Income Heterogeneity of Immigrants and House Price Dynamics

Flavia Paoloni* Lisa Timm†

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Abstract

This paper examines how changes in the local immigrant population stock with heterogeneous income levels affect house price growth in the Netherlands. Using administrative microdata from 2006 to 2020, we distinguish immigrants into four income groups and estimate their effects on property values. To address potential endogeneity in residential location choices, we employ a shift-share instrumental variable strategy based on historical settlement patterns interacted with national immigration shocks by origin and income group. The results vary across income groups and local housing markets. In the short run, a mean annual increase in the stocks of middle-low-income immigrants raises annual property-value growth by 0.17-0.20 percentage points, whereas a mean low-income change reduces it by 0.05-0.06 percentage points. These patterns appear primarily in less urban municipalities. Native population growth responses vary across immigrant income groups, but the evidence does not establish native out-migration as the primary mechanism behind the estimated house price effects. Overall, the findings show that aggregate estimates can mask important differences in the local housing price effects of immigration.

Keywords: Housing prices, immigration, urban areas
JEL Codes: J61, R23, R31

∗Paoloni: University of Amsterdam (e-mail:f.paoloni2@uva.nl).
†Timm: Luxembourg Institute of Socio-Economic Research (LISER) (lisa.timm@liser.lu).
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Results in this paper are based on non-public microdata from Statistics Netherlands (CBS). In principle, part of these microdata is accessible for statistical and scientific research. For further information: microdata@cbs.nl.

1 Introduction

The impact of immigration on housing markets is a central issue in contemporary public and policy debates, particularly given concerns about housing affordability. Immigration changes the size and composition of local populations and, in turn, the demand for residential space. Where housing supply adjusts slowly to population growth, an increase in housing demand can put upward pressure on property values (Saiz, 2003, 2007). However, the extent to which immigration affects local housing markets may depend not only on the number of immigrants settling in an area, but also on their economic resources and housing choices.

Existing literature on the relationship between immigration and housing markets often treats immigrants as a homogeneous group. While a few studies consider differences in immigrants' educational attainment and skill composition (Cabral & Steingress, 2026; Sá, 2015), the role of income differences has received less attention. Income is particularly relevant because it may influence households' purchasing power and the segments of the housing market they could access. Higher-income immigrants may be better positioned to purchase homes or demand housing in more expensive neighborhoods, whereas lower-income immigrants may be more concentrated in less expensive housing segments. Consequently, changes in the income composition of the immigrant population may generate different patterns of housing demand. Income-heterogeneous inflows can also affect property values through broader neighborhood dynamics, including shifts in local amenity demand and native residential mobility. Incumbent residents may adjust their residential choices in response to demographic changes. These adjustments, together with possible housing-supply responses, imply that the relationship between changes in the immigrant population and property values may differ across income groups, geographical settings, and time horizons.

This paper examines how annual changes in the local immigrant stock across different income levels affect local house prices in the Netherlands. We distinguish immigrants arriving in the Netherlands according to four income categories—low, middle-low, middle-high, and high—defined relative to the income distribution of their destination municipality. Our main explanatory variable is the annual change in the local stock of immigrants in each category, scaled by the postcode's lagged total population. This measure captures changes in the size of the local immigrant population relative to the existing population, rather than gross arrivals alone. We examine its relationship with two complementary measures of residential property values: the annual administrative tax assessment value (*Waardering Onroerende Zaken*, WOZ) and a repeat-sales price index constructed from housing transactions. The former provides broad coverage of the local housing stock, while the latter captures price changes among properties that are sold more than once. We further investigate whether the estimated responses differ between more

urban and less urban municipalities and whether they evolve over a three-year horizon. Finally, we examine changes in native population growth as a complementary indicator of potential residential adjustment.

The Netherlands provides an ideal empirical setting to analyze these dynamics. First, the country receives immigrants with a broad range of income profiles. Institutional arrangements, including the 30% tax rule and the highly skilled migrant visa program (*Kennismigrantenvisa*), contribute to the attraction of foreign workers with different income and skill levels. In particular, these policies provide a relevant institutional context for examining the housing-market implications of immigrant income heterogeneity (Timm, Giuliodori, & Muller, 2025). Second, the Dutch housing market has experienced substantial price appreciation alongside sustained immigration and growing concerns about housing affordability. Between 2006 and 2020, average residential selling prices increased by approximately 31%. Third, the Dutch administrative data infrastructure provides an opportunity to study these dynamics at a highly disaggregated geographical level. By linking individual population registers from Statistics Netherlands (CBS) with administrative real estate records from the Land Registry (Kadaster), we construct a panel covering 2,349 four-digit postcodes across 341 municipalities, representing more than 80% of the national population and housing stock. These data allow us to link changes in the local immigrant population, classified by income, to neighborhood-level property value developments.

Identifying the effect of changes in the local immigrant population on property values is challenging because residential location choices are endogenous. Immigrants may be attracted to neighborhoods with improving economic conditions, better amenities, or appreciating property values. Conversely, housing costs may influence where immigrants with different income levels choose to settle. These location choices can generate a correlation between changes in the immigrant population and local property value growth even in the absence of a causal relationship. To address this concern, we employ a shift-share instrumental variable strategy that combines historical settlement patterns with subsequent national changes in the immigrant population by origin and income category. Specifically, we interact each postcode's 1995 share of the national population from a given origin region with subsequent national changes in the immigrant population from that origin region and income category. This generates predicted local changes in the immigrant population stock based on pre-existing settlement patterns and national demographic shifts. The identifying assumption is that, conditional on postcode and year fixed effects and the included local controls, these predicted changes affect local property value growth only through their effect on the local immigrant population stock. We assess this assumption using alternative instrument constructions, leave-one-out specifications, and additional specification checks.

Our findings reveal substantial heterogeneity in the estimated property value responses. In

the baseline specifications, increases in the stocks of middle-low-income immigrants are associated with higher annual WOZ value growth, whereas increases in the stocks of low-income immigrants are associated with lower growth. Evaluated at the mean change in the respective immigrant stocks, these estimates correspond to an increase of approximately 0.17-0.20 percentage points for middle-low-income immigrants and a decrease of 0.05-0.06 percentage points for low-income immigrants. These income-specific patterns are sensitive to the inclusion of additional local controls, while estimates for the aggregate immigrant population and the two higher-income categories are less precisely estimated in the full sample. The repeat-sales results provide a complementary perspective, with a positive baseline association for middle-low-income immigrants that is also sensitive to additional controls. Taken together, the baseline estimates point to differences in property-value responses across immigrant income groups, although the strength of the evidence varies across specifications and outcome measures.

An important dimension of this heterogeneity concerns the characteristics of receiving housing markets. The geographical analysis shows that positive WOZ responses are concentrated in municipalities with fewer than 100,000 inhabitants and in areas outside the four largest Dutch cities. In these less urban areas, increases in the overall immigrant population stock and in the stocks of high-income and middle-low-income immigrants are associated with higher property value growth. By contrast, estimates for municipalities with more than 100,000 inhabitants and for the four largest cities are generally statistically indistinguishable from zero. These findings indicate that the relationship between changes in the immigrant population and property values depends on the characteristics of the receiving housing market. Differences in housing-stock composition, tenure structure, initial immigrant presence, and local market conditions may contribute to this geographical heterogeneity, although the analysis does not identify which of these factors drives the differences.

We further examine how these relationships evolve over a three-year horizon. The longer-horizon estimates reveal patterns that differ from the annual results. The controlled pooled specification is negative and statistically significant, while the income-specific estimates vary in sign and are generally less precisely estimated. In particular, the negative three-year point estimates for middle-low-income immigrants contrast with their positive short-run estimates, whereas the low-income estimates become positive at the three-year horizon. These patterns suggest that the relationship between changes in the immigrant population stock and property value growth may evolve over time. To explore one possible dimension of residential adjustment, we additionally examine changes in native population growth. he results show negative and statistically significant estimates for high- and middle-high-income immigrants in specifications with additional controls, while the middle-low-income response is sensitive to the inclusion of controls and the low-income estimates are less robust. These results provide additional

evidence of heterogeneous demographic responses across immigrant income groups, although they do not establish native out-migration as the mechanism underlying the estimated property value changes.

This paper contributes to three strands of the literature. First, it contributes to research on immigration and housing markets by examining heterogeneity in immigrant inflows according to income, rather than treating immigration as a homogeneous population shock (Akbari & Aydede, 2012; Gonzalez & Ortega, 2013; Sá, 2015; Braakmann, 2019). By separating incoming immigrants into income groups, we show that aggregate estimates can mask opposing responses within the same national housing market. Second, the paper contributes to the literature on the spatial incidence of immigration by using granular spatial data to identify localized price responses and examine heterogeneity across urban and less urban settings (Accetturo et al., 2014; Mussa, Nwaogu, & Pozo, 2017). Third, we contribute to research on residential sorting and the longer-run adjustment of housing markets by examining price dynamics alongside changes in the native population. In doing so, we connect the immediate effects of immigrant inflows to the possibility that household relocation and changes in neighborhood composition shape subsequent local housing market outcomes.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the data and presents descriptive statistics. Section 4 introduces the empirical framework and shift-share identification strategy. Section 5 presents the main results, including robustness checks and heterogeneity across local housing markets. Section 6 discusses the findings and Section 7 concludes.

2 Related literature

This paper contributes to the literature on immigration and housing markets by examining how the income composition of immigrant inflows shapes local house price dynamics. Immigration acts as a positive population shock that increases local housing demand and exerts upward pressure on prices and rents, particularly when supply is inelastic (Saiz, 2003, 2007). Most empirical studies find that immigrant inflows boost housing prices—such as Akbari and Aydede (2012) in Canada, Gonzalez and Ortega (2013) in Spain, Degen and Fischer (2017) in Switzerland, Hyslop et al. (2019) in New Zealand, and Moallemi and Melser (2020) in Australia. However, studies in other settings document negative or negligible price responses in target neighborhoods, such as Sá (2015) and Braakmann (2019) in the UK, as well as Accetturo et al. (2014) in Italy. Reconciling these contrasting empirical findings requires evaluating three key dimensions: immigrant heterogeneity, spatial and temporal scales of adjustment, and native behavioral sorting.

Most of the literature treats immigrants as a homogeneous group, despite differences in pur-

chasing power, skills, and housing preferences that may shape the local housing markets they enter (Albert & Monras, 2022). Sá (2015) finds that negative house price effects in the United Kingdom are concentrated in areas receiving less-educated immigrants, while Cabral and Steingress (2026) find larger shelter price effects in US counties receiving more highly educated immigrants, particularly where building permits are scarce. Related work also highlights the importance of immigrant characteristics in shaping local economic outcomes (Monras, 2020). This paper extends the literature by classifying incoming immigrants into income quartiles at the municipality level using Dutch administrative data.

The geographic scale of analysis can explain differences in estimated house price effects. Aggregate estimates capture changes in overall housing demand, whereas neighborhood-level estimates also reflect the spatial redistribution of households. In Italy, Accetturo et al. (2014) find that immigration raises city-level house prices but reduces relative price growth in districts receiving larger inflows. Mussa, Nwaogu, and Pozo (2017) identify price effects in both immigrant-receiving and neighboring US metropolitan areas, highlighting the potential for spatial spillovers. These patterns may also depend on local housing supply constraints, which determine how strongly additional demand translates into prices rather than construction (Glaeser, Gyourko, & Saiz, 2008; Saiz, 2010). Using four-digit postcode data in the Netherlands, this paper estimates localized price responses.

Furthermore, housing market adjustments unfold over distinct temporal horizons. In the short run, supply constraints and construction lags dictate that demand shocks translate directly into price increases (Saiz, 2003; Unal, Hayo, & Erol, 2024). Over longer horizons, market clearing occurs through filtering, residential construction, endogenous labor supply expansion (Monras, 2020), and shifts in local amenities (Sanchis-Guarner, 2023). As emphasized by Sanchis-Guarner (2023), capturing the full equilibrium effect of immigration requires evaluating medium-term spatial adjustments rather than immediate price reactions. Following this insight, we evaluate house price growth over a three-year horizon alongside annual changes, isolating structural medium-term adjustments from short-term market noise.

Finally, the mechanism proposed to explain negative localized price responses is native out-migration or residential displacement (commonly termed "native flight") (Sá, 2015; Fernández-Huertas Moraga, Ferrer-i-Carbonell, & Saiz, 2019; Boje-Kovacs et al., 2024). Inflows can induce pre-existing residents to relocate or avoid target neighborhoods due to changing amenity preferences or perceived social distance, generating a secondary supply outflow (Hatton & Tani, 2005; Larkin et al., 2019; Andersson, Malmberg, & Vitali, 2021). However, the empirical magnitude of native displacement remains actively debated, with recent neighborhood-level evidence suggesting incumbent out-migration responses can be minimal (Peruffo & Check, 2026). Native sorting also depends on skill and socio-economic complementarities (Card & DiNardo, 2000;

Mocetti & Porello, 2010). We contribute to this mechanism literature by tracking changes in the native population growth at the postcode level across incoming immigrant groups, testing whether affluent foreign inflows attenuate native flight relative to lower-income arrivals.

3 Data

To examine how neighborhood house prices respond to immigrant inflows, we combine individual-level administrative registers from Statistics Netherlands (CBS) with real estate transaction records from the Land Registry (Kadaster). While our demographic and overall housing market panel spans 1995 to 2022, granular tax register data on individual incomes are consistently available starting in 2006. Consequently, our analysis of immigrant heterogeneity by income group focuses on the 2006–2020 period.

Spatial Unit and Sample Selection. We conduct our analysis at the four-digit postcode level (PC4), which we use interchangeably with "neighborhood" and "postcode". With an average territory of 2.5 km^2, four-digit postcodes represent a localized geographic scale where residents directly experience local demographic changes and neighborhood amenities (Veldhuizen, Stronks, & Kunst, 2013). To link our demographic data with rich neighborhood characteristics—such as population density, local infrastructure, and housing stock composition—we merge our panel with the regional CBS database (*Kerncijfers Wijken en Buurten*, KWB).

To construct a reliable panel, we apply a series of sample selection criteria, summarized in Table 1. First, we restrict our sample to a balanced panel of four-digit postcodes that exist continuously between 1995 and 2022. Second, we drop postcodes with zero inhabitants in any given year. Third, to avoid outlier distortions, we exclude postcodes experiencing year-on-year immigration shifts exceeding 100%. Finally, we impose a minimum population threshold in 1995 at the 30th percentile of the national distribution (1,011 inhabitants) to filter out sparsely populated industrial or rural tracts.

Table 1: Number of postcodes by selection step

Filtering Step	N postcodes
All postcodes	4,056
> 0 inhabitants	3,978
Immigrant growth rate < 100%	3,416
30th pct population (1995)	2,349

Note: Each line represents a sample selection step. Postcode refers to a four-digit postcode.
Source: CBS Microdata

Our final estimation sample comprises 2,349 postcodes, with an average of 4,914 inhabitants

older than 18 years old (including 519 immigrants) and 2,772 dwellings per postcode. This sample covers over 80% of the total Dutch population, immigrant population, and national housing stock.

Immigration. Our main regressor of interest is the change in the local immigrant population as a share of the total postcode population in the previous year. Drawing on CBS administrative registers, we define immigrants as foreign-born individuals who settle in a Dutch municipality from abroad at age 18 or older. Our empirical analysis focuses on immigrants moving to the Netherlands for labor, family, and student motives.[1] To account for heterogeneity in purchasing power, we classify incoming immigrants into five income groups: total immigrant population, low, middle-low, middle-high, and high income. We measure income using the total wage on which wage tax and social insurance contributions are calculated, as reported by Statistics Netherlands; these records cover the universe of registered residents in the Netherlands and are available continuously from 2006 onward. Income groups are defined by an immigrant's observed annual income in the year of arrival, relative to the income distribution of the total population in the destination municipality. Each immigrant's income group is assigned at arrival and held fixed thereafter, so that subsequent changes in an individual's income do not mechanically alter their classification. Individuals with zero observed income or missing income are assigned to the lowest income category. Income at arrival provides an observable measure of immigrants' relative economic resources, but it does not fully capture their purchasing power in the housing market. In the Netherlands, access to mortgage credit depends not only on the value of the property relative to the loan but also on income-related borrowing constraints and households' broader financial circumstances. These income measures capture relative income position at arrival, but they do not capture wealth, savings, household size, existing debt, or differences in access to credit.

