January 2024

Warmth of the Welcome: Immigration and Local Housing Returns

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UTEP HUNT INSTITUTE
FOR GLOBAL COMPETITIVENESS

WORKING PAPER SERIES 1 FALL 2023

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JEL Classification: J61, R23, R31

Keywords: *Immigration, Housing Returns, Instrumental Variables, Heterogeneous Effects*

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First version: June 24, 2023

Abstract

We study the effect of immigration on home values in the U.S. Applying a county-level instrument for immigration, we find that immigration increases local house price appreciation and decreases its within-county spatial dispersion. Our estimates suggest that, on average, a one percentage point increase in the immigrant share of the local population raises house price appreciation by approximately 7 percent and reduces the dispersion of housing return within a county by about 1.5 percentage points. We also show that such effects are strikingly heterogeneous across counties and appear to be determined by local culture. Using several proxies for attitudes toward immigration at the county level, we find that immigration boosts housing returns and limits its spatial dispersion *only* in counties with residents who are younger, more educated, and less racially biased. Our findings highlight that the effect of immigration on home values (or the lack thereof) is highly contingent on natives' attitudes toward immigrants.

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1 Introduction

At all points in its history, a significant share of the U.S. population has been made up of immigrants. According to the U.S. Census, in 2022, 13.6% of the U.S. population (more than 45 million people) are foreign-born, nearly tripled since its historical low of 4.8% in 1970.[1] Immigration remains one of the most contentious social and political issues debated in legislatures, across social media, and at dinner tables alike. In the United States, these issues have led to a huge number of academic studies analyzing the complex and multifaceted consequences of immigration. In this paper, we join this stream of literature and study the impact of immigration on local house price appreciations. We focus on house prices for two reasons. First, housing is often the largest single asset owned by a family, and housing debt usually accounts for the lion's share of a household's total liability. In its effect on house prices, immigration must also alter native households' asset allocation, wealth accumulation, and consumption. Second, house prices are a crucial indicator of the strength of the local economy (Hwang and Quigley, 2006) and the area's quality of life (Albouy, 2008). Examining the impact of immigration on home values helps us to understand if immigrants make a community a better place.

Immigration can affect house prices in several ways. Perhaps the most direct effect is the increased demand for housing, which in the absence of a supply response will raise housing prices. Furthermore, immigrants also bring to the area skills (Ottaviano and Peri, 2012b) and innovativeness (Burchardi et al., 2020), job opportunities (Hong and McLaren, 2015), and investments (Burchardi et al., 2019). All of these contribute to the vibrancy and diversity of the local economy, which can boost home values. However, immigration can negatively affect natives by intensifying labor market competition (Card, 1990, 2001; Borjas, 2003) and overcrowding public services (Cnaan, 2002; Gould et al., 2009). Furthermore, animosity and prejudice may lead some to distance themselves from immigrants. These may induce "native flight" and drive home values down. Additionally, new to the area, immigrants may be more financially vulnerable than natives, and such instability may impose negative externalities on their neighbors. For example, Lin et al. (2016) document that immigrants are more likely to be delinquent on their mortgages, which could hurt neighborhood home values via spillover effects (Lin et al., 2009; Anenberg and Kung, 2014; Gerardi et al., 2015).

[1]See https://www.census.gov/quickfacts/fact/table/US/PST045222#PST045222 (accessed on April 21, 2023).

When empirically analyzing the effect of immigration on home values, a fundamental challenge is that immigration is endogenous. A positive correlation between an influx of foreign-born newcomers and rising house prices does not imply causation. It could simply be that immigrants choose to come to areas with strong growth and ample job opportunities, and economic growth induces both immigration and home value appreciation. In general, determinants of both immigration and house prices are numerous and cannot be exhaustively controlled. Therefore, it is difficult to pin down the causal effect of immigration on house prices. We overcome this challenge by employing the instrument, *immigration shock*, developed by Burchardi et al. (2019, 2020) to estimate the causal link between immigration and housing returns. Applying this county-level instrument for immigration, we document that, on average, a one percentage point increase in the share of immigrants (as a percentage of the local population) raises housing return by approximately 7 percent. Such an effect is both statistically and economically significant. Immigration turns out to be responsible for about one third of county-level housing returns over our sample period.

We also explore the impact of immigration on the spatial dispersion of house price appreciation, a largely overlooked effect. Within each county, we use zip-code house price movements to measure the spatial dispersion of housing returns. We find that, within a given county, immigration reduces housing return dispersion. Our estimates suggest that on average, a one percentage point increase in the share of immigrants reduces housing return dispersion (measured using the standard deviation of the zip-code level house price appreciation) by about 1.5 percentage points, suggesting that immigration reduces within-county return dispersion by about 20% over our sample period. Our findings point to a crucial distributive impact of immigration through the housing wealth channel. In contrast to the phenomenon that immigration tends to hurt low-skilled workers and, as a result, exacerbates income inequality, we show that immigration makes house price appreciation more evenly distributed within a county.

We additionally examine the heterogeneity of home price response to immigration across geographies, focusing on the role of local attitudes toward immigrants. For example, immigrant-friendly areas may have less "native flight". Additionally, feeling welcomed and supported, immigrants may better integrate into the community and contribute more to the local economy. Both are likely to increase home values in the area. In this study, we examine how the effect of immigration on housing returns varies with respect to natives' attitudes toward immigrants. While it is difficult to measure these directly, we employ three county-level population characteristics: 1) educational attainment, 2) age of the population, and 3) racial bias measured using the Implicit Association Test (IAT) scores. To rule out reverse causality, we measure the education and age of the local population using information predating our sample period, making them plausibly exogenous to subsequent immigration. We show that the effect of immigration on housing returns is strikingly heterogeneous across counties. Immigration boosts housing returns and limits its spatial dispersion *only* in counties with younger and more educated populations. Using the county-specific time-invariant component estimated from panel data of racial bias IAT scores, we obtain consistent results. These findings are corroborated by evidence from examining the effect of immigration on county population changes. We find that immigration significantly increases population size only in counties that are immigrant-friendly.

We make several contributions to the literature. First, applying a newly developed instrument for immigration, we provide new evidence supporting a causal link between immigration and local house price appreciation. In contrast to previous studies that use a standard shift-share instrument (Saiz, 2007; Ottaviano and Peri, 2012a; Sanchis-Guarner, 2023), the instrument we adopt addresses the concern that local ancestry (share) of immigrants may not be exogenous. Additionally, we are the first to look into the effect of immigration on the spatial dispersion of housing returns. By doing so, we shed light not only on how much house price appreciation is caused by immigration but also on how this additional wealth is spatially allocated. Our analysis reveals a distributive effect of immigration on housing wealth, which should be taken into consideration when formulating immigration policies. More broadly, our analysis contributes to the literature that studies the consequences of immigration. While much of the previous literature has been focused on immigrants' labor market impact on natives (e.g., wage and unemployment), our findings point to an asset valuation channel through which the well-being of natives is affected. In other words, immigration influences the value of both native workers' human capital and other assets of theirs such as housing.

We also contribute to the literature by documenting that the impact of immigration on housing returns is geographically heterogeneous and dependent on local residents' attitudes toward immigration. The effect of immigration on housing returns is neither unilaterally determined by immigration alone nor uniformly distributed to all places alike. Instead, we show that it is the interplay between local culture and immigration that determine housing returns. As a result, immigration-induced house price appreciation is available only in limited circumstances. For example, we show that immigration increases housing returns only in counties with a younger and more educated population and areas with less racial bias.

