Immigration and Homeownership *

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Abstract

We study the effect of immigration on homeownership, a key pathway for household wealth accumulation. Using a shift-share approach to isolate plausibly exogenous variation in immigrant inflows across US counties, we document that immigrant inflows lead to lower homeownership among US-born households. The decline in homeownership is stronger in areas with inelastic housing supply and areas where immigrants are more likely to be home buyers. Immigrant inflows raise house-price-to-income ratios, suggesting the key role of declining affordability. The decline is more pronounced among the young, white, and single men. A difference-in-differences analysis exploiting the Venezuelan exodus in 2014 as an independent source of variation in immigration corroborates these findings. Overall, immigration-induced housing demand can create financial barriers to homeownership.

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1 Introduction

Immigration to the United States has surged to historically high levels in recent years, reshaping the social and economic fabric of communities across the country. This influx has sparked intense debate, with concerns that immigrant inflows intensify competition for housing and, in turn, hurt native residents' chances of becoming homeowners (Badarinza and Ramadorai, 2025). Homeownership is the primary vehicle for household wealth accumulation (Campbell, 2006), with returns that rival equities yet are less volatile over the long run (Jordà et al., 2019). Its importance is reflected in policy: the mortgage interest deduction is among the largest tax expenditures in the US (Sommer and Sullivan, 2018), and countries such as Canada and Australia exempt primary residences from capital gains tax. Any barriers to owning a home can therefore have lasting implications for long-term financial well-being.

The effect of immigration on homeownership of native households is ambiguous. On the one hand, immigrant inflows can facilitate homeownership by increasing employment or wages through innovation (Terry et al., 2026; Dimmock et al., 2022). On the other hand, increased demand pressure in the housing market can reduce homeownership rates among natives (Saiz, 2007; Li et al., 2024).[1] Furthermore, both forces could fall unevenly across native households. Yet there is little direct evidence on how immigration affects native homeownership, or on its incidence across native households.

In this paper, we study the effect of immigrant inflows on native households' homeownership by leveraging detailed microdata from the American Community Survey (ACS), which is well suited to answer this question for two reasons. First, the ACS records immigration status alongside homeownership and mortgage access, allowing us to measure these outcomes among the US-born (natives) at the county level and so isolate the effect

[1] Reflecting a widespread concern that foreign housing demand raises prices for locals, many governments restrict noncitizens or nonresidents from purchasing residential property, ranging from near-total bans (Canada and New Zealand), to separate-approval requirements (Australia, Denmark, and Switzerland), to additional stamp duties or surcharges (Singapore and the UK).

on natives. This is essential because immigrants differ from natives in their neighborhood locations (Cutler et al., 2008), homeownership propensities (Borjas, 2002; Haliassos et al., 2017; Abdul-Razzak et al., 2015), and mortgage access (Cookson et al., 2025); absent this distinction, changes in overall homeownership could partly reflect the shifting composition of residents rather than any effect on natives, a concern that is far from negligible given that immigrants make up 13.9%[2] of the US population. Second, the ACS records each household's demographic characteristics, including age, race, and family structure, alongside its homeownership status, allowing us to measure homeownership across groups of natives and thereby identify who is affected.

A natural starting point is to regress native homeownership on observed local immigration, but such an estimate may be biased if unobserved local factors that affect homeownership are also correlated with immigration. We address this concern with two complementary research designs with independent identifying variations. The first is a shift-share approach that isolates the changes in immigration plausibly uncorrelated with local economic and demographic trends. The second, a difference-in-differences analysis of the Venezuelan exodus in 2014, exploits a large and sudden inflow driven by a crisis abroad rather than by local economic conditions. Because the two designs are subject to different threats, their agreement provides more credible evidence than either alone.

In the shift-share design, we impute local immigration by interacting the historical county shares of immigrants (as of 1980) with the *national* immigration trends by immigrant country of origin, a design widely used in research on the economic impact of immigration (Altonji and Card, 1991; Card, 2001). We include county fixed effects, state-year fixed effects, and time-varying county controls, so the identifying variation comes from the *changes* in local imputed immigration net of time-varying state factors and controls. The imputed measure is a strong predictor of observed immigration, consistent with the

[2]This figure is the foreign-born share of the US population (46.2 million people) as of 2022. Source: U.S. Census Bureau, *The Foreign-Born Population in the United States: 2022*, American Community Survey Briefs, ACSBR-019, 2024, https://www2.census.gov/library/publications/2024/demo/acsbr-019.pdf.

well-documented role of immigrant networks in attracting new arrivals from the same country. The key identifying assumption is the exogeneity of these cross-sectional shares (Goldsmith-Pinkham et al., 2020): that the 1980 county shares of immigrants by country of origin, fixed decades before our sample, are uncorrelated with local native homeownership conditional on the fixed effects and controls, other than through their effect on current immigration.

We support this assumption with a battery of tests: historical immigrant shares are balanced on most county characteristics, are uncorrelated with mortgage-supply factors and with prior changes in homeownership, and our estimates are robust to allowing counties with different initial conditions to follow different trajectories.

Using this identification strategy, we establish our central result: higher immigrant inflows into a county lower homeownership rates among native households of that county. Since access to mortgage credit is a key pathway of homeownership, we examine this channel and find similar declines in mortgage access rates for native households, further supporting our findings.

What explains these declines? We trace them to an immigration-driven increase in housing demand. Counties with higher immigration inflows experience higher house prices and rents relative to income; they also have higher shares of both owner and rental units that are unaffordable to low-income families using the HUD Comprehensive Housing Affordability Strategy data. That these increases appear in both segments indicates a broad rise in housing demand. The decline in native homeownership is accompanied by a decline in native mortgage access, consistent with the higher cost of housing making home purchase less attainable for native households. The price response is concentrated where housing supply is inelastic (Saiz, 2010): prices rise sharply with immigrant inflows where supply cannot easily expand, but barely respond where supply is elastic, as expected if immigration raises prices by adding to housing demand.

If the decline reflects competition for owner-occupied housing, it should be concentrated in the immigrant inflows most likely to buy. Consistent with this prediction, the declines in homeownership and mortgage access are driven by high-skilled inflows, who have higher earnings and greater purchasing power than low-skilled inflows, and by inflows from high-affinity origin countries, where affinity is proxied by the origin-country homeownership rate.

Who among natives bears these effects is central to immigration's distributional consequences. The decline in homeownership is concentrated among younger adults relative to those over 40, consistent with life-cycle models in which younger households hold less wealth and rely more on mortgage financing (Sodini et al., 2023), leaving them most exposed to affordability constraints. The effects are also larger for single men, and to a lesser extent single women, than for married households, and for white natives. Using panel data on renter-to-owner transitions, we confirm that the most affected groups are also those most likely to be moving into homeownership. The uneven consequences are visible in the Home Mortgage Disclosure Act (HMDA) data: as immigrant inflows rise, lending to likely first-time buyers falls, while refinancing and borrowing for second residences rise, consistent with existing homeowners benefiting from the rise in house prices.

We consider several alternative explanations and find that none fully accounts for the results. The decline could reflect sorting, if wealthier natives leave high-immigration counties and mechanically lower measured homeownership. Because the ACS records whether a household moved in the past year, we can restrict the analysis to non-movers directly; this yields similar declines in homeownership and mortgage access, pointing to affordability rather than selective out-migration. The results are also stable when we exclude one state or group of states at a time, which additionally speaks to misreporting of undocumented immigrants: because undocumented populations vary across regions, a pattern that survives dropping any region is unlikely to be driven by such misreporting.

Our second design delivers the same conclusions from entirely different variation. Beginning in 2014, a severe political and economic crisis in Venezuela triggered one of the largest emigration waves in recent Western Hemisphere history, generating a sharp and plausibly unanticipated immigration shock. Using a difference-in-differences design, we compare changes in native housing outcomes across counties with varying pre-existing Venezuelan exposure before and after the onset of the exodus. Consistent with our shift-share estimates, counties with greater exposure to the Venezuelan inflow experienced significant declines in native homeownership and mortgage access. The agreement extends beyond the average effect to its incidence: the declines are again concentrated among younger, single, and white natives, the same households identified by the shift-share.

Our paper contributes to multiple strands of literature. First, we add to the body of research examining the impact of immigration on the housing market. Prior studies have shown that immigrant inflows drive up housing prices, either by increasing demand for housing services (Saiz, 2007, 2010) or through capital inflows (Badarinza and Ramadorai, 2018; Li et al., 2024). However, higher housing prices do not necessarily reduce homeownership, as they may be offset by rising local economic activity and wages (Terry et al., 2026; Ottaviano and Peri, 2012). Most of the housing literature focuses on geographic aggregates, such as local house prices, as the primary outcome and remains silent on who is affected. By contrast, we examine household-level homeownership outcomes, which allows us to move beyond average price effects and characterize whether natives are affected by immigration, and if so, what are the distributional consequences for natives. We show that, despite potential local economic offsets, immigrant inflows reduce homeownership among natives, especially the young, white, and single men.

More broadly, our paper contributes to the growing literature emphasizing the heterogeneous economic effects of immigration. High-skilled immigrants disproportionately drive innovation, entrepreneurship, and productivity growth (e.g., Bernstein et al., 2022; Gupta, 2023; Gupta et al., 2024), and we show that this heterogeneity also matters for household finance: inflows of high-skilled immigrants, who typically have stronger labor-market prospects and greater purchasing power, lead to larger declines in native homeownership. Relatedly, Howard et al. (2024) analyze the staggered roll-out of increased immigration enforcement to document that undocumented, likely low-skilled, immigrants contribute substantially to construction labor and housing supply. By using shift-share and difference-in-differences designs, we can isolate the plausibly exogenous variation in overall immigrant inflows, which primarily consist of legal immigrant inflows, to study the impact of natives' homeownership. Our findings highlight that increased demand for owner-occupied housing primarily comes from legal immigrants and complements Howard et al. (2024).

Our study also contributes to the literature on the determinants of homeownership (Goodman and Mayer, 2018; Sodini et al., 2023; Allen et al., 2024). Compared to existing research focused on broader aggregates (e.g., McCabe (2018)), we leverage geographically disaggregated data to provide new insights into how immigration affects homeownership patterns.[3]

2 Data and Summary Statistics

To study the effect of immigrant inflows on native residents' homeownership, we combine multiple data sets. In this section, we briefly describe the data sources and key variables. Internet Appendix A contains a detailed description of data and variable definitions.

Data on immigration: We define immigrants as foreign-born individuals whose parents are not US citizens and natives as individuals born in the US or born abroad to US parents. We impute county-level immigration by combining cross-sectional shares with time-series shifts over the period 2005–2019, as described in Section 3.2. The cross-sectional shares are constructed from the 1980 Census of Population and Housing, while

[3]There is a large literature on the US mortgage market using the geographically disaggregated HMDA data. Our study differs in two important ways. First, the granular ACS data allows us to study homeownership of native residents; on the contrary, the HMDA data do not record immigration status and hence do not have the capacity to distinguish natives and immigrants. Second, mortgage borrowing does not fully capture homeownership for reasons such as cash-financed home purchases, which are known to account for a high fraction of home purchases in places such as Los Angeles (Han and Hong, 2024).

the time-series shifts, national population changes by country of origin, are obtained from the annual Current Population Survey (CPS).

Data on homeownership and mortgage access: The primary data source we use to measure household homeownership status and mortgage access is the American Community Survey (ACS). The ACS is a large-scale nationally representative survey that is conducted yearly, and covers about 1% of the entire population since 2005. We rely on the ACS because its microdata combine a large sample size with rich individual, household, and geographic information. These advantages make the ACS data the backbone for various government programs and regulations.[4] In our setting, the ACS microdata allows us to distinguish whether a respondent is a native or an immigrant individual. In addition, the data contains information on households' ownership of dwelling and mortgage status at a disaggregated geographic level. Furthermore, it includes demographic characteristics (e.g., age) that can be important determinants of homeownership.

We use the ACS microdata samples from 2005 to 2019. We exclude the earliest years in the ACS (2000 to 2004) as no place smaller than states can be identified. The sample ends in 2019 to ensure that the results are not affected by the COVID-19 pandemic. Following the Census Bureau[5], we define homeownership and mortgage access at the household-house level. We restrict the sample to adult native households, namely, households whose household heads are native adult individuals. For a household in the sample, homeownership is an indicator that equals 1 if the household owns its current dwelling; mortgage access is an indicator that equals 1 if a household has a mortgage, deed of trust, or similar debt secured by its current housing unit.

While survey-based measures of consumption and income are often criticized for recall bias, underreporting, and measurement error (e.g., Koijen et al. (2014)), these concerns

[4]For instance, the federal banking regulators rely on the ACS to measure median family income at the census tract level to designate low- and moderate-income census tracts for implementing the Community Reinvestment Act regulations. The Department of Housing and Urban Development also relies on the ACS to produce the Low- and Moderate-Income Summary Data and the Comprehensive Housing Affordability Strategy data for its various programs.

[5]Source: https://fred.stlouisfed.org/series/RSAHORUSQ156S.

are less applicable to homeownership and mortgage status. Ownership of a home and the presence of a mortgage are salient and well-defined, making them less prone to reporting errors that typically affect flow variables like expenditures. Prior work in household finance has found that survey respondents accurately report major balance sheet items, including homeownership and mortgage obligations, with minimal misclassification (e.g., Bucks and Pence (2008)). Therefore, these specific variables are unlikely to suffer from the types of systematic biases that often undermine survey-based measures of consumption and income.

We aggregate ACS microdata from Public Use Microdata Areas (PUMAs) to counties using the Geocorr crosswalks; for each county-year, we compute homeownership and mortgage access rates among adult native households. As a robustness check, we re-estimate at the PUMA level.

We also use the Home Mortgage Disclosure Act (HMDA) data to construct county-year log mortgage origination amount by loan purpose (purchase loans for primary residences, purchase loans for non-primary residences, and refinancings) from 2005 to 2019.

Data on housing affordability: To measure housing affordability at county-year level, we first use hedonic regressions to adjust house values and rents in the ACS microdata for quality differences. Then, we construct price-to-income and rent-to-income ratios by combining adjusted house values and rents from ACS with income measures from three official sources, namely Quarterly Census of Employment and Wages (QCEW), Quarterly Workforce Indicators (QWI), and Internal Revenue Service (IRS) Statistics of Income.

We complement ACS-based affordability with HUD's Comprehensive Housing Affordability Strategy (CHAS) data. For each county we compute the share of owner (rental) units unaffordable to households earning 80% of county median family income, using HUD's value-to-income and rent-to-income affordability standards. These measures capture unaffordability in the low-to-moderate portion of the local house value and rent distribution.

Other data sources: In addition, we obtain housing elasticities at the metropolitan statistical area (MSA) level used in Saiz (2010) and construct county-level control variables from the Census and ACS data. We convert nominal amounts to real amounts in 2019 dollars using the Personal Consumption Expenditures (PCE) price index sourced from FRED.

In Section 3.3, we further examine the potential correlation between immigration and mortgage supply factors. We follow Mian and Sufi (2017) to construct a measure of buyer income overstatement at county level between 2002 and 2005 as the difference in the growth in income according to mortgage applications (HMDA) and the IRS. Additionally, we classify shadow bank lenders among HMDA lenders following Buchak et al. (2018) and Fuster et al. (2019) and compute the market share of shadow bank originations.

