transactions	2014–2025	Portal Estadístico del Notariado
Δ log(appraisal value/m^2)	Log-change in appraisal value per square metre *(robustness)*. Only available for municipalities with more than 25,000 inhabitants	2005–2025	Ministerio de Transporte y Movilidad Sostenible
Rent price index	Municipal rent price index *(robustness)*	2015–2023	Índice de Precios de la Vivienda en Alquiler (IPVA), Instituto Nacional de Estadística (INE)
Δ Native population	Change in native (Spanish-born) registered population	2005–2025	Padrón Municipal / Censo Anual de Población (INE)
Panel B: Treatment variable			
Δ Immigrant population	Change in foreign-born registered population	2005–2025	Padrón Municipal 2005–2022; Censo Anual de Población 2023–2025 (INE)
Panel C: Instruments			
Bartik shift-share $\hat{Z}_{i,t}$	Settlement shares by origin nationality (2005 base year) interacted with gravity-purified national inflows by origin country	2014–2025	Shares: Padrón Municipal (INE). Purified flows: origin-country GDP (World Bank WDI)
Spatial gravity shifter $\widehat{\text{Pull}}^{\text{exog}}_{it}$	Inverse-distance-squared weighted average of predicted immigrant inflows from neighbouring municipalities	2014–2025	Constructed from Bartik predictions + municipal centroids (IGN / Catastro)
Panel D: Controls			

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(continued)

Variable	Description	Period	Source
Δ log Construction firms	Log-change in number of firms in the construction sector	2012–2025	Explotación estadística Directorio Central de Empresas (DIRCE, INE)
Δ log Residential share	Log-change in the share of residential properties over total urban properties	2014–2025	Dirección General del Catastro (Ministerio de Hacienda)
Δ Unemployment rate	Change in annual average registered unemployment rate	2006–2025	Servicio Público de Empleo Estatal (SEPE)
Bartik employment index $B_{i,t}$	Municipality employment-share-weighted national sectoral employment growth; shares from the 2011 Population Census	2014–2025	Shares: Censo de Población y Viviendas 2011 (INE). National growth: Encuesta de Población Activa (EPA, INE)
Panel E: Mechanism variables			
Δ log Total firms	Log-change in total number of registered firms	2014–2025	Explotación estadística Directorio Central de Empresas (DIRCE, INE)
Δ log Service-sector firms	Log-change in number of service-sector firms	2014–2025	Explotación estadística Directorio Central de Empresas (DIRCE, INE)
Δ log Self-employment	Log-change in Social Security affiliated workers (Seguridad Social, Ministerio de Inclusión, Seguridad Social y Migraciones)	2014–2025	Tesorería General de la Seguridad Social (TGSS)
Δ log Disposable income	Log-change in mean net disposable income per capita	2014–2023	Estadística de los declarantes del Impuesto sobre la Renta de las Personas Físicas, Agencia Tributaria (AEAT)
Panel F: Supply elasticity proxies (cross-section, base year)			
Urban developable land	Share of urban developable land over total municipal surface	2014–2025	Dirección General del Catastro (Ministerio de Hacienda)
Housing stock per capita	Total registered real-estate units per resident, by land use (2014 baseline)	2014	Dirección General del Catastro (Ministerio de Hacienda)
Coastal location	Binary indicator for municipalities bordering the sea	Time-invariant	Instituto Geográfico Nacional (IGN)

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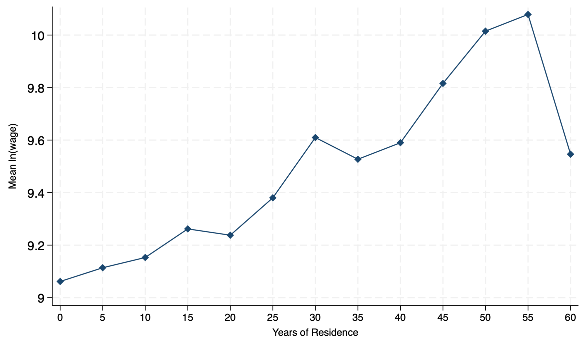
(continued)

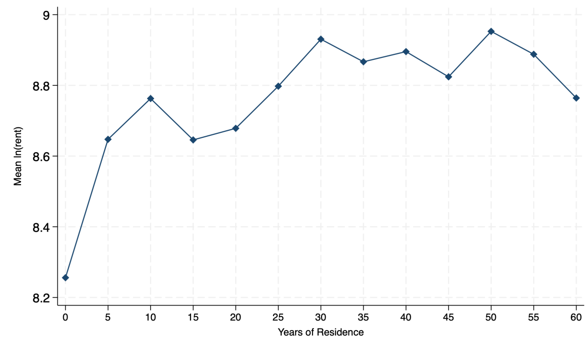
Variable	Description	Period	Source
Panel G: Urban classification			
Degree of urbanization	EUROSTAT three-category classification (City / Towns & Suburbs + Rural)	Time-invariant	EUROSTAT / INE
Urban hierarchy (Synthetic Regions, SR)	Sistema de clasificación de Regiones Sintéticas (SR1 / SR2 / SR3)	Time-invariant	Own calculations based on Polèse et al. (2007)