The remainder of our paper proceeds as follows: Section 2 provides a background on the related literature, Section 3 describes our data and empirical methodology, Section 4 presents empirical results, Section 5 conducts supplemental analyses examining the impact of immigration on the size of the local population, Section 6 discusses our findings, and Section 7 offers concluding remarks.

2 Literature Review

2.1 Housing market implications of immigration

There has been an extensive literature on the impact of immigration on housing markets; see Saiz (2007). However, establishing a causal relationship remains challenging due to the co-determination of housing prices and immigration location choices. Some studies exploit the impact of immigration on housing markets using large immigration shocks as natural experiments, such as the arrival of Cuban refugees (or "Mariel Boatlift") in 1980 (Saiz, 2003) and the suspension and closure of Canada's investor immigration program in 2012 (Pavlov and Somerville, 2020). However, these studies look at very large unexpected immigration shocks at a specific point in time and therefore the findings may not be generalizable.

Several studies aim to quantify the causal effects of immigration on housing market outcomes using shift-share (Bartik, 1991; Blanchard et al., 1992) instruments. However, there is a lack of consensus. On the one hand, some studies find a positive impact of immigration on house prices due to the increased demand caused by new arrivals. Ottaviano and Peri (2006) study a sample of 160 metropolitan statistical areas and find that, in those with an increased share of foreign-born, U.S. natives experience a significant increase in rents. Saiz (2007) finds that an immigration inflow of 1% of a city's population increases both housing rents and prices by about 1%. Ottaviano and Peri (2012a) find an elasticity of rents to immigration around 0.8 and an elasticity of housing prices around 2.3 in metropolitan areas. Sharpe (2019) improves on the traditional shift-share instrument approach by controlling for endogenous sorting of immigrants and finds a significantly attenuated but still positive effect of immigration on rental prices. Using Italian provincial-level data, Sanchis-Guarner (2023) argues that immigrants not only cause an immediate increase in housing demand but also induce natives to move into the same location. In particular, 10 additional immigrants attract 3 natives to relocate to the same province. On the other hand, using data at the local authority level from England and Wales, Sá (2015) finds a negative impact of immigration on house prices due to the "flight" of U.K. natives at the top of the wage distribution. Her estimated elasticity of housing prices to immigration is about -1.7.

Some studies also examine the regional heterogeneity of house price effects of immigration. Saiz and Wachter (2011) find that, within metropolitan areas, neighborhoods (i.e., census tracts) with a higher immigrant share have a relatively lower housing value appreciation. Causal channels include natives potentially having preferences for living with other natives, individuals of the same racial group, or individuals of high socioeconomic status. Similarly, using the district-level data from 20 Italian cities, Accetturo et al. (2014) find that, within cities, districts with a higher immigrant share have a lower house price relative to the city average due to the native flight effect. In particular, 10 additional immigrants induce 6 natives to relocate to other districts of the city.

2.2 Identifying exogenous immigration shocks

To obtain a causal inference, many immigration studies employ shift-share instruments (Bartik, 1991; Blanchard et al., 1992), which combine local shares and national shifts (two non-random sources of variation) to isolate a random (exogenous) component of an endogenous explanatory variable of interest. It has become a powerful tool for developing instrumental variables for causal inference and is widely used to isolate exogenous variation in market size (Acemoglu and Linn, 2004), trade reform (Kovak, 2013), import competition (Autor et al., 2013), fiscal stimulus (Wilson, 2012; Nakamura and Steinsson, 2014), humanitarian aid (Nunn and Qian, 2014), credit supply (Greenstone et al., 2020), labor market routine activities (Autor and Dorn, 2013), and industrial robotization (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020), etc; see Goldsmith-Pinkham et al. (2020) for an extensive literature review.

Jaeger et al. (2018) and Sharpe (2019) question the validity of such instruments in the study of immigration impacts, due to the existence of notable historic and persistent differences between high- and low-immigration destinations (Blanchard et al., 1992; Glaeser et al., 1995). To address this concern, instead of using past realized immigration or ancestry shares as the share factor, Burchardi et al. (2019, 2020) predict the pre-existing ancestry distribution, where the prediction is exogenous to characteristics of the destination U.S. county and bilateral factors of the origin country and destination U.S. county. This addresses the concern of Jaeger et al. (2018) and Sharpe (2019) that immigration location choices both in the present and the distant past may be correlated with unobserved local factors.

3 Data and Methodology

3.1 Data

Our study uses multiple datasets, which fall into three categories: 1) immigration, 2) local house prices, and 3) county characteristics. In this section, we describe the source of each dataset and explain how they are used in our analysis.

3.1.1 Immigration

Following Burchardi et al. (2020), we focus on non-European immigration given that our sample period starts in 1980. We obtain from the U.S. Census Bureau county-level data on non-European immigration and population. To match the frequency of the instrument that we adopt, we calculate immigration as the fraction of immigrants in a county's population (in percent) on a 5-year basis. Specifically, we have

$$Immigration^{i}_{t,t-5} = \frac{\#\, of\ Immigrants^{i}_{t,t-5}}{Population^{i}_{t-5}} \times 100, \tag{1}$$

where the immigration share of county i, $Immigration^{i}_{t,t-5}$, is calculated by dividing the number of non-European immigrants arrived in county i between years $t-5$ and t by the start-of-period population of the county (multiplied by 100).

To identify a causal relationship between immigration and house price appreciation, we apply the county-level instrument (Burchardi et al., 2019, 2020), *Immigration Shock*$^{i}_{t,t-5}$.[2] Here, we explain the intuition behind *Immigration Shock* and briefly outline the steps to construct it. A more detailed and technical description of the instrument can be found in the Appendix. To address the concern that pre-existing ancestries may be endogenous, Burchardi et al. (2019, 2020) develop a method to predict ancestries. The rationale is that at a given point in time, migration from a foreign country to a U.S. county depends on (i) a push factor, causing emigration from that foreign country to the entire U.S. (e.g., wars and political turmoil in the origin country or the economic and life-of-quality disparity between the origin country and the U.S.), and (ii) a pull factor, causing immigration from all origins going to a specific U.S. county (e.g., regional economic growth and labor market conditions). The interaction between the time-series variation in origin-specific push factor and destination-specific pull factor generates quasi-random variation in the allocation of migrants across U.S. counties. For example, we expect a large community of ancestry from India living in Fresno County, CA in 1980 if (i) many Indian immigrants moved to the U.S. in 1900, and it coincides with (ii) Fresno in 1900 was an attractive destination to all immigrants.

Combining this rationale above and a rigorous leave-out strategy, Burchardi et al. (2020) construct a county-level instrument for non-European immigration in two steps. First, following Burchardi et al. (2019), they predict the pre-existing foreign ancestry for each U.S. county using (i) the number of migrants arriving in the entire U.S. (excluding the region in which the destination county in question is located) from a given origin country starting in 1880 and (ii) the share of foreign migrants from European countries (where most of the immigrants come from before the 1980's) who settle in a given destination county.[3] Note that the leave-out strategy excludes the destination county and the foreign origin in question and the broad categories they belong. For example, when predicting foreign ancestries for Fresno County, CA, West Coast will be left out. Similarly, when predicting Indian ancestry, its broad category - non-European immigration - is excluded. By leaving out factors at the destination-county (and its region) level and the origin-country (and its broad category) level, the predicted ancestry does not suffer from the concern that immigrants from a particular origin may possess specific characteristics, which

[2] We obtain *Immigration Shock* from the authors' website: https://www.immigrationshock.com/immigration-shocks.