In Section 4.4, we use the Survey of Income and Program Participation (SIPP) microdata to examine transition probabilities from renters to homeowners among natives. The SIPP data distinguish natives and immigrants and follow a large number of survey respondents over time, enabling us to examine transitions into homeownership. We compute one-year renter-to-owner transition rates among natives.

Table 1 presents the summary statistics of key variables in our county-year sample.

3 Empirical Approach

We are interested in estimating the impact of immigration on homeownership. We first present evidence for immigrants' housing demand to motivate our empirical analysis. To establish causality, we adopt a shift-share approach to isolate the changes in immigration that are uncorrelated with local economic and demographic changes that could affect homeownership. To do so, we leverage the different timing and size of the *national* flow of immigrants. In this section, we describe the shift-share design and verify its validity; we present the second design, the Venezuelan natural experiment, in Section 5.

3.1 Immigrants' Housing Demand

Immigration can affect homeownership of native residents through opposing channels. On the one hand, immigrant inflows can facilitate homeownership by increasing employment or wages through innovation (Terry et al., 2026; Dimmock et al., 2022). On the other hand, increased demand pressure in the housing market can reduce homeownership rates among natives (Saiz, 2007; Li et al., 2024).

Immigrants' housing demand exists in two segments. In the owner-occupied market, immigrants who buy homes compete directly with prospective native buyers and bid up house prices. Figure 1 Panel (a) shows the histogram of homeownership rate among immigrants across counties. On average, more than 55% of immigrants become homeowners after they move to the US; there is substantial variation across counties, with the bulk of the mass near the equal-weighted and the population-weighted mean. Panel (b) focuses on immigrants' share of homeowners, namely, the share of homeowners that are immigrants. Across counties, the equal-weighted average is 4.3% while the population-weighted average is 12.8%, suggesting that immigrants' share of homeowners is higher in larger counties. Both measures indicate immigrants' demand in the owner-occupied housing market. In the rental market, immigrants who rent raise rental demand and push up rents. Either way, immigrant inflows raise the cost of housing relative to local incomes, reducing affordability in both segments. In Section 4.2, we examine affordability in both the owner-occupied and rental markets.

Of these two segments, the owner-occupied market is the one that bears directly on native homeownership: immigrants who are able and inclined to own compete for the same homes as prospective native buyers, while those who are not add primarily to rental demand. Two attributes therefore determine whether an immigrant inflow weighs on native homeownership: purchasing power, which we proxy with skill, and affinity for homeownership, which we proxy with the homeownership rate in the country of origin. In Section 4.3, we show that immigrants with greater purchasing power or a stronger affinity for homeownership are substantially more likely to be homeowners and that it is the inflows of such immigrants that drives the impact on native homeownership.

3.2 The Shift-Share Approach to Impute Immigration and Regression Specification

To empirically examine the impact of immigration on homeownership, a natural starting point is to regress local homeownership on local immigration. When we use the observed immigration for estimating such a regression, the coefficient estimate provides *prima facie* evidence of the correlation between immigration and homeownership. It may be biased if unobservable local characteristics affecting homeownership (captured in the error term) are correlated with the observed local population. For instance, if immigrants are attracted to counties with certain economic and demographic characteristics, and these characteristics systematically encourage or discourage homeownership, the coefficient estimate would be biased.

We adopt a shift-share approach to isolate the changes in immigration that are uncorrelated with local factors that could affect homeownership. Specifically, let $P_{i,k,t}$ denote the population of people born in country k living in county i in year t, with k equal to US for US-born individuals (native population) or $j \neq US$ for a country/country groups of origin for foreign-born individuals (immigrant population). Using this notation, the observed immigration is thus:

$$immigration_{i,t} = \frac{\sum_{k \neq US} P_{i,k,t}}{\sum_k P_{i,k,t}} \tag{1}$$

To isolate the change in immigration that are uncorrelated with local economic and demographic changes that could affect homeownership, we impute the local population of individuals from country k using:

$$\widehat{P_{i,k,t}} = s_{i,k,1980} \times P_{k,t} \tag{2}$$

where $s_{i,k,1980} = {}^{P_{i,k,1980}}/_{P_{k,1980}}$ reflects the historical county shares of people from country k as of 1980 ("share") and $P_{k,t}$ is the national population of people from country k ("shift"). We then use the imputed local population components to calculate the imputed immigration:

$$\widehat{immigration}_{i,t} = \frac{\sum_{k \neq US} \widehat{P_{i,k,t}}}{\sum_k \widehat{P_{i,k,t}}} \tag{3}$$

To meaningfully capture the main sources of immigration, we aggregate the countries of origin of immigrants into the following 15 countries or country-groups (Mayda et al., 2022) for our measurement: Mexico, Canada, Rest of Americas, Western Europe, Eastern Europe, China, Japan, Korea, Philippines, India, Rest of Asia, Africa, Oceania, Vietnam, and Rest of the World. To facilitate the examination of the key variation, we also aggregate across the foreign countries and country groups of origin to calculate the historical (composite) county shares of immigrants as of 1980,

$$s_{i,1980} = \frac{\sum_{k \neq US} P_{i,k,1980}}{\sum_{k \neq US} P_{k,1980}}. \tag{4}$$

Figure 2 presents the geographic distribution of the historical (composite) county shares of immigrants as of 1980 ($s_{i,1980}$). We construct the analogue for the historical county share of the overall population (consisting of both natives and immigrants) $n_{i,1980} = {}^{P_{i,1980}}/_{P_{1980}}$ as a benchmark. Counties that accounted for a larger fraction of the corresponding population are shaded in darker colors in both maps. There is significant variation across the US, both within and across states. In Internet Appendix Figure IA.2, we separately plot the historical county share of immigrants ($s_{i,k,1980}$) by foreign country of origin and find similar cross-sectional variation.

Figure 3 shows the time-series "shift" components in our shift-share measure. In Panel (a), we tabulate the total number of immigrants in the US by country of origin as of 1980. In Panel (b), we show the cumulative growth of immigrants during our sample period. There is substantial variation both in terms of the initial representation by immigrant country of origin and in terms of the timing and size of subsequent immigrant inflows.

With the shift-share measure to impute local immigration (equation (3)), we estimate the following regression equation to estimate the impact of immigration on homeownership and mortgage access:

$$y_{i,t} = \alpha_i + \pi_{s(i),t} + \beta \cdot \widehat{immigration}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{5}$$

In this equation, i indexes county and t indexes year. As we include the county fixed effects α_i in this specification, we estimate the impact of immigrant inflow on the changes of homeownership and mortgage access. The inclusion of the county fixed effects also control for the impact of time-invariant spatial factors. The state-year fixed effects $\pi_{s(i),t}$ control for time-varying state-level factors affecting the outcome variables of interest. We include a set of time-varying economic and demographic county-level factors $X_{i,t}$ to control for known factors influencing native residents' homeownership outcomes that are not absorbed by our fixed effects such as financial sophistication, life-cycle stages, and racial and ethnic composition. Specifically, the control variables include the log of the adult population, the log of the average personal income among native adults, the shares of native individuals who are (non-Hispanic) White, African American, Asian, and Hispanic, the average age of the native population, the share of natives living in urban area, the employment rate among natives, the share of natives who are male, and share of natives who are married.

The shift-share approach has been widely used in empirical research on the economic impact of immigration (Altonji and Card, 1991; Card, 2001). A key assumption underlying this approach is that the imputed immigration is a strong predictor of the observed immigration. In Internet Appendix Table IA.1, we show that this assumption holds in our setting, which is consistent with the well-documented role of immigrant networks in attracting new arrivals from the same country.

3.3 Validating the Identifying Assumption

The key identifying assumption is that the historical county shares of immigrants in 1980, decades before the beginning of the analysis period, are not correlated with local native homeownership conditional on the fixed effects and control variables, other than via their impact on current immigration. Formally, this requires that the historical county shares of immigrants $s_{i,k,1980}$ are uncorrelated with the residuals in equation (5). In other words, our identification relies on the exogeneity of cross-sectional shares, $s_{i,k,1980}$ (Goldsmith-Pinkham et al., 2020).[6] We conduct several tests to alleviate the concern about spurious correlations between cross-sectional shares and the error term.

Fixed effects and control variables: Including county fixed effects, state-year fixed effects, and time-varying local controls in our regression specification rules out several alternative explanations. A potential threat to causal identification is that counties may have persistent economic, cultural, or institutional characteristics that both attract immigrants and independently affect homeownership outcomes. County fixed effects absorb these time-invariant local factors, eliminating this source of spatial confounding. State-year fixed effects further control for time-varying state-level policies and shocks that may simultaneously influence immigration and homeownership. Finally, the inclusion of time-varying local economic and demographic controls in equation (5) mitigates remaining concerns arising from evolving local conditions. Furthermore, the substantial geographic dispersion of historical immigration across the US shown in Figure 2 lends credence to the notion that historical immigration is unlikely to be spuriously correlated with spatial confounders.

Covariate balance: We assess the plausibility of the exogeneity of cross-sectional immigrant shares (Goldsmith-Pinkham et al., 2020) by examining whether local economic and demographic characteristics in 2005 (the first year of our sample) are correlated with

[6] Alternatively, the identification of shift-share designs can also be achieved via exogenous shifts (Borusyak et al., 2022).

historical county share of immigrants. Specifically, following Goldsmith-Pinkham et al. (2020), we study correlations with historical county shares of immigrants $s_{i,k,1980}$ from the five origin countries or country-groups that receive the largest Rotemberg weights and with the historical (composite) county shares of immigrants $s_{i,1980}$. Rotemberg weights quantify the sensitivity of the shift-share estimator to misspecification in individual origin-specific shares. Details of the Rotemberg decomposition are reported in Internet Appendix Table IA.2.

Table 2 presents the balance test results. Because our baseline specification in equation (5) includes state-year fixed effects, identification comes from within-state variation in immigration inflows. Accordingly, we include state fixed effects in the balance tests to net out differences across states in county characteristics. We find that historical county shares of immigrants from India, Other Americas (excluding Canada and Mexico), Africa, China, and Other Asia (excluding China, Japan, Korea, Philippines, India, and Vietnam), the top five countries/country groups by the Rotemberg weights, are positively correlated with county population size and negatively correlated with native urbanization rates and shares of natives with high-school degree, but show no systematic correlation with other demographic or economic characteristics. We find similar patterns when we use the historical (composite) county share of immigrants ($s_{i,1980}$). In our regression analyses, we include these county characteristics as time-varying control variables to further alleviate concerns that differential demographic or economic trends confound our estimates.

Mortgage supply factors: As mortgage debt is an important method for households to attain homeownership, another potential threat to identification arises from spurious correlation between imputed immigration and mortgage credit supply factors. The supply side of mortgage credit has undergone substantial changes in our sample period. Most notable is the rise of securitization since the 90s which ultimately resulted in mortgage expansion and lax lending standards leading up to the Global Financial Crisis. Another significant development is the rise of shadow banks in mortgage lending after the Global

Financial Crisis, driven by both technological advancements that expedite application processing and regulatory arbitrage opportunities (Fuster et al., 2019; Buchak et al., 2018). Although the aggregate and broader impacts of these credit supply factors have been neutralized by the state specific time fixed effects, one may be concerned that spatial differences in the credit supply factors may be correlated with imputed immigration and therefore bias our estimates.

We examine the potential correlation between historical county shares of immigrants ($s_{i,1980}$) and mortgage supply factors in Figure 4. In Panel (a), we focus on income overstatement among home buyers during 2002–2005. Following Mian and Sufi (2017), we define county-level buyer income overstatement as the difference in the growth in income according to self-reported income in HMDA mortgage applications and the IRS. We residualize the historical county shares of immigrants and county-level buyer income overstatement with respect to baseline county-level controls and state fixed effects. We also report the estimated coefficient from the underlying regression along with its corresponding p-value. There is no systematic correlation between immigration and pre-GFC mortgage income overstatement.

In Panel (b), we focus on the shadow bank expansion in mortgage origination. We classify shadow bank mortgage lenders following Buchak et al. (2018) and Fuster et al. (2019) in the HMDA data and calculate the county-level market share of shadow banks in 2016. We estimate the conditional correlation between shadow bank mortgage origination and historical county shares of immigrants using the same approach as in the previous panel. The correlation is not statistically distinguishable from zero.

Persistent homeownership trends: Another threat to identification arises from the possibility that unobserved, persistent local factors jointly influence both immigration and homeownership over time. If homeownership *changes* exhibit persistence, and counties experiencing adverse shocks, such as long-run declines in economic conditions, also attract higher immigration flows for reasons unrelated to our mechanism, then subsequent declines in homeownership may reflect these underlying trends rather than the causal effect of immigration. In this case, our estimates would be biased. To address this concern, we examine the conditional correlation between the historical county shares of immigrants and changes in native homeownership rates prior to our sample period in Figure 5, using the same approach as in the previous figure. Specifically, Panel (a) examines the change in native homeownership rates from 1980 to 1990, while Panel (b) examines the change from 1990 to 2000. We find that these correlations are weak, as well.

Differential initial conditions: A remaining concern is that counties with different initial conditions may have followed systematically different homeownership trajectories over time, independent of immigration inflows. To address this possibility, we augment the baseline specification by interacting initial county characteristics with year fixed effects, thereby allowing counties with different starting conditions to respond differently to aggregate shocks in each year. Estimates from the augmented specification, reported in Internet Appendix Table IA.5, remain qualitatively and quantitatively similar to our baseline estimates.

4 Results

In this section, we present our main results, provide evidence for the mechanism, and discuss several alternative explanations.

4.1 Homeownership and Mortgage Access

Table 3 presents estimates on the effect of immigration on native residents' homeownership and mortgage access. Columns 1 and 2 show that homeownership rates among natives are lower in counties with higher immigrant inflows. The effect remains significant after controlling for time-varying local demographic and economic characteristics (Column 2). Moving from the 25th percentile to the 75th percentile of immigration across counties is associated with a decrease in homeownership of 5.85 percentage points among natives.

Columns 3 and 4 present analogous results for mortgage access. Since taking out a mortgage is a major pathway to homeownership, reduced mortgage access could explain part of the decline in homeownership. We find that mortgage access among natives is lower in counties with higher immigrant inflows. Column 4 shows that moving from the 25th percentile to the 75th percentile of immigration across counties is associated with a decrease in mortgage access of 6.53 percentage points.

Panels (a) and (b) of Figure 6 present binscatter plots of homeownership and mortgage access against immigration, further confirming that the negative effect of immigration on natives' homeownership is a robust pattern across the entire distribution of immigrant inflows and not driven by any outliers.

Section 3.1 shows immigrants' demand in the owner-occupied housing market. Internet Appendix Table IA.3 shows that immigrant inflows significantly raise the immigrant share of homeowners, confirming that inflows translate into greater demand for owner-occupied housing.

4.2 Housing Affordability

Panel (a) of Table 4 presents the effect of immigration on housing affordability. For each county, we calculate the price-to-income (PTI) ratio as the ratio of quality-adjusted local house value to average income. We use three different sources of data to measure income: QCEW, QWI, and IRS. Across these data sources, we find that an increase in immigrant inflows is associated with a significant rise in the PTI ratio, indicating lower housing affordability. The coefficient estimates imply that moving from the 25th percentile to the 75th percentile of immigration across counties is associated with a 15% to 24% increase in the PTI ratio, depending on the income measure.