Housing Prices. To measure local housing market responses, we employ two complementary price indicators: the municipal property tax assessment value (*Waardering Onroerende Zaken*, WOZ) and a repeat-sales price index. The WOZ value, assessed annually by municipalities for tax purposes, estimates the market value of every residential property using structural features, square footage, and recent transactions of comparable units within the neighborhood (see Appendix B.3 for detailed information on the WOZ calculation methodology).

Second, we construct a Case and Shiller (1987) repeat-sales price index using the universe of real estate transaction prices for existing owner-occupied dwellings recorded by the Land Registry, setting 2015 as the base year. The repeat-sales methodology provides the key advantage

[1]Asylum seekers and refugees residing in central reception facilities are excluded because their spatial placement is governed by state quota allocations rather than voluntary market choices. Dröes and Koster (2023) study narrow corridors around refugee settlement centers in the Netherlands and find local decreases in house prices in areas close to refugee pathways.

of controlling for unobserved, time-invariant housing quality by holding property-specific characteristics constant across transactions.[2] This index tracks realized market prices across 56,500 to 126,500 annual transactions (40–50 sales per postcode-year on average).

Comparing these two indicators offers distinct empirical advantages. The WOZ value provides full-population coverage across all residential properties annually, though with an administrative lag reflecting past market trends. Because municipal tax valuations reflect the aggregate average value of the housing stock—capturing structural upgrades, expansions, and high-end residential development—they absorb both price shifts and quality improvements. In contrast, the repeat-sales index captures immediate, realized transaction prices—specifically overrepresenting more frequently traded housing types.

Our analysis focuses on owner-occupied housing prices rather than rents. Although our WOZ-based outcome captures assessed property values for properties covered by the data, including rental properties where present, it does not measure rents paid by tenants. We do not directly estimate the effects of immigration on rental prices due to data availability constraints. Moreover, the unregulated private rental sector accounts for approximately 10–13% of the Dutch housing stock, while owner-occupied housing represents a substantially larger segment of the market. We therefore focus on owner-occupied property values, for which we can construct consistent measures at the required spatial resolution. This choice allows us to study an important segment of the housing market, but it does not capture potential effects of immigration on rents or on households in the rental sector.

3.1 Descriptive Statistics

Our final estimation sample comprises 2,349 four-digit postcodes across 341 Dutch municipalities, covering approximately 10.1 million adult residents and 9.7 million housing units at baseline (1995). Table 2 presents summary statistics across postcodes and years. The median neighborhood in our sample contains 5,450 adult inhabitants (older than 18) and 4,295 dwellings.

Immigrant shares exhibit substantial variation across postcodes and over time. On average, immigrants constitute 9% of a neighborhood's adult population, with an interquartile range spanning from 3.3% at the 25th percentile to 10.9% at the 75th percentile. This local variation in immigrant concentration provides the primary identifying variation for our empirical framework.[3]

Figure 1 documents the evolution of immigration to the Netherlands over the sample period

[2]Hedonic regression models represent a common alternative for constructing house price indices. However, administrative Land Registry transaction data lack the granular property-level structural attributes required for a hedonic specification.

[3]Appendix Figure D.1 illustrates the distribution of immigrant shares across municipalities in the estimation sample in 1995.

Table 2: Summary Statistics across Postcodes (2006–2020)

	Mean	St. Dev.	25th Pct.	Median	75th Pct.	N
Avg. WOZ value by PC4 (x 1,000)	239.2	89.5	182.0	226.4	276.9	32,487
Δ Avg. WOZ by PC4 (%)	1.7	5.7	-2.4	1.4	5.4	32,345
Repeat-Sales Index	109.6	20.9	100.0	107.2	116.9	32,895
Δ Repeat-Sales Index (%)	1.1	12.7	-4.3	1.5	6.8	32,846
Housing Stock	2,772	1,737	1,360	2,521	3,846	33,085
Δ Housing Stock (%)	22.7	342.4	-1	9	32	33,085
Share of rental units (%)	39.4	16.4	27.4	35.9	48.8	32,160
Share of owner-occupied units (%)	58.8	16.8	49.1	62.6	71.0	32,167
Population:						
Population age ≥ 18	4,914	2,846	2,544	4,510	6,796	33,085
Δ Population (%)	-4.7	863	-13	12	52	33,084
Immigrants age > 18	519	730.7	98	276	618	33,085
Δ Migrants (%)	-3	185	-1	5	18	33,084
Migrant share (%)	8.9	9.0	3.3	5.8	10.9	33,085
Avg. household size	2.2	0.3	2.1	2.3	2.4	32,649
Income:						
Avg. income per worker (x 1,000)	30.0	6.1	27.2	29.9	33.1	27,700
Share of low-income immigrants (%)	56.2	10.2	49.7	56.0	62.4	33,085
Share of middle-low-income immigrants (%)	15.9	5.9	12.0	15.6	19.2	33,085
Share of middle-high-income immigrants (%)	19.1	6.6	14.9	18.3	22.3	33,085
Share of high-income immigrants (%)	12.3	6.0	8.1	11.0	15.2	33,085

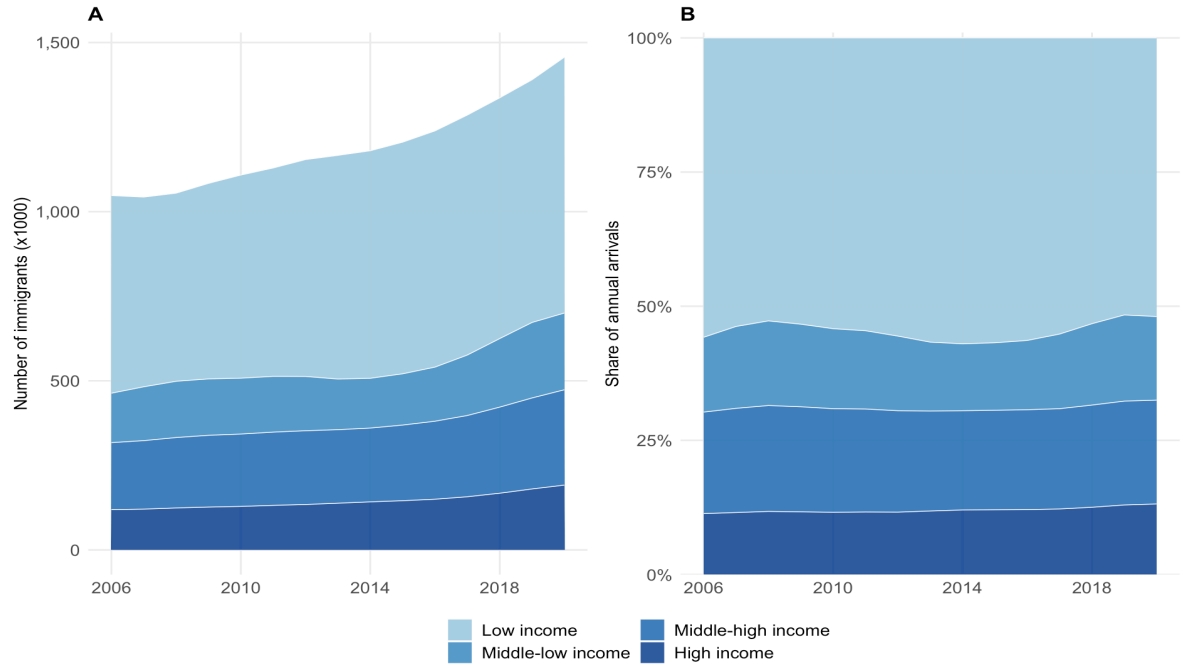
Notes: This table presents summary statistics across 2,349 four-digit postcodes and years. Δ denotes the year-on-year percentage change. Rental and owner-occupied shares are calculated relative to total local housing stock. Immigrant, low-income, and high-income shares are measured relative to the adult population as of January 1st.
Sources: CBS Microdata; *Kerncijfers Wijken en Buurten* (KWB).

and the changing income composition of immigrants. Panel A shows the annual number of new adult immigrants overall and by income group, while Panel B reports each group's share of the total. These descriptive patterns establish the scale of immigration and the extent to which the composition of incoming cohorts varies over time. They also provide context for the empirical strategy, which exploits variation in immigrant inflows across both income groups and locations.

Additional descriptive evidence on the geographical and origin composition of immigration is provided in Appendix Figures D.7-D.10, documenting the distribution of immigrants across origin regions and receiving municipalities, as well as the geographical patterns of migration flows.

A potential concern with treating local immigrant arrivals as structural neighborhood demand shocks is the presence of short-term seasonal migration or hyper-mobile populations. However, administrative registry data indicate that immigration spells in our sample reflect durable residential decisions. Approximately 35% of foreign-born individuals who arrived be-

Figure 1: Inflows of immigrants by income group



Notes: The left panel, A, displays the number of immigrants per year by income group; the right panel, B, shows the share of each immigrant income group out of total immigrants by year.
Sources: CBS Microdata; *Kerncijfers Wijken en Buurten* (KWB).

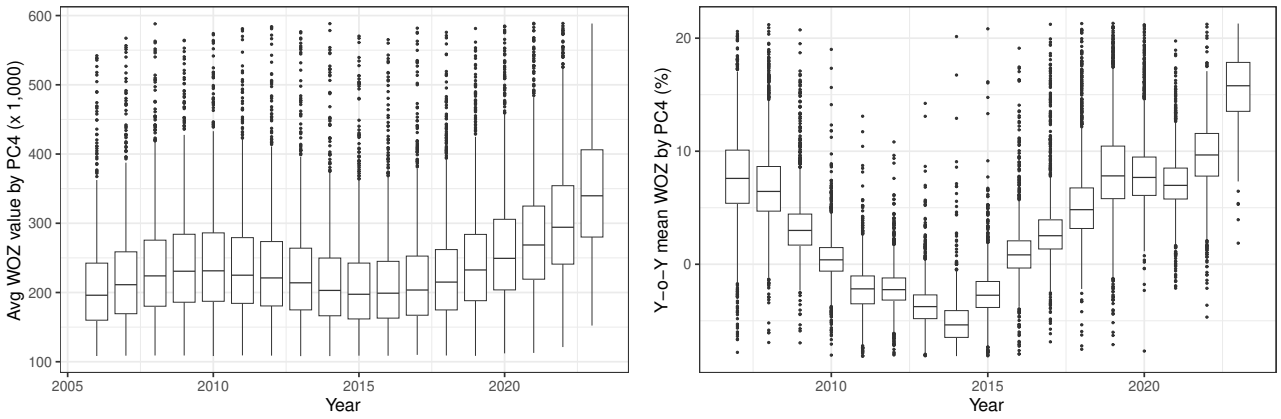
tween 1995 and 2015 remained continuously registered in the Netherlands through 2022 (Appendix Figure D.4). Conditional on completing an immigration spell, 75% of immigrants stay in the country for at least one year, with a median stay duration of approximately two years. Within the country, the median immigrant completes 2 to 3 housing spells, with 75% of individual address stays exceeding one year (Appendix Table D.6). The limited prevalence of short-term seasonal stays confirms that immigrant arrivals represent sustained multi-year neighborhood demand shifts.

Figure 2 illustrates the level and annual growth rate of municipal property valuations (WOZ) across neighborhoods over time. Average WOZ values grew at an annual rate of 1.7% across postcodes, accompanied by pronounced macro-level fluctuations—most notably the market contraction between 2011 and 2015, followed by rapid appreciation.

The repeat-sales transaction index exhibits a strong co-movement with the WOZ valuation series (Appendix Figure D.2), with a national year-on-year correlation coefficient of 0.86 (Appendix Figure D.3). The repeat-sales index exhibits slightly milder price contractions during the 2011–2015 downturn, consistent with transaction selection mechanisms where property owners delay sales during market troughs.

Finally, cross-sectional correlations highlight key structural determinants of local price ap-

Figure 2: Distribution of Municipal Property Values (WOZ) across Postcodes over Time



Notes: The left panel displays the distribution of average WOZ property valuations across postcodes; the right panel shows the year-on-year percentage growth rate. Box plots display the interquartile range (25th to 75th percentiles), with median lines and whiskers extending to 1.5 × IQR. Sample consists of 2,349 four-digit postcodes (PC4).
Sources: CBS Microdata; *Kerncijfers Wijken en Buurten* (KWB).

preciation. Over the sample period, WOZ property appreciation is positively correlated with the baseline share of high-income households ($\rho = 0.76$) and the share of owner-occupied housing ($\rho = 0.41$), while negatively correlated with the local rental housing share ($\rho = -0.42$). Furthermore, house price growth was significantly stronger in large municipalities ($> 100,000$ inhabitants; Appendix Table D.3), motivating our spatial heterogeneity analysis across urban and less urban environments in Section 5.

4 Empirical Framework

We examine how the relationship between immigration and house prices varies with immigrants' position in the income distribution. Income shapes housing market dynamics through several channels. First, purchasing power influences tenure choice and access to credit, enabling higher income immigrants to enter the owner-occupied market sooner and exert upward pressure on house prices. Second, income influences neighborhood choice and amenity demand; as Duijn and Rouwendal (2021) establish, households across all demographics value a higher neighborhood share of high-income residents. High-income immigrants may thus generate positive neighborhood externalities—such as enhanced commercial amenities and local tax revenues—that are prized by native households. Third, income-driven sorting affects residential integration, as incumbent residents may prefer co-locating with higher income cohorts. Although individual preferences are unobserved, these mechanisms imply that high- and low-income immigrant inflows trigger distinct housing demand shocks and neighborhood spillovers. Motivated by these theoretical channels, we differentiate immigrant inflows by in-

come tier and estimate their localized impact on house price growth.

Our baseline specification is:

$$\Delta \log P_{i,t} = \beta^j \left(\frac{\Delta M^j_{i,t-1}}{\text{Pop}_{i,t-2}} \right) + \boldsymbol{\gamma}' X_{i,t-2} + \boldsymbol{\theta}'(W_i \times \delta_t) + \sigma_i + \delta_t + \varepsilon_{i,t}, \tag{1}$$

where the unit of observation is postcode i in year t. The dependent variable, $\Delta \log P_{i,t}$, denotes the annual change in the natural logarithm of house prices, evaluated separately using municipal tax valuations (WOZ) and our repeat-sales price index. Our main explanatory variable, $\Delta M^j_{i,t-1}/\text{Pop}_{i,t-2}$, is the annual change in the local stock of immigrants in income category $j \in \{\text{Total}, \text{Low}, \text{Middle-Low}, \text{Middle-High}, \text{High}\}$, scaled by the baseline postcode population at time $t-2$. Immigrants are classified into municipal-level income quartiles in their year of arrival, with the low-income tier also incorporating non-working immigrants. This measure captures the change in the local immigrant population stock relative to the pre-existing postcode population.[4]

The coefficient β^j measures the relationship between this population-scaled change in the immigrant stock and annual property value growth. Since the dependent variable is the change in log property values, β^j is a semi-elasticity. To convey the economic magnitude of the estimates, we also report the implied response evaluated at the sample mean of the relevant explanatory variable, giving the approximate change in annual property-value growth associated with a mean change in the local immigrant stock. To isolate the causal effect of immigrant inflows, we control for a vector of lagged, time-varying postcode characteristics $X_{i,t-2}$, comprising changes in the local unemployment rate, total housing stock, and working-age population (aged 15–64). Furthermore, postcodes with different baseline structures may experience different long-run trends. We account for this by incorporating $W_i \times \delta_t$, interacting postcode attributes at the starting year of the sample, W_i—specifically the logarithm of average WOZ property value and logarithm of the median income—with year fixed effects. Because the specification is in first-differences, fixed postcode-level unobservables affecting price levels are eliminated. Postcode fixed effects, σ_i, absorb time-invariant differences in average house price growth across postcodes. Year fixed effects, δ_t, absorb aggregate macro-financial shocks, such as national interest rate movements or housing policy changes. Finally, all regressions are weighted by 2006 postcode population to ensure results are representative of the overall housing market and to account for market-size heteroskedasticity. Standard errors are clustered at the municipality level to allow for spatial and serial correlation across postcodes.