Notes: The estimation sample covers 699 municipalities with more than 10,000 inhabitants (2014 population threshold), excluding País Vasco and Navarra due to data limitations. The panel spans 2014–2025, yielding 7,689 observations (11 annual periods × 699 municipalities). All regressions are weighted by 2014 municipal population. *Period* refers to the availability of the series, not the estimation window.

Appendix B. Sumplementary figures and tables



(a) Panel A: Wages



(b) Panel B: Imputed rent

Figure Appendix B.1: Assimilation profiles by years of residence, Spain.
Notes: Each panel plots the weighted mean of predicted values from flexible OLS regressions of log wages (Panel A) and log imputed rent (Panel B) on years of residence indicators, quartic potential experience, education level, occupation, survey year and gender. Weighted means computed using personal weights. Source: EU-SILC 2021–2023.

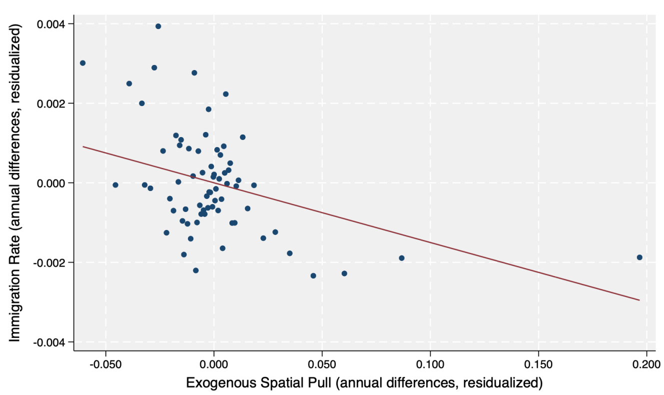


Figure Appendix B.2: Net Immigration Rate and Exogenous Spatial Pull: Residualized Relationship.
Notes: Binned scatter plot (70 quantiles) of the residualized net immigration rate ($\Delta M_{c,t}/Pop_{c,t-1}$) against the residualized exogenous spatial pull ($\text{Pull}_{c,t}^{\text{exog}}$). Both variables are residualized with respect to province fixed effects, province-specific linear trends, year fixed effects, and the full set of demand and supply controls. The negative slope indicates that municipalities experiencing larger own immigration inflows are surrounded by municipalities receiving relatively fewer immigrants, consistent with spatial sorting within metropolitan areas and provinces. The slope of the fitted line is -0.015 (SE $= 0.005$). All specifications weighted by 2014 municipal population. Standard errors clustered at the municipal level.

Table Appendix B.1: Instrument Validity: Cross-Period Placebo Tests

	Dependent Variable: Δ Outcomes (2014–2020)						
	Δ log Price	Δ Native Pop.	Δ Construction Firms	Δ Urban Area	Δ Residential Share	Δ Tourism Share	Δ Affiliates
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{M}_{c,2020-2025}$	0.771	0.130	0.748	0.747	0.037	0.635	-0.389
	(0.653)	(0.103)	(0.620)	(0.665)	(0.040)	(1.751)	(0.274)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	46	46	46	46	46	46	46
Observations	699	699	699	699	699	699	699

Notes: Each column reports a separate regression of the 2014–2020 change in the outcome variable on the shift-share instrument constructed from 2020–2025 immigrant flows. All specifications include province fixed effects and controls for local demand conditions, housing supply, and the exogenous spatial pull. Regressions are weighted by 2014 municipal population. Standard errors clustered at the province level are reported in parentheses.*$p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table Appendix B.2: Origin Countries Included in the Shift-Share Instrument

Europe		Africa	
Germany	Romania	Algeria	Nigeria
Bulgaria	Russia	Morocco	Senegal
France	Ukraine		
Italy	United Kingdom		
Poland			
Portugal			
Latin America		**Asia**	
Argentina	Paraguay	China	
Bolivia	Peru	Pakistan	
Brazil	Dominican Rep.		
Chile	Uruguay		
Colombia	Venezuela		
Cuba			
Ecuador			

Notes: The 28 origin countries listed account for the largest immigrant stocks registered in Spain over the sample period 2014–2025. Settlement shares by country of origin are computed from the 2005 *Padrón Municipal* (INE).