We complement our analysis by using an unaffordability measure from the HUD's CHAS data. Column 4 reports the estimated effects of immigration on the share of owner units that are unaffordable to families earning less than 80% of the county's median family income. Counties with higher immigration have a higher share of homes that are unaffordable to low-income families. This finding suggests that immigrant inflows put upward pressures on the low-to-moderate portions of the house price distribution, complementing existing evidence that foreign capital inflows predominantly affect higher-end segments of the real estate markets (Badarinza and Ramadorai, 2018; Li et al., 2024).

In Panel (b), we examine affordability measures in the rental housing market. The county-level rent-to-income (RTI) ratio is the ratio of quality-adjusted local rents (from ACS) to average income (from QCEW, QWI, or IRS). The HUD-defined rental unaffordability rate reflects the share of rental units that are unaffordable to families earning less than 80% of the county's median family income. Across the measures, we find that an increase in immigrant flows leads to lower affordability in the rental market.[7]

4.3 Tests of Mechanisms

In this subsection, we examine the role of immigrant inflows and the resulting upward demand pressure in the owner-occupied housing market as a potential explanation for the decline in natives' homeownership. House prices may increase if immigration-driven demand pushes prices upward, reducing native households' ability to purchase homes. These effects would be stronger in places where housing supply is inelastic or in places where immigrants are more likely to be home buyers, possibilities that we explore next.

Housing supply elasticity: The extent to which immigration-induced housing demand impacts house prices depends crucially on housing supply elasticity. When the housing stock can expand rapidly to accommodate additional demand from the incoming immigrants, price pressures are limited. However, when supply is inelastic, house

[7] In untabulated results, we find that immigration leads to a modest positive impact on income, consistent with the notion that immigrant inflows can improve housing affordability by increasing employment or wages through innovation (Terry et al., 2026; Dimmock et al., 2022) or through the spillover effects of the housing net worth channel (Mian and Sufi, 2014). Despite the modest positive impact on income, immigrant inflows increase house prices and rents by a larger magnitude and hence worsen housing affordability.

prices are more likely to surge in response to increased demand. Saiz (2010) documents substantial variation in housing supply elasticity across US metropolitan areas, with geographical constraints—such as water bodies or steep terrain—playing a central role. He constructs an index measuring the ease of housing expansion, showing that flat areas with fewer natural barriers exhibit greater elasticity, while supply is more rigid in geographically constrained regions.

As Saiz (2010)'s housing supply elasticity measure is available only at the MSA level and for a subset of MSAs, we conduct MSA-level analyses in Table 5. We construct all MSA-level variables used here similarly as their county-level counterparts and restrict the sample to MSAs with non-missing Saiz elasticity data. In Column 1, we show that higher immigration leads to higher house prices and lower affordability in this sample, as well. We then split the sample into four quartiles based on the Saiz elasticity measure, defining MSAs in the three lowest quartiles as having "inelastic" housing supply and the rest as having "elastic" supply. Columns 2 and 3 show that the increase in house prices is concentrated in MSAs with inelastic housing supply; in contrast, the effect of immigration on house prices in MSAs with elastic housing supply is economically smaller and statistically insignificant. In Columns 4 to 6, we repeat the analyses for the price-to-income ratio. The results confirm that higher immigration leads to deteriorating housing affordability, especially in MSAs with inelastic housing supply.

Immigrants' purchasing power: We examine whether the effects of immigration vary with immigrants' likely purchasing power in the housing market. If increased competition from immigrant home buyers drives the decline in natives' homeownership, the effects should be stronger where immigrants have a greater ability to purchase homes. High- and low-skilled immigrants differ in their earnings potential and access to mortgage credit (Cookson et al., 2025). We use educational attainment as a proxy for immigrant skill. We define immigrants with at least a high school degree as high-skilled immigrants and immigrants without a high school degree as low-skilled immigrants. Internet

Appendix Figure IA.1 Panel (a) shows that high-skilled immigrants are more likely to be homeowners than low-skilled immigrants. We therefore examine the heterogeneous effect on native homeownership by immigrant skill, as proxied by educational attainment. In addition to the country of origin, the CPS reports respondents' educational attainment. As before, we define immigrants with at least a high school degree as high-skilled immigrants and immigrants without a high school degree as low-skilled immigrants. We impute skill-specific local immigration by interacting the historical county shares by country of origin (as of 1980) with the national skill-specific population by country of origin.

Table 6 shows the heterogeneous effect of immigration by the skill levels of immigrants. Column 1 shows that an increase in the inflow of high skilled immigrants is associated with a statistically significant reduction in homeownership rates among natives. In contrast, the coefficients on low-skilled immigrants are smaller in magnitude and statistically insignificant, suggesting that low-skilled immigration has a more muted effect on homeownership rates. Similar patterns are present for mortgage access in Column 3: inflows of high-skilled immigrants into a county significantly lower mortgage access among natives in that county while inflows of low-skilled immigrants have no significant effect. Collectively, the results highlight that the skill composition of immigrants is an important determinant of their impact on housing markets.

Immigrants' affinities for homeownership: We also examine the role of affinities for homeownership. Affinities are commonly thought of as the mass lived experience of expectations around a given institution in a specific culture. For example, Blau et al. (2011) use the relative female-to-male labor force participation rates in origin countries as a measure of cultural norms around women's labor supply. In the context of homeownership, we follow Gorback and Schubert (2025) to analogously define homeownership affinity as the homeownership rate in one's country of origin. We use multiple sources to measure homeownership rates in the countries of origin. Our main source is the Census microdata from the IPUMS International. For countries not available in the IPUMS International, we use ownership rates reported by official statistics agencies or data from nationally representative household surveys conducted by non-governmental organizations. For each country, we collect data in the year closest to 2019. From these sources, we obtain homeownership data for 121 countries, representing the origin of more than 92% of the US immigrant population as of 2019. We classify a country of origin as low-affinity if it has a lower homeownership rate than that of the US (68.7%, the median measured in our sample in Table 1) and high-affinity otherwise. Consistent with affinity capturing demand for homeownership, Internet Appendix Figure IA.1 Panel (b) shows that high-affinity immigrants are more likely than low-affinity immigrants to be homeowners, reflecting their stronger demand for owner-occupied housing.

We hypothesize that the inflow of high-affinity immigrants is associated with a larger negative impact on homeownership compared to the inflow of low-affinity immigrants. Table 6 compares the effects of immigration from high- versus low-affinity origin countries. Column 2 shows that counties receiving larger inflows of high-affinity immigrants have lower homeownership among native households. Meanwhile, immigration from low-affinity countries is not significantly associated with the homeownership rate. Similarly, Column 4 shows that mortgage access is more affected in counties with larger inflows of high-affinity immigrants, while the effect of low-affinity immigrants is less pronounced. Together, these results support the notion that inflows of immigrants with high ownership affinity increase housing demand to a greater extent, making it more difficult for natives to secure a home.

4.4 Heterogeneity

If immigration lowers homeownership by making home purchase less affordable, its effect should fall unevenly across native households: largest for those closest to becoming homeowners, for whom higher prices are most likely to tip the decision against a purchase. The pattern of incidence is therefore informative about the mechanism. We decompose native households into mutually exclusive demographic groups, construct group-specific county-level outcomes, and estimate equation (5) for each; Figure 7 reports the results.

We begin with age (Panel (a)). The decline in homeownership is concentrated among younger households and is smaller for older ones, consistent with younger, first-time buyers being most exposed to an affordability shock. Because homeownership is a primary channel of wealth accumulation, this gradient suggests immigration may widen wealth inequality across generations.

We consider the heterogeneity by race and ethnicity in Panel (b). We consider three groups of native households: non-Hispanic white, black, and others. The estimates show that white native households are most negatively affected by immigrant inflows.

In Panel (c), we examine family structure. Single men, and to a lesser extent single women, experience substantially larger declines in homeownership than married households.

Panel (d) shows that immigrant inflows lead to a larger decrease in homeownership among more educated native households than less educated households.

To verify that the affected groups are indeed those most likely to be buying, we examine the transition probabilities from renters to homeowners in the SIPP data. As Figure 8 shows, the renters most likely to become owners are precisely the groups whose homeownership falls most with immigrant inflows: the young, the non-Hispanic white, the more educated, and, among single renters, men. Marital status is the one exception: married renters have the highest transition rate, yet married households are the least affected. This may be because, for married couples, the decision to own depends not only on affordability but also on family circumstances such as childbearing (van Doornik et al., 2024).

We further examine mortgage originations by different purposes using data from the HMDA to shed more light on the potential differential effects on first-time home buyers and existing homeowners. As existing homeowners could benefit from the immigration-induced housing demand through either additional home equity accumulation from house price appreciation or higher rental income for landlords, we expect the net effect of immigration to be much more muted or even overturned for existing homeowners. Although the HMDA data do not contain precise information on first-time home buyers, its loan purpose decomposition is useful for this analysis: While purchase loans for primary residences are used by first-time home buyers and existing homeowners, purchase loans for non-primary residences and refinance loans are unambiguously used by existing homeowners. Estimates reported in Table 7 confirm this prediction: While originations of purchase loans for primary residences, mainly taken up by first-time home buyers, are negatively affected by immigrant inflows, originations of mortgages taken by existing homeowners (Columns 2 and 3) are positively associated with immigrant inflows.

4.5 Alternative Interpretations and Robustness

So far, we have documented that an inflow of immigrants into a county is associated with a decline in both homeownership rates and mortgage access among natives, and provided further evidence suggesting that the increased demand from immigrant home buyers and the ensuing lower affordability is a key mechanism explaining the results. In this section, we consider several alternative explanations for our findings and present evidence suggesting that these alternatives are unlikely to be the primary drivers of our results.

Selective out-migration by the affluent natives: A competing explanation is that the observed decline in homeownership does not reflect affordability constraints but rather a sorting effect. Specifically, if affluent natives–who can afford to buy a home–choose to move out of high-immigration counties and purchase homes elsewhere (e.g., Sá (2015); Agarwal et al. (2024)), then the observed decline in homeownership within those counties would be driven by composition, rather than the impact of immigration-induced housing demand. First, prior literature (Card, 2001) suggests that immigrant inflows do not systematically trigger native outflows, and hence the specifications used in this paper are informative about the effect of immigration on natives' homeownership (Peri and Sparber, 2011). Second, if the sorting hypothesis explains the results fully, then among natives who do not move, we should see no decline in homeownership and mortgage access. This is because the decline observed in the full sample would be solely driven by the movers rather than affordability constraints.

In Panel (a) of Table 8, we restrict the analysis to natives who stay in the same PUMAs as last year and continue to find a statistically significant decline in both homeownership and mortgage access of similar magnitude in this sample of non-movers. This directly contradicts the sorting hypothesis. If sorting were the primary driver, the decline should dissipate when excluding movers. The persistence of the decline among non-movers reinforces the interpretation that immigrant inflows reduce natives' chance to become homeowners rather than simply reshuffling homeownership across locations. In Panel (b), we examine county migration flows using the IRS data. Although this data does not distinguish immigrants and natives, it covers the overall population migration patterns across counties and hence is useful for us to examine whether immigrant inflows into US counties are correlated with domestic migration flows. We find no systematic correlation between immigrant inflows and subsequent overall migration flows, consistent with the findings of Card (2001). In sum, the evidence implies that native migration does not explain our findings.

Measurement error related to use of geographical cross-walks: In Internet Appendix Table IA.4, we conduct additional robustness checks to address the concern about the measurement errors stemming from the imperfect mapping between PUMAs, the smallest identifiable geographic unit in the ACS microdata, and counties. In both the analysis at the time-consistent PUMA level and the analysis in the subsample of counties that PUMAs can be uniquely mapped into counties, the estimated effects of immigration remain qualitatively and quantitatively similar to our baseline estimates, implying that the potential measurement errors stemming from the geographic crosswalks do not affect our results.

Measurement issues related to undocumented immigrants: Another concern for our estimation arises from the potential mis-measurement of immigration due to undocumented immigrants. If undocumented immigrants are hesitant to respond truthfully to questions about citizenship and residency status (Van Hook and Bachmeier, 2013) or are less willing to respond to survey invitations, our measure of immigration drawn from survey data may contain measurement errors. The classical measurement errors would make it harder for us to detect any effects, raising the bar for empirical investigation. To the extent that undocumented immigrants are concentrated in certain geographies, we would expect to find unstable estimates across different geographic subsets if undocumented immigrants lead to not only pure classical measurement errors but biases.

To assess this, we sequentially re-estimate our main specifications, excluding one region (a group of states) at a time. Figure 9 plots the coefficient estimates along with 95% confidence intervals. We find stable coefficient estimates when we exclude a census region, a census division, or a group of peripheral states at a time. We find similar estimates when we exclude one state at a time (Internet Appendix Figure IA.3). We also find stable estimates when we exclude one country or country group of origin from the construction of the shift-share measure of immigration at a time (Internet Appendix Figure IA.4), further affirming that undocumented immigrants do not drive our results.

More broadly, while measuring the number of undocumented immigrants is inherently challenging, the ACS remains the cornerstone data source for both government agencies and leading research organizations. The widely used residual method, the primary approach to estimate undocumented immigrants employed by the U.S. Department of Homeland Security as well as the Migration Policy Institute, the Center for Migration Studies of New York, and the Pew Research Center (e.g., Passel and Krogstad (2025)), relies directly on ACS and CPS microdata because these surveys provide the most representative and detailed information on the U.S. population.

Robustness to alternative controls and weighting: Columns 1–5 of Internet Appendix Table IA.5 report estimates from specifications that introduce year-specific controls for (composite) historical county share of immigrants ($s_{i,1980}$), origin-specific county share of immigrants ($s_{i,k,1980}$), initial homeownership rates, and pre-period measures of housing affordability and also 2005 covariates. These specifications allow counties with different initial characteristics to respond differently to aggregate shocks in each year, and hence address a remaining concern that counties with different initial conditions may have followed systematically different homeownership trajectories over time, independent of immigration inflows. Across all specifications, the estimated effect of immigration on homeownership remains negative and statistically significant. Lastly, Column (6) shows that the results are robust to using equal weights instead of population weights.

Together, these tests indicate that our findings are not driven by differential trends associated with baseline county characteristics or by the choice of weighting scheme.

Robustness to using individual-based homeownership: Internet Appendix Table IA.6 reports the results when we use the ACS individual-level sample, instead of the household-level sample, to construct county-level homeownership and mortgage access rates. We restrict the sample to all native adults and calculate county-level mean homeownership and mortgage access rates among adult native individuals using the ACS individual weights. We find similar estimates to our baseline estimates in Table 3.

5 A Natural Experiment: The Venezuelan Exodus

To complement our shift-share design, we bring a second, independent research design to bear on the same question: a difference-in-differences analysis of the Venezuelan exodus. The two designs rest on different identifying assumptions: the shift-share on the exogeneity of historical (1980) immigrant shares, the natural experiment on parallel trends around a large, plausibly unanticipated shock. Because the two designs exploit different sources of variation, their agreement provides strong evidence of a causal effect.

The Venezuelan design also speaks to a natural concern with the shift-share: that counties with higher 1980 immigrant shares were already on differential homeownership trends. While we address that concern by showing that historical immigrant shares are uncorrelated with most baseline county characteristics, mortgage supply conditions, and pre-period homeownership trends, the exodus provides independent reassurance, since it is orthogonal to the long-standing settlement patterns underlying the shift-share.