[4]It should not be interpreted as a measure of gross immigrant arrivals, since changes in the local stock may also reflect departures and other changes in local population composition.

4.1 Identification: shift-share instrumental variable strategy

The main identification challenge in estimating β^j via OLS is that immigrant location choices are endogenously determined. We highlight two main identification concerns. The first is reverse causality: local housing prices directly influence immigrants' location decisions. If lower income immigrants, constrained by housing affordability, systematically settle in postcodes with lower or stagnant property values, this induces a spurious negative correlation between immigrant inflows and house price growth. Conversely, if higher income immigrants select into areas experiencing rapid price appreciation—interpreting rising values as a signal of neighborhood quality—this creates a spurious positive correlation where appreciating neighborhoods attract more affluent migrants over time. Localized economic shifts, such as infrastructure investments, public transit expansions, or municipal amenity upgrades, simultaneously boost property valuations and attract new residents. Because these unobserved shocks ($\varepsilon_{i,t}$) are positively correlated with both house price growth and incoming foreign migration, standard OLS specifications suffer from an upward bias.

To estimate the causal effect of immigrant inflows across income groups on local house prices, we implement a shift-share instrumental variable (SSIV) strategy, following Bartik (1991) and Card (2001) and the more recent shift-share literature (Goldsmith-Pinkham, Sorkin, & Swift, 2020; Borusyak, Hull, & Jaravel, 2025). Specifically, we use the SSIV to predict annual postcode-level immigrant inflows for each of the five income tiers. The intuition is to predict which postcodes are more exposed to subsequent immigration inflows using settlement patterns established before our house price estimation period.

The instrument combines two components. The first is each postcode's share of the national population from a given origin region in 1995. This historical share measures the postcode's pre-existing connection to that origin group. The second is the subsequent change in national immigration from that origin region, measured separately by immigrant income category. This national change captures the timing and scale of the inflow from each origin. By combining the two components, the instrument predicts larger immigration changes in postcodes that historically had stronger settlement links to origin regions experiencing larger subsequent national inflows.

The approach is motivated by immigrant network effects: new arrivals often settle near established co-national communities, where they may obtain information about housing, employment, and local services and draw on existing social networks (Munshi, 2003; Zorlu & Mulder, 2008). Historical settlement patterns therefore provide a way to predict differences in local exposure to subsequent national immigration changes without relying solely on contemporaneous postcode-level settlement decisions. The instrument captures predicted exposure rather than actual immigration itself; its validity depends on whether this predicted exposure affects

housing-price growth through immigration rather than through other channels.

Formally, for each immigrant income group $j \in \{\text{Total, Low, Middle-Low, Middle-High, High}\}$, the predicted immigrant exposure instrument $Z^j_{i,t-1}$ in postcode i and year $t-1$ is defined as:

$$Z^j_{i,t-1} = \sum_c \underbrace{\left(\frac{M_{c,i,t_0}}{M_{c,t_0}}\right)}_{\text{Share}} \times \underbrace{\left(\frac{\Delta M^j_{c,t-1}}{\text{Pop}_{i,t-2}}\right)}_{\text{National Shift}}, \tag{2}$$

where $t_0 = 1995$ denotes our baseline period, c indexes 21 distinct origin regions, and j denotes the income quartile.[5] The baseline share, $M_{c,i,t_0}/M_{c,t_0}$, represents the proportion of foreign-born individuals from origin c residing in postcode i in 1995 relative to the national total for origin c. The shift variable, $\Delta M^j_{c,t-1}$, measures the annual change in national immigrant arrivals from origin c in income group j at time $t-1$. Dividing the national inflow change, the shift, by the postcode population, $\text{Pop}_{i,t-2}$, puts the predicted exposure on a scale comparable to the endogenous immigration variable in equation (1). Thus, postcodes with larger historical shares of an origin group receive greater predicted exposure when national inflows from that origin increase.

The first-stage regression corresponding to baseline equation (1) is:

$$\frac{\Delta M^j_{i,t-1}}{\text{Pop}_{i,t-2}} = \theta^j Z^j_{i,t-1} + \boldsymbol{\gamma}' X_{i,t-2} + \boldsymbol{\theta}'(W_i \times \delta_t) + \sigma_i + \delta_t + \nu^j_{i,t-1}. \tag{3}$$

For $Z^j_{i,t-1}$ to be a valid instrument, two conditions must be satisfied: instrument relevance and conditional exclusion. First, relevance requires that historical 1995 location shares strongly predict subsequent local immigrant inflows when interacted with aggregate national shifts. This mechanism is motivated by the role of co-ethnic networks in facilitating job search, housing search, and social integration. Previous studies document the importance of immigrant networks in shaping location choices (Munshi, 2003) and provide evidence of co-ethnic settlement patterns in the Netherlands (Zorlu & Mulder, 2008). Across all baseline specifications, we assess first-stage strength using the Kleibergen–Paap r_k F-statistic. Second, conditional on the controls and fixed effects, the instrument must affect local house price growth only through its effect on immigrant inflows.

To establish whether historical settlement patterns reflect co-ethnic networks, we compare the spatial concentration of immigrant groups across origin categories versus income groups.

[5]Origin countries are aggregated into 21 regions based on visa status (e.g., EU/EFTA), geographical proximity, and historical inflow volumes (for details see Table D.4). Major origin groups with large inflow volumes—such as Turkey, Indonesia, Germany, and Poland—are maintained as standalone categories to prevent small-sample noise from contaminating baseline shares.

Specifically, we calculate the Herfindahl–Hirschman Index (HHI) for each origin group:

$$\text{HHI}_c = \sum_i \left(\frac{M_{c,i}}{M_i} \right)^2, \tag{4}$$

where $M_{c,i}$ denotes the stock of origin c in postcode i and M_i is the total foreign-born population in i. Descriptive evidence is provided in Appendix Table D.5. The concentration patterns help characterize the spatial distribution of origin groups, although they do not, by themselves, establish the validity of the instrument.

Following the shift-share identification framework of Goldsmith-Pinkham, Sorkin, and Swift (2020), our identification strategy exploits the exogeneity of baseline settlement shares. Because spatial variation in exposure is driven by pre-existing 1995 settlement patterns across postcodes, the exclusion restriction requires that, conditional on controls and fixed effects, historical 1995 origin shares affect house price growth between 2006 and 2020 *solely* through their influence on instrument-predicted immigrant inflows. Relying on share exogeneity provides two distinct econometric advantages in our setting: it ensures consistency even if national origin-income shocks capture broader macroeconomic trends, and fixing shares at 1995 decouples instrument exposure from recent neighborhood gentrification trends (Borusyak, Hull, & Jaravel, 2025).

This exclusion restriction assumption may be violated if historical settlement patterns are correlated with local economic characteristics that subsequently affect housing demand independently of immigration. For example, postcodes with larger historical shares of a particular origin group may be more exposed to certain industries or labor-market developments. If those industries subsequently expand or contract, local employment, income, and housing demand may change even apart from the new immigration predicted by the instrument.

Our specification addresses several potential sources of confounding. First, taking first-differences eliminates time-invariant location characteristics, while postcode fixed effects (σ_i) control for postcode-specific trends in price growth. Year fixed effects (δ_t) account for shocks common to all postcodes in a given year. Second, interactions between baseline house prices and baseline income and year fixed effects ($W_i \times \delta_t$) allow price trajectories to differ flexibly with initial local conditions. Third, lagged, time-varying controls ($X_{i,t-2}$) further account for observed changes in local unemployment, housing stock, and working-age population. These controls reduce the scope for certain alternative explanations but cannot eliminate every potential time-varying local shock.

We assess the identifying assumptions using several complementary exercises. First, we conduct a pre-trend falsification test to examine whether future values of the instrument predict current house price growth. The absence of significant leading effects would be consistent with the identifying assumptions, although it would not prove the exclusion restriction (see Table E.9).

Second, to eliminate potential own-observation feedback bias—where a postcode's own inflows might contaminate the aggregate national shift—our shift-share instrument is constructed using a leave-one-out formulation that explicitly excludes postcode i's own contribution.

We also examine whether the predicted shift-share instrument is systematically related to observed time-varying local economic characteristics. Following Goldsmith-Pinkham, Sorkin, and Swift (2020), we regress the predicted instrument for each immigrant category on changes in local housing supply, working-age population, and unemployment, including postcode and year fixed effects. Appendix Table E.8 reports the results. Across all income groups j, the shift-share predicted inflows exhibit near-zero, statistically negligible correlations with local housing supply changes and working-age population dynamics. Similarly, controlling for fixed effects attenuates the relationship between the instrument and local unemployment rates toward zero. Furthermore, the within-R^2 values remain low across all specifications (0.070 to 0.122). This low explanatory power indicates that observable time-varying local economic drivers explain very little of the spatial exposure generated by the instrument. Combined with our postcode and year fixed effects, these balance results confirm that historical 1995 settlement patterns do not systematically track contemporaneous local economic shocks, supporting the conditional exogeneity of the shift-share instrument.

Finally, we assess whether our income-specific results are driven by the income classification. We tabulate the income distribution of immigrants within each major origin region in Table D.7 and find that immigrants from the same broad origin region are distributed across multiple income categories, and the degree of dispersion differs substantially across origins. We also verify that using fixed national income thresholds rather than municipal-relative income ranks yields similar estimates. This robustness check reduces concern that the results depend on the use of municipality-relative income classification.

5 Results

We first show that the shift-share instrumental variable strategy yields a strong and relevant instrument. After that, we discuss the estimation results for the main outcomes of the tax assessment value (WOZ) and the repeat-sales price index.

Table 3 shows the estimation results for the first stage, using 1995 shares interacted with national-level year-on-year change of the stock of immigrants by region of origin and income type. Using the shifts per income type, we build an instrument for every income type of immigrants. This instrument is a strong predictor of the contemporaneous year-on-year change of the stock of immigrants per neighborhood, as indicated by a positive and statistically significant coefficients across all specifications. For example, a one-percentage-point increase in the pre-

dicted inflow of high-income immigrants leads to an actual increase of 0.828 percentage points relative to neighborhood population.

Table 3: First-stage coefficients

	All migrants		High income		Middle-High income		Middle-Low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\frac{\Delta M^j_{i,t-1}}{Pop_{i,t-2}}$	0.697***	0.531***	0.889***	0.827***	0.300**	0.259**	0.713***	0.613***	0.828***	0.613***
	(0.106)	(0.149)	(0.187)	(0.211)	(0.101)	(0.113)	(0.042)	(0.050)	(0.039)	(0.060)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls		x		x		x		x		x
N	30,048	20,663	30,048	20,663	30,048	20,663	30,048	20,663	30,048	20,663
Adj. R^2	0.278	0.296	0.343	0.368	0.143	0.163	0.273	0.289	0.179	0.168
IV KP F-statistic	43.0	12.8	22.6	15.4	8.8	5.3	287.3	148.4	447.9	108.1

Note: First stage, as in Equation (3), with an income-type specific SSIV variable, using 1995 shares. One column per income-range of immigrant. Outcomes measured in 2007 - 2020. Standard errors in parentheses, clustered by municipality. The regression is weighted by the postcode-level population in 2006. "IV KP F-statistic" reports the Wald statistic for weak instruments (Kleibergen-Paap rk F-statistic) accounting for clustered standard errors. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

The adjusted R^2 is between 0.14 and 0.34, depending on the income group. The Kleibergen–Paap rk F-statistics indicate strong first-stage relationships for the low- and middle-low-income groups. The statistics are also above the conventional threshold in the specifications for the aggregate immigrant population and high-income immigrants, although the values are lower once additional controls are included. For middle-high-income immigrants, the corresponding statistics are 8.8 without controls and 5.3 with controls, indicating a comparatively weak first stage. The second-stage estimates for this group should therefore be interpreted with particular caution. Overall, the first-stage results support the relevance of the instrument for most groups, but do not provide equally strong evidence across all income categories.

Table 4 and Table 5 report second-stage IV estimates of the effect of immigration on tax assessment values, measured by the WOZ administrative valuation, and on the Case-Shiller repeat-sales index respectively. Identifying variation is driven by a shift-share instrument that isolates exogenous changes in immigrant inflows via historical settlement patterns interacted with national sending-country flows. All specifications include year and four-digit postcode fixed effects; even-numbered columns add time-varying local controls for unemployment, housing stock, and working-age population.

In Table 4 the pooled estimates are positive but statistically insignificant, indicating that the average relationship for the immigrant population as a whole is estimated imprecisely. The estimates also vary across the income categories.

Middle-low income inflows generate a statistically significant positive effect on the WOZ

Table 4: Second-stage coefficients for tax assessment value (WOZ)

	Outcome: change in log tax assessment value									
	All		High income		Middle-High income		Middle-Low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\widehat{\frac{\Delta M^{j}_{i,t-1}}{\text{Pop}_{i,t-2}}}$	1.680	1.863	1.016	-1.321	9.560	5.543	4.012*	3.360	-0.597*	-0.735
	(2.263)	(3.137)	(10.241)	(9.364)	(17.004)	(18.314)	(2.245)	(3.096)	(0.308)	(1.834)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls:		x		x		x		x		x
N	30,048	20,706	30,048	20,706	30,048	20,706	30,048	20,706	30,048	20,706
Avg outcome	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169
Avg regressor	0.0021	0.0021	0.0003	0.0003	0.0004	0.0004	0.0005	0.0005	0.0008	0.0008
SD regressor	0.0064	0.0064	0.0015	0.0015	0.0021	0.0021	0.0022	0.0022	0.0049	0.0049
IV KP F-statistic	43.0	12.8	22.6	15.4	8.8	5.3	287.3	148.4	447.9	108.1
Impact at mean regressor	0.0035	0.0039	0.0003	-0.0004	0.0038	0.0022	0.0020	0.0017	-0.0005	-0.0006

Note: Second-stage coefficients, as in Equation (1), with an income-type specific SSIV variable, using 1995 shares. One column per income-range of immigrant. Controls include the year-on-year change in the unemployment rate, housing stock and working-age population. The outcome is measured in 2006 - 2020. Standard errors are clustered by municipality. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

value. In the baseline specification (column 7), the estimated effect evaluated at the mean regressor (0.0005) implies a 0.17 to 0.20 percentage point increase in tax assessment value, representing roughly 10% to 12% of the sample average annual property appreciation (0.0169). Conversely, low-income immigrant inflows exert a negative and statistically significant impact on house prices (column 9), although the estimate is no longer statistically significant when additional controls are included (column 10). Evaluated at the mean regressor (0.0008), the implied reduction of 0.0005 to 0.0006 represents a 3% to 4% drag relative to mean property appreciation. These income-specific estimates become statistically not significant when the additional local controls are included. The results therefore provide suggestive evidence of differences across income categories in the baseline specification. The estimates for high- and middle-high-income immigrants are also imprecise (columns 3-6), and the relatively weak first stage for the middle-high-income group warrants additional caution. Consequently, while point estimates for upper-income tiers lean positive, we cannot draw statistically reliable conclusions for these groups.

Table 5 presents estimates using the Case-Shiller repeat-sales price index as the dependent variable. We treat these as a validation exercise rather than a primary result. The repeat-sales index is constructed from repeated property-level transactions, making it a market-based, transaction-price measure of house price growth that is free from the administrative smoothing inherent in the WOZ valuation. In principle, this makes it a sharper signal of true market conditions. In practice, however, it is subject to two important limitations in our setting. First, because it requires at least two transactions on the same property, it is based on a selected subsample of

properties, and the selection may be correlated with neighborhood change — precisely the margins we are studying. Second, as shown in Table 2 and Appendix Figure D.2, the index exhibits substantially greater cross-neighborhood dispersion and lower average year-on-year variation than the WOZ measure, generating less statistical power.