[3] "Region" refers to the nine US census divisions, which, on average, cover 5 adjacent states.

could make them endogenously chosen where to settle.

The second step applies the canonical shift-share approach by interacting the predicted pre-existing ancestry in a given destination county with current nationwide immigration from a given origin country and then summing up across foreign origins. Figure 1 plots the map of non-European immigration and immigration shock for the 2000-2005 and 2005-2010 periods.

[Figure 1 about here.]

3.1.2 Local house prices

To measure county-level house price appreciation as well as within-county dispersion of housing returns, we use house price indices at the county and zip-code levels. We obtain county-level house price index (HPI) from the Federal Housing Finance Agency (FHFA). This yearly constant-quality house price index is constructed using the repeated-sales method and is available for 2,402 U.S. counties since 1975 (Bogin et al., 2019a,b,c). We compute the five-year housing return (in percent) for county i as follows

$$Housing\ Return^{i}_{t,t-5} = (\log HPI^{i}_{t} - \log HPI^{i}_{t-5}) \times 100. \quad (2)$$

To construct the within-county dispersion of housing returns, we obtain house price indices at the zip-code level, also from the FHFA.[4] We first calculate, for each zip-code j within county i, the housing return over the same five-year period as for the county-level housing return. We then calculate the standard deviation of housing returns across zip codes within a given county.[5] Specifically, using all zip codes in county i we calculate within-county spatial dispersion of housing return as follows

$$Return\ Dispersion^{i}_{t,t-5} = Std.\ Dev.\ \left(Housing\ Return^{j(i)}_{t,t-5}\right). \quad (3)$$

Figure 2 plots the map of housing return and within-county dispersion for the last two five-year periods

[4]FHFA zip-code level house price indices start at different points in time across different zip codes, some much later than 1975. Therefore, relative to county-level house price appreciation, our sample is smaller when examining within-county housing return dispersion.

[5]We map zip codes to counties using the ZIP-COUNTY crosswalk files provided by the U.S. Department of Housing and Urban Development (HUD)'s Office of Policy Development and Research.

in our sample, with four colors representing the four quartiles.

[Figure 2 about here.]

3.1.3 County characteristics

To explore the heterogeneity of the effect of immigration on house prices across counties, we use an array of county characteristics to proxy for natives' attitudes toward immigrants. We obtain county-level data on educational attainment for adults age 25 and older and the age of population from the 1980 U.S. Census. To measure implicit racial bias, we use data from Project Implicit.[6] It collects data from millions of respondents on the Implicit Association Test (IAT), which has been widely adopted in sociology and psychology research to capture implicit racial bias.

Our final sample covers 2,402 U.S. counties across 50 states and the District of Columbia. Summary statistics are presented in Table 1. Over our sample period, the average five-year housing return is 17.274 percent, with a maximum of 48.799 percent over the 1975-1980 period and a minimum of 1.306 percent over the 2005-2010 period. The dispersion of zip-code level housing returns within a county is relatively stable over time, with an average of 5.202 percent. Immigration accounts for 0.818 percent of a county's population on average, with a maximum of 0.965 percent over the 1995-2000 period and a minimum of 0.482 over the 2005-2010 period.

[Table 1 about here.]

3.2 Empirical methodology

Our baseline regression takes the following form:

$$Y^i_{t,t-5} = \alpha + \beta \cdot Immigration^i_{t,t-5} + \lambda_t + \mu^i + \epsilon^i_t, \tag{4}$$

where the dependent variable $Y^i_{t,t-5}$ is either $Housing\ Return^i_{t,t-5}$ or $Return\ Dispersion^i_{t,t-5}$, λ_t denotes year fixed effects, μ_i denotes county fixed effects, and ϵ^i_t is the idiosyncratic error. We begin by estimating Equation (4) using the conventional fixed-effects (FE) estimator, which allows us to first look into the

[6] See https://www.projectimplicit.net/

association between immigration and housing returns. To further test causality, we apply the fixed effects instrumental variables (FE-IV) estimator with *Immigration* being instrumented by the *Immigration Shock*. A sufficient condition for *Immigration Shock* to be a valid instrument is that any confounding factors that drive house price appreciation in a given U.S. county post-1975 do not systematically correlate with pre-1975 immigration from a given origin to other regions within the U.S. interacted with the simultaneous settlement of European migrants in that U.S. destination. If such a condition is satisfied, the predicted immigration using *Immigration Shock* is exogenous. We believe this assumption is plausible. To violate it, the confounding factor would have to, before 1975, systematically attract European immigrants to a particular U.S. county while simultaneously attracting a large number of non-European immigrants to other U.S. counties outside the area. Additionally, this factor must also be an important determinant of housing return and its dispersion after 1975.

Following Burchardi et al. (2020), we estimate Equation (4) with year and county fixed effects. Our FE estimates, admittedly, are susceptible to reverse causation problems (e.g., immigrants tend to move to counties with higher or lower housing returns and return dispersions) and omitted variable biases (e.g., local housing demand and supply conditions and other unobservables). As in Burchardi et al. (2020), we circumvent these issues using *Immigration Shock* to estimate the causal impact of immigration. Assuming our identifying assumption is valid, our FE-IV parameter estimates, even in the presence of omitted confounding factors, are consistent because any confounding factors that drive a U.S. county's post-1975 housing returns and return dispersions are orthogonal to our *predicted* immigration using the immigration shock.

4 Empirical Results

4.1 Overall impact of immigration on housing markets

Table 2 presents the FE and FE-IV estimation results. Our fixed-effects estimates suggest that immigration equal to 1% of a county's population is associated with a significant increase in housing return of 5.901 percentage points. Also, our point estimate indicates a negative but insignificant association between immigration and return dispersion. When immigration is instrumented by the *Immigration Shock*, our FE-IV estimates suggest that an immigration inflow equal to 1% of a county's population causes a significant increase in housing return by 6.933 percentage points.[7] Additionally, immigration equal to 1% of a county's population reduces the within-county dispersion by 1.555 percentage points. Our findings are both statistically and economically significant. Given that the five-year immigration is, on average, 0.818% of a county's population, these estimates suggest about one-third of county-level housing returns over our sample period are attributable to immigration. The impact of immigration on the spatial dispersion of housing return is also quite substantial. Without immigration, the dispersion of housing returns within a county would have been higher by 1.272 percentage points, suggesting that immigration reduces within-county return dispersion by approximately 20 percent.

[Table 2 about here.]

4.2 Heterogeneous effects by educational attainment

Previous literature almost unequivocally finds an association between higher educational attainment and pro-immigration attitudes. In a meta-analysis of the determinants of attitude toward immigration, Dražanová (2022) reports that out of a sample of 31 studies that examine education, 27 find that more educated individuals are less anti-immigration. Four other studies find an insignificant effect, and not a single one shows the opposite. This association may be due to different exposures to labor market competition from immigrants (Scheve and Slaughter, 2001; Mayda, 2006). In particular, less-educated native workers fear being forced to compete for jobs with low-skilled immigrants willing to work for lower wages, and this may explain why less-educated natives are more anti-immigration. Other studies argue that education fosters "educated preferences", such as cultural values (Hainmueller and Hiscox, 2007) and social trust (Margaryan et al., 2021), which shape attitudes toward immigration beyond just pure self-interest. Regardless of why more education is linked to the pro-immigrants attitude, the strong association between the two gives confidence that education attainment is a valid proxy for immigrant-friendliness.