5.1 Background and Empirical Design

Beginning in 2014, Venezuela experienced a severe political and economic crisis that triggered one of the largest emigrations in the Western hemisphere. Following the death of Hugo Chávez in 2013, his successor Nicolás Maduro presided over a dramatic economic collapse: GDP contracted by 45% between 2013 and 2018, inflation exceeded 100% by 2015 and reached 1.35 million percent by the end of 2018, and approximately 90% of the population lived in poverty by 2018.[8] The crisis generated a massive emigration wave: by 2019, over four million Venezuelans had fled the country.

Figure 10 shows that the exodus generated a sharp increase in Venezuelan immigrants in the United States. The figure plots the cumulative growth of Venezuelan-born immigrants relative to a 2013 baseline alongside immigrants from other major Latin American regions and the all-country aggregate. While immigration from these comparison groups grew modestly over the decade, Venezuelan immigration surged dramatically after 2014, underscoring that the exodus represents a discrete, origin-specific shock rather than a general increase in Latin American immigration. Venezuelan immigrants in the U.S. are also notably highly educated: 57% of Venezuelan-born adults hold at least a bachelor's

[8] See, e.g., Gunadi (2021) and the references therein for a detailed account of the Venezuelan crisis. The economic collapse was accompanied by severe shortages of food and medicine, rising crime rates, and political repression following antigovernment protests in 2014 and a constitutional crisis in 2017.

degree, compared to 20% among all U.S. Hispanics.[9]

We exploit this shock in a difference-in-differences (DID) design with continuous treatment intensity to estimate the effect of the Venezuelan immigrant inflows on native homeownership. Venezuelan immigrants arriving after the exodus tended to settle in counties with pre-existing Venezuelan communities, and Gunadi (2021) shows that these location choices are driven by geographic proximity and climatic similarity rather than local labor market conditions, generating plausibly exogenous cross-county variation in immigrant inflows. We estimate the following dynamic specification for the period of 2010 to 2019:

$$y_{c,t} = \alpha_c + \gamma_{s(c),t} + \sum_{t \neq 2010} \beta_t \left(\text{Treat}_c \times \mathbb{1}_t\right) + X'_{c,t}\Gamma + \varepsilon_{c,t}, \tag{6}$$

where Treat_c is the pre-existing Venezuelan exposure, measured as the fraction of Venezuelan-born immigrants in the county population based on the 2005–2009 ACS five-year estimates and 1_t denote yearly indicators. We include the same set of fixed effects and time-varying controls as in equation (5). The Venezuelan exposure is zero in about 78% of the counties and has a cross-sectional standard deviation of 0.05 percentage points, reflecting the high geographic concentration of Venezuelans. The first sample year 2010 serves as the omitted base period, and the coefficients β_t trace out the differential evolution of outcomes across counties with varying Venezuelan exposure.

Identifying assumption: Identification relies on the assumption that, conditional on the fixed effects and controls, counties with higher Venezuelan exposure were not differentially exposed to unobserved shocks that coincide with the exodus. This identifying assumption does not require random assignment of Venezuelan exposure across counties, nor does it require that high- and low-exposure counties have similar characteristics in levels. Rather, what we rely on is the parallel trends assumption: outcomes for counties

[9] Pew Research Center, "Facts on Hispanics of Venezuelan Origin in the United States," 2024, https://www.pewresearch.org/race-and-ethnicity/fact-sheet/us-hispanics-facts-on-venezuelan-origin-latinos/.

with different pre-existing Venezuelan exposure would have trended similarly absent the exodus. If the β_t coefficients for the pre-exodus years 2011–2013 are close to zero, this supports the validity of this assumption. Nonetheless, we show in Internet Appendix Figure IA.5 that there is no systematic relationship between the pre-existing Venezuelan exposure and the demographic or economic characteristics of counties' native populations.

Predictability of Venezuelan inflows: We first verify that counties with higher pre-existing Venezuelan exposure indeed received disproportionately more Venezuelan immigrants following the exodus. Figure 11 Panel (a) compares the cumulative growth in Venezuelan immigrant population (scaled by total county population) for counties with above- versus below-median pre-existing Venezuelan exposure. While the two groups differ substantially in levels, they grew at similar rates through 2013, after which counties with higher Venezuelan exposure experienced a markedly steeper increase in their Venezuelan population. Panel (b) shows the conditional dynamic patterns. We estimate the dynamic specification (equation (6)) using the annual change in the Venezuelan immigrant population scaled by the county's 2010 population as the dependent variable. We plot the *cumulative* coefficients $\hat{B}_T = \sum_{t=2011}^{T} \hat{\beta}_t$ to show the conditional cumulative growth. The estimates confirm a sharp, persistent increase in Venezuelan immigration into high-exposure counties beginning in 2014. The pre-2014 cumulative coefficients are close to zero, indicating no differential pre-trends in Venezuelan inflows.

5.2 Effects on Native Homeownership

Figure 12 plots the estimated β_t coefficients from equation (6) along with 95% confidence intervals for native homeownership in Panel (a) and native mortgage access in Panel (b). Two features stand out. First, the coefficients for the pre-exodus years 2011–2013 are statistically indistinguishable from zero, supporting the parallel trends assumption: counties with higher and lower pre-existing Venezuelan exposure were on similar homeownership trajectories prior to the exodus. Second, the coefficients become increasingly negative after 2014 and are statistically significant from 2015 onward, consistent with a persistent adverse effect of immigration on native homeownership that accumulates as Venezuelan inflows intensify.

To summarize these dynamics in a single estimate, we replace the yearly indicators in equation (6) with a single post-2014 indicator:

$$y_{c,t} = \alpha_c + \gamma_{s(c),t} + \beta\,(\text{Treat}_c \times \text{Post}_t) + X'_{c,t}\Gamma + \varepsilon_{c,t}, \tag{7}$$

where Post_t is an indicator for years 2014 and after; all other variables are defined as in equation (6). The coefficient β captures the average differential change in outcomes for counties with greater pre-existing Venezuelan share of county population after the onset of the exodus.

A one-standard-deviation increase in pre-existing Venezuelan exposure (0.05 percentage points) lowers native homeownership and mortgage access by roughly 0.07 percentage points each over the post-exodus period (Internet Appendix Table IA.7). Because Venezuelan exposure is highly concentrated, these per-standard-deviation magnitudes are not directly comparable to our shift-share estimates, which reflect variation in overall immigration. We therefore read the Venezuelan design as corroborating the direction and incidence of the effect rather than its precise magnitude.

A key finding from our shift-share analysis is that the effects of immigration on homeownership are concentrated among specific demographic groups. If the Venezuelan exodus operates through the same economic channels, we should observe similar heterogeneity patterns in the treatment effect. We next estimate the same post-exodus specification separately across demographic subgroups. Figure 13 presents the coefficient estimates and 95% confidence intervals.

The effects are largest for younger natives, declining monotonically with age (Panel (a)), consistent with younger households being marginal home buyers most sensitive to affordability. The effects are concentrated among white natives (Panel (b)) and single men (Panel (c)). Panel (d) reveals that more-educated natives experience the largest declines, consistent with Venezuelan immigrants being disproportionately college-educated.

A design built on entirely different variation recovers the same incidence. The effects are again largest for younger natives, for single men and to a lesser extent single women relative to married households, and for white natives. That two independent designs identify the same groups bearing the burden, and not just the same average effect, provides strong evidence that immigration lowers native homeownership through housing affordability, with the cost falling on marginal buyers.

6 Conclusion

International immigration has surged to historically high levels in recent years; this influx has sparked economic as well as political debates. In this paper, we study how immigration into the US affects the financial well-being of the local communities immigrants settle in. We focus on homeownership, a key pathway for households to accumulate wealth. We use the ACS microdata to accurately measure homeownership and mortgage access among natives across counties from 2005 to 2019, overcoming the inherent composition issues in reported homeownership statistics.

Across two independent research designs, a shift-share approach and a difference-in-differences analysis of the Venezuelan exodus, we find that immigrant inflows lower native homeownership and mortgage access by raising house prices and worsening affordability. The effect is concentrated in areas with inelastic housing supply, where demand cannot easily be accommodated, and is driven by inflows of high-skilled and high-affinity immigrants, who are more likely to compete for owner-occupied housing. The burden falls unevenly across native households, concentrated among the young, white, and single men. Both designs recover this same incidence.

Our findings speak to the *ex ante* ambiguous relationship between immigration and native homeownership and highlight how immigration-induced housing demand can create financial barriers to homeownership, especially for younger adults. These barriers are unlikely to be transitory: as population aging and below-replacement fertility in developed economies sustain demand for immigrant labor, immigration of the kind we study is likely to persist, making the question of who among natives bears its cost increasingly central to housing and credit policy.

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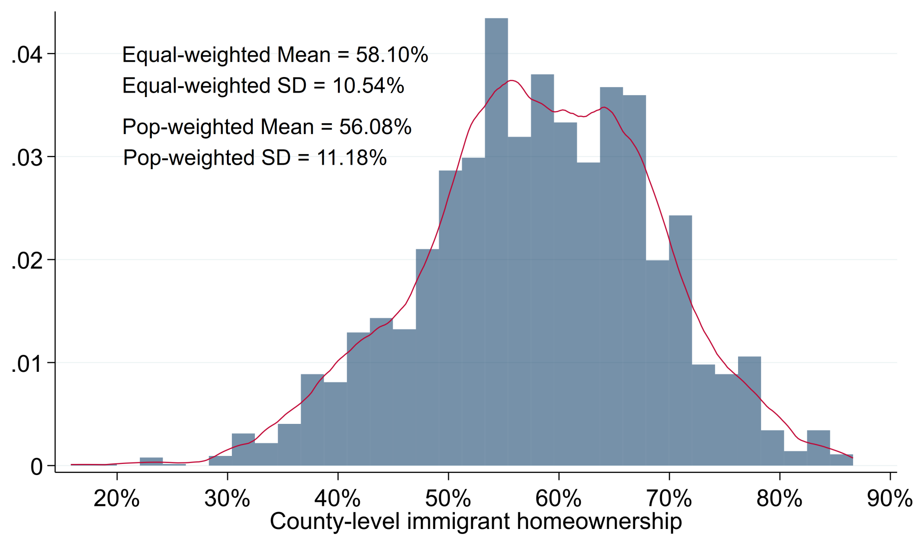
Figure 1: **Immigrants’ housing demand**

This figure plots the cross-county distribution of immigrant homeownership outcomes using ACS data from 2005–2019. Each observation is a county-level average over the sample period. Panel (a) shows the distribution of immigrant homeownership rate (the share of immigrants that are homeowners). Panel (b) shows the distribution of immigrants’ share of homeowners (the share of homeowners that are immigrants). We report the equal-weighted and population-weighted (where we use the county-level average population over the sample period as weights) means and standard deviations. For ease of visualization, we only include the range between 0% and 15% in Panel (b) (only 4.8% of the observations in the long right tail are above 15%).

(a) Immigrants’ ownership rate



(b) Immigrant share of homeowners

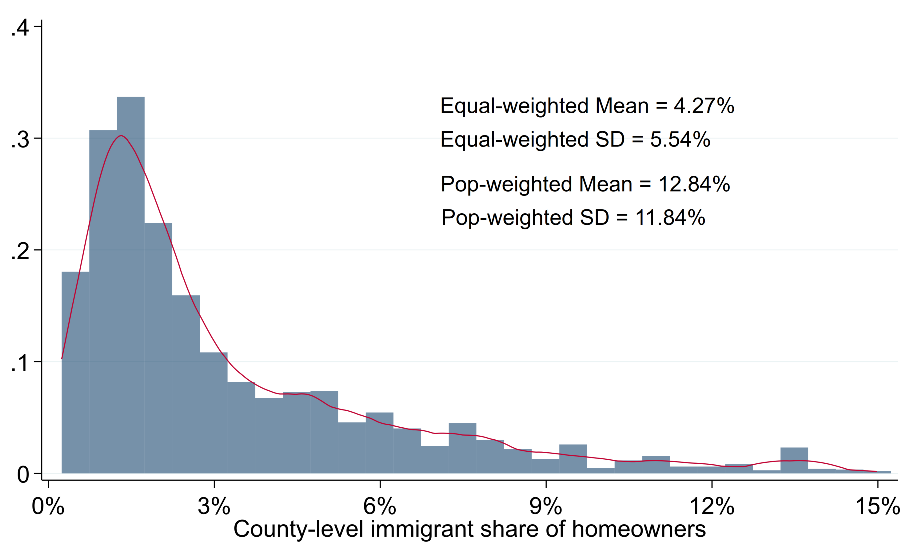
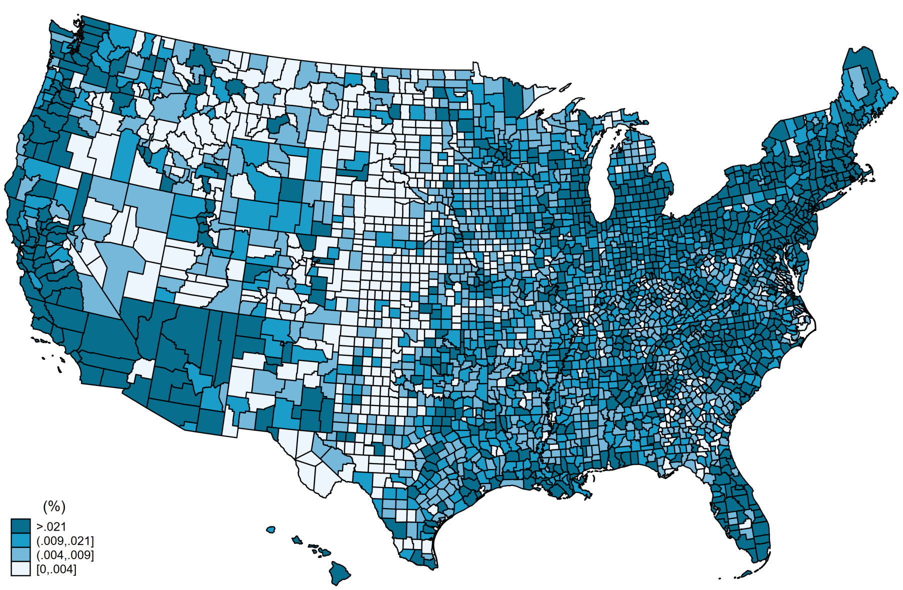


Figure 2: **Historical geographic distribution of overall and immigrant population in 1980**

This figure shows the geographic distribution of the overall and immigrant population across US counties in 1980 using the 1980 Census of Population and Housing data. Panel (a) corresponds to the historical county share of the overall population consisting of both natives and immigrants ($n_{i,1980} = {}^{P_{i,1980}}/_{P_{1980}}$) and Panel (b) corresponds to the historical county share of immigrant population ($s_{i,1980} = \sum_{k \neq US} P_{i,k,1980} / \sum_{k \neq US} P_{k,1980}$).