Table 5: Second-stage coefficients for repeat-sales index

	Outcome: change in repeat sales index									
	All		High income		Middle-High income		Middle-Low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\frac{\widehat{\Delta M^{j}_{i,t-1}}}{\text{Pop}_{i,t-2}}$	0.972**	-0.269	-1.737	-3.878***	4.175	0.448	1.731***	1.513	0.064	-1.558
	(0.416)	(0.478)	(1.637)	(1.206)	(3.505)	(6.441)	(0.512)	(1.424)	(0.322)	(1.972)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls:		x		x		x		x		x
N	30,518	20,774	30,518	20,774	30,518	20,774	30,518	20,774	30,518	20,774
Avg outcome	0.0107	0.0107	0.0107	0.0107	0.0107	0.0107	0.0107	0.0107	0.0107	0.0107
Avg regressor	0.0021	0.0021	0.0003	0.0003	0.0004	0.0004	0.0005	0.0005	0.0008	0.0008
SD regressor	0.0064	0.0064	0.0015	0.0015	0.0021	0.0021	0.0022	0.0022	0.0049	0.0049
IV KP F-statistic	53.5	12.9	22.3	15.5	9.3	4.9	228.9	121.1	357.0	91.3
Impact at mean regressor	0.0020	-0.0006	-0.0005	-0.0012	0.0017	0.0002	0.0009	0.0008	0.0001	-0.0013

Note: Second-stage coefficients, as in Equation (1), with an income-type specific SSIV variable, using 1995 shares. One column per income-range of immigrant. Controls include the year-on-year change in the unemployment rate, housing stock and working-age population. The outcome is measured in 2006 - 2020. Standard errors in parentheses, clustered by municipality. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

The repeat-sales results show some similarities with the WOZ assessment results, while also highlighting differences in property-value dynamics across the two measures. Middle-low-income immigrant inflows generate a positive and statistically significant estimate in the baseline specification (1.731, column 7). Evaluated at the mean regressor, this corresponds to an appreciation of approximately 0.0009, accounting for roughly 8% of average annual repeat-sales growth. However, this estimate becomes statistically insignificant when additional controls are included (column 8). Low-income immigrant inflows show a negative point estimate when controls are included (column 10), consistent with the direction of the WOZ estimate. Evaluated at the mean regressor, this corresponds to a reduction of approximately 0.0013, or around 12% of average annual repeat-sales growth. This estimate, however, is also statistically insignificant.

Two notable departures from the WOZ valuations are observable. The pooled estimate in column (1) is positive and statistically significant (0.972), but flips sign to −0.269 upon the inclusion of time-varying controls (column 2). The high-income effect was positive but imprecisely estimated in the WOZ baseline, the repeat-sales index reveals a negative and highly statistically significant coefficient once controls are included (column 4), implying an impact at the mean regressor of −0.0012. These sign reversals suggest that year-on-year variation in repeat-sales are

sensitive to high-frequency cyclical volatility, credit conditions, and compositional shifts in active market segments—factors that can closely track and confound concurrent macroeconomic and high-tier immigration trends. The repeat-sales estimates provide a complementary perspective on local housing-market dynamics. While some baseline patterns are consistent with the WOZ results, the estimates also reveal differences across income groups and specifications. This highlights the importance of considering the distinct measurement properties of administrative valuations and transaction-based price indices when assessing local housing-market responses.

5.1 Robustness checks

In this section, we demonstrate that our baseline estimates are robust to our sample selection criteria and examine the performance of alternative shift-share instrumental variable (SSIV) formulations and spatial aggregation levels.

Table 6 presents the second-stage results across these sensitivity checks. Column (2) evaluates sensitivity to the postcode inclusion threshold outlined in Table 1. While our baseline sample restricts attention to postcodes above the 30th percentile of the 1995 housing stock distribution, column (2) relaxes this threshold to the 20th percentile, incorporating smaller and lower-density postcodes. Because our regressions are weighted by the postcode population in 2006, the estimated parameters are virtually identical to the baseline in column (1): the estimate for middle-low-income immigrants remains 4.014, while the low-income estimate remains -0.600. This confirms that our primary selection criterion does not induce sample selection bias.

Column (3) examines the effect of aggregating the data from the four-digit postcode level up to the municipality level. As expected, aggregating to whole municipalities reduces the sample size from $30,048$ to $4,365$ observations and averages out neighborhood variation. At this broader spatial scale, point estimates attenuate toward zero across all income groups: the pooled estimate is -1.089, middle-low income immigrant stock changes attenuate to 0.887, and low-income ones yield -0.384.

Columns (4) and (5) test the sensitivity of our IV strategy to variations in the construction of the shift-share instrument. Column (4) refines the shift component by replacing broader regional sending-area aggregates with disaggregated, country-level origin flows. The core pattern of income-based heterogeneity persists strongly under country-level shifts. In particular, the positive impact for middle-low-income immigrants remains large and becomes highly statistically significant (6.645), while low-income inflows maintain a negative point estimate (-1.676). Column (5) replaces our baseline 1995 settlement shares with a rolling 10-year lagged share structure. Under this alternative specification, the point estimates remain stable and closely aligned with the baseline across all income groups (e.g., the pooled estimate is 1.648, and Middle-Low income yields 4.200).

Table 6: Robustness of SSIV

	Outcome: change in log tax assessment value				
$\widehat{\frac{\Delta M^j_{i,t-1}}{\text{Pop}_{i,t-2}}}$	Baseline (1)	Sample 20th Pct (2)	Municipality level (3)	Country-level shifts (4)	10y-lagged shares (5)
All	1.680	1.676	-1.089	-0.071	1.648
	(2.263)	(2.263)	(3.313)	(2.346)	(2.043)
High income	1.016	1.006	-9.031	3.333	1.007
	(10.241)	(10.239)	(8.169)	(6.396)	(7.768)
Middle-High income	9.560	9.577	-13.939	8.083	12.598
	(17.004)	(17.049)	(19.054)	(8.311)	(16.858)
Middle-Low income	4.012*	4.014*	0.887	6.645***	4.200
	(2.245)	(2.247)	(5.301)	(0.349)	(1.756)
Low income	-0.597*	-0.600*	-0.384	-1.676	-0.957
	(0.308)	(0.308)	(0.418)	(2.788)	(0.173)
FE: Year	x	x	x	x	x
FE: PC4	x	x	x	x	x
N	30,048	29,998	4,365	24,555	30,040

Note: Second-stage coefficients, as in Equation (1), with a income-type specific SSIV variable. One column per sample, one row per regression. The outcome is measured in 2006 - 2020. Standard errors in parentheses, clustered by municipality. Column (2) is estimated on a different sample of postcodes, column (3) considers municipality-level aggregate variables, columns (4) and (5) present a variation in the SSIV. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

Overall, these checks confirm that our primary baseline findings are not driven by arbitrary sampling cut-offs, demonstrate that disaggregating shifts to individual sending countries strengthens our baseline results, and highlight the empirical necessity of analyzing housing market adjustments at fine spatial scales.

As an additional robustness check, we verify that our results are not confounded by own-observation feedback bias. This mechanical endogeneity can arise in shift-share frameworks if a large or rapidly growing postcode i contributes significantly to the national total, causing local unobserved shocks to contaminate the national shift component. To rule this out, we re-estimate our baseline models using a leave-one-out shift-share instrument ($\Delta M^j_{c,-i,t-1}$), which explicitly subtracts postcode i's own inflows from the national origin-specific aggregate. The second-stage coefficients remain virtually identical to our baseline estimates across all income groups, confirming that local feedback effects do not bias our main results. Finally, we test whether our findings are sensitive to how immigrant income tiers are defined. While our baseline specification relies on municipality-relative income ranks, we re-classify foreign-born arrivals using fixed national income thresholds. Using national-level income cut-offs yields point estimates that remain close to our baseline coefficients, demonstrating that our main results capture structural income dynamics rather than artifactual local ranking shifts.

5.2 Heterogeneity across local housing markets

Next, we turn to heterogeneity by sub-samples of geographic areas. The baseline sample contains neighborhoods across the entire country. However, housing and immigration dynamics may differ by region, for example in dense urban centers versus less densely populated areas. We split the sample into two complementary sets: first, postcodes located in municipalities with at least 100,000 inhabitants in 2015, reflecting more urban and densely populated areas ($N = 487$ postcodes across 17 municipalities). In what follows, we refer to municipalities with more than $100,000$ inhabitants as "urban" and those below this threshold as "less urban." Second, we distinguish the four largest cities (Amsterdam, Rotterdam, The Hague, and Utrecht). This distinction follows Hekwolter, Nijskens, and Heeringa (2017), who note that housing markets in major metropolitan hubs experience distinct structural dynamics compared to the rest of the country.

We present descriptive statistics for urban and less urban municipalities in Appendix Table D.3 and highlight the main distinctions here. On average, postcodes in less urban municipalities contain a smaller population and fewer immigrants, resulting in a substantially lower immigrant share. Specifically, less urban postcodes contain an average of 4,541 inhabitants, compared to 6,455 inhabitants in urban municipalities. The immigrant share averages 18% in urban municipalities, but only 6.5% in less urban postcodes. While the housing stock is smaller in less densely populated postcodes, average household size is larger, and the share of owner-occupied units is significantly higher at 63% on average, compared to 44% in urban municipalities.

We report the second-stage heterogeneity results for our leading property value measure (the WOZ value) across these sub-samples in Table 7. The estimates reveal stark geographic divergence: the positive property value effects of immigration are overwhelmingly driven by less densely populated areas (municipalities with $< 100,000$ inhabitants and outside the "Big 4" cities).

Specifically, for the set of postcodes in less urban municipalities (column 3) and outside the Big Four cities (column 5), the estimated coefficients are large, positive, and statistically significant. For instance, the baseline effect for all migrants is 8.156 in smaller municipalities and 5.849 outside the Big 4. When broken down by income tiers, high-income immigrant inflows in non-Big-4 areas drive massive positive responses (12.128), and middle-low income inflows also show robust positive valuation effects (5.586). In sharp contrast, second-stage estimates for the year-on-year change in WOZ value are statistically indistinguishable from zero across all immigrant tiers in the four big cities and large urban municipalities ($> 100,000$ inhabitants).

Potential explanations for this urban-rural heterogeneity involve market tightness, demographic salience, and housing structure. Hekwolter, Nijskens, and Heeringa (2017) characterize housing markets in large Dutch cities as heavily "overheated," marked by rapid transac-

Table 7: Second-stage coefficients for different samples

$\widehat{\frac{\Delta M^{j}_{i,t-1}}{\text{Pop}_{i,t-2}}}$	*Outcome: change in log tax assessment value*				
		Municipalities		Cities	
	Baseline	>100k	< 100k	Big 4	Non-Big 4
	(1)	(2)	(3)	(4)	(5)
All	1.863	-1.202	8.156***	-2.525	5.849***
	(3.137)	(2.398)	(3.637)	(7.721)	(1.869)
High income	-1.321	-8.995	13.696***	-8.589	12.128***
	(9.364)	(7.658)	(7.034)	(14.016)	(4.649)
Middle-High income	5.543	-14.817	15.169***	-19.662	13.055***
	(18.314)	(20.052)	(4.478)	(42.781)	(3.000)
Middle-Low income	3.360	-0.020	5.817***	-1.414	5.586***
	(3.096)	(4.164)	(1.129)	(7.240)	(0.900)
Low income	-0.735	0.275	-0.521	0.159	-1.914
	(1.834)	(2.073)	(2.424)	(0.881)	(1.955)
FE: Year	x	x	x	x	x
FE: PC4	x	x	x	x	x
Controls	x	x	x	x	x
N	20,706	5,301	15,405	2,261	18,445
N Postcodes	2,349	487	1,862	211	2,138
N Municipalities	341	17	324	4	337

Note: Column (1) presents the baseline model. Columns (2) and (3) split municipalities by a population threshold of 100,000 inhabitants in 2015. Columns (4) and (5) distinguish between the "Big 4" (Amsterdam, Den Haag, Rotterdam and Utrecht) and remaining non-Big 4 cities. Second-stage coefficients, as in Equation (1), with an income-type specific SSIV variable, using 1995 shares. One column per sample. The outcome is measured in 2006 - 2020. All specifications include postcode and year fixed effects and control variables. Standard errors in parentheses, clustered by municipality. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

tions above asking prices and structural supply bottlenecks. In such tightly constrained environments, prices are largely driven by macro-financial conditions, bidding wars, and structural shortages rather than marginal demographic or immigrant shocks. This is reflected in the descriptive data showing an average annual WOZ growth rate of 3% in urban municipalities versus 2% in less urban areas. By contrast, in less densely populated areas, demographic changes may represent more salient shifts in local housing demand, potentially translating into more visible property-value adjustments. Differences in housing stock composition, tenure structure, and initial immigrant presence may also contribute to the observed geographical heterogeneity. However, our analysis does not identify the specific mechanisms underlying these differences.

Immigration is far less common in smaller, less urban areas, making demographic changes

more visible and economically salient to incumbent residents. Survey data from the World Values Survey (Table E.13) and findings by Card, Dustmann, and Preston (2005) using the European Social Survey indicate that residents in smaller towns report lower baseline exposure and lower stated comfort levels regarding neighbors of different nationalities, languages, or races compared to residents in major cities with more than 500,000 inhabitants. While these surveys are indicative rather than directly matched to our exact postcode sample, they suggest that residential sorting and local market capitalization of immigrant inflows may interact with regional differences in social composition and openness.

The predominance of owner-occupied housing in less urban areas shapes how local housing markets clear. In owner-dominated submarkets, price adjustments via the WOZ tax assessment value reflect transaction-based pricing and homeownership demand channels more directly than in rental-heavy urban neighborhoods, where rent controls and institutional landlords may mute official valuation responses.

5.3 Medium-term house price dynamics

The baseline estimates examine the relationship between annual changes in the local immigrant population stock and annual property value growth. However, these contemporaneous relationships may not capture how local property values evolve over a longer measurement horizon. To investigate this dimension, we re-estimate the baseline specification using the three-year change in WOZ property values as the dependent variable, $\log P_{i,t} - \log P_{i,t-3}$. The population-scaled change in the local immigrant stock and the corresponding shift-share instrument remain unchanged. This exercise examines whether the estimated relationship differs when property value changes are measured over a longer period. Table 8 represents the results. For the aggregate immigrant population, the specification including additional local controls yields a negative and statistically significant coefficient. Evaluated at the mean change in the immigrant population stock, this corresponds to an estimated response of approximately -3.02 percentage points.