Table Appendix B.3: Immigration and Housing Prices: Spatial Spillover Robustness

	Dependent Variable: Δ log Average Transaction Price			
	(1)	(2)	(3)	(4)
	Panel A. 2SLS + Endogenous Spatial Pull (OLS)			
ΔImmigration	2.017***	1.990***	1.931***	0.607**
	(0.402)	(0.392)	(0.382)	(0.267)
ΔSpatial Pull$^{\text{endog}}$	-0.138***	-0.140***	-0.126***	-0.139***
	(0.033)	(0.031)	(0.030)	(0.023)
KP F-stat	115.4	113.3	112.0	211.5
R-Squared	0.121	0.127	0.130	0.184
	Panel B. 2SLS + Endogenous Spatial Pull (Instrumented)			
ΔImmigration	2.065***	2.035***	1.972***	0.661**
	(0.409)	(0.398)	(0.388)	(0.267)
ΔSpatial Pull$^{\text{endog}}$	-0.095***	-0.099***	-0.086***	-0.107***
	(0.033)	(0.030)	(0.029)	(0.022)
KP F-stat	59.6	58.6	57.6	107.8
SW F-statistic				
ΔImmigration	136.7	135.9	132.2	223.7
ΔSpatial Pull$^{\text{endog}}$	123.4	123.9	122.4	120.2
R-Squared	0.120	0.126	0.130	0.184
Year FE	Yes	Yes	Yes	Yes
Housing Supply Controls	No	Yes	Yes	Yes
Demand Controls	No	No	Yes	Yes
Province FE	No	No	No	Yes
Province × Trend	No	No	No	Yes
Clusters	699	699	699	699
Observations	7,689	7,689	7,689	7,689

Notes: The dependent variable throughout is the change in log average transaction price. Both panels instrument ΔImmigration with the shift-share predictor $\widehat{M}$. Panel A includes the endogenous spatial pull ΔSpatial Pull$^{\text{endog}}$ as an OLS control, treating it as exogenous. Panel B instruments ΔSpatial Pull$^{\text{endog}}$ with the exogenous spatial pull ΔSpatial Pull$^{\text{exog}}$. Columns (1)–(4) add controls sequentially: year fixed effects only; adding housing supply controls; adding local demand controls; and adding province fixed effects together with province-specific linear trends. All specifications are weighted by 2014 municipal population. Standard errors are clustered at the municipal level and reported in parentheses.*$p < 0.10$, **$p < 0.05$, *** $p < 0.01$.

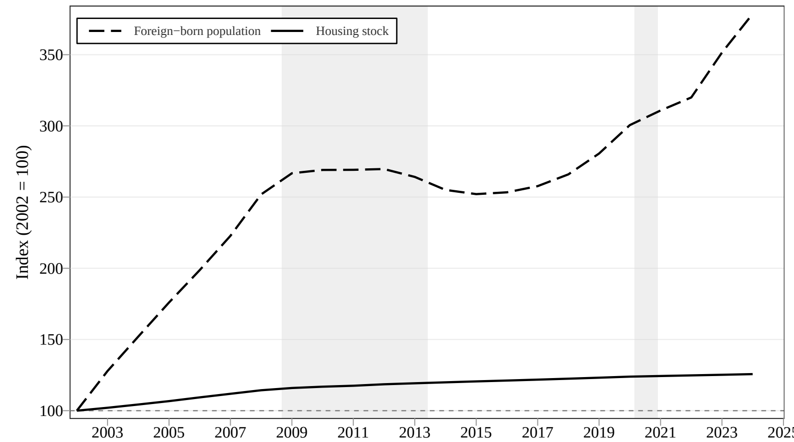
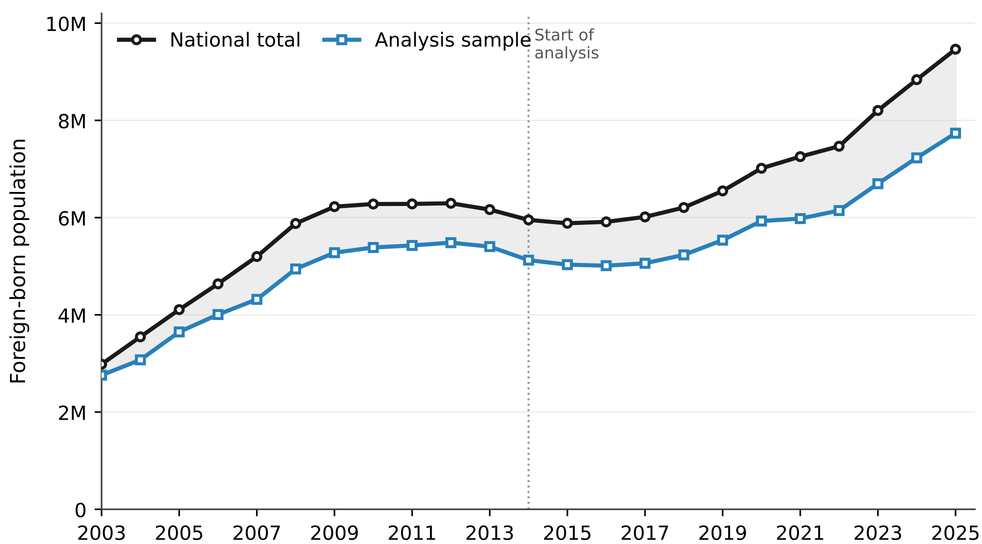


Figure Appendix B.3: Foreign-born population and housing stock, Spain 2002–2024 (index, 2002 = 100).