We use the percentage of adults in a county with a high school diploma or higher in 1980 to measure a county's educational attainment. We classify a county's educational attainment as low if the percentage of adults with a high school diploma or higher in 1980 is in the bottom 50 percent and high if

[7]The last column of Table 2 also presents the first-stage regression. The immigration shock has a significantly positive impact on the endogenous variable immigration with a t-statistic of 10.55, which suggests that the immigration shock is not a weak instrument.

the percentage is in the top 50 percent. Figure 3 plots the map of U.S. counties by their educational attainment.

[Figure 3 about here.]

Regression results presented in Table 3 suggest that an immigration inflow significantly stimulates the housing return and reduces within-county dispersion in counties with high educational attainment. In counties with low educational attainment, immigration does not have any significant impact on the housing return or within-county dispersion. In particular, an immigration inflow equal to 1% of a county's population causes a significant increase in housing return by 7.111 percentage points and a significant decrease in within-county dispersion by 1.711 percentage points in counties with high educational attainment. In counties with low educational attainment, however, these values are 0.829 and 0.306, and both statistically insignificant.

[Table 3 about here.]

4.3 Heterogeneous effects by the share of young population

Attitudes toward immigration also correlate with age and/or generation cohorts. According to a survey conducted by the Pew Research Center in 2016, respondents from younger generations report a more favorable view of immigrants than their older counterparts. Respondents are asked whether immigrants in the U.S. "strengthen our country because of their hard work and talents," or whether they "are a burden on our country because they take our jobs, housing, and health care." 76% of Millennials (born after 1980) held the former, more favorable, view of immigrants. In stark contrast, only 48% of Baby Boomers (born 1946-1964) and 41% of those in the Silent Generation (born in 1928-1945) agreed with such an assessment.[8] Additionally, looking at the effect of age on attitudes toward immigration, Dražanová (2022) finds 18 published studies indicating that older people are more anti-immigration, while only one finds the opposite. Therefore, we use the age of the local population as a proxy of natives' attitudes toward immigration, and we hypothesize that counties with a younger population are more immigrants-friendly.

[8]See https://www.pewresearch.org/short-reads/2016/04/15/americans-views-of-immigrants-marked-by-widening-partisan-generational-divides/ (accessed on April 27, 2023).

To explore the heterogeneous effects across age groups, we use the percent of population under age 65 as the share of young population. We classify a county's young population as low if the share of young population is in the bottom 50 percent and high if the share is in the top 50 percent. Figure 4 plots the map of U.S. counties by their share of young population.

[Figure 4 about here.]

Regression results in Table 4 suggest that the stimulating effects of immigration on housing returns are only significant in counties with a high percentage of young population. In particular, an immigration inflow equal to 1% of a county's population causes a significant increase in housing return by 7.475 percentage points and a significant decrease in within-county dispersion by 1.676 percentage points in counties with a larger share of young population. In counties with a smaller share of young population, however, these values are -1.732 and -0.143, and both statistically insignificant.

[Table 4 about here.]

4.4 Heterogeneous effects by local racial bias

Intertwined with immigration is the issue of race and ethnicity. Prior to the passage of the 1965 Immigration and Naturalization Act, immigrants to the United States were mostly from European counties and predominantly non-Hispanic whites. Since 1965, the regions of origin of immigrant population have shifted dramatically. The share (and the number) of immigrants from Mexico, Asia, and the rest of the Latin American countries increased rapidly. According to the Pew Research Center, in 2018, immigrants from Mexico (25%), Asia (28%), and other Latin American countries (25%) each account for approximately a quarter of the U.S. foreign-born population, rising from respectively from 6%, 3%, and 4% from about half a century ago. In other words, the 1965 Immigration and Naturalization Act not only ushered in a new era of immigration but also created a natural divide between immigrants and natives along racial and ethnic lines (i.e., non-Hispanic whites versus minorities). Given immigrants during our sample period are mostly racial minorities, it is reasonable to think that racial prejudice may be associated with anti-immigrant sentiments.

We measure implicit racial bias at the county level using the Race Implicit Association Test (IAT) scores. The IAT is based on the idea that we make connections more quickly between pairs of ideas that are already related (e.g., flower + pleasant) in our minds than we do between pairs of ideas that are unfamiliar to us (e.g., insect + pleasant). The race IAT test measures the strength of associations between racial categories (e.g., European American versus African American) with evaluations (e.g., good versus bad), and a larger value on the IAT measure reflects a greater racial bias in favor of European American over African American.

We retrieve the time-invariant county-specific component of IAT to measure county-level racial bias. In particular, we first average the IAT scores across white respondents within each county and for each year between 2004 and 2020. We then run a panel data regression of the average IAT score against two-way fixed effects and use the estimates of county fixed effects as the measure of county-level racial bias, which does not change over time. We classify a county's racial bias as high if its racial bias measure is in the top 50 percent and low if the measure is in the bottom 50 percent. Figure 5 plots the map of U.S. counties by racial bias.

[Figure 5 about here.]

Regression results in Table 5 suggest that the stimulating effects of immigration on housing returns are only significant in counties with low racial bias. In particular, an immigration inflow equal to 1% of a county's population causes a significant increase in housing return by 6.982 percentage points and a significant decrease in within-county dispersion by 1.588 percentage points in counties with low racial bias. In counties with high racial bias, however, these values are -0.776 and -0.562, and both are statistically insignificant.

[Table 5 about here.]

5 Effects of immigration on population change

In this section, we supplement our main analysis by examining the impact of immigration on the changes in the local population. By doing so, we achieve two important purposes. First, population changes induced by immigration have been identified as a crucial driver of house prices (Sanchis-Guarner, 2023). Immigration by itself increases the local population. Additionally, the influx of immigrants may either attract or displace natives. Using immigration shock as an instrument, we provide new causal evidence on how immigration shifts the local population. Furthermore, similar to housing return and its spatial dispersion, how the local population responds to immigration should also depend on the attitudes of local residents toward immigrants. Examining the responsiveness of the local population to immigration and how it may vary with respect to county characteristics provides new insights into why local culture may affect housing returns. Define population changes as $\frac{\Delta Population^i_{t,t-5}}{Population^i_{t-5}}$, we can estimate the following regression

$$\frac{\Delta Population^i_{t,t-5}}{Population^i_{t-5}} = \gamma + \delta \cdot Immigration^i_{t,t-5} + \lambda_t + \mu^i + \epsilon^i_t. \tag{5}$$

A smaller δ, *ceteris paribus*, indicates that immigration causes a greater exodus of natives, which possibly reflects a more anti-immigration attitude. Therefore, we expect δ to be significantly larger in counties with a younger and more educated population and areas with lower racial bias.