The corresponding baseline estimate without additional controls is statistically insignificant. Thus, the negative pooled relationship is conditional on the inclusion of the additional controls and should not be interpreted as a specification-invariant result. For middle-low-income immigrants, the three-year coefficients are negative in both specifications, contrasting with the positive baseline estimates for annual WOZ growth. However, neither coefficient is statistically significant. For low-income immigrants, the estimates are positive, with statistical significance only in the specification without additional controls. The high- and middle-high-income estimates are also imprecise and do not support definitive conclusions about their medium-term responses. Taken together, these results suggest that the relationship between changes in the local

Table 8: Second-stage coefficients for three-year change in tax assessment value

	Outcome: 3-year change in log tax assessment value									
	All		High income		Middle-High income		Middle-Low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\widehat{\frac{\Delta M^{j}_{i,t-1}}{\text{Pop}_{i,t-2}}}$	-1.107	-14.397*	8.078	-19.120	63.404	-91.060	-10.127	-15.550	3.797*	2.119
	(4.914)	(7.789)	(22.760)	(25.537)	(55.626)	(64.587)	(11.253)	(16.087)	(2.019)	(5.797)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls:		x		x		x		x		x
N	25,427	17,178	25,427	17,178	25,427	17,178	25,427	17,178	25,427	17,178
Avg outcome	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388
Avg regressor	0.0021	0.0021	0.0003	0.0003	0.0004	0.0004	0.0005	0.0005	0.0008	0.0008
SD regressor	0.0064	0.0064	0.0015	0.0015	0.0021	0.0021	0.0022	0.0022	0.0049	0.0049
Impact at mean regressor	-0.0023	-0.0302	0.0024	-0.0057	0.0254	-0.0364	-0.0051	-0.0078	0.0030	0.0017

Note: Outcome: three-year log change in WOZ value at the four-digit postcode level, defined as $\Delta_3 \log(\text{P}_{i,t}) = \log(\text{P}_{i,t}) - \log(\text{P}_{i,t-3})$. Second-stage coefficients, as in Equation (1), with an income-type specific SSIV variable, using 1995 shares. The outcome is measured in 2006 - 2020. Standard errors in parentheses, clustered by municipality. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

immigrant population stock and property value growth may differ depending on the measurement horizon. In particular, the negative middle-low-income and positive low-income point estimates contrast with the corresponding short-run patterns. However, the income-specific three-year estimates are not sufficiently precise to establish that the initial price responses reverse over time. The negative pooled estimate is also sensitive to the inclusion of controls. Changes in the native population provide an additional, although indirect, perspective on possible residential adjustment. We examine these responses in the following section.

5.4 Native population responses and residential adjustment

To examine whether changes in the local immigrant population are accompanied by changes in the native population, we estimate the relationship between the population-scaled change in the immigrant stock and annual native population growth at the postcode level. Native population growth is defined as the annual change in the native population relative to the lagged native population stock. This outcome provides a complementary measure of local demographic adjustment, although it does not distinguish between native out-migration, changes in native in-migration, and other demographic processes.

The results indicate heterogeneous native population responses across immigrant income categories. In specifications including additional controls, increases in the stocks of high-income and middle-high-income immigrants are associated with statistically significant reductions in native population growth. The estimated coefficients in column 4 and column 6 are −4.051 and −8.083, respectively. These negative estimates suggest that areas experiencing increases in the

stocks of these immigrant groups also experience weaker native population growth.

Table 9: Second-stage coefficients for change in natives

	Outcome: native population growth									
	All		High income		Middle-High income		Middle-Low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\widehat{\frac{\Delta M^j_{i,t-1}}{\text{Pop}_{i,t-2}}}$	-0.567	-1.040*	-3.547**	-4.051**	-6.911***	-8.083**	-1.646***	-1.791	0.738***	1.502
	(0.407)	(0.560)	(1.611)	(1.701)	(1.981)	(3.354)	(0.569)	(1.088)	(0.147)	(0.922)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls:		x		x		x		x		
N	30,736	20,868	30,736	20,868	30,736	20,868	30,736	20,868	30,736	20,868
Avg outcome	0.0033	0.0033	0.0033	0.0033	0.0033	0.0033	0.0033	0.0033	0.0033	0.0033
Avg regressor	0.0021	0.0021	0.0003	0.0003	0.0004	0.0004	0.0005	0.0005	0.0008	0.0008
SD regressor	0.0064	0.0064	0.0015	0.0015	0.0021	0.0021	0.0022	0.0022	0.0049	0.0049
IV KP F-statistic	53.9	13.1	22.5	15.1	9.3	5.1	230.0	148.1	371.3	111.4
Impact at mean regressor	-0.0012	-0.0022	-0.0011	-0.0012	-0.0028	-0.0032	-0.0008	-0.0009	0.0006	0.0012

Note: Second-stage coefficients, as in Equation (1), with income-type specific SSIV variable, using 1995 shares. One column per income-range of immigrant. Controls include the year-on-year change in the unemployment rate, housing stock and working-age population. The outcome is measured in 2006 - 2020. Standard errors in parentheses, clustered by municipality. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

For middle-low-income immigrants, the estimated relationship is negative in both specifications, but statistical significance is limited to the specification without additional controls. For low-income immigrants, the baseline estimate is positive and statistically significant, while the estimate becomes statistically insignificant when additional controls are included. The pooled specification also yields a negative coefficient that is statistically significant only with additional controls.

These findings provide evidence of heterogeneous native population responses across immigrant income categories. However, changes in native population growth cannot be interpreted as direct evidence of native out-migration. A reduction in native population growth may reflect increased out-migration, reduced native in-migration, or other demographic changes. Moreover, the estimates do not establish that native population adjustments mediate the estimated property-value responses.

Taken together, the native population results provide complementary evidence on local demographic changes associated with changes in the immigrant population stock. They suggest that residential adjustment may differ across immigrant income categories, but do not identify a specific displacement mechanism or establish that native mobility explains the differences in property-value dynamics.

6 Discussion

The results show that the estimated relationship between changes in the local immigrant population stock and property value growth varies across immigrant income categories, geographical settings, and measurement horizons. However, the strength and precision of the estimated relationships differ across specifications. This section discusses the main findings, their possible interpretation, and the limitations of the empirical analysis.

6.1 Income heterogeneity in local property value responses

The baseline estimates indicate different property-value responses across immigrant income categories. Increases in the stocks of middle-low-income immigrants are associated with higher annual WOZ growth, whereas increases in the stocks of low-income immigrants are associated with lower growth. These patterns are economically meaningful when evaluated at the mean change in the respective immigrant stocks. However, their statistical significance is sensitive to the inclusion of additional local controls. The results therefore provide suggestive evidence of income-related heterogeneity, rather than robust evidence of opposing effects across the two groups.

One possible interpretation is that differences in income are associated with differences in housing demand, including the types of properties households can afford and the locations in which they settle. However, the income categories in this analysis are defined relative to the income distribution of the destination municipality. They should therefore be understood as relative income groups, rather than direct measures of absolute purchasing power or housing market resources.

The repeat-sales estimates offer a complementary perspective. The positive baseline estimate for middle-low-income immigrants is directionally consistent with the WOZ results, but becomes statistically insignificant when additional controls are included. Results for other income groups also differ across the two property-value measures. In particular, the pooled repeat-sales estimate changes sign with the inclusion of controls, while the controlled high-income estimate is negative and statistically significant. These differences caution against interpreting the two measures as providing uniform confirmation of the same income-specific effects.

The differences between WOZ and repeat-sales estimates may partly reflect their distinct measurement properties. WOZ valuations provide broad coverage of the housing stock but may adjust differently from transaction prices because of their administrative valuation process. The repeat-sales index captures realized price changes for properties sold more than once, but relies on a selected subset of transactions and may be more sensitive to variation in market activity. Consequently, the two measures capture related but not identical dimensions of local property-

value dynamics.

Income categories should also be interpreted as relative income positions within the destination municipality, rather than direct measures of permanent purchasing power or housing-market resources. In particular, the lowest category includes non-working immigrants and individuals with zero or missing observed income. Income does not capture wealth, savings, household composition, or access to credit, all of which may influence housing choices. The estimated heterogeneity should therefore be understood as differences across observed income categories.

6.2 Geographical heterogeneity

One of the clearest patterns in the analysis concerns geographical heterogeneity. Positive WOZ responses are concentrated in less urban municipalities and areas outside the four largest Dutch cities. In these locations, increases in the overall immigrant population stock and in the stocks of high-income and middle-low-income immigrants are associated with higher property-value growth. By contrast, estimates for the largest urban markets are generally statistically indistinguishable from zero.

These differences suggest that the property-value consequences of local population changes depend on the characteristics of the receiving housing market. Several factors could contribute to this pattern. Differences in housing-stock composition and tenure structure may influence the extent to which changes in local demand are reflected in assessed property values. The higher prevalence of owner-occupied housing in less urban municipalities may also result in different valuation responses compared with rental-intensive urban neighborhoods. In addition, differences in initial immigrant population shares and local housing-market conditions may affect the relative importance of subsequent demographic changes.

These explanations remain possible interpretations rather than mechanisms established by the empirical analysis. In particular, the geographical estimates do not independently identify the role of housing-supply constraints, tenure, or local preferences. Moreover, statistical significance in one geographical subsample and insignificance in another does not necessarily imply that the corresponding coefficients are statistically different. Formal tests of coefficient equality are therefore important for assessing the extent of geographical heterogeneity.

6.3 Property value dynamics over different horizons

The three-year estimates indicate that the relationship between changes in the local immigrant population stock and property value growth may differ from the annual relationship. The controlled pooled specification yields a negative and statistically significant estimate, while the

income-specific coefficients are generally imprecise. In particular, the negative point estimates for middle-low-income immigrants contrast with their positive annual WOZ estimates, while the low-income point estimates become positive over the three-year measurement horizon.

These differences suggest that annual property-value responses should not automatically be interpreted as persistent changes in local property values. Nevertheless, the estimates do not establish that the initial responses are reversed. The pooled negative estimate is sensitive to the inclusion of controls, and the income-specific estimates do not provide sufficiently precise evidence of systematic reversals. The three-year analysis should therefore be interpreted as evidence that estimated property-value relationships differ across measurement horizons, rather than as evidence of a particular dynamic adjustment mechanism.

6.4 Native population responses

The analysis of native population growth provides an additional perspective on potential local adjustment. The estimates indicate negative native population growth responses to increases in the stocks of high- and middle-high-income immigrants in specifications with additional controls. For middle-low-income immigrants, the negative relationship is sensitive to the inclusion of controls, while the low-income estimates are not robust.

These patterns suggest that changes in the immigrant population may be accompanied by heterogeneous changes in native population growth. However, native population growth does not directly identify residential mobility. It combines the effects of native in-migration, out-migration, and other demographic changes. Furthermore, the analysis does not establish whether changes in native population growth mediate the estimated property-value responses. Consequently, these findings provide complementary evidence on local demographic adjustment, but do not establish native displacement as the primary mechanism underlying the housing-market results.

6.5 Further considerations

The findings should be interpreted alongside several empirical limitations. First, the strength of the first-stage relationship differs across immigrant income categories. In particular, the instrument is weaker for middle-high-income immigrants, making the corresponding second-stage estimates less reliable. The precision of the estimated effects also varies across outcomes, specifications, and geographical subsamples. Some income-specific patterns are sensitive to the inclusion of additional local controls, while the three-year estimates are generally less precise. Consequently, the results provide suggestive evidence of heterogeneous property-value responses rather than robust evidence of opposing effects across all income groups.

Second, although the shift-share strategy uses historical settlement patterns and national changes in the immigrant population to address endogenous residential location choices, the exclusion restriction remains a demanding assumption. Historical settlement patterns may be correlated with local characteristics that influence subsequent housing-market developments independently of immigration. The robustness checks provide some reassurance regarding the sensitivity of the results to alternative sample definitions, income thresholds, and spatial aggregation levels, but they cannot fully rule out these concerns.

Third, the analysis draws on two complementary measures of property values: administrative tax assessment values, which provide broad coverage of the housing stock, and a repeat-sales index, which captures transaction price changes for properties sold multiple times. The two measures provide different perspectives on local property-value dynamics, but their estimates are not uniformly consistent. In particular, the positive baseline estimate for middle-low-income immigrants is directionally consistent across both measures, although it becomes statistically insignificant when additional controls are included. The repeat-sales estimates also display differences for other income groups, highlighting the importance of accounting for the distinct measurement properties of the two outcomes.

Finally, changes in assessed property values and transaction prices reflect developments in housing wealth and homeownership costs, but do not necessarily translate into equivalent changes in rents or the housing costs faced by tenants. The analysis therefore provides evidence on local property-value dynamics rather than a comprehensive assessment of housing affordability or the distribution of housing costs across households.

Overall, the findings suggest that the local property-value consequences of changes in the immigrant population depend on both the income composition of these changes and the characteristics of receiving housing markets. Aggregate estimates may conceal important differences across local contexts. This highlights the value of considering demographic composition alongside local housing-stock characteristics, tenure structure, and property-value developments when assessing changes in local housing demand.

For housing planning, these findings suggest that local authorities may benefit from considering migration and population composition alongside indicators of housing supply, property values, housing availability, and residential mobility. The geographical differences in the estimates also indicate that a uniform approach to housing planning may not adequately reflect differences between large urban centers and less urban municipalities. An increase in property values may benefit existing homeowners while making entry into homeownership more difficult for prospective buyers, whereas the implications for renters depend partly on how rents and the rental housing stock respond. Although the present analysis does not estimate these broader effects, it motivates a more locally differentiated approach to monitoring housing-market pres-

sures and evaluating the adequacy of housing provision.

7 Conclusion

This paper examines how the income composition of changes in the local immigrant population shapes property value dynamics in the Netherlands. Using detailed administrative data at the four-digit postcode level and a shift-share instrumental variable strategy, we investigate how these relationships vary across immigrant income groups, geographical settings, and measurement horizons.

Our findings highlight important heterogeneity in local property-value responses. In the baseline estimates, increases in the stocks of middle-low-income immigrants are associated with higher annual growth of the tax assessment value, whereas increases in the stocks of low-income immigrants are associated with lower growth. Although the precision of these estimates is sensitive to the inclusion of additional local controls, the baseline patterns point to differences in property value responses across immigrant income groups. The geographical analysis further reveals that positive property value responses are concentrated in less urban municipalities, where changes in the immigrant population appear more closely associated with local property value developments.

Extending the analysis to a three-year horizon reveals different patterns from the annual estimates, suggesting that the relationship between immigration and property values may vary over time. The analysis of native population growth also points to heterogeneous demographic responses across immigrant income groups, although it does not establish residential displacement as the underlying mechanism.

Taken together, these findings highlight the importance of accounting for both the income composition of immigration and the characteristics of receiving housing markets. Aggregate estimates may conceal meaningful differences in local property value dynamics, emphasizing the value of examining immigration and housing-market developments at a more disaggregated level. While the sensitivity of some estimates across specifications calls for caution in interpreting individual income-specific effects, the analysis provides evidence that the relationship between immigration and property values is heterogeneous across both space and population composition.

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A Appendix

Table A.1: Literature overview, most to least recent

Authors	Country	Region / Scale	Type of migrant	Main result
Cabral and Steingress (2026)	US, 2000–2020	Counties	High-educated vs. low-educated	Larger shelter price increases from highly educated inflows, higher where supply is inelastic
Boje-Kovacs et al. (2024)	Denmark, 1987–2017	Neighborhoods & building units	Non-Western, refugees	0.3% ↓ house prices due to incumbent native sorting
Sanchis-Guarner (2023)	Spain, 2001–2012	Provinces	Foreign-born	1% inflow → 3.3% ↑ house prices
Moallemi and Melser (2020)	Australia	Suburbs / Postcodes	Foreign-born	Positive house price responses to immigration
Braakmann (2019)	UK, 2003–2012	Local authorities	Foreign-born	Negligible/negative localized price responses
Fernández-Huertas Moraga, Ferrer-i-Carbonell, and Saiz (2019)	Spain, 1998–2008	Neighborhoods (census tracts, N = 28,523)	Foreign-born	0.33% ↑ native outflow; 50% ↑ housing construction
Hyslop et al. (2019)	New Zealand	Regional Council areas	Foreign-born	Immigrant inflows boost regional house prices
Degen and Fischer (2017)	Switzerland, 2001–2010	Municipalities	Foreign-born	Immigrant inflows boost local housing prices
Mussa, Nwaogu, and Pozo (2017)	US, 2002–2012	MSA (N = 275) & neighboring MSAs	Foreign-born	0.8% ↑ local house/rental prices; 9.6% ↑ house prices in surrounding MSAs
Sá (2015)	UK, 2003–2010	Local authorities (N = 170)	Foreign-born, education	1.7% ↓ house prices; 0.05% ↑ native net out-migration
Accetturo et al. (2014)	Italy, 2003–2010	20 large cities & districts	Foreign-born	0.5% ↑ city house prices; 0.2% ↓ district house prices; 0.6 ↑ native outflow
Gonzalez and Ortega (2013)	Spain, 2000–2010	Provinces (N = 50)	Foreign-born, working age	2% ↑ house prices; 1.2–1.5% ↑ new house construction
Akbari and Aydede (2012)	Canada, 1996–2006	CMA (N = 258)	Immigrants (recent vs. settled)	0.1–0.12% ↑ house prices (driven by settled migrants >10 yrs)
Saiz (2007)	US, 1980–2000	MSA	Foreign-born	1% inflow → 1% ↑ house prices and rents
Saiz (2003)	US, 1974–1983	MSA (Miami vs. FL)	Low-skilled (Mariel boatlift)	8–11% ↑ low-quality housing rents; 8% ↑ additional in Hispanic areas

B Data appendix

B.1 Postcode selection

In the following, we describe in detail the selection of postcodes. Using comprehensive data on population per postcode from 1995 - 2022, the goal is to construct a balanced panel of postcodes. The variables of interest for this study are the change in the stock of immigrants and the stock of population. Firstly, 4,056 four-digit postcodes are consecutively available between 1995-2022. In the next steps, we exclude postcodes that ever have a registered population of 0 inhabitants, with the reference point being January 1^{st}. Next, we exclude postcodes that exhibit an absolute growth rate of immigrants greater than 100% as they may be outliers in the analysis. The last restriction on the sample is the stock of inhabitants in 1995, the first year of observations. We exclude very sparsely populated postcodes, as we are interested in changes in the demographic composition. Therefore, we present a sample selected on a minimum threshold of inhabitants, defined as the 10th, 20th and 30th percentiles of the population distribution in 1995.