Notes: Both series indexed to 100 in 2002. Foreign-born population is the national total from the Padrón Municipal (2002–2022) and Censo Anual de Población (2023-2025) (INE). Housing stock is the national estimate of total dwellings (PV_t), constructed from the 2001, 2011 and 2021 Census of Dwellings and updated annually by adding completed free-market and subsidised dwellings and rehabilitation-created units, net of demolished stock (Ministerio de Vivienda y Agenda Urbana, 2025). Shaded areas indicate the financial crisis (2008-2013) and the COVID-19 pandemic (2020–2021). The divergence between the two series after 2014 — when immigration resumes its upward trend while housing stock growth remains subdued — provides the aggregate motivation for the supply inelasticity hypothesis tested in the empirical analysis. Source: Padrón Municipal (INE); Ministerio de Vivienda y Agenda Urbana, *Estimación del Parque de Viviendas* (2025).

Figure Appendix B.4: Sample coverage vs. national immigration stock, 2003–2025



	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Sample share (%)	86.1	85.5	84.7	84.1	84.3	84.5	84.5	82.4	82.2	81.6	81.7	81.7

Notes: $N = 699$ municipalities. Share is computed as sample population divided by the national total of foreign-born resident population registered in the Padrón Municipal and Censo Anual de Población (INE).

Appendix C. Degree of Urbanization and Urban Hierarchy Additional Results

The implementation of the EUROSTAT degree of urbanization classification is quite straightforward. Since this classification is already predefined at the European level, we merge the existing spatial database with the specific municipalities that comprise our analysis sample. Table Appendix C.1 outlines the resulting distribution.

Table Appendix C.1: Sample Composition by Urban Classification

Classification	**Category**	**Municipalities**
Degree of urbanization		
	City	171
	Town & Suburb + Rural Area	528
	Total	*699*

Notes: Sample comprises all Spanish municipalities with more than 10,000 inhabitants. Degree of urbanization follows the Eurostat–OECD grid-based typology. Urban hierarchy follows the classification of Polèse et al. (2007).

Appendix C.1. Heterogeneity by Urbanization Degree on Alternative Outcomes

Table Appendix C.2: Regression Results by Urban Status

	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	Long Diff. (5)
Panel A. Dep. Variable: Δ^h *Native Mobility*					
Urban	0.050	0.015	-0.042	-0.146	-0.241
	(0.074)	(0.079)	(0.091)	(0.121)	(0.167)
Non-Urban	0.066	0.125*	0.221***	0.388***	0.699**
	(0.062)	(0.066)	(0.074)	(0.094)	(0.296)
Panel B. Dep. Variable: $\Delta^h \log$ *Total Affiliation*					
Urban	0.318	0.316	0.299	0.261	0.456
	(0.192)	(0.200)	(0.225)	(0.280)	(0.499)
Non-Urban	-0.626***	-0.471***	-0.273	-0.114	0.289
	(0.170)	(0.178)	(0.204)	(0.266)	(0.645)
Panel C. Dep. Variable: $\Delta^h \log$ *Total Firms*					
Urban	0.215*	0.367***	0.488***	0.651***	0.892***
	(0.124)	(0.107)	(0.115)	(0.134)	(0.200)
Non-Urban	0.462***	0.419***	0.467***	0.511***	0.940***
	(0.096)	(0.100)	(0.118)	(0.144)	(0.356)
Panel D. Dep. Variable: $\Delta^h \log$ *Services Firms*					
Urban	-0.044	0.049	0.097	0.158	0.027
	(0.171)	(0.155)	(0.166)	(0.188)	(0.251)
Non-Urban	0.521***	0.480***	0.551***	0.630***	1.177***
	(0.130)	(0.134)	(0.150)	(0.180)	(0.244)
Panel E. Dep. Variable: $\Delta^h \log$ *Median Income*					
Urban	0.260**	0.989***	–	–	1.198***
	(0.117)	(0.231)	–	–	(0.447)
Non-Urban	0.608***	0.824***	–	–	0.348
	(0.145)	(0.278)	–	–	(0.495)
Panel F. Dep. Variable: $\Delta^h \log$ *Construction Firms*					
Urban	-0.563	-0.262	-0.572	-0.727	-0.663
	(0.465)	(0.407)	(0.488)	(0.561)	(1.215)
Non-Urban	0.896***	0.723**	0.831**	0.917*	1.266
	(0.319)	(0.313)	(0.387)	(0.494)	(1.559)
Panel G. Dep. Variable: $\Delta^h \log$ *Available Urban Land*					
Urban	-0.212	-0.334	-0.157	-0.127	1.123
	(0.228)	(0.240)	(0.277)	(0.312)	(0.768)
Non-Urban	-0.048	0.041	-0.196	-0.425	-1.858**