We present the results in Table 6. Overall, an immigration inflow of 1% of a county's population causes an increase in the county's total population by 0.278%, and this effect is not statistically significant; see Column (1). This result suggests that immigration leads to native flight, which almost offsets the effect of immigration to the point that the elasticity of population change to immigration is close to zero. Column (2) shows that immigration has a larger effect on population change in counties with high educational attainment, as defined in Section 4.2, with an elasticity of 0.322. However, this effect remains statistically insignificant. In Column (3), the elasticity is found to be close to 0.6 and statistically significant in counties with high share of young population (as defined in Section 4.3). In counties with low racial bias, as defined in Section 4.4, the elasticity of population change to immigration is estimated to be 0.45 and statistically significant; see Column (4). Together, these results are in line with our expectations. In general, immigration leads to native flight, even in counties that are friendly to immigrants. The magnitude of native flight, however, depends on the immigrant-friendliness of a county. Immigration significantly increases the population size in counties more friendly to immigrants but has no significant impact in counties that are less friendly.

[Table 6 about here.]

6 Discussion of the results

In this section, we synthesize our housing return and population results and discuss the implications of our findings. First, we find that immigration increases housing return only in more immigrant-friendly counties. This suggests that, in less friendly areas, immigrants are more likely viewed as negative amenities, which causes more natives to relocate to a different county. Inter-county native flight counterbalances the additional housing demand from immigrants. As a result, house prices appreciate less in these counties relative to the immigrant-friendly ones. Directly measuring the magnitude of inter-county flight, our population results tell a consistent story. We document a greater elasticity to population change in immigrant-friendly counties.

Additionally, native flights can take place at the inter-county as well as intra-county levels. In other words, when immigrants arrive, some natives relocate to a different county (i.e., inter-county flight), and some others move to a different zip code within the same county (i.e., intra-county flight). While the former affects county-level housing returns, our housing return dispersion results could be driven by intra-county native flight. For example, immigrants arrive at low-appreciation zip codes and increase housing demand in those places. In immigrant-friendly areas, natives are less likely to fly from those zip codes to other high-appreciation zip codes. As a result, the additional demand from immigrants is mostly capitalized into prices in the immigrant-receiving zip codes, and this equalizes housing returns across zip codes. In contrast, in less friendly counties, the additional demand from immigrants is more likely to be counterbalanced by natives moving to high-appreciation zip codes. This explains why housing return dispersion in unfriendly areas remains mostly unchanged.

7 Conclusion

In this study, we analyze the effect of immigration on house prices. Applying a county-level instrument for non-European immigration, we find that immigration increases local house price appreciation and decreases its within-county spatial dispersion. Our estimates suggest that on average, a one percentage point increase in the immigrant share of the local population raises house price appreciation by approximately 7 percent (about 40% of the average 5-year housing return) and reduces the dispersion of housing return within a county by 1.5 percentage points (about 30% of the average 5-year housing return dispersion).

We also show that such effects are strikingly heterogeneous across counties and appear to be determined by local culture. Using several proxies for attitudes toward immigration, we find that immigration boosts housing returns and limits its spatial dispersion *only* in counties with residents who are younger, more educated, and less racially biased. Our findings highlight the effect of immigration on home values (or the lack thereof) is highly contingent on natives' attitudes toward immigrants.

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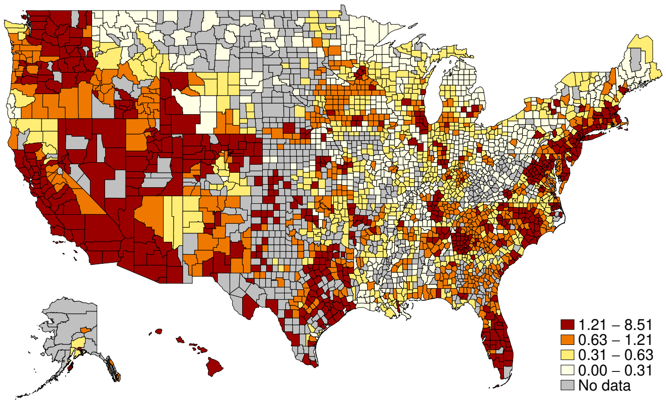
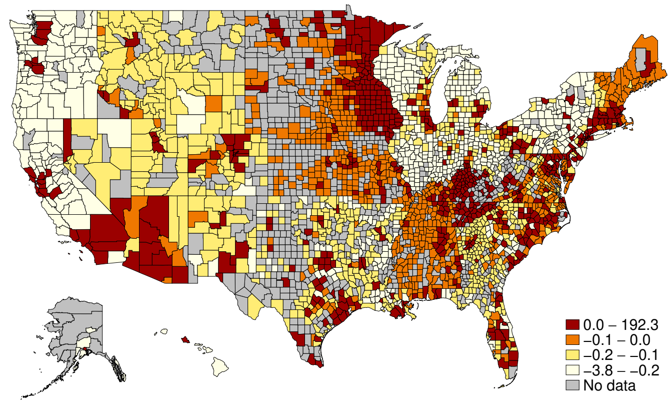
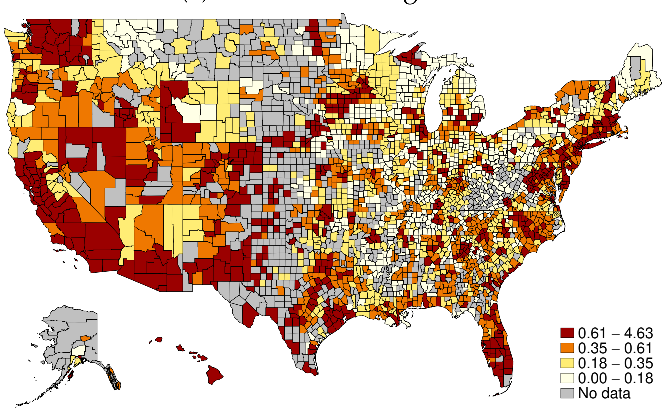