B.2 Individuals

We combine datasets on individuals, house transactions and values and neighborhoods from Statistics Netherlands (CBS) and Land Registry (Kadaster). These datasets cover the whole territory of the Netherlands. Demographic information is available for every resident in the Netherlands: date and place of birth, country of origin, gender, parents' dates and places of birth and country of origin. Immigrants living in the Netherlands for at least four months are required to register the residential address at the Dutch municipality, together with the date of arrival and departure and the type of immigration. There are four immigration types: 1) Immigration, settlement from abroad; 2) Administrative inclusion, resettlement following a removal of the person without them ever leaving the Netherlands; 3) Emigration, removal of a person from the registry when departing abroad for at least 8 months; 4) Administrative discharge, removal from registry when the person is unreachable. We select type 1) immigrants. The linked employer-employee dataset contains information on their monthly gross and net wages, hours worked and dates of employment for regularly employed individuals. Due to the registration requirement, every individual is linked to their house address and dates of start and end of residence. If the house has been sold, for every sale the Land registry records transaction price, date, house value at the time of the transaction, recent house value, tenure type.
Characteristics of neighborhoods are reported in *Kerncijfers wijken en buurten* (KWB) for the years 1995, 1997, 1999, 2001, and from 2003 onwards. In these datasets, the characteristics are reported at the municipality, district (*wijk*) and neighborhood (*buurt*) levels. We aggregate the data of

neighborhoods (*buurt*) to four-digit postal code level. A postcode might contain more than one neighborhood.

B.3 Tax assessment value (WOZ)

To assess statutory residential property values (Waardering onroerende zaken, WOZ), Dutch municipalities employ automated valuation models (AVMs) that estimate the market value of unsold properties based on transaction prices of comparable local sales. Non-arm's-length transactions or sales occurring under non-standard market conditions are systematically excluded from the estimation sample. The econometric model incorporates key structural and locational attributes, including property type, building volume and floor size, plot size, construction year, physical location, and overall maintenance status. To maintain data accuracy, municipalities supplement market comparables with physical and remote verification checks. These include spatial audits using aerial imagery to detect structural alterations (e.g., extensions or dormers), physical neighborhood surveys, review of online real estate listings, cross-validation against Land Registry (Kadaster) plot records, and direct owner inquiries regarding recent internal renovations. Crucially, WOZ values are determined retrospectively with a one-year lag (e.g., the reference date for the 2022 WOZ valuation is January 1, 2021). Because unobserved internal property characteristics (e.g., interior finish quality) are not fully captured by administrative records, statutory WOZ valuations can deviate from realized transaction prices during periods of rapid market adjustment, underscoring the importance of pairing WOZ assessments with repeat-sales transaction indices.

C Repeat-sales index

The repeat sales index represents the price appreciation in a given area over time. Using repeated sales of the same property allows us to control for property-specific time-invariant characteristics. We obtain the repeat sales index following Bailey, Muth, and Nourse (1963). The model is given by:

$$r_{itt'} = \sum_{j=1}^{T} \beta_j x_j + u_{itt'} \tag{5}$$

where $r_{itt'}$ is the natural logarithm of the ratio of the final sales price in year t' to the initial sales price in year t for each transaction pair of dwelling i. The variable x_j takes value -1 if time j is the year of initial sale, 1 if j is the year of final sale, and 0 in all other periods. The OLS estimate $\hat{\beta}_j$ gives the log price aggregate index in year j.

To estimate the regression, we use the set of properties sold at least twice from 1995 to 2023.

This yields a number of transaction pairs for house i equal to the number of times the house has been sold minus 1.
First, we create dummy variables x_j, then the natural logarithm of the ratio of final and initial sales prices. Finally, we estimate the regression for each dwelling i. The coefficient $\hat{\beta}_j$ represents the house price index per four-digit postcode.
Almost half of the dwellings sold in our sample have been transacted only once. Among the four-digit postcodes in the 30 selected municipalities, there are 48 postcodes with houses sold only once between 1995 and 2023. Within postcodes there is considerable heterogeneity in how many years pass between two transactions for the same house. The range goes from 0 to 34. On average across postcodes, the average sale time of a house is 6 years, with the 75th percentile being 8 years. Thus, houses sold once every 25 years are outliers.
The drawback of this methodology is that the variance increases with the interval of time between transactions. Hence, the OLS estimate is not efficient (Ghysels et al., 2013). The houses sold more than twice may not be representative of the whole sample, leading to a selection bias. A possible solution for this issue is offered in Case and Shiller, 1987. In their specification, they include a term to capture the imperfections of the housing market. Also, they have a component increasing with the length of the holding interval. Their estimation approach has three steps:

1. Estimate regression (5) and store residuals
2. Weighted least square regression of the residuals squared on a constant and on the time interval between transactions
3. GLS regression of (5), where the weights are the inverse of the square root of the fitted values from point 2.

Moreover, the repeat sales index does not consider what might determine the price of a property at a given point in time.

Then, we calculate the repeat sale index over time per postcode, using the Case and Shiller method. The steps are the following:

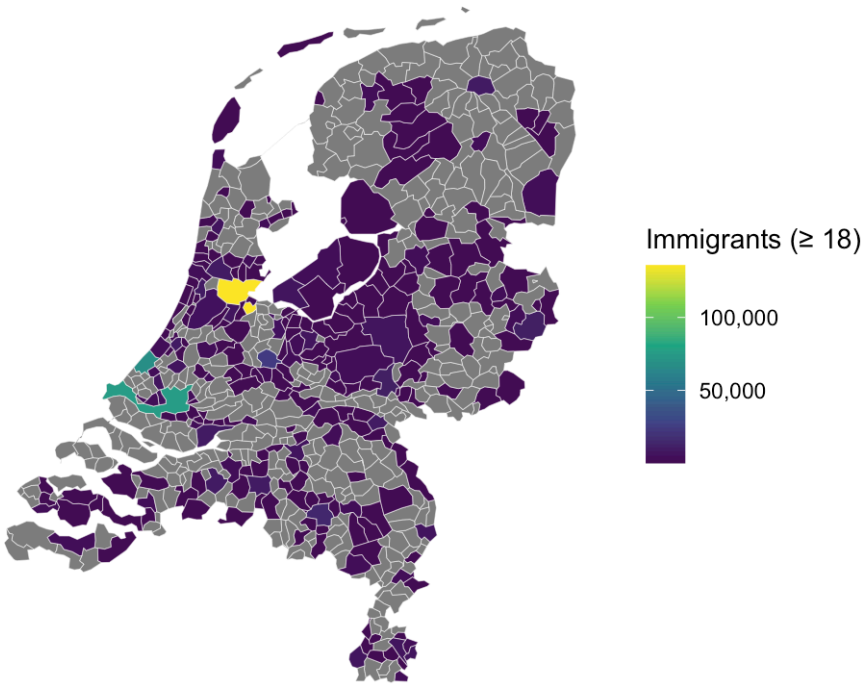
- Select a postcode and keep only the unique combinations of property identifier and sale date.
- Keep properties that are sold more than once If the subset for that postcode has more than 10 observations – this could imply that there could be few houses sold multiple times – proceed as follows for every year and postcode:
- Create a dummy variable per year from 1995-2023 and per property unit identifier

- Per unit, if the earliest sale date is equal to the dummy year, assign -1, this is because the first sale date should have -1. If the latest date is the same as the dummy year, assign 1. Otherwise 0.
- For houses with more than 2 sales date, per property identifier, calculate the following ratio: $log(\text{sale price}_t/\text{sale price}_{t-1})$
- Run the regression: $log(\text{sale price}_t/\text{sale price}_{t-1}) \sim$ dummy
  - Calculate the interval between sales year
  - Take the square of the residuals
  - Run the regression: squared residuals on time interval with constant
  - Store the fitted values
- For the third step: store the inverse of the square root of the fitted values: $\frac{1}{\sqrt{(fittedvalues)}}$
- Run the regression: ratio on all dummies per year with weights the inverse residuals, without constant.
- Save the exponential of the coefficients.

D Additional Statistics

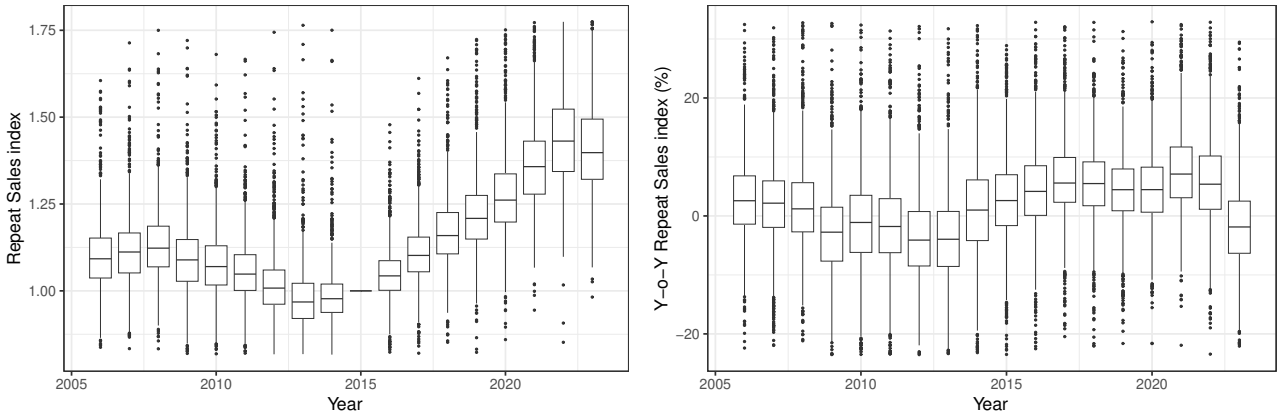
Figure D.1 illustrates the distribution of immigrant shares across municipalities in the estimation sample in 1995. The distribution provides descriptive evidence on the extent of geographical variation in immigrant presence, which motivates our analysis of how local housing-price dynamics respond to immigrant inflows. The empirical strategy used to identify these effects is described in the next section.

Figure D.1: Number of immigrants in 1995 per municipality



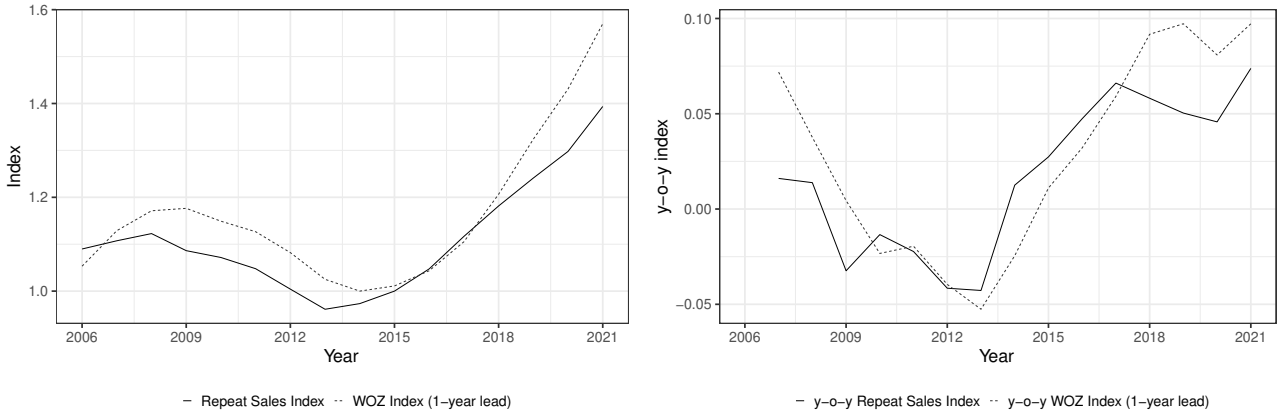
Notes: The map of the Netherlands shows the number of immigrants per municipality in 1995, in the sample selected.
Sources: CBS Microdata; *Kerncijfers Wijken en Buurten* (KWB).

Figure D.2: Levels and year-on-year (%) change of Repeat Sales Index across postcodes



Note: Levels of repeat sales index (LHS) and year-on-year change of repeat sales index (RHS) across years and postcodes. For every year, the boxplot shows the distribution of repeat sales index values across neighborhoods. Per year, the box shows the interquartile range (25th to 75th Percentile) and the line reflects the median. The whiskers reflect the range of values within median ±1.5× interquartile range. Dots reflect data points outside of the whiskers. Sample of 2,349 postcodes as outlined in Table 1.
Source: CBS Microdata, Kerncijfers Wijken en Buurten (KWB)

Figure D.3: Country aggregated index of WOZ value and Repeat Sales Index



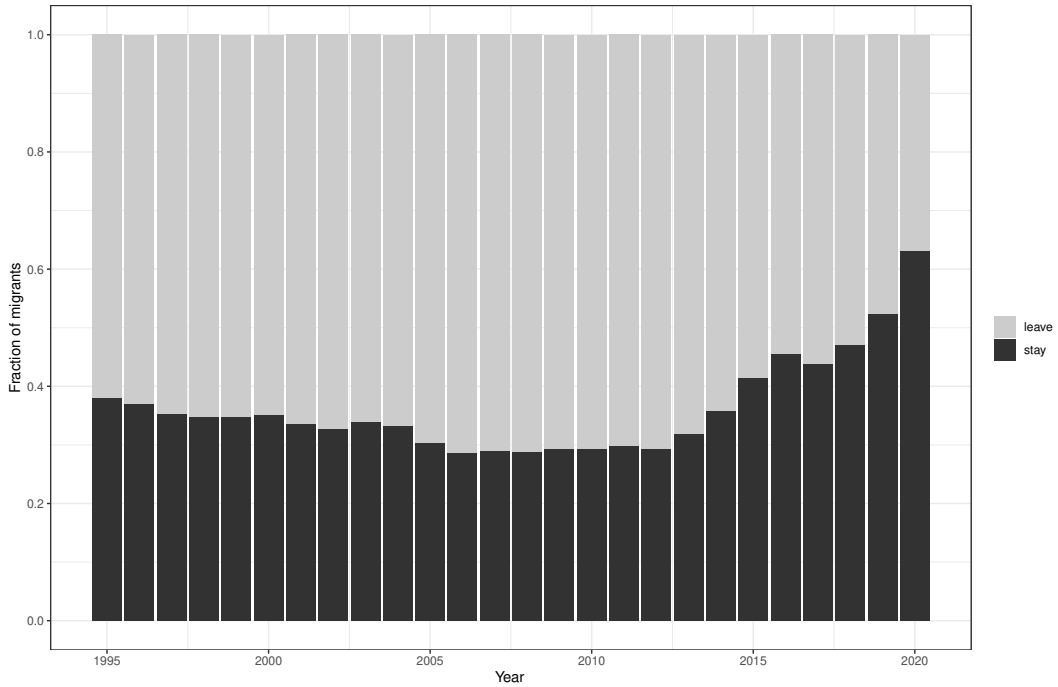
Note: Country wide index of WOZ index and repeat sales index. Both series are a weighted mean across neighborhoods, weighted by the number of dwellings. Both are index in 2015. The left-hand side shows the level of the index and the right hand side shows the year-on-year growth. The correlation between national level year-on-year WOZ and year-on-year repeat sales index is 0.86. Sample of 2,349 postcodes as outlined in Table 1.
Source: CBS Microdata, Kerncijfers Wijken en Buurten (KWB)

Table D.2: Descriptives by income quartiles

	All individuals	Income quartile			
		1	2	3	4
Average age	30.3	30.0	28.8	30.9	34.7
Fraction female	49.8%	56.3%	52.9%	38.7%	29.0%
Duration first address	448.1	441.8	449.7	478.5	419.9
Duration migration	856.1	806.0	793.5	983.5	1071.5
Share from origin:					
Poland	13.0%	5.3%	22.4%	27.8%	4.6%
Middle-Eastern Europe excl Poland	11.9%	10.4%	16.1%	14.1%	5.9%
EU	9.5%	9.2%	7.1%	8.3%	18.8%
GIPS	8.7%	7.1%	9.8%	11.4%	9.2%
Middle East	7.8%	12.8%	2.9%	2.0%	2.8%
Non-EU	7.6%	7.5%	9.4%	6.5%	6.5%
Germany	5.8%	7.0%	5.1%	3.4%	6.0%
Observations	2,103,236	1,081,273	430,784	400,016	191,163

Notes: Demographic statistics: Average age and fraction (share) of females. Duration measures: Mean duration spent at the first address (in days) and mean duration of the migration spell (in days). Origin shares: Percentage breakdown for the top 7 origin regions (indented under a "Share from origin:" sub-header). Sample size: Total number of observations per income quartile and overall.