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	$h = 1$ (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)	Long Diff. (5)
	(0.235)	(0.261)	(0.319)	(0.384)	(0.906)
Panel H. Dep. Variable: Δ^h log *Residential Share*					
Urban	0.017	0.024	0.035	0.050	0.045
	(0.025)	(0.027)	(0.034)	(0.044)	(0.081)
Non-Urban	0.012	0.013	0.010	−0.004	0.015
	(0.022)	(0.024)	(0.029)	(0.037)	(0.176)
Panel I. Dep. Variable: Δ^h log *Hospitality Share*					
Urban	−1.079	−0.546	−0.459	−0.896	0.094
	(1.260)	(0.999)	(1.004)	(1.257)	(3.059)
Non-Urban	2.973**	2.472**	2.718**	3.196**	3.835
	(1.350)	(1.066)	(1.135)	(1.345)	(3.490)
Province FE	Yes	Yes	Yes	Yes	Yes
Province × Trend	Yes	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes
Clusters	699	699	699	699	46
Observations	7,689	6,990	6,291	5,592	699

Notes: Each column reports a 2SLS regression for a different time horizon h. All panels disaggregate the geographic immigration shocks by urban status using *Non-Urban* municipalities as the omitted base category. Coefficients report effects for the base category and the differential effects for *Urban* municipalities. Median Income (Panel E) reports the long difference up to 2023 and omits horizons $h = 3$ and $h = 4$ due to data constraints in the logs. All first-stage regressions display strong instrument relevance, with Kleibergen–Paap rk Wald F statistics well above weak-instrument thresholds. Standard errors clustered at the municipality level for cols (1)–(4) and at the province level for col (5) are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix C.2. Heterogenity by Urban Hierarchy Classification

To further test the robustness of the heterogeneous results, we use the urban hierarchy proposed in Polèse et al. (2007). This classification relies on population thresholds and road travel times. Municipalities are first categorized into major metropolitan nodes based on population size: SR1 (>1 million inhabitants) and SR2 (>250,000 inhabitants). Remaining mainland locations are classified as Central (SRC) if their driving time from the geographical centroid to the nearest SR1 or SR2 core is under 60 minutes, and as Peripheral (SRP) otherwise, while island municipalities are automatically designated as Ultra-Peripheral (SRUP). Travel-distances are computed via the Google Maps API under ideal conditions (i.e. without traffic jams). Finally, to ensure comparability, these categories are aggregated into three final hierarchical levels: the top tier (SR1) combines the original SR1 and SR2 nodes; the intermediate tier (SR2) corresponds to Central locations (SRC); and the peripheral tier (SR3) groups together the remaining Peripheral (SRP) and Ultra-Peripheral (SRUP) municipalities.

Table Appendix C.3: Sample Composition by Urban Hierarchy

Classification	**Category**	**Municipalities**
Urban hierarchy		
	SR1 (Large cores)	13
	SR2 (Medium municipalities)	386
	SR3 (Small municipalities)	300
	Total	*699*

Notes: Sample comprises all Spanish municipalities with more than 10,000 inhabitants. Degree of urbanization follows the Eurostat–OECD grid-based typology. Urban hierarchy follows the classification of Polèse et al. (2007).

Table Appendix C.4 reports the estimates. As with urbanization degree, identification rests on within-category variation in immigration flows. Estimates therefore capture the causal effect of an immigration shock within each urban hierarchy tier. Total marginal effects by group and horizon are shown in Figure Appendix C.1.

In the short run ($h = 1$), the price response is concentrated in medium-tier (SR2) municipalities whereas low-tier (SR3) municipalities show no effect vis-à-vis large municipalities (SR1). In the long-difference setup, medium and small municipalities that received the immigration shock show higher prices (4.2 and 2.9 percentage points respectively) than the large ones. The large-municipality response dissipates at the four-year horizon and beyond, while medium (SR2) and small (SR3) municipalities continue to accumulate price pressure, with total long-run effects of 3.433% and 2.097%, respectively (Figure Appendix C.1).

Regarding urban hierarchy, in large urban cores (SR1) immigration shocks attract additional native residents but only at short horizons ($h = 1, 2$). On the other hand, within small municipalities (SR3) the native response is positive and stronger than in non-urban municipalities.