(a) Overall population in 1980



(b) Immigrant population in 1980

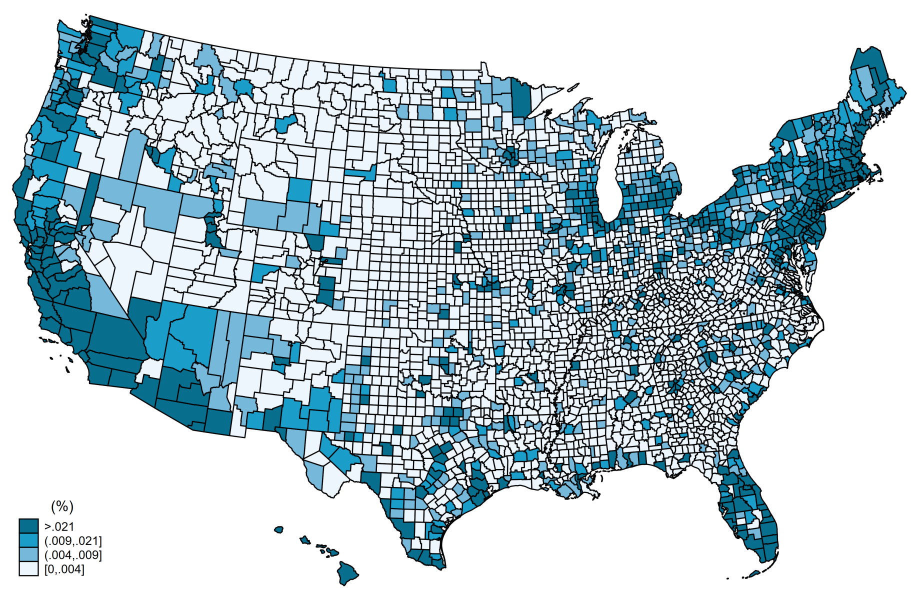
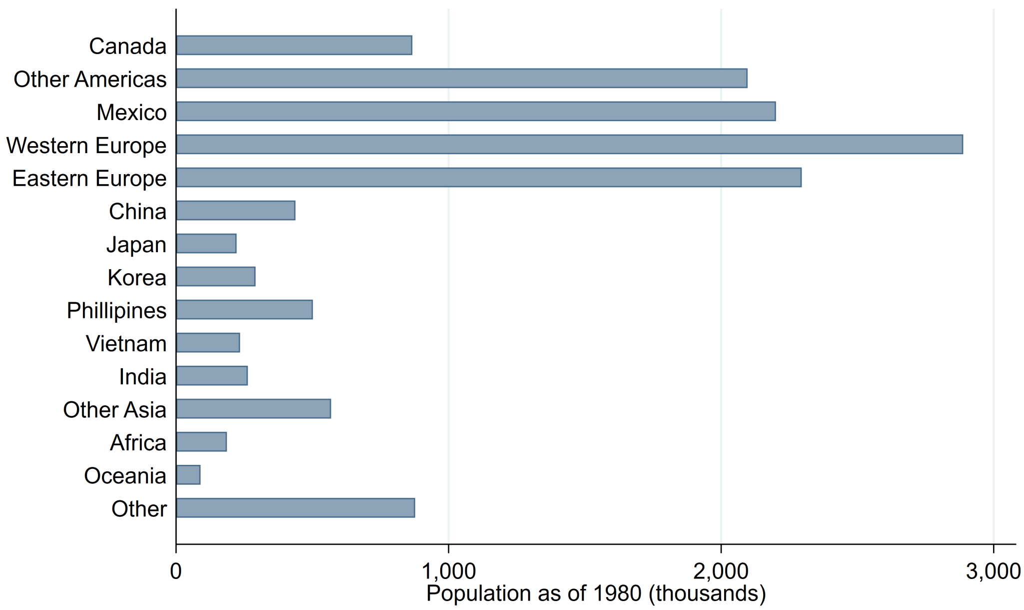


Figure 3: **National trends of immigrants**

This figure shows the initial population size by immigrant country of origin as of 1980 (source: the 1980 Census of Population and Housing data) in Panel (a) and the cumulative growth of immigrants by country of origin relative to the 1980 baseline (source: the annual CPS data) in Panel (b).

(a) Total number of immigrants by country of origin in 1980



(b) Cumulative growth of immigrants by country of origin

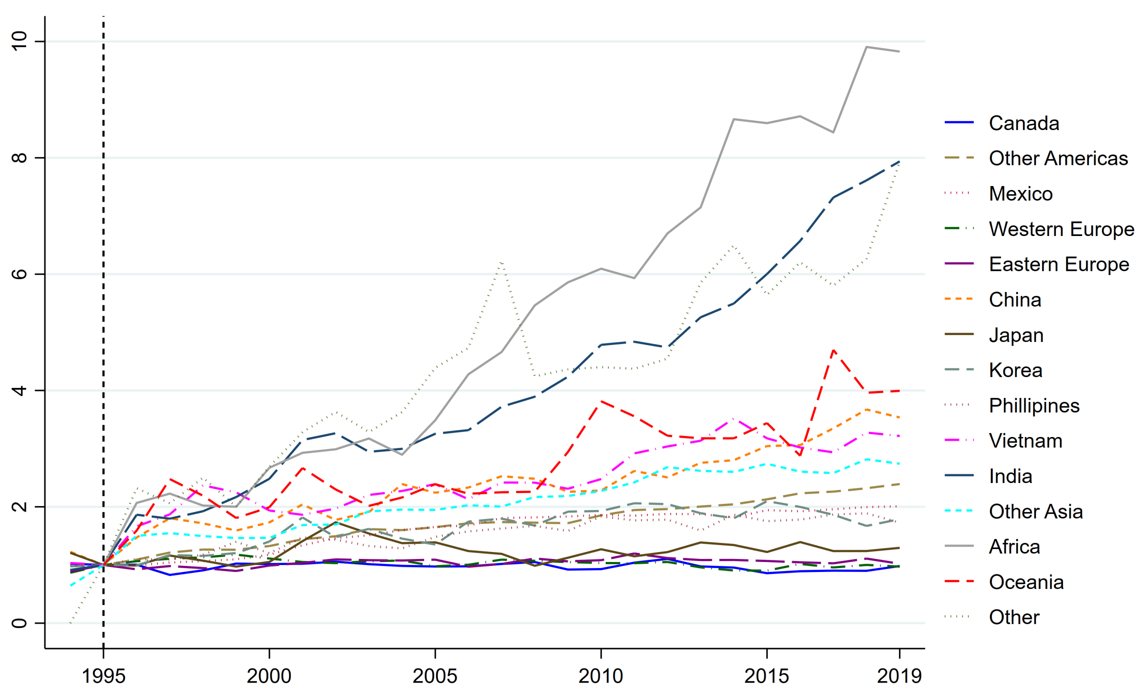
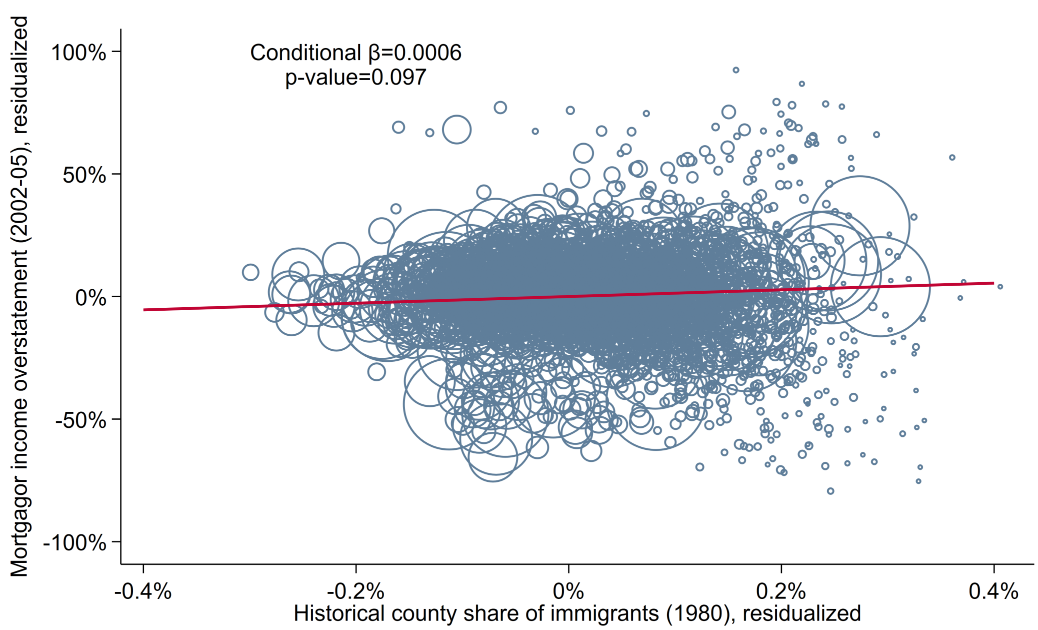


Figure 4: **Correlation between immigration and mortgage supply factors**

This figure examines the correlation between historical county shares of immigrants ($s_{i,1980}$) and mortgage supply factors, income overstatement among mortgage borrowers during the pre-crisis period (2002–2005) in Panel (a) and the share of mortgage originations by shadow banks in 2016 in Panel (b). Both the historical county shares of immigrants and mortgage supply factors are residualized with respect to baseline county-level controls and state fixed effects. Each bubble represents a county in our sample and the size of the bubble represents the adult population of the county in 1980. We also report the estimated coefficient from the underlying linear regression along with its corresponding p-value; in this regression, we use the 1980 adult population as weight and cluster standard errors at the state level.

(a) Income overstatement among mortgagors (2002–2005)



(b) Shadow bank mortgage origination (2016)

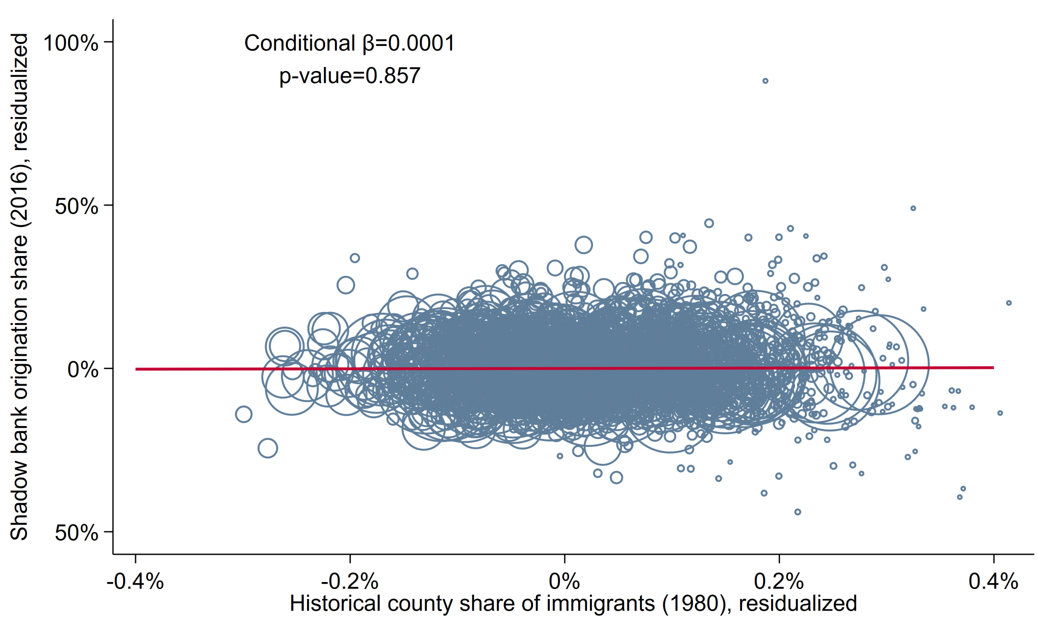
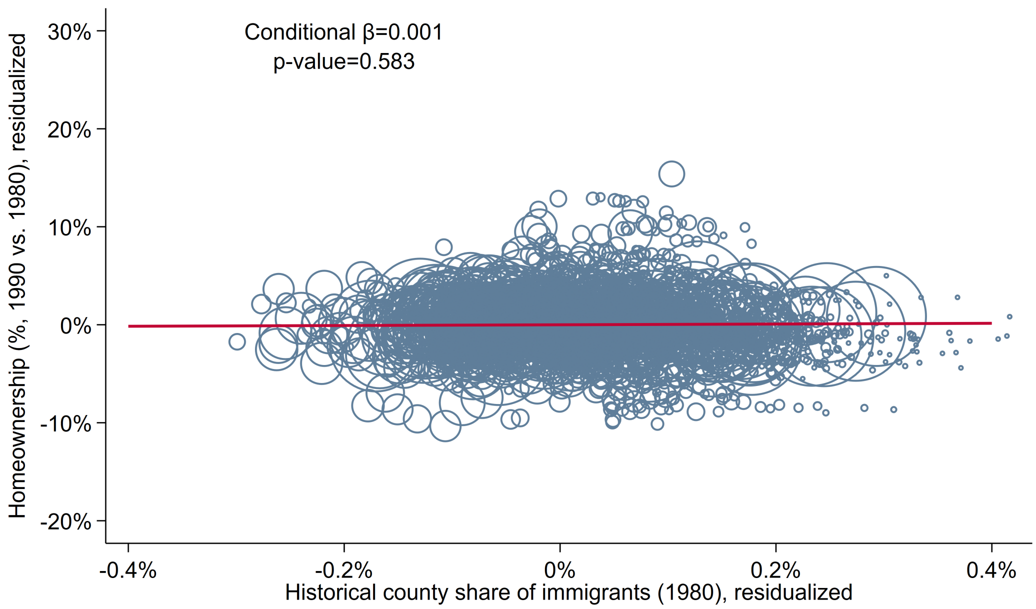


Figure 5: **Correlation between immigration and previous trends in native homeownership**

This figure examines the correlation between historical county shares of immigrants ($s_{i,1980}$) and changes in native homeownership rates prior to our sample period. Panel (a) examines the change from 1980 to 1990 while Panel (b) examines the change from 1990 to 2000 (source: decennial Census). Both the historical county shares of immigrants and the changes in home-ownership rate are residualized with respect to baseline county-level controls and state fixed effects. Each bubble represents a county in our sample and the size of the bubble represents the adult population of the county in 1980. We also report the estimated coefficient from the underlying linear regression along with its corresponding p-value; in this regression, we use the 1980 adult population as weight and cluster standard errors at the state level.