Figure D.4: Fraction of immigrants staying / leaving by 2022



Note: Fraction of immigrants still in the Netherlands by year 2022. All immigrants ≥ 18 upon arrival. By year of first move.
Source: CBS Microdata

Table D.3: Descriptive statistics for subsamples

	Sample: Urban Municipalities, N PC4=487	
	Mean	SD
Housing & Property Outcomes:		
WOZ growth rate ($\Delta \log P_{i,t}$)	0.030	0.071
Repeat-sales index growth	0.016	0.115
Demographics & Labor Market:		
Total population ($\text{Pop}_{i,t}$)	6,455	2,997
Immigration share	18.2%	12.3%
Unemployment rate	2.67%	1.20%
Average income per capita (€)	30,362	5,981
Housing stock	3,932	1,973
Share owner-occupied	44.1%	19.0%
Immigrant Share (M^j/Tot Immigrants):		
High-income share	14.4%	7.3
Mid-high income share	18.4	5.2
Mid-low income share	13.3	4.7
Low-income share	54.9	8.4

	Sample: Rural Municipalities, N PC4=1,862	
	Mean	SD
Housing & Property Outcomes:		
WOZ growth rate ($\Delta \log P_{i,t}$)	0.019	0.054
Repeat-sales index growth	0.017	0.129
Demographics & Labor Market:		
Total population ($\text{Pop}_{i,t}$)	4,541	2,676
Immigrant share	6.5%	5.2%
Unemployment rate	2.12%	1.05%
Average income per capita (€)	29,852	3,940
Housing stock	2,470	1,532
Share owner-occupied	62.5%	14.0%
Immigrant Share (M^j/Tot Immigrants):		
High-income share	11.7	5.4
Mid-high income share	19.4	6.9
Mid-low income share	17.0	5.9
Low-income share	56.0	10.6

Note: Descriptive statistics across four-digit postcodes and years. Δ denotes the year-on-year percentage change. Immigrant shares are relative to the population on Jan 1st in a given year. Shares are defined as the number of immigrants over total number of immigrants per four-digit postcode.
Source: CBS Microdata, Kerncijfers Wijken en Buurten (KWB)

Table D.4: Groups used for SSIV

Group	Countries
Antilles	
China	
EFTA	Liechtenstein, Norway, Switzerland
GIPS	Greece, Italy, Portugal, Spain
Germany	
India	
Indonesia	
Middle East	Israel, Yemen, Iraq, Iran, Afghanistan, Jordan, Pakistan, Lebanon
Middle-Eastern Europe excl. Poland	Bulgaria, Estonia, Hungary, Latvia, Lithuania, Croatia, Romania, Slovenia, Slovakia, Czech Republic
Middle-South America	
Morocco	
Non-EU Europe	Iceland, Serbia, North Macedonia, San Marino, Russia, Andorra, Montenegro, Moldova, Belarus, Ukraine, Bosnia and Herzegovina, Albania, Monaco, Gibraltar, Isle of Man, Kosovo, Kazakhstan, Georgia, Azerbaijan, Armenia
North Africa	Tunisia, Syria, Egypt, Algeria
North EU	Austria, Belgium, Cyprus, Denmark, France, Finland, Great Britain, Ireland, Luxembourg, Malta, Sweden
Oceania, AUS, NZ	Australia, New Zealand
Poland	
Remaining Africa	African countries except for countries in category "North Africa"
Remaining Asia	
Suriname	
Turkey	
US, Canada	

Note: We aim to construct groups of origin countries that are similar in size by using the following criteria: visa status (i.e. grouping EFTA countries), geographic proximity, language proximity. Some countries are kept as their own category dues to large immigration flows (i.e. Turkey, Indonesia, Germany, Poland).
Names of countries and continents refer to geographical entities as classified by CBS.

Table D.5: Herfindahl-Hirschman Index for immigrants by country of origin, 2006 - 2022

Origin group	HHI (all)	HHI (high income)	HHI (low income)	Mean (all)	SD (all)	Total inflow (all)
Antilles	0.08	0.07	0.08	73	80	665,062
China	0.13	0.14	0.17	51	60	342,583
EFTA	0.69	0.81	0.79	21	12	13,855
GIPS	0.05	0.07	0.05	64	67	902,010
Germany	0.05	0.05	0.06	59	79	879,345
India	0.08	0.14	0.04	69	85	646,985
Indonesia	0.10	0.10	0.13	24	18	124,236
Morocco	0.08	0.07	0.09	141	184	1,499,972
Middle East	0.04	0.04	0.03	68	82	949,480
Middle-Eastern Europe excl. Poland	0.05	0.06	0.06	61	53	617,345
Middle-South America	0.06	0.07	0.06	47	60	1,106,404
Non-EU Europe	0.03	0.04	0.02	52	45	997,182
North Africa	0.37	0.21	0.51	46	94	1,505,925
North EU	0.04	0.06	0.04	71	53	251,886
Oceania, Australia, NZ	0.56	0.67	0.59	29	25	30,510
Poland	0.05	0.04	0.05	65	87	1,108,929
Remaining Africa	0.06	0.05	0.06	78	120	1,387,515
Remaining Asia	0.05	0.14	0.05	53	52	737,796
Suriname	0.12	0.12	0.11	137	229	1,395,224
Turkey	0.07	0.06	0.08	149	184	1,762,391
US/Canada	0.22	0.29	0.25	50	69	218,718

Table D.6: Descriptive statistics for immigration and housing

	25th Pct.	Mean	Median	75th Pct.	N
Age at immigration	23	30,9	28	35,6	2,674,225
Number of migration spells	1	1,14	1	1	2,674,225
Duration of migration spells (days)	292	1141	653	1,431	1,400,039
Number of address spells	x	x	x	x	2,674,225
Duration at address (days)	161	727.7	381	880	5,248,119

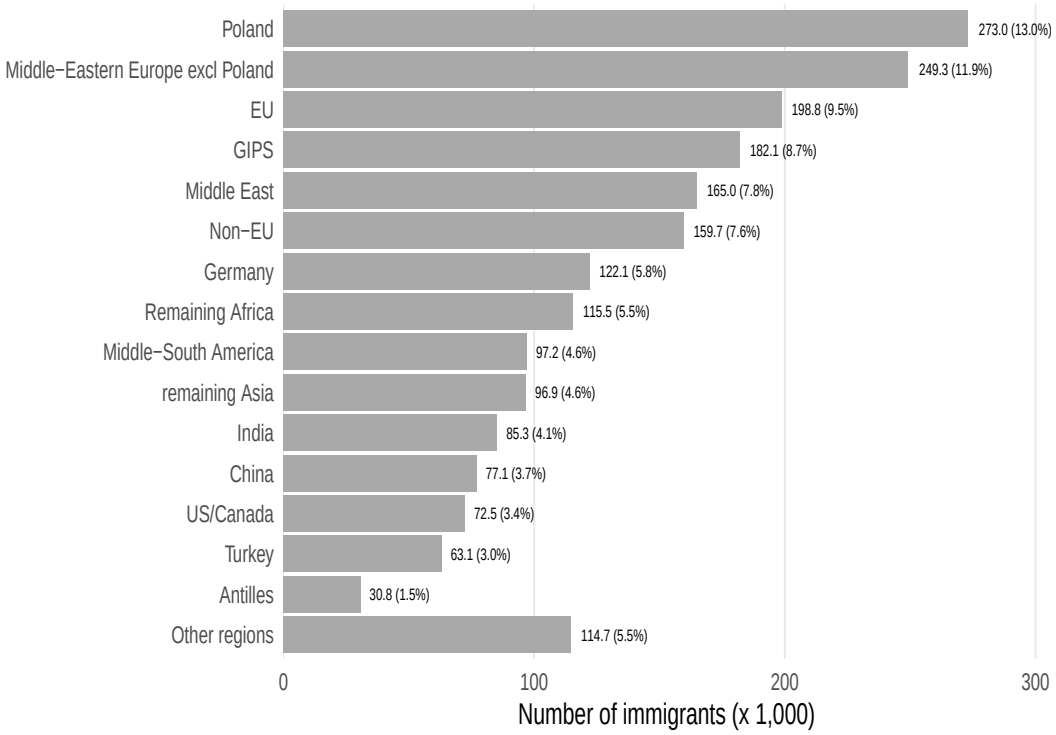
Note: Number and moments of immigration and address spells for immigrants. Duration is conditional on completing a spell.
Sample: All immigrants arriving between 1995 and 2021, age ≥ 18 years upon arrival.
Source: CBS Microdata

Table D.7: Income Composition within Origin Groups (%)

	Income			
Origin region	Low (%)	Middle-low (%)	Middle-high (%)	High (%)
Antilles	41.9	18.4	25.6	14.0
China	55.1	16.0	19.0	9.8
EFTA	54.8	10.9	14.5	19.7
EU	50.9	9.3	15.3	24.4
GIPS	46.1	12.7	22.6	18.6
Germany	64.3	10.1	12.2	13.3
India	36.8	10.0	21.9	31.3
Indonesia	72.4	9.7	9.2	8.6
Middle East	66.0	14.0	13.0	7.0
Middle-Eastern Europe excl Poland	47.6	18.3	21.9	12.1
Middle-South America	48.1	19.9	19.1	12.3
Morocco	67.1	11.6	15.8	5.6
Non-EU	53.2	13.0	19.1	14.7
North Africa	57.9	15.4	17.7	9.1
Oceania, Australia, NZ	46.6	9.5	15.0	26.9
Poland	30.5	22.1	39.4	8.0
Remaining Africa	51.1	18.6	21.7	8.6
Suriname	50.0	11.7	23.8	14.6
Turkey	63.3	12.3	16.5	7.9
US/Canada	53.2	7.7	11.9	27.1
remaining Asia	51.0	19.7	18.8	10.4

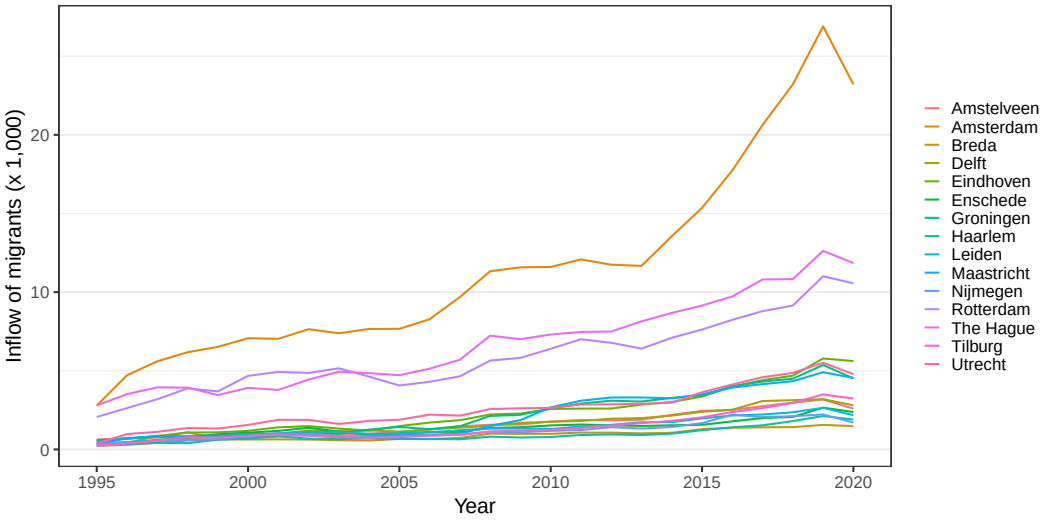
Notes: This table presents the income composition within regions of origin of immigrants across postcodes and years. The percentages are share of each income tier within the region of origin group.
Sources: CBS Microdata; *Kerncijfers Wijken en Buurten* (KWB).