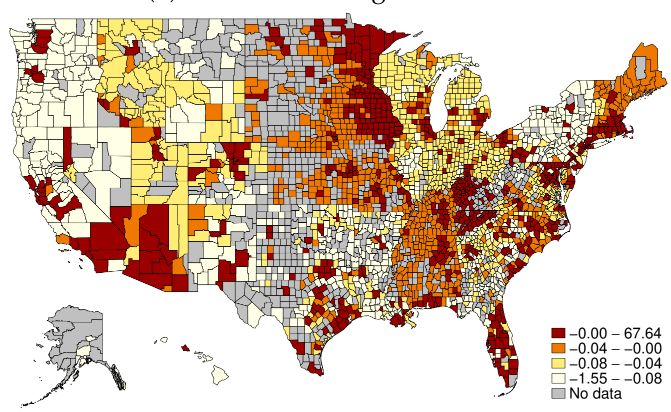
(a) 2000-2005 immigration



(b) 2000-2005 immigration shock

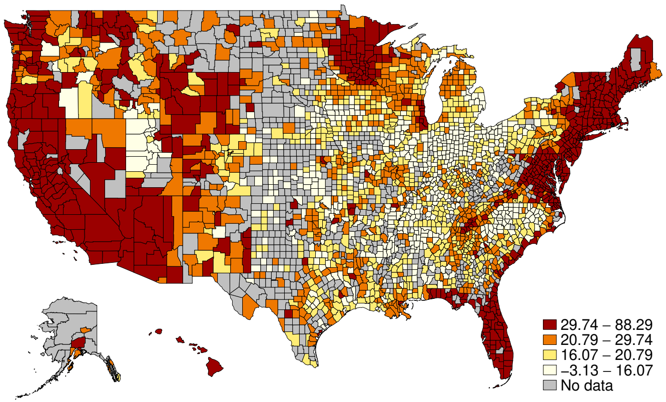


(c) 2005-2010 immigration

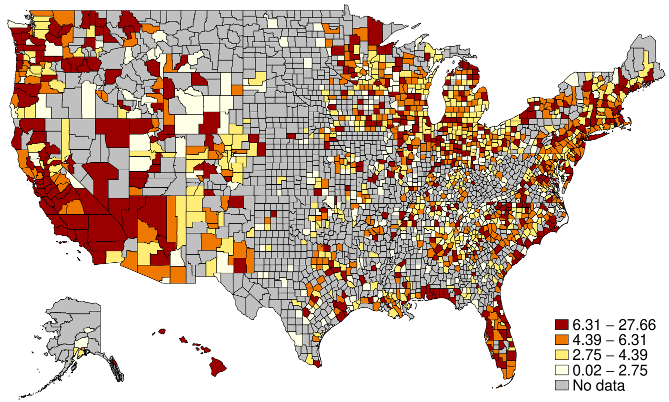


(d) 2005-2010 immigration shock

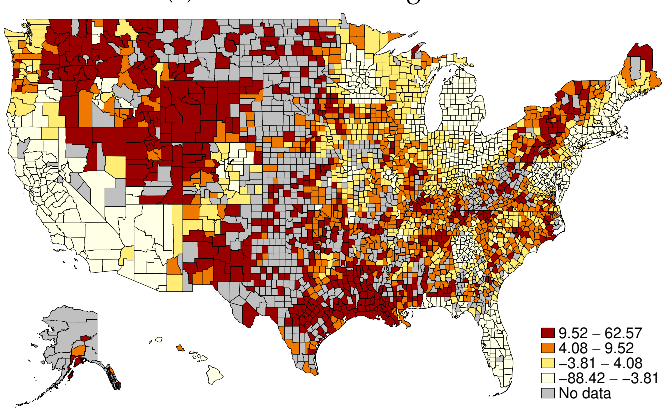
Figure 1: U.S. map of county-level non-European immigration and immigration shock