Table Appendix C.4: Immigration and Housing Prices: Heterogeneity by Urban Status

	Dependent Variable: Δ^h log Average Transaction Price				
	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	Long Diff. (5)
Urban Hierarchy (SR)					
Δ^hImmigration *(Large)*	0.383	0.635**	0.947**	0.705	−0.773
	(0.382)	(0.317)	(0.419)	(0.613)	(1.259)
Δ^hImmigration $\times$ Medium (SR2)	0.832**	1.058***	1.338***	1.937***	4.206**
	(0.342)	(0.268)	(0.328)	(0.538)	(1.775)
Δ^hImmigration$\times$Small (SR3)	−0.656	−0.161	0.242	1.086*	2.870**
	(0.492)	(0.418)	(0.420)	(0.625)	(1.336)
KP F-stat	60.1	55.1	51.2	40.4	11.4
SW-F: Δ^hImm.	532.9	564.4	446.6	359.3	294.5
SW-F: Δ^hImm. $\times$ Medium (SR2)	513.6	423.6	307.0	257.3	31.0
SW-F: Δ^hImm. $\times$ Small (SR3)	834.7	829.9	693.3	565.1	316.4
Province FE	Yes	Yes	Yes	Yes	Yes
Province $\times$ Trend	Yes	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes
Clusters	699	699	699	699	46
Observations	7,689	6,990	6,291	5,592	699

Notes: Each column reports a 2SLS regression for a different time horizon h using the preferred specification (province fixed effects, province-specific linear trends, full demand and supply controls, and spatially exogenous pull). Panel A instruments Δ^hImmigration with the shift-share predictor $\widehat{M}^h$ and Δ^hImmigration$\times$Non-Urban with $\widehat{M}^h\times$Non-Urban. Panel B further disaggregates by urban hierarchy, using *Large Urban* as the omitted category, so that β_1 captures the effect in large urban municipalities, while β_2 and β_3 capture the differential effects in medium urban (SR2) and small/rural municipalities (SR3), respectively. All interaction terms are instrumented with the corresponding interaction of the shift-share predictor. All urban classification indicators are included as controls but not reported. KP F-stat is the Kleibergen–Paap rk Wald F statistic for weak identification. SW-F reports the Sanderson–Windmeijer multivariate F statistic for each endogenous regressor separately. All specifications are weighted by 2014 municipal population. Standard errors are clustered at the municipal level in columns (1)–(4) (699 clusters) and at the province level in column (5) (46 clusters), and are reported in parentheses.*$p < 0.10$, **$p < 0.05$, *** $p < 0.01$.

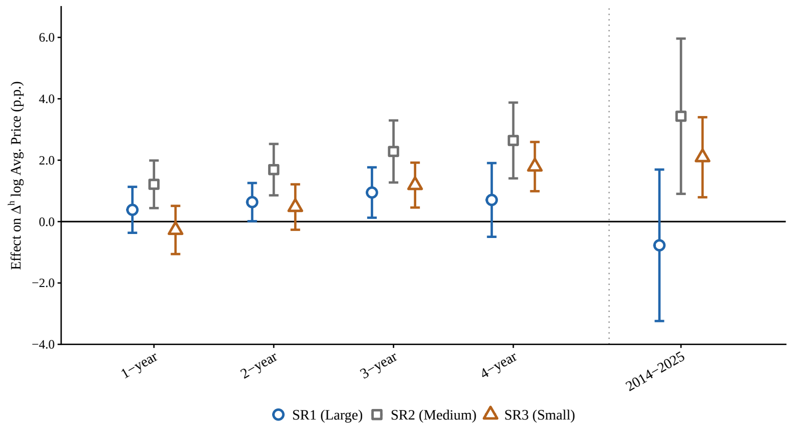

Figure Appendix C.1: Dynamic Causal Effects of Immigration on Housing Prices by Urban Hierarchy.

Notes: Each point reports the 2SLS estimate of the total marginal effect of a 1 pp increase in the net immigration rate on the h-period log change in average transaction prices (in pp), computed as the linear combination of the baseline coefficient and the relevant interaction term. Error bars denote 95% confidence intervals. See Table Appendix C.4 for full specification details.