Figure D.5: Absolute count (x 1,000) and relative percentage share of immigrants



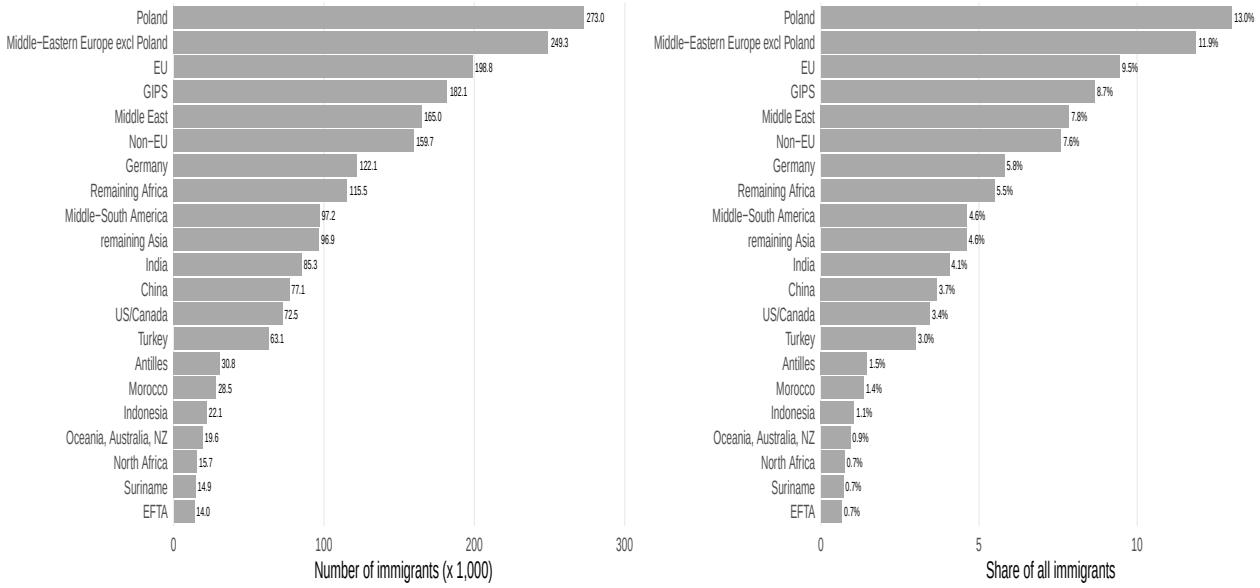
Note: Absolute count (in thousands) and relative percentage share of immigrants from the top regions of origin, with remaining regions grouped into "Other regions."
Source: CBS Microdata

Figure D.6: Annual trend in immigrant inflow (x 1,000)



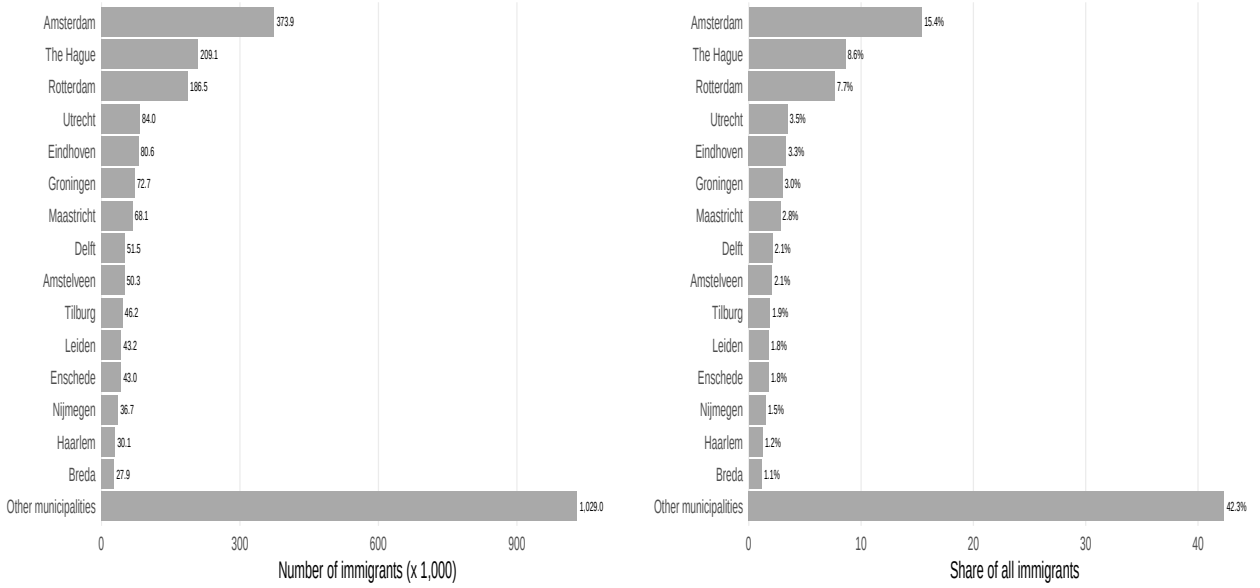
Note: Annual trend in immigrant inflow (x 1,000) over time (up to the year 2020) for each of the top receiving municipalities.
Source: CBS Microdata

Figure D.7: Immigrants across regions of origin



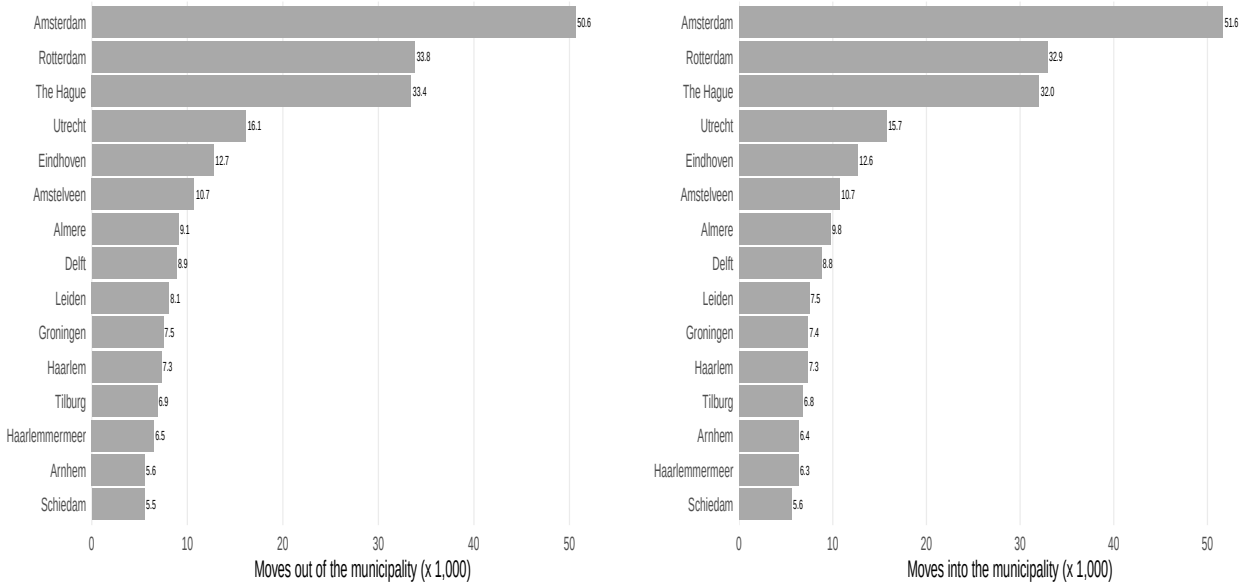
Note: Panel left: Total number of immigrants (x 1,000) broken down across all regions of origin. Panel right Percentage share of total immigrants across all regions of origin.
Source: CBS Microdata

Figure D.8: Immigrants for each of the top receiving municipalities



Note: Panel left: Total number of immigrants (x 1,000) by each of the top receiving municipalities, with all remaining municipalities aggregated into an "Other municipalities" category. Panel right: Percentage share of all immigrants for each top receiving municipality, as well as the combined share of all other municipalities.
Source: CBS Microdata

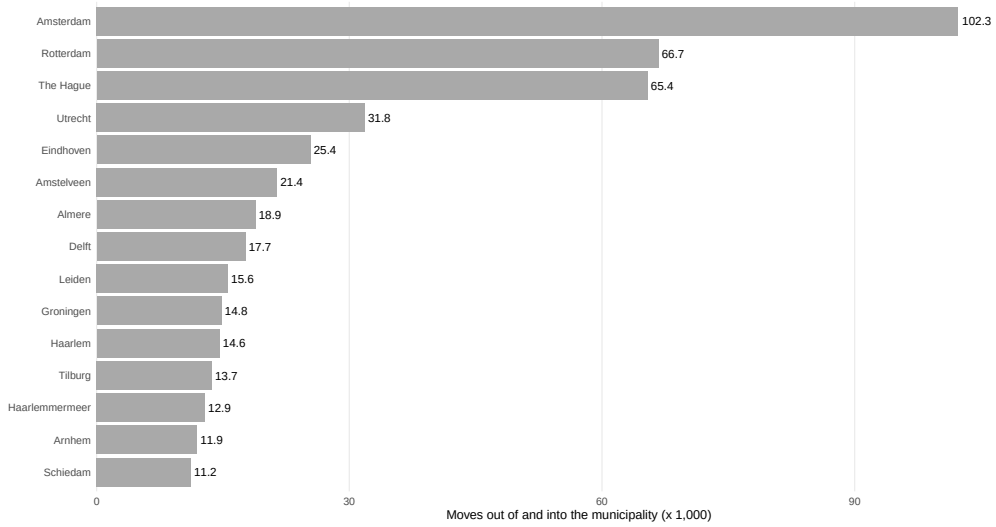
Figure D.9: Immigrants for each of the top receiving municipalities



Note: Panel left: Top municipalities with the highest number of outgoing moves (x 1,000) to other municipalities. Panel right: Top municipalities with the highest number of incoming moves (in thousands) from other municipalities

Source: CBS Microdata

Figure D.10: Immigration flows between the top 15 most connected municipalities



Note: Immigration flows between the top 15 most connected municipalities. The area of each bubble indicates the volume of moves (x 1,000) from the origin municipality (y-axis) to the destination municipality (x-axis).
Source: CBS Microdata

E Additional Results

Table E.8: Balance Test: Regression of Shift-Share Instrument on Local Time-Varying Controls

	Outcome: Shift-Share Instrument ($Z^j_{i,t-1}$)									
	All		High Income		Mid-High Income		Mid-Low Income		Low Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Unemployment Rate	-0.008*	-0.009	-0.002	0.001	-0.006**	-0.002	-0.018**	-0.006	0.018**	-0.002
	(0.005)	(0.007)	(0.001)	(0.000)	(0.003)	(0.001)	(0.008)	(0.004)	(0.008)	(0.003)
Lagged Housing Stock Change	0.000	0.000**	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Working-age population change	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FE: Year	X	X	X	X	X	X	X	X	X	X
FE: PC4	X	X	X	X	X	X	X	X	X	X
Observations	20,868	20,868	20,868	20,868	20,868	20,868	20,868	20,868	20,868	20,868
R^2 Within	0.082	0.081	0.071	0.073	0.089	0.091	0.121	0.118	0.122	0.121

Notes: Standard errors clustered at the municipality level in parentheses. The dependent variable in each column pair is the predicted shift-share instrument ($Z^j_{i,t-1}$) for the respective income tier j. All models include year and four-digit postcode fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.9: Regression of change in WOZ value on leads of Shift-Share Instrument

	Outcome: First stage / Shift-Share Instruments									
	All		High income		Middle-High income		Middle-Low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Instrument Coefficient	1.833	1.953	17.529**	18.247**	6.799	7.701	1.096	2.393	-0.739	-0.981**
	(1.349)	(1.375)	(8.115)	(8.852)	(5.036)	(5.249)	(2.597)	(2.841)	(0.482)	(0.473)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls:		x		x		x		x		x
N	27,745	20,749	27,745	20,749	27,745	20,749	27,745	20,749	27,745	20,749
R^2	0.693	0.703	0.697	0.706	0.694	0.704	0.691	0.699	0.689	0.698
Adj. R^2	0.665	0.674	0.670	0.678	0.666	0.676	0.662	0.671	0.661	0.670

Notes: Standard errors clustered at the municipality level in parentheses. The dependent variable in each column is the change in the log of WOZ value and the main regressor is the lead predicted shift-share instrument for the respective income tier j. All models include year and four-digit postcode fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: CBS Microdata

Table E.10: First stage coefficients with controls

	All migrants		High income		Middle-high income		Middle-low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Z^j_{i,t-1}$	0.531***	0.531***	0.827***	0.828***	0.259**	0.259**	0.613***	0.612***	0.613***	0.615***
	(0.149)	(0.149)	(0.211)	(0.210)	(0.113)	(0.114)	(0.050)	(0.051)	(0.060)	(0.059)
Total origin share (tot_origin_sh)		0.239		-0.049		-0.036		0.102		0.230
		(0.257)		(0.063)		(0.071)		(0.069)		(0.174)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls	x	x	x	x	x	x	x	x	x	x
N	20,663	20,663	20,663	20,663	20,663	20,663	20,663	20,663	20,663	20,663
Adj. R^2	0.296	0.296	0.368	0.368	0.163	0.163	0.289	0.290	0.168	0.168
IV KP F-statistic	12.77	12.77	15.37	15.55	5.25	5.23	148.37	145.74	107.08	108.13

Note: First stage, as in Equation (3), with a income-type specific SSIV variable, using fixed-1995 shares. One column per income-range of immigrants. Outcomes measured in 2006 - 2020. Standard errors in parentheses, clustered by municipality. The regression is weighted by the housing stock. "IV KP F" reports the Wald statistic for weak instruments (Kleibergen-Paap rk statistic) accounting for clustered standard errors. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

Table E.11: First stage coefficients - Municipality level

	All migrants	High income	Middle-High income	Middle-Low income	Low income
	(1)	(2)	(3)	(4)	(5)
$Z^j_{i,t-1}$	0.924***	1.325***	0.442**	0.833***	0.868***
	(0.142)	(0.328)	(0.175)	(0.030)	(0.075)
FE: Year	x	x	x	x	x
FE: Municipality	x	x	x	x	x
N	4,365	4,365	4,365	4,365	4,365
Adj. R^2	0.309	0.620	0.273	0.565	0.263
IV F-statistic	342.4	1318.6	121.5	1943.4	495.2

Note: First stage using municipality-level variables with income-type specific SSIV variable, using 1995 shares. One column per income-range of immigrant. Outcomes measured in 2006 - 2020. Standard errors in parentheses, clustered by municipality. The regression is weighted by the postcode-level population in 2006. "IV F" statistic reports the Cragg-Donald F-statistic under homoskedasticity. Table E.10 shows that the first stage coefficients hardly change when including controls. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

Table E.12: Three-year change in tax assessment value over three-year difference immigrant inflows

	Outcome: 3-year change tax assessment value									
	All		High income		Middle-High income		Middle-Low income		Low income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\frac{\Delta^3 M^j_{i,t-1}}{Pop_{i,t-2}}$	-57.881	-47.115	-9.156	-14.685	-40.622	-98.597	-4.031	-8.404	-18.166**	-12.769**
	(56.478)	(33.689)	(17.155)	(14.336)	(47.193)	(72.034)	(9.263)	(9.713)	(7.074)	(6.193)
FE: Year	x	x	x	x	x	x	x	x	x	x
FE: PC4	x	x	x	x	x	x	x	x	x	x
Controls:		x		x		x		x		x
N	20,824	15,543	20,824	15,543	20,824	15,543	20,824	15,543	20,824	15,543
Avg outcome	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388
Avg regressor	0.0063	0.0063	0.0008	0.0008	0.0012	0.0012	0.0012	0.0012	0.0030	0.0030
SD regressor	0.0135	0.0135	0.0030	0.0030	0.0037	0.0037	0.0039	0.0039	0.0092	0.0092
Impact at mean regressor	-0.3646	-0.2968	-0.0073	-0.0117	-0.0487	-0.1183	-0.0048	-0.0101	-0.0545	-0.0383

Note: Endogenous regressor $\frac{\Delta^3 M^j_{i,t-1}}{Pop_{i,t-2}}$: 3-year change of the immigration stock of income group j per four-digit postcode. Outcome: 3-year change of WOZ value per four-digit postcode. Second stage coefficients, as in Equation (1), with an income-type specific SSIV variable, using 1995 shares. The outcome is measured in 2006 - 2020. Standard errors in parentheses, clustered by municipality. Statistical significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: CBS Microdata

Table E.13: Excerpt from World Values Survey Wave 6 (2010 - 2014), by size of town

	Size of town (x 1,000)				
	10 - 20	20 - 50	50 - 100	100 - 500	> 500
% who *rather not* have neighbors from the following group:					
Immigrants / foreign workers	19.8	23.7	18.4	17.4	10.1
People of a different race	8	10.4	8	6.2	4.1
People who speak a different language	12.8	18.1	13.3	12.9	7.7
People of a different religion	3.7	3	1.7	2.9	2.4
% respondents who trust					
Neighborhood	74.9	71.7	71.2	64.9	50.3
People of another nationality	33.2	35.3	35.3	38.4	39.7
% respondents to agree for job priority:					
Natives over immigrants	43.9	39.2	35.5	32	24.3
Number of respondents	187	691	4141	419	169

Note: Selection of questions from Wave 6 of the World Values Survey (2010 - 2014).
For the neighborhood questions, survey participants are presented a list of sociodemographic groups and are asked to indicate all groups they would *rather not* have as neighbors. The tables show the percentage of respondents that indicate "immigrants / foreign workers" in their answer. Options are: drug addicts, people of another race, people with AIDS, immigrants / foreign workers, homosexuals, people from a different religion, heavy drinkers, unmarried couples living together, people who speak a different language.
For the questions on trust, survey participants indicate their agreement on a 5 point scale from "Trust completely" to "Do not trust at all". The table above shows the percentage of respondents indicating "Trust completely" or "Trust somewhat".
For the question on job security, the table shows the percentage of respondents indicating "Agree" from the options "Agree", "Neither" and "Disagree".
Source: World Values Survey Wave 6: 2010 - 2014