Lost connections, lost opportunities: The impacts of immigration on social capital and local income*

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Abstract

This paper examines the impacts of immigration on social capital and local labor market outcomes. We use the economic connectedness measures provided by the Social Capital Index data, which captures the extent to which individuals have access to economic opportunities through networks and community ties. Using a fixed effects instrumental variable approach with shift-share instrumental variables that exploits historical immigration patterns, we find that areas with higher immigration shares exhibit weaker economic connectedness between individuals of low and high socioeconomic statuses. Additionally, an increase in the immigration share in an area significantly reduces the average income of non-college graduate workers, affecting both native-born and foreign-born populations. The decline in economic connectedness following increased immigration in an area may be a potential mechanism underlying this decrease in the average income. These findings suggest that policies fostering greater economic connectedness in regions experiencing rising immigration could help mitigate the negative economic impacts of immigration on low-skilled workers.

JEL Classification: J61, J15, R23, R12

Keywords: Social capital, economic connectedness, immigration, local income, heterogeneity analysis

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1 Introduction

Immigration has long been a driving force in transforming the economic, social, and cultural environments of nations around the globe. As immigrant populations grow, their impacts on local economies (Borjas, 2003; Peri, 2016; Jaeger et al., 2018) and social interactions becomes more apparent. Immigrants not only contribute to the workforce but also influence relationships and connections within communities. Social capital, defined as the networks and connections among individuals, plays an important role in local economies (Jackson et al., 2017) and how people access opportunities (Granovetter, 1973). This paper examines the relationship between immigration, social capital, and local income, focusing on how changes in social connections caused by the arrival of immigrants affect economic outcomes.

To examine whether immigration has a significant impact on social capital, we use the Social Capital Index (SCI) data, which are derived from Facebook social networks by Chetty et al. (2022a,b). The SCI data provide comprehensive measures of social capital across U.S. counties in three dimensions: economic connectedness (EC), cohesiveness, and civic engagement. In this paper, we focus on EC, which measures the extent to which individuals have access to economic opportunities through their networks and community ties, particularly those involving connections with individuals from high socioeconomic status (SES) backgrounds.[1] EC is decomposed into "exposure to high SES" and "friending bias" (Chetty et al., 2022b). Exposure to high SES measures the potential opportunity to connect with high-SES individuals, regardless of whether those connections are actually formed, while friending bias captures the tendency to form friendships with high-SES people.

We combine the county-level EC data with the American Community Survey (ACS) to construct county-level immigration shares. To address potential reverse causality stemming from the endogeneity between immigrants' countries of origin and choice of destination, we employ a shift-share instrumental variable (IV) approach, following Bartik (1991). We utilize arguably exogenous variations in the composition of immigrants' countries of origin, particularly during three key historical decades: the 1910s (World War I), the 1920s (the Quota Acts of 1921 and 1924), and the 1960s (the Quota Acts of 1965). These historical periods are selected based on prior literature (Jaeger et al., 2018; Tabellini, 2020), as they are associated with significant immigration shocks in the U.S.

We find that an increase in the immigration share within a county significantly decreases the EC of low-SES individuals. Similarly, an increased immigration share also reduces the EC of high-SES individuals in relation to other high-SES individuals. Our results suggest that these decreases are driven by a surge in exposure to low-SES individ-

[1] An individual's SES is determined by factors such as income, education, and occupation. For a more detailed definition of SES, refer to the work by Chetty et al. (2022a).

uals after an increase in the immigration share, rather than by heightened friending bias of both low- and high-SES individuals toward high-SES individuals. As EC is closely related to individuals' economic opportunities and outcomes (Chetty et al., 2022a), our findings on reduced EC after a heightened immigration share within a county suggest the potential for declines in wages and earnings for individuals in that area. To investigate this possibility, we aggregate the ACS data to construct three county-level income measures: average wage, average earnings, and average total income. Using a fixed effects instrumental variable (FE-IV) approach with the shift-share IVs for immigration shares, we find strong adverse effects of immigration shares on all three local income measures.

Our heterogeneity analysis further shows that an increase in the immigration share disproportionately affects low-skilled workers (those without a college degree), leading to a reduction in their average income. In contrast, the average income of high-skilled workers rises as the immigration shares in an area increases. These findings suggest the presence of a substitution effect between native-born and immigrant workers in the low-skilled labor market, while a complementarity appears to exist between high-skilled workers and immigrants, potentially driven by a division of labor due to increased exposure to low-skilled workers. Additionally, the negative effects of immigration are even more pronounced for existing foreign-born individuals than for U.S.-born individuals.

This paper provides three important contributions to the existing literature. First, we provide evidence of a negative effect of immigration on social capital, particularly the EC of both low- and high-SES individuals. To our knowledge, only a few previous studies have examined the relationship between immigration and social capital (Bailey et al., 2020). By emphasizing the role of EC, we offer new insights into how immigration affects social connections within a neighborhood. Second, we reaffirm some aspects of previous findings even after including more recent data by demonstrating that there are two impacts: a negative but insignificant impact of immigration on natives' local income (e.g., Card, 2001) and a significantly negative impact on the local income of low-skilled workers (e.g., Borjas, 2003). Our findings suggest that social capital, and specifically EC, serves as an additional channel through which immigration affects local income, beyond the traditional explanation of labor market competition. Third, we provide evidence that while increased immigration shares