Table Appendix C.5: Immigration Shocks and Local Outcomes: Heterogeneity by Urban Hierarchy

	$h = 1$ (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)	Long Diff. (5)
Panel A. Dependent Variable: Δ^h Native Mobility					
Δ^hImmigration *(Large)*	0.274**	0.251**	0.206	0.081	−0.157
	(0.116)	(0.122)	(0.131)	(0.141)	(0.248)
Δ^hImmigration × Medium (SR2)	−0.139	−0.088	−0.009	0.161	0.578
	(0.092)	(0.093)	(0.098)	(0.106)	(0.389)
Δ^hImmigration × Small (SR3)	−0.115	−0.063	0.023	0.219*	0.603**
	(0.110)	(0.115)	(0.123)	(0.132)	(0.253)
KP F-stat	60.1	55.1	51.2	40.4	11.4
Panel B. Dependent Variable: Δ^h log Total Affiliation					
Δ^hImmigration *(Large)*	0.654***	0.722***	0.811***	0.810**	0.017
	(0.215)	(0.234)	(0.282)	(0.368)	(0.711)
Δ^hImmigration × Medium (SR2)	−0.683***	−0.731***	−0.810***	−0.843***	0.718
	(0.208)	(0.221)	(0.260)	(0.322)	(0.792)
Δ^hImmigration × Small (SR3)	−1.305***	−1.243***	−1.161***	−1.035***	0.155
	(0.231)	(0.252)	(0.302)	(0.398)	(0.831)
KP F-stat	59.5	54.4	50.3	39.5	11.6
Panel C. Dependent Variable: Δ^h log Total Firms					
Δ^hImmigration *(Large)*	0.140	0.314***	0.448***	0.618***	0.758*
	(0.147)	(0.110)	(0.117)	(0.145)	(0.417)
Δ^hImmigration × Medium (SR2)	0.376***	0.376***	0.490***	0.614***	1.447***
	(0.091)	(0.073)	(0.088)	(0.115)	(0.535)
Δ^hImmigration × Small (SR3)	0.390***	0.300**	0.236	0.176	0.368
	(0.145)	(0.124)	(0.146)	(0.190)	(0.441)
KP F-stat	60.1	55.1	51.2	40.4	11.4

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	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	Long Diff. (5)
Panel D. Dependent Variable: Δ^h log *Services Firms*					
Δ^hImmigration *(Large)*	0.181	0.343**	0.498***	0.666***	0.307
	(0.180)	(0.139)	(0.164)	(0.220)	(0.380)
Δ^hImmigration $\times$ Medium (SR2)	−0.022	−0.072	−0.051	−0.061	0.376
	(0.099)	(0.091)	(0.136)	(0.190)	(0.453)
Δ^hImmigration $\times$ Small (SR3)	0.333*	0.225	0.106	0.074	0.666
	(0.183)	(0.158)	(0.198)	(0.273)	(0.521)
KP F-stat	60.1	55.1	51.2	40.4	11.4
Panel E. Dependent Variable: Δ^h log *Median Income*					
Δ^hImmigration *(Large)*	−1.052***	−0.773***	–	–	1.109**
	(0.234)	(0.202)	–	–	(0.548)
Δ^hImmigration $\times$ Medium (SR2)	0.945***	0.912***	–	–	0.381
	(0.251)	(0.222)	–	–	(0.431)
Δ^hImmigration $\times$ Small (SR3)	0.153	0.189	–	–	0.821
	(0.287)	(0.267)	–	–	(0.714)
KP F-stat	101.0	83.8	–	–	6.8
Panel F. Dependent Variable: Δ^h log *Construction Firms*					
Δ^hImmigration *(Large)*	−0.653	−0.200	−0.321	−0.007	1.102
	(0.534)	(0.412)	(0.430)	(0.558)	(1.179)
Δ^hImmigration $\times$ Medium (SR2)	0.743**	0.466	0.388	−0.094	−1.831
	(0.373)	(0.328)	(0.366)	(0.460)	(1.121)
Δ^hImmigration $\times$ Small (SR3)	1.331**	1.284***	1.336***	1.064*	0.515
	(0.546)	(0.450)	(0.469)	(0.605)	(1.574)
KP F-stat	59.8	54.1	48.7	38.1	10.1
Panel G. Dependent Variable: Δ^h log *Urban Surface Area*					
Δ^hImmigration *(Large)*	−0.551*	−0.771**	−0.628*	−0.614	2.269***
	(0.305)	(0.333)	(0.324)	(0.401)	(0.505)
Δ^hImmigration $\times$ Medium (SR2)	0.345	0.467	0.347	0.374	−2.179***
	(0.343)	(0.375)	(0.367)	(0.449)	(0.838)
Δ^hImmigration $\times$ Small (SR3)	0.314	0.508	0.498	0.172	−3.137***
	(0.391)	(0.424)	(0.504)	(0.609)	(0.924)
KP F-stat	60.0	55.1	51.1	40.4	11.6
Panel H. Dependent Variable: Δ^h log *Residential Share*					
Δ^hImmigration *(Large)*	0.040	0.051	0.075*	0.101*	0.093
	(0.027)	(0.031)	(0.041)	(0.054)	(0.107)
Δ^hImmigration $\times$ Medium (SR2)	−0.025	−0.030	−0.052	−0.074	−0.026
	(0.021)	(0.024)	(0.031)	(0.040)	(0.096)
Δ^hImmigration $\times$ Small (SR3)	−0.045	−0.041	−0.050	−0.065	−0.079
	(0.028)	(0.030)	(0.043)	(0.057)	(0.143)
KP F-stat	60.1	55.0	51.0	39.5	11.3
Panel I. Dependent Variable: Δ^h log *Hospitality Share*					
Δ^hImmigration *(Large)*	−4.403	−3.464	−4.087	−5.237**	−1.378
	(3.018)	(2.434)	(2.498)	(2.652)	(2.651)
Δ^hImmigration $\times$ Medium (SR2)	4.861	3.805	4.332	4.911*	−2.995
	(2.920)	(2.549)	(2.863)	(2.930)	(2.162)