(a) Homeownership rate among natives (1990 vs. 1980)



(b) Homeownership rate among natives (2000 vs. 1990)

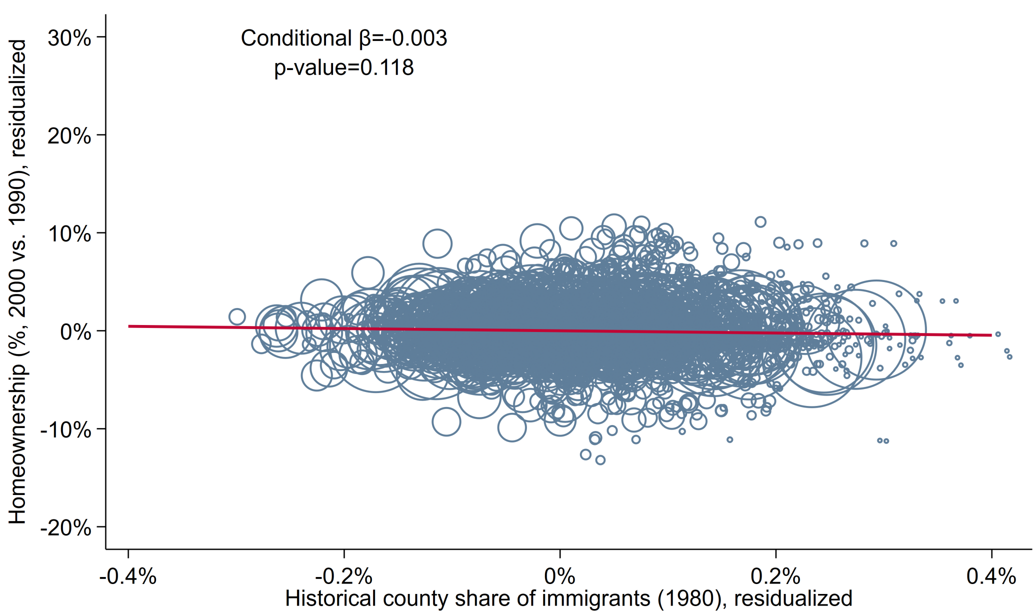
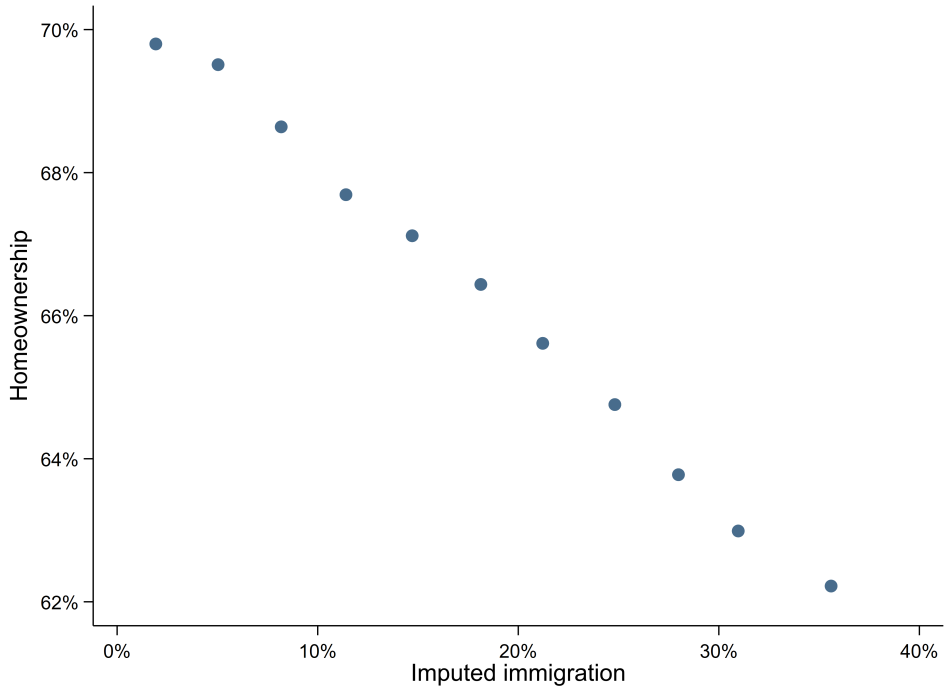


Figure 6: **Binscatter estimates of the effect of immigration**

This figure shows the binscatter plots of the effect of immigration on native homeownership (Panel (a)) and native mortgage access (Panel (b)) constructed using ACS. We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). County fixed effects, state-year fixed effects, and time-varying county controls are included in the regressions. The sample period is 2005–2019. We use the adult population in a county-year as weights. Binscatter plots are created following Cattaneo et al. (2024).

(a) Native homeownership



(b) Native mortgage access

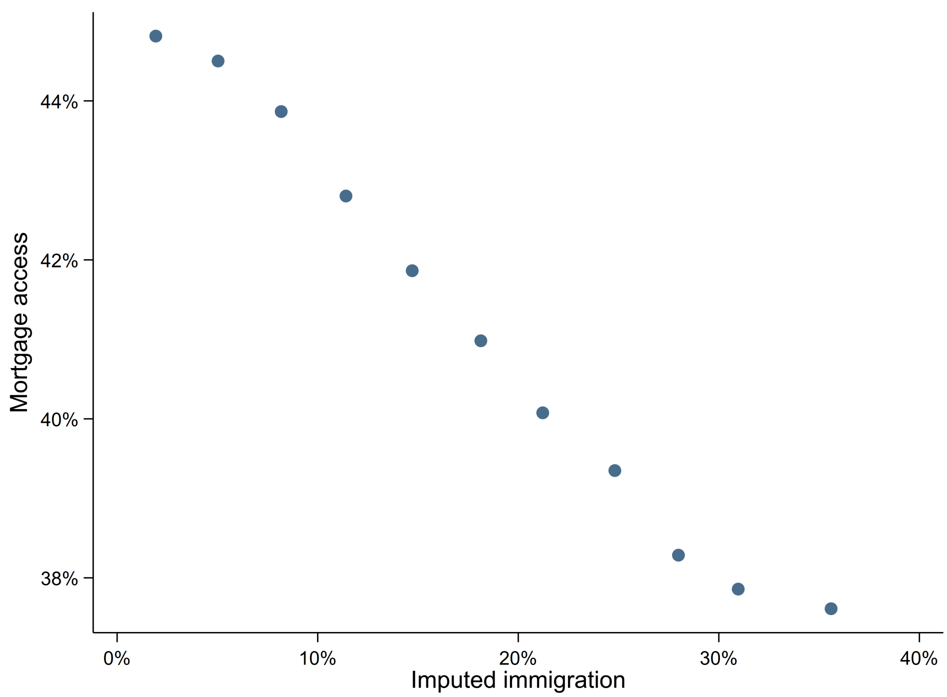
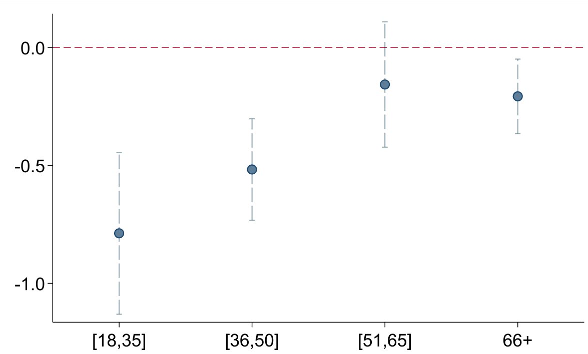


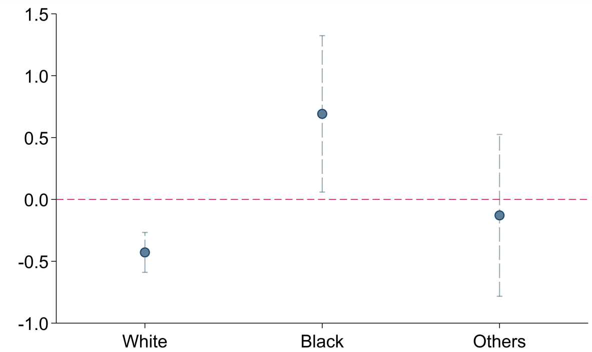
Figure 7: **Heterogeneous effects of immigration on homeownership by demographic characteristics**

This figure presents the coefficient estimates and 95% confidence intervals of the heterogeneous effects of immigration on native homeownership in percentage points. The specifications are similar to Column 2 of Table 3 and are estimated separately across age groups (Panel (a)), racial groups (Panel (b)), family structures (Panel (c)), and education levels (Panel (d)). We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). County fixed effects, state-year fixed effects, and time-varying county controls are included in the regressions. The sample period is 2005–2019. We use the adult population in a county-year as weight; standard errors are clustered at the state level.

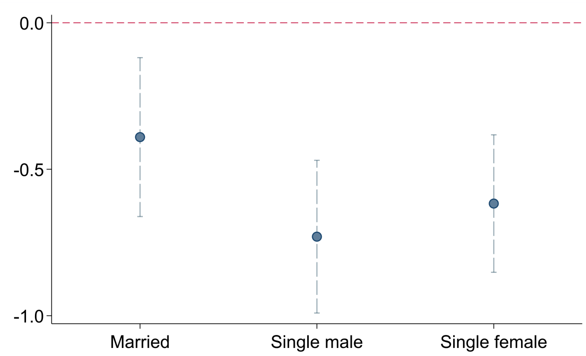
(a) Age



(b) Racial Group



(c) Family Structure



(d) Education

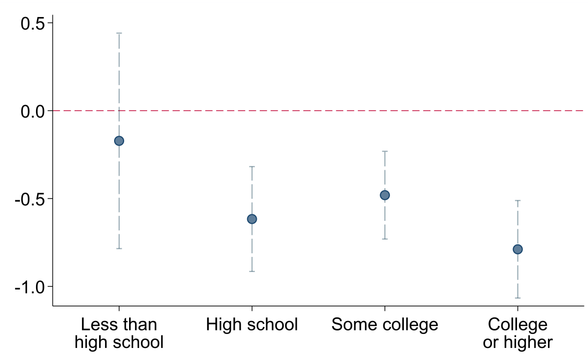


Figure 8: **Native renters' transition into homeownership by demographic characteristics**

This figure plots the average one-year renter-to-owner transition rates among native renters, separately by age groups (Panel (a)), racial groups (Panel (b)), family structure (Panel (c)), and education levels (Panel (d)). We use the 2014 and 2018 SIPP panels to construct annual renter-to-owner transition rates over 2013–2019 and report the averages across these years.

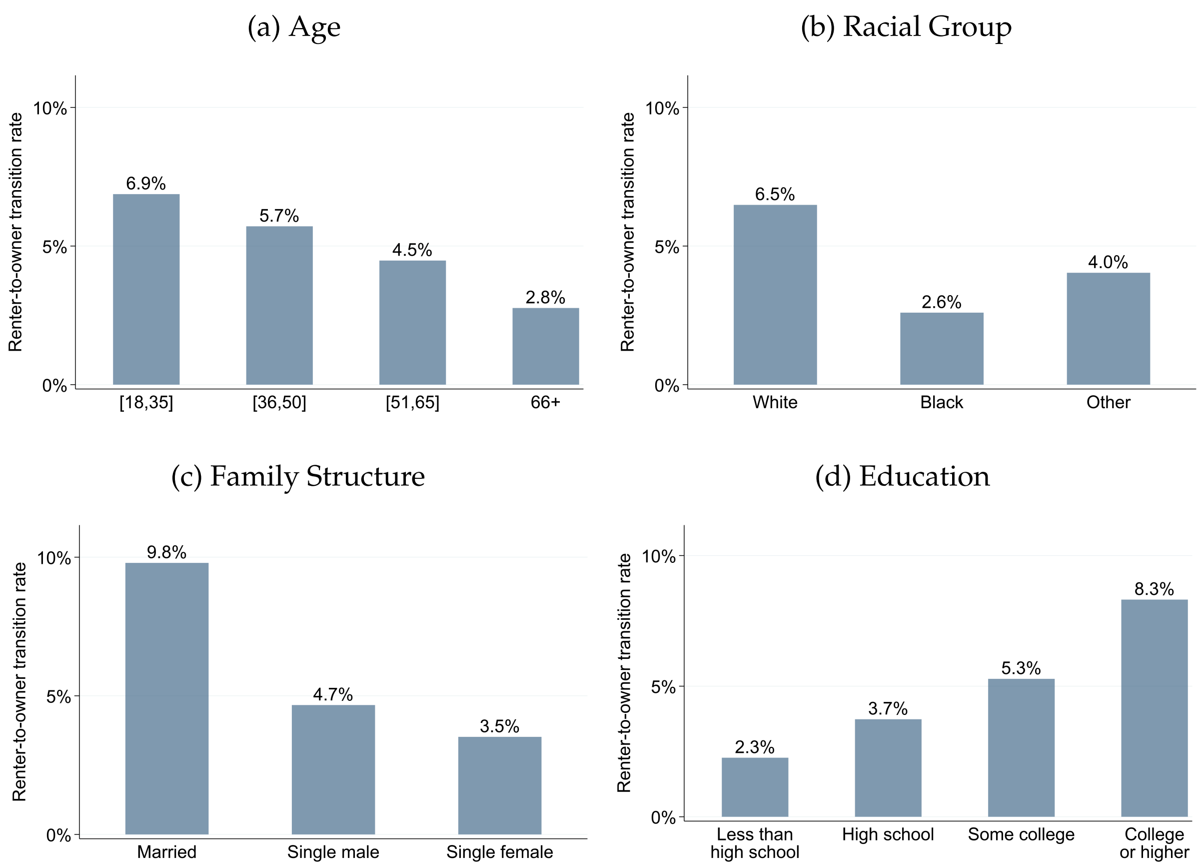
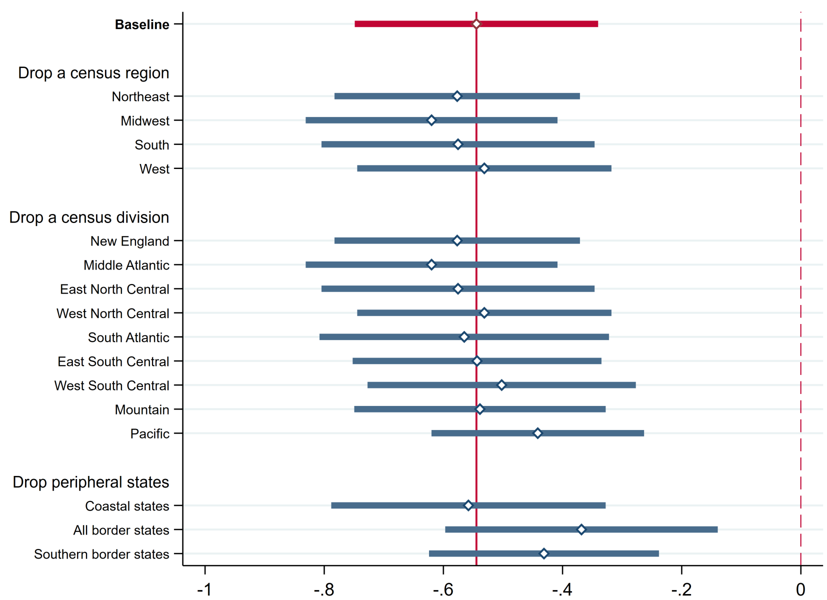


Figure 9: **Stability of the effect of immigration: Exclude one region at a time**

This figure plots the coefficient estimates and their 95% confidence intervals from a series of regressions where we estimate the effect of immigration on native homeownership (Panel (a)) and native mortgage access (Panel (b)). We denote the estimates in Table 3 Columns 2 and 4 as the baseline. In subsequent regressions, we exclude one region (a census region, a census division, or a group of peripheral states) at a time. We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). County fixed effects, state-year fixed effects, and time-varying county controls are included in the regressions. The sample period is 2005–2019. Estimates are population-weighted; clustering is at the state level.