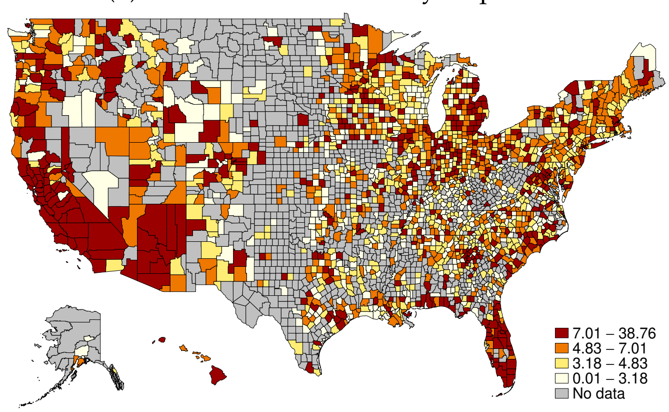
(a) 2000-2005 housing return



(b) 2000-2005 within-county dispersion



(c) 2005-2010 housing return



(d) 2005-2010 within-county dispersion

Figure 2: U.S. map of county-level housing return and within-county dispersion

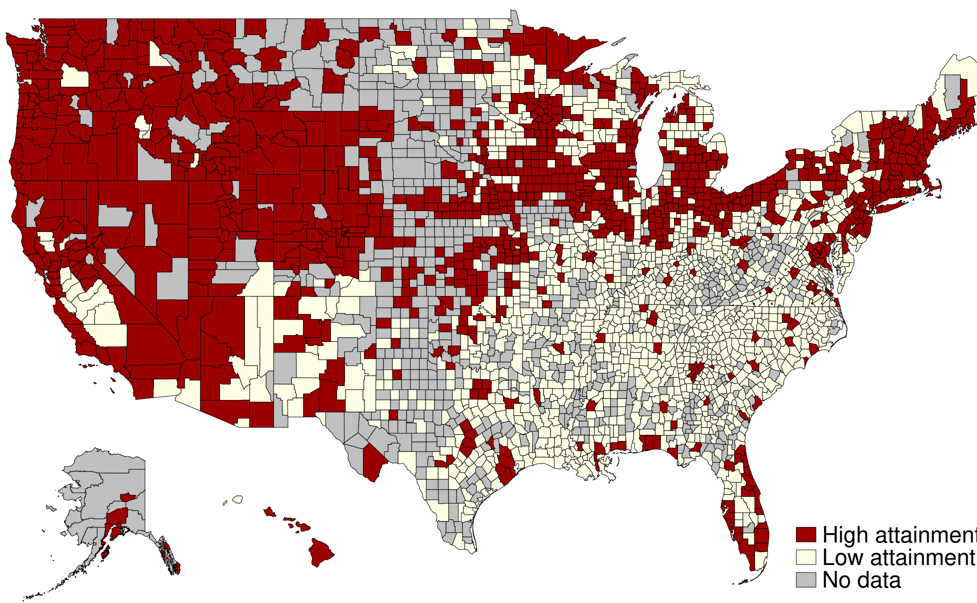


Figure 3: U.S. map of educational attainment

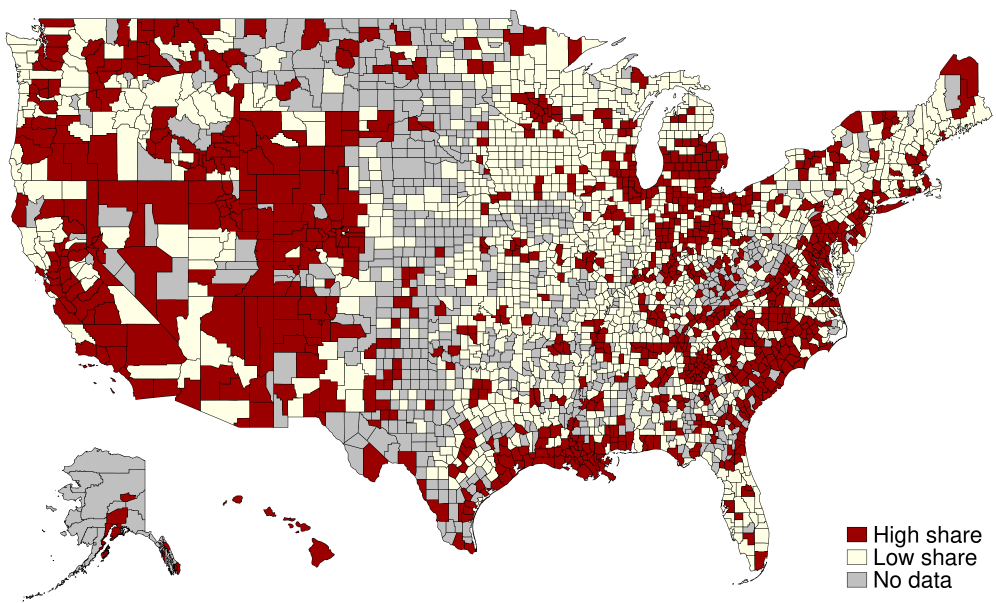


Figure 4: U.S. map of the share of young population

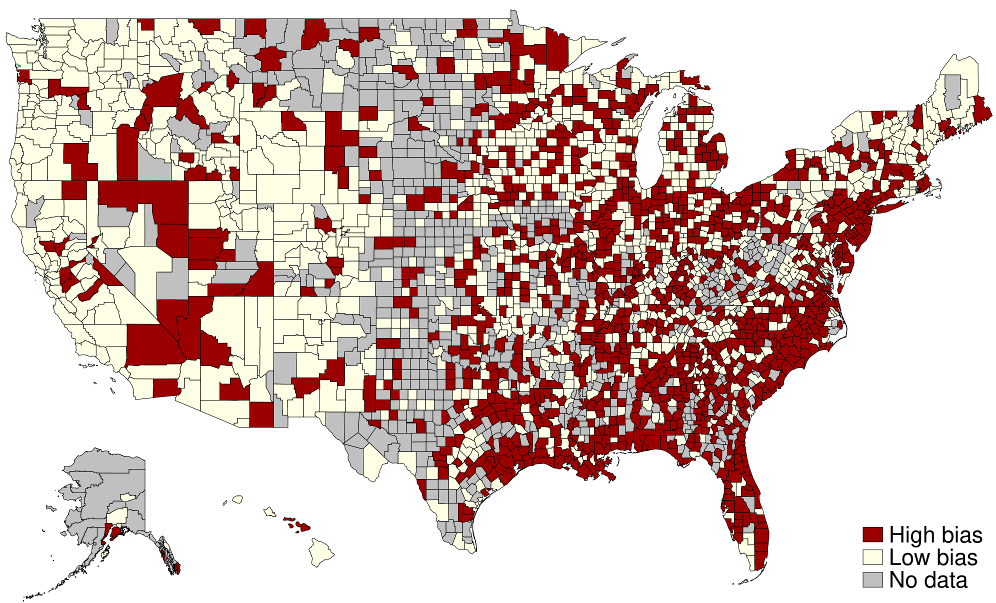


Figure 5: U.S. map of racial bias

Table 1: Summary statistics

	Year	Obs	Mean	Std Dev
Housing return	1980	407	48.799	14.960
	1985	869	15.451	15.292
	1990	1069	18.349	18.139
	1995	1437	17.517	13.013
	2000	2034	20.017	8.296
	2005	2402	25.615	15.102
	2010	2402	1.306	14.412
	All	10620	17.274	17.570
Within-county dispersion	1980	112	5.653	3.834
	1985	474	6.848	4.145
	1990	601	5.057	2.944
	1995	849	4.665	2.742
	2000	1268	4.931	3.002
	2005	1624	4.857	3.022
	2010	1956	5.517	3.575
	All	6884	5.202	3.292
Immigration	1980	404	0.889	1.039
	1985	865	0.740	1.106
	1990	1067	0.854	1.205
	1995	1435	0.952	1.189
	2000	2032	0.965	1.145
	2005	2400	0.949	1.009
	2010	2400	0.482	0.470
	All	10603	0.818	1.023
Immigration shock	1980	406	1.846	13.670
	1985	867	0.539	8.670
	1990	1067	0.721	12.862
	1995	1435	0.235	7.725
	2000	2032	0.119	6.459
	2005	2400	0.059	4.348
	2010	2400	0.028	1.557
	All	10607	0.262	7.137

Housing return is the log difference between the FHFA housing price index of a county and its 5-year lagged value, multiplied by 100. Within-county dispersion is the standard deviation of zip-code level housing returns (defined similarly as the county-level housing returns) over the same five-year period within each county. Immigration is the number of non-European immigration inflow over the same five-year period, divided by the start-of-period population of the county, and then 100. Immigration shock is calculated by Burchardi et al. (2019, 2020).

Table 2: Overall impact of immigration on housing markets

	DV: County housing return		DV: Within-county dispersion		
	FE	FE-IV	FE	FE-IV	First Stage
Immigration	5.901***	6.933***	-0.559	-1.555***	
	(3.94)	(3.85)	(-1.86)	(-11.30)	
Year=1985	-33.63***	-33.83***	2.311***	2.593***	0.203**
	(-9.16)	(-9.53)	(4.68)	(5.27)	(3.03)
Year=1990	-32.02***	-32.44***	0.791	1.322*	0.404***
	(-8.49)	(-9.23)	(1.14)	(2.05)	(5.41)
Year=1995	-34.39***	-35.04***	0.652	1.441*	0.638***
	(-9.04)	(-12.01)	(0.81)	(2.10)	(7.17)
Year=2000	-32.74***	-33.51***	1.122	2.027**	0.759***
	(-10.39)	(-13.68)	(1.31)	(2.90)	(7.54)
Year=2005	-27.44***	-28.25***	1.151	2.083**	0.790***
	(-10.13)	(-10.65)	(1.25)	(2.79)	(7.58)
Year=2010	-48.97***	-49.29***	1.486	1.873*	0.325***
	(-13.73)	(-15.33)	(1.66)	(2.42)	(3.87)
Immigration shock					0.0277***
					(10.55)
Constant	46.63***	46.34***	4.512***	4.781***	0.269**
	(20.05)	(17.73)	(7.29)	(7.05)	(3.40)
Observations	10603	10603	6871	6871	10603
Adjusted R^2	0.401		0.050		0.241

All regressions include county fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Heterogeneous effects by educational attainment

	DV: County housing return		DV: Within-county dispersion	
	Low attainment	High attainment	Low attainment	High attainment
Immigration	0.829	7.111***	0.306	-1.711***
	(0.05)	(4.31)	(0.26)	(-12.86)
Year=1985	-29.59***	-34.86***	3.565***	2.221***
	(-6.51)	(-9.22)	(4.16)	(4.13)
Year=1990	-30.58***	-31.91***	1.578	1.245
	(-4.98)	(-9.84)	(1.91)	(1.86)
Year=1995	-30.13***	-35.27***	0.990	1.478*
	(-3.65)	(-11.27)	(0.92)	(2.14)
Year=2000	-26.64**	-34.95***	1.409	2.155**
	(-2.65)	(-14.28)	(1.36)	(3.10)
Year=2005	-23.22*	-26.67***	1.576	2.006**
	(-2.00)	(-9.59)	(1.48)	(2.78)
Year=2010	-43.04***	-52.55***	2.249**	1.728*
	(-7.45)	(-15.44)	(2.90)	(2.04)
Constant	45.56***	46.35***	2.873***	5.494***
	(10.46)	(16.66)	(3.42)	(7.43)
Observations	5285	5273	3055	3778

All regressions include county fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Heterogeneous effects by the share of young population

	DV: County housing return		DV: Within-county dispersion	
	Low share	High share	Low share	High share
Immigration	-1.732	7.475***	-0.143	-1.676***
	(-0.28)	(4.41)	(-0.16)	(-11.44)
Year=1985	-26.68***	-35.26***	2.141	2.554***
	(-5.61)	(-10.98)	(1.66)	(4.52)
Year=1990	-21.97***	-34.84***	-0.159	1.501*
	(-4.66)	(-9.92)	(-0.11)	(2.33)
Year=1995	-23.72***	-36.86***	-0.211	1.602*
	(-6.67)	(-11.61)	(-0.12)	(2.39)
Year=2000	-20.41***	-36.40***	0.120	2.288**
	(-4.78)	(-15.70)	(0.07)	(3.23)
Year=2005	-16.42**	-29.34***	0.190	2.331**
	(-3.15)	(-13.20)	(0.10)	(3.07)
Year=2010	-38.87***	-52.23***	0.590	2.020*
	(-11.39)	(-15.48)	(0.39)	(2.40)
Constant	42.23***	46.55***	5.179***	4.819***
	(11.84)	(17.13)	(4.87)	(6.24)
Observations	5300	5297	2991	3875