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	$h = 1$ (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)	Long Diff. (5)
Δ^hImmigration × Small (SR3)	4.987	3.781	4.393	5.816**	1.867
	(3.259)	(2.614)	(2.733)	(2.836)	(2.971)
KP F-stat	60.1	55.2	51.2	40.5	11.3
Province FE	Yes	Yes	Yes	Yes	Yes
Province × Trend	Yes	Yes	Yes	Yes	No
Demand Controls	Yes	Yes	Yes	Yes	Yes
Supply Controls	Yes	Yes	Yes	Yes	Yes
Spatial Pull Exog.	Yes	Yes	Yes	Yes	Yes
Clusters	699	699	699	699	46
Observations	7,689	6,990	6,291	5,592	699

Notes: Each column reports a 2SLS regression for a different time horizon h. All panels disaggregate the geographic immigration shocks by urban status using *Large Urban* municipalities as the omitted category. Coefficients report effects for the base category and differential effects for Medium (SR2) and Small/Rural (SR3) structures. Median Income (Panel E) omits horizons $h = 3$ and $h = 4$ due to data constraints in the logs. KP F-stat and SW F-stat represent the Kleibergen–Paap rk Wald and Sanderson–Windmeijer multivariate F statistics, respectively. Standard errors clustered at the municipality level for columns (1)–(4) and at the province level for column (5) are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

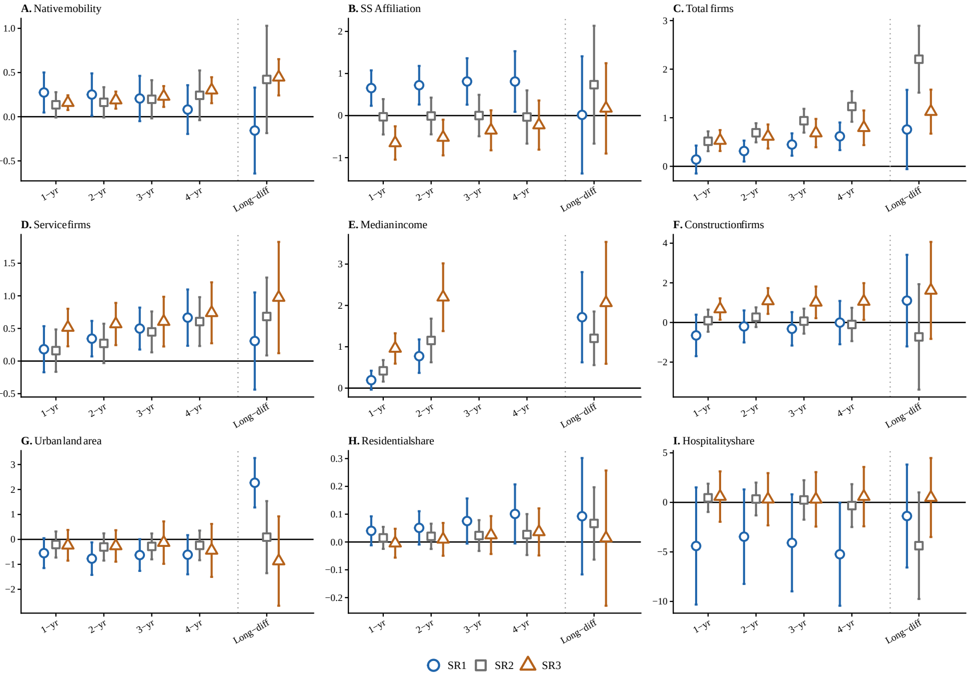

Figure Appendix C.2: The effect of immigration on other outcomes of interest by urban hierarchy

Notes: Figure reports 2SLS estimates of the effect of a one-unit increase in the net immigration flow, normalized by base-year population, on the indicated outcome. Rolling-window horizons span 1–4 years; the rightmost point corresponds to the long-difference specification (2014–2025 for all outcomes except median disposable income, available for 2020–2023 only). All specifications include province fixed effects, province-specific linear trends, year fixed effects, and the baseline controls, weighted by 2014 population. Standard errors are clustered at the municipal level in rolling-window specifications and at the province level in long-difference specification. Bars denote 95% confidence intervals.