(a) Native homeownership (%)



(b) Native mortgage access (%)

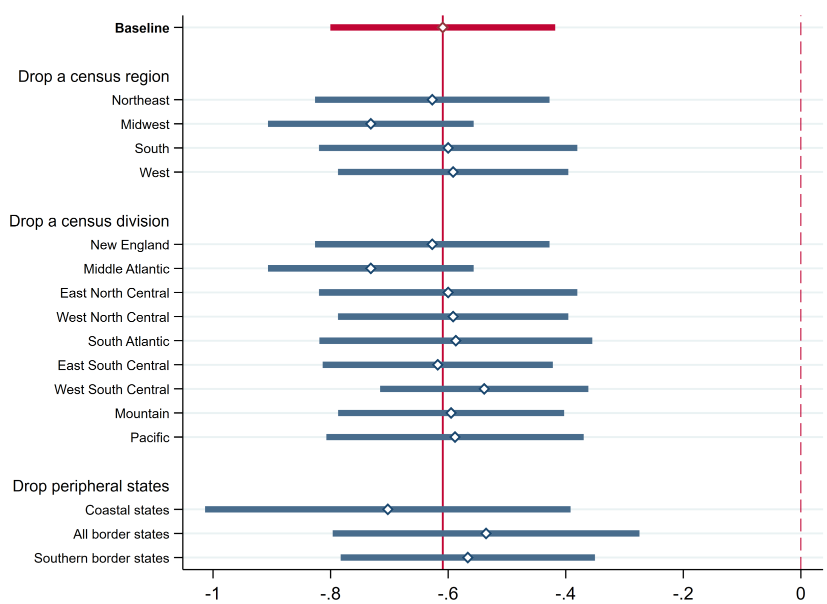


Figure 10: **Cumulative immigrant growth: Venezuelan vs. other origins**

This figure compares the cumulative growth of Venezuelan immigrants with that of immigrants from other origins: the rest of South America (excluding Venezuela), Mexico, Central America, and all countries of origin combined. Immigrant populations are normalized to their respective 2013 levels.

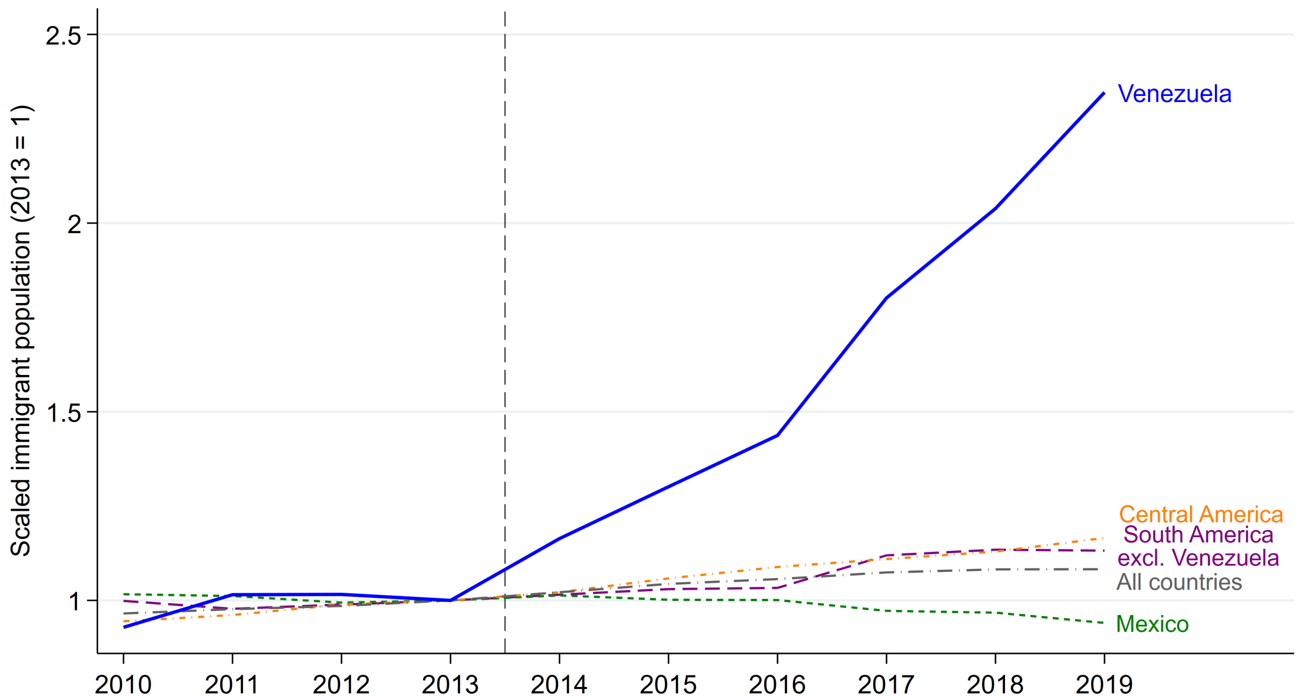
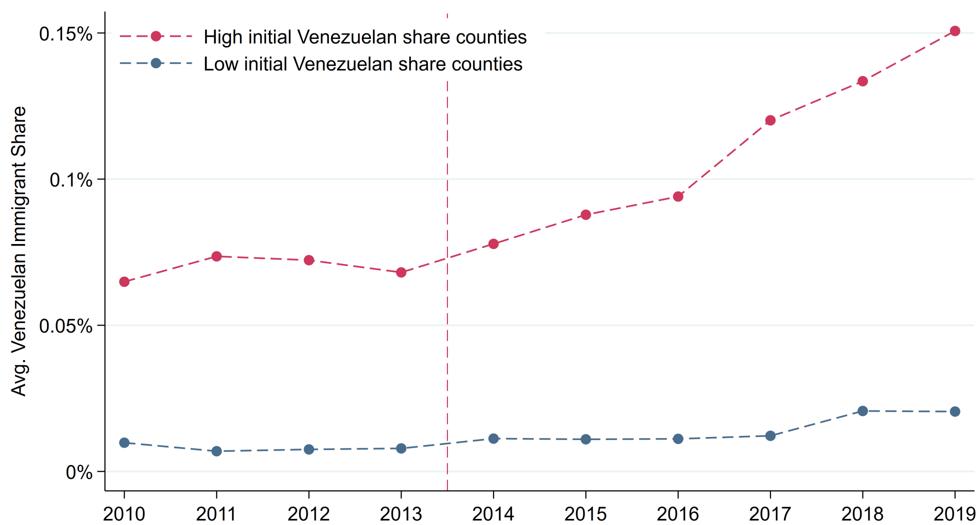


Figure 11: **Cumulative Venezuelan inflows by pre-existing Venezuelan exposure**

This figure shows the cumulative Venezuelan inflows across U.S. counties by pre-existing Venezuelan exposure. The county-level Venezuelan exposure is the fraction of Venezuelan-born immigrants in the county population based on the 2005–2009 ACS five-year estimates. In Panel (a), we compare the cumulative growth in Venezuelan immigrant population (scaled by total county population) for counties with above- versus below-median pre-existing Venezuelan exposure. In Panel (b), we plot the cumulative coefficients and their associated 95% confidence intervals from estimates of the dynamic effects of exposure to the exodus on the annual change in the Venezuelan immigrant population scaled by the county's 2010 population. County fixed effects, state-year fixed effects, and time-varying county controls are included. The sample period is 2010–2019. We use the adult population in a county-year as weight. Standard errors are clustered at the state level; the corresponding standard errors are reported in parentheses. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

(a) Unconditional cumulative growth



(b) Conditional cumulative growth

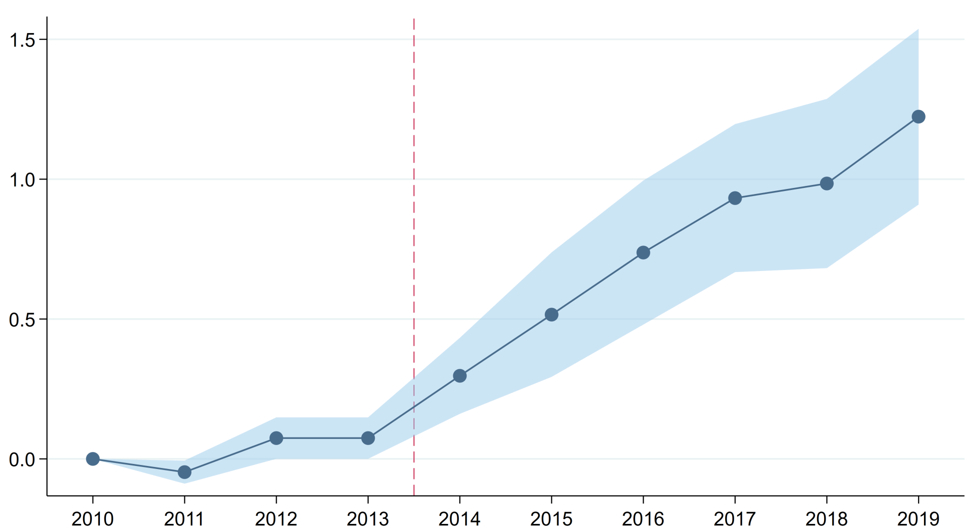
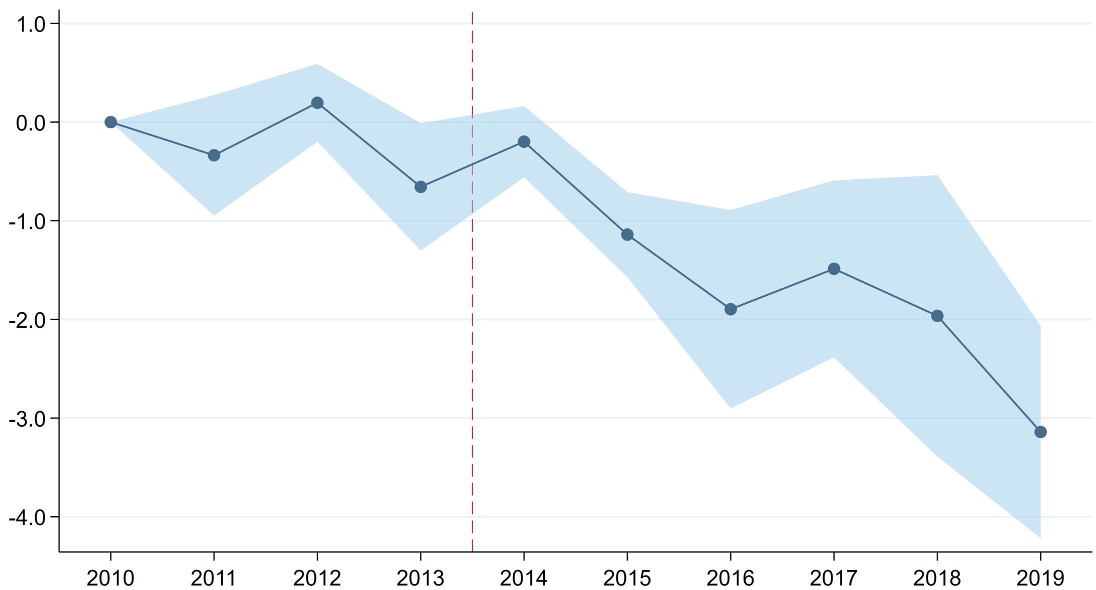


Figure 12: **Dynamic effects of the Venezuelan exodus on native homeownership**

This figure plots the estimated coefficients $\hat{\beta}_t$ and their associated 95% confidence intervals from the event-study specification in equation (6), where the dependent variable is native homeownership (%) in Panel (a) and native mortgage access (%) in Panel (b). The county-level Venezuelan exposure is the fraction of Venezuelan-born immigrants in the county population constructed from 2005–2009 ACS five-year estimates. The year 2010, the first year in the sample, is the omitted base period. County fixed effects, state-year fixed effects, and time-varying county controls are included. The sample period is 2010–2019. Observations are weighted by county adult population. Standard errors are clustered at the state level.

(a) Native homeownership (%)



(b) Native mortgage access (%)

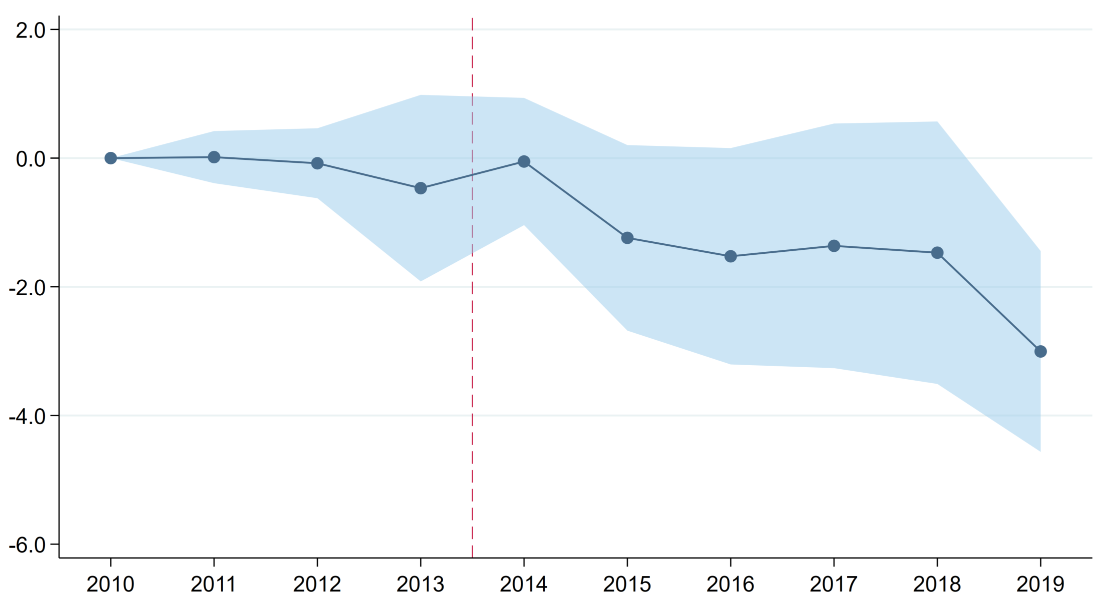
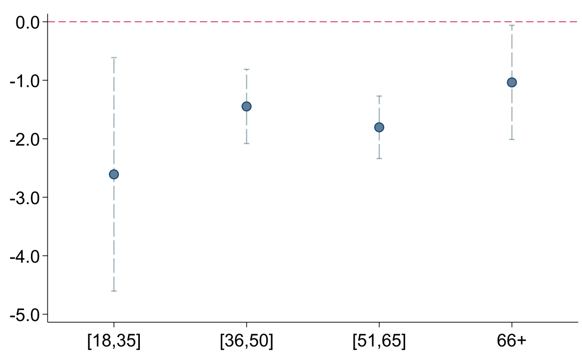


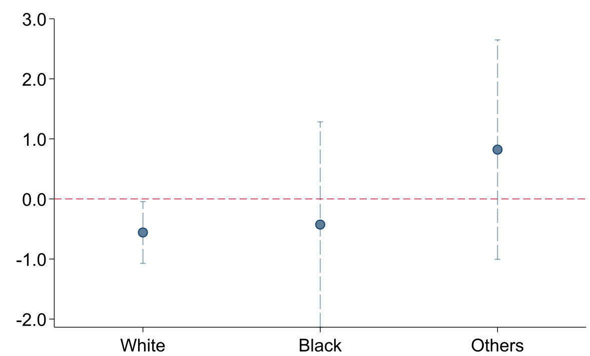
Figure 13: **Heterogeneous effects of the Venezuelan exodus on native homeownership by demographic characteristics**

This figure presents the coefficient estimates and 95% confidence intervals from the DID specification in equation (7), estimated separately across age groups (Panel (a)), racial groups (Panel (b)), family structures (Panel (c)), and education levels (Panel (d)). The dependent variable is native homeownership (%). The treatment variable is the share of Venezuelan immigrants in the county population averaged over 2005–2009, interacted with a post-2014 indicator. County fixed effects, state-year fixed effects, and time-varying county controls are included. The sample period is 2010–2019. Observations are weighted by county adult population. Standard errors are clustered at the state level.