All regressions include county fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Heterogeneous effects by racial bias

	DV: County housing return		DV: Within-county dispersion	
	High bias	Low bias	High bias	Low bias
Immigration	-0.776	6.982***	-0.562	-1.588***
	(-0.01)	(5.03)	(-0.12)	(-13.66)
Year=1985	-24.98	-39.66***	2.277	2.445***
	(-0.58)	(-10.00)	(0.97)	(5.57)
Year=1990	-24.36	-36.61***	0.121	1.824***
	(-0.39)	(-10.74)	(0.04)	(3.31)
Year=1995	-26.94	-37.31***	-0.0438	1.944***
	(-0.27)	(-9.02)	(-0.01)	(3.54)
Year=2000	-22.95	-37.30***	0.451	2.495***
	(-0.19)	(-13.19)	(0.09)	(4.26)
Year=2005	-18.25	-30.92***	0.588	2.367***
	(-0.14)	(-13.76)	(0.11)	(3.66)
Year=2010	-42.03	-52.56***	0.752	2.274**
	(-0.63)	(-13.06)	(0.24)	(2.83)
Constant	43.34**	49.46***	4.952***	4.767***
	(2.80)	(16.20)	(5.77)	(7.27)
Observations	5308	5289	3418	3447

All regressions include county fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Effects of immigration on population change

	(1) Overall	(2) High attainment	(3) High share	(4) Low bias
Immigration	0.278	0.322	0.598**	0.450**
	(0.71)	(1.00)	(2.68)	(2.83)
Year=1985	-2.127***	-2.669***	-2.755***	-2.792**
	(-3.40)	(-3.63)	(-4.18)	(-3.14)
Year=1990	-2.863**	-2.901***	-3.449***	-3.584***
	(-3.16)	(-3.33)	(-3.38)	(-3.90)
Year=1995	-1.575*	-1.860*	-2.047**	-1.792*
	(-2.01)	(-2.23)	(-3.06)	(-2.31)
Year=2000	-1.042	-1.788*	-1.692*	-1.540
	(-1.32)	(-2.19)	(-2.29)	(-1.89)
Year=2005	-4.397***	-4.776***	-4.665***	-5.009***
	(-5.29)	(-5.32)	(-6.05)	(-5.92)
Year=2010	-4.326***	-5.097***	-5.509***	-4.699***
	(-5.06)	(-5.16)	(-7.64)	(-5.13)
Constant	7.485***	8.292***	9.360***	7.623***
	(11.60)	(12.06)	(16.32)	(10.56)
Observations	10603	5273	5297	5289

Column (1) presents the overall effect of immigration on a county's population change, where both immigration and population change are measured as a percentage of the county's start-of-period population. Columns (2) to (4) present the effects in counties with high educational attainment, high share of young population, and with low racial bias, respectively. All regressions include county fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix: Immigration shock

We briefly describe the immigration shock constructed by Burchardi et al. (2019, 2020) here following their notations. Please refer to these two papers for details. Their immigration and ancestry data are obtained from the Integrated Public Use Microdata Series (IPUMS) samples of the 1880, 1900, 1910, 1920, 1930, 1970, 1980, 1990, and 2000 waves of the U.S. Census, and the 2006-2010 five-year sample of the American Community Survey. The dataset cover 3,141 U.S. counties, 195 foreign countries, and 10 census waves.

Let $A_{o,d,t}$ denote the number of residents with ancestry from o who reside in d at t, where o is a foreign origin country and d is a destination U.S. county. Burchardi et al. (2019) propose to identify variations in $A_{o,d,t}$ that are exogenous to both d-specific local factors and (o, d)-specific bilateral factors, using the following regression:

$$A_{o,d,t} = \delta_{o,r(d)} + \delta_{c(o),d} + \delta_t + X'_{o,d}\zeta + \sum_{\tau=1880}^{t} a_{r(d),\tau} \left(I_{o,-r(d),\tau} \frac{I_{Europe,d,\tau}}{I_{Europe,\tau}} \right) + v_{o,d,t}, \tag{A1}$$

where $r(d)$ denotes the region (i.e., census division) of the destination county and $c(o)$ denotes the continent of the origin country.

In Equation (A1), the first three terms on the right-hand side denote the origin country $\times$ destination region fixed effects, the origin continent $\times$ destination county fixed effects, and the time fixed effects. The $X_{o,d}$ variables include a series of time-invariant controls for the (o, d) bilateral characteristics. $I_{o,-r(d),\tau}$ is the total number of migrants arriving from o at time τ who settle in counties outside the region where d is located. Similarly, $I_{Europe,d,\tau}$ is the number of migrants arriving from Europe at time τ who settle in the county d and $I_{Europe,\tau}$ is the total number of migrants arriving from Europe at time τ.

Estimating Equation (A1) for each $t = 1980, 1985, ..., 2010$ separately using all non-European origin countries gives parameter estimates $\widehat{a}_{r(d),\tau}$. The predicted ancestry is then constructed as:

$$\widehat{A}_{o,d,t} = \sum_{\tau=1880}^{t} \widehat{a}_{r(d),\tau} \left(I_{o,-r(d),\tau} \frac{I_{Europe,d,\tau}}{I_{Europe,\tau}} \right)^{\perp}, \tag{A2}$$

where $\perp$ means that the interaction term in parentheses is residualized with respect to all of the controls in Equation (A1).

Given the predicted ancestry, Burchardi et al. (2020) apply the shift-share approach to isolate exogenous immigration shocks through the following regression:

$$I_{o,d,t} = \delta_{o,r(d)} + \delta_{c(o),d} + \delta_t + X'_{o,d}\theta + b_t \left[\widehat{A}_{o,d,t-1} \times \left(I_{o,-r(d),t} \frac{I_{Europe,r(d),t}}{I_{Europe,-r(d),t}} \right) \right] + u_{o,d,t}, \tag{A3}$$

where $\widehat{A}_{o,d,t-1}$ is the lagged predicted ancestry.

The immigration shock is constructed as the predicted immigration inflows, added up across foreign origins, i.e.,

$$\widehat{I}_{d,t} = \sum_o \widehat{b}_t \left[\widehat{A}_{o,d,t-1} \times \left(I_{o,-r(d),t} \frac{I_{Europe,r(d),t}}{I_{Europe,-r(d),t}} \right) \right]. \tag{A4}$$

When predicting the immigration flows, Burchardi et al. (2020) choose not to use the realized number of residents with ancestry from o who reside in d ($A_{o,d,t-1}$) but the predicted number ($\widehat{A}_{o,d,t-1}$), because where migrants settle within the U.S. may be correlated with unobserved factors that also affect local economies. The predicted number $\widehat{A}_{o,d,t-1}$ is orthogonal to both d-specific local factors and (o, d)-specific bilateral factors.

Taking India as the origin country o and Fresno county as the destination d, the instrument in Equation (A4) predicts a large immigration shock to Fresno county at $t = 1980, 1985, ..., 2010$ if (1) many Indians migrate to the U.S. at t to settle down in Census divisions other than the Pacific or (2) there is a large predicted pre-existing community of Indian ancestry in Fresno county. The latter is because Fresno is an attractive destination for all migrants (proxied by European migrants) in the distant past, at a time of large Indian migrations to other Census divisions of the U.S. than the Pacific.