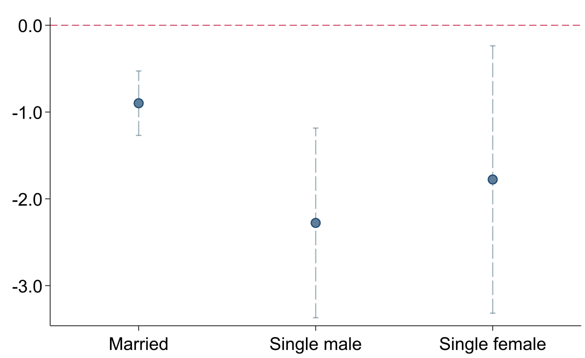
(a) Age



(b) Racial Group



(c) Family Structure



(d) Education

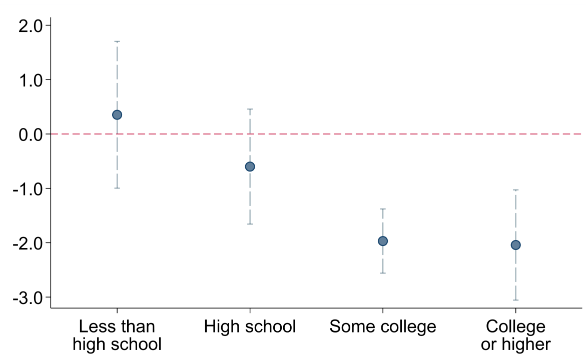


Table 1: **Summary statistics**

This table presents summary statistics of the county-year panel. We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). Homeownership and mortgage access rates of natives (US-born) come from ACS. Mortgage originations by purpose come from HMDA. Housing affordability measures come from quality-adjusted house values and rents from ACS scaled by income (QCEW, QWI, or IRS) and HUD CHAS. Demographic controls are constructed from the Census and ACS data. Monetary values are expressed in 2019 dollars, adjusted using the PCE price index. See Section 2 and Internet Appendix A for details on data and variables. The sample period is 2005 to 2019 for all variables except for the HUD unaffordability rates (2009 to 2019); all statistics are adjusted by county-year adult population.

	Obs.	Mean	Std. Dev.	25%	50%	75%
Imputed immigration (%)	46,248	11.18	11.81	3.21	7.14	13.94
Homeownership and mortgage access of natives:						
Homeownership (%)	46,248	67.40	9.75	62.51	68.68	73.96
Mortgage access (%)	46,248	42.99	8.93	37.62	42.94	48.43
Mortgage origination amount ($000,000s):						
Purchase, principal residence	43,855	1,962.63	3,626.63	159.62	774.19	2,277.99
Purchase, second residence or investment	43,855	233.03	548.89	14.99	62.80	212.51
Refinance	43,855	2,542.04	6,084.34	171.69	780.72	2,502.23
Housing affordability:						
PTI (QCEW)	46,031	5.96	2.50	4.30	5.22	6.85
PTI (QWI)	46,031	5.74	2.40	4.14	5.04	6.60
PTI (IRS)	46,031	6.20	2.68	4.46	5.46	7.17
HUD owner unaffordability rate (%)	32,189	47.98	23.05	28.53	43.61	65.28
RTI (QCEW)	46,031	0.19	0.05	0.16	0.19	0.22
RTI (QWI)	46,031	0.19	0.04	0.16	0.18	0.21
RTI (IRS)	46,031	0.20	0.05	0.17	0.19	0.23
HUD rental unaffordability rate (%)	32,189	17.63	13.30	7.15	13.51	26.11
Demographic controls:						
Adult population (000s)	46,248	483.20	737.25	76.68	253.23	638.26
Avg. personal income of natives ($000s)	46,248	41.13	11.62	33.08	38.66	46.38
White natives (%)	46,248	78.68	15.12	70.07	82.01	90.74
Hispanic natives (%)	46,248	11.03	13.55	2.64	5.73	13.99
African American natives (%)	46,248	12.63	13.19	2.83	8.01	18.10
Asian natives (%)	46,248	1.99	3.87	0.35	0.93	1.97
Average age of natives	46,248	47.05	2.62	45.35	47.08	48.66
Natives living in urban areas (%)	46,248	75.31	42.62	68.96	100.00	100.00
Native unemployment rate (%)	46,248	7.03	3.02	4.83	6.44	8.69
Native adults with high-school degree (%)	46,248	90.81	4.57	88.60	91.74	94.08
Male natives (%)	46,248	49.22	1.23	48.41	49.14	49.92
Married natives (%)	46,248	50.02	7.63	45.54	50.62	55.28

Table 2: **Covariate balance**

This table reports the relationships between 2005 county characteristics and the historical county shares of immigrants ($s_{i,k,1980}$) from the top five countries or country-groups by Rotemberg weights (Columns 1–5) and the historical (composite) county shares of immigrants $s_{i,1980}$ (Column 6). We include state fixed effects to eliminate any characteristics variation driven by state-level differences. To meaningfully capture the main sources of immigration, we aggregate the countries of origin of immigrants into the 15 countries or country-groups (Mayda et al., 2022) for our measurement; "Other Americas" include all of the Americas excluding Mexico and Canada and "Other Asia" include all of Asia excluding China, Japan, Korea, Philippines, India, and Vietnam. We use the 1980 population in a county as weight. Standard errors are clustered at the state level; the corresponding standard errors are reported in parentheses. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Historical county shares of immigrants					
	$s_{i,k,1980}$					$s_{i,1980}$
	(1) India	(2) Other Americas	(3) Africa	(4) China	(5) Other Asia	(6) Composite
Log(adult population)	0.376***	0.273*	0.309**	0.183	0.459**	0.392**
	(0.124)	(0.144)	(0.143)	(0.169)	(0.225)	(0.172)
Log(natives' average personal income)	0.647	0.844**	0.905**	2.404*	0.386	0.339
	(0.583)	(0.361)	(0.346)	(1.297)	(0.436)	(0.261)
White natives (%)	-0.013*	-0.014	-0.011*	-0.013	-0.007	-0.011**
	(0.007)	(0.009)	(0.006)	(0.008)	(0.006)	(0.004)
Hispanic natives (%)	0.008	0.038	0.016	0.017	0.012	0.020*
	(0.008)	(0.032)	(0.013)	(0.015)	(0.010)	(0.012)
African American natives (%)	-0.002	-0.010	-0.007	-0.023*	-0.002	-0.005
	(0.006)	(0.010)	(0.006)	(0.012)	(0.008)	(0.006)
Asian natives (%)	0.186	0.152	0.034	0.896***	0.083	0.099
	(0.149)	(0.228)	(0.114)	(0.113)	(0.116)	(0.112)
Average age of natives	0.016	0.005	0.029	0.058	0.034	0.033
	(0.016)	(0.035)	(0.024)	(0.038)	(0.033)	(0.026)
Natives living in urban areas (%)	-0.006***	-0.005**	-0.005**	-0.006**	-0.007**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Native unemployment rate (%)	-0.030	-0.064*	-0.034	0.010	-0.056	-0.050*
	(0.022)	(0.036)	(0.021)	(0.019)	(0.037)	(0.027)
Native adults with high-school degree (%)	-0.013	-0.040**	-0.018*	-0.045**	-0.022**	-0.023***
	(0.008)	(0.016)	(0.009)	(0.019)	(0.010)	(0.008)
Male natives (%)	0.004	-0.051	0.017	0.056	0.050	0.038
	(0.033)	(0.089)	(0.044)	(0.049)	(0.056)	(0.049)
Married natives (%)	0.004	-0.032***	-0.022***	-0.064**	-0.009	-0.009
	(0.013)	(0.011)	(0.005)	(0.031)	(0.010)	(0.007)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.424	0.395	0.380	0.607	0.313	0.380
Observations	3,072	3,072	3,072	3,072	3,072	3,072

Table 3: **The effect of immigration on natives' homeownership and mortgage access**

This table shows the effect of immigration on native homeownership and mortgage access constructed using ACS. We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). Columns 1 and 2 use county-level native homeownership rate, whereas Columns 3 and 4 use county-level mortgage access rate. County fixed effects and state-year fixed effects included and denoted at the bottom; in some columns, we additionally include time-varying county controls and denote them at the bottom. The sample period is 2005–2019. We use the adult population in a county-year as weight. Standard errors are clustered at the state level; the corresponding standard errors are reported in parentheses. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Homeownership (%)		Mortgage access (%)	
	(1)	(2)	(3)	(4)
Imputed immigration (%)	-0.787***	-0.545***	-0.739***	-0.609***
	(0.083)	(0.102)	(0.100)	(0.095)
Controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
R^2	0.947	0.954	0.943	0.952
Observations	46,248	46,248	46,248	46,248

Table 4: **The effect of immigration on housing affordability**

This table shows the effect of immigration on housing affordability measures. Panel (a) focuses on the owner-occupied housing market. The county-level PTI is the ratio of quality-adjusted local house value (from ACS) to average income (from QCEW, QWI, or IRS) . Column 4 reports the effects on the HUD-defined owner unaffordability rates. Panel (b) focuses on the rental housing market. The county-level RTI is the ratio of quality-adjusted rents (from ACS) to average income (from QCEW, QWI, or IRS). Column 4 reports the effects on the HUD-defined rental unaffordability rates. We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). County fixed effects, state-year fixed effects, and time-varying county controls are included and denoted at the bottom. The sample period is 2005–2019 for log(PTI) and log(RTI) and 2009–2019 for the HUD unaffordability rates. We use the adult population in the county-year as weights. Standard errors are clustered at the state level; the corresponding standard errors are reported in parentheses. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

(a) Affordability in owner-occupied housing

	Log(PTI)			HUD owner unaffordability rate (%)
	(1) QCEW	(2) QWI	(3) IRS	(4)
Imputed immigration (%)	0.021***	0.022***	0.014**	0.812*
	(0.007)	(0.007)	(0.006)	(0.476)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
R^2	0.959	0.960	0.963	0.981
Observations	46,031	46,031	46,031	32,189

(b) Affordability in rental housing

	Log(RTI)			HUD rental unaffordability rate (%)
	(1) QCEW	(2) QWI	(3) IRS	(4)
Imputed immigration (%)	0.027***	0.028***	0.019***	0.644***
	(0.006)	(0.007)	(0.005)	(0.236)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
R^2	0.914	0.913	0.918	0.962
Observations	46,031	46,031	46,031	32,189

Table 5: **Heterogeneous effect of immigration by housing supply elasticity (Saiz, 2010)**

This table shows the effect of immigration on house values and affordability. We adopt a shift-share approach to impute local immigration by interacting the historical distribution of immigrants across MSAs (as of 1980) with the national inflows of immigrants by immigrant country of origin (the MSA-equivalent to our county-level measure as detailed in Section 3.2). House values are quality-adjusted measures constructed from ACS data. Columns 1–3 report the effect of immigration on log house values at the MSA level. Columns 4–6 report the effect on log of PTI (quality-adjusted local house value divided by average income from IRS). We divide the sample into four quartiles based on Saiz's measure of housing supply elasticity, and classify the top quartile as MSAs with elastic housing supply, while the remaining three quartiles are categorized as MSAs with inelastic housing supply. MSA fixed effects, state-year fixed effects, and time-varying MSA controls are included and denoted at the bottom. The sample period is 2005–2019. We use the adult population in the MSA-year as weights. Standard errors are clustered at the MSA level; the corresponding standard errors are reported in parentheses. We use ***, **, and * to denote significance at 1%, 5%, and 10% level (two-sided), respectively.

	Log(house price)			Log(PTI)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All MSAs	MSAs with inelastic housing supply	MSAs with elastic housing supply	All MSAs	MSAs with inelastic housing supply	MSAs with elastic housing supply
Imputed immigration (%)	0.006***	0.006***	-0.002	0.006***	0.007***	-0.003
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.989	0.990	0.968	0.984	0.986	0.960
Observations	3,810	2,805	1,005	3,810	2,805	1,005

Table 6: **Heterogeneous effects of immigration by immigrant characteristics**

This table studies the effect of immigration, by the skill levels and homeownership affinities of immigrants, on native homeownership and mortgage access constructed using ACS. We define immigrants with at least a high school degree as high-skilled immigrants and immigrants without a high school degree as low-skilled immigrants. Homeownership affinity is measured by the homeownership rate in an immigrant's country of origin. We adopt a shift-share approach to impute skill-specific local immigration by interacting the historical county shares by country of origin (as of 1980) with the national skill-specific population by country of origin (details in Sections 3.2 and 4.3). County fixed effects, state-year fixed effects, and time-varying county controls are included and denoted at the bottom. The sample period is 2005–2019. We use the adult population in a county-year as weight. Standard errors are clustered at the state level; the corresponding standard errors are reported in parentheses. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Homeownership (%)		Mortgage access (%)	
	(1)	(2)	(3)	(4)
Imputed high-skilled immigration (%)	-0.464***		-0.474***	
	(0.097)		(0.134)	
Imputed low-skilled immigration (%)	0.209		0.070	
	(0.213)		(0.199)	
Imputed high-affinity immigration (%)		-0.817***		-0.747***
		(0.102)		(0.141)
Imputed low-affinity immigration (%)		-0.105		-0.437
		(0.242)		(0.367)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
R^2	0.954	0.954	0.952	0.952
Observations	46,248	46,248	46,248	46,248

Table 7: **The effect of immigration on mortgage origination**

This table shows the effect of immigration on mortgage origination using HMDA. We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). County fixed effects, state-year fixed effects, and time-varying county controls are included and denoted at the bottom. The sample period is 2005–2019. We use the adult population in the county-year as weights. Standard errors are clustered at the state level; the corresponding standard errors are reported in parentheses. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Log(origination amount)		
	(1)	(2)	(3)
	Purchase Principal residence	Purchase Second residence or investment	Refinance
Imputed immigration (%)	-0.019**	0.041***	0.057***
	(0.009)	(0.009)	(0.012)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes
R^2	0.994	0.978	0.990
Observations	43,855	43,855	43,855

Table 8: **Homeownership and mortgage access of non-movers**

Panel (a) shows the effect of immigration on homeownership and mortgage access for the sub-sample of native non-movers. Native non-movers are households who stayed in the same residence or moved but within the origin PUMA (the smallest identifiable geographic unit in the ACS microdata). Essentially, this set of natives have stayed within a county since the previous year. Panel (b) examines whether immigration affects county migration flows over the following year using IRS data. The outcome variables are log outflows, log inflows, and the net outflow rate, defined as outflows minus inflows divided by the current year population. We adopt a shift-share approach to impute local immigration by interacting the historical county shares by country of origin (as of 1980) with the national population by country of origin (details in Section 3.2). County fixed effects, state-year fixed effects, and time-varying county controls are included and denoted at the bottom. The sample period is 2005–2019. We use the adult population in a county-year as weight. Standard errors are clustered at the state level; the corresponding standard errors are reported in parentheses. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

(a) Outcomes among non-movers

	(1) Homeownership among non-movers (%)	(2) Mortgage access among non-movers (%)
Imputed immigration (%)	-0.507***	-0.592***
	(0.102)	(0.100)
Controls	Yes	Yes
County FE	Yes	Yes
State $\times$ Year FE	Yes	Yes
R^2	0.950	0.952
Observations	46,248	46,248

(b) County migration pattern

	(1) Log(migration outflows)	(2) Log(migration inflows)	(3) Net outflow rate (%)
Imputed immigration (%)	0.010	-0.003	0.091
	(0.007)	(0.006)	(0.069)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes
R^2	0.998	0.997	0.442
Observations	45,840	45,840	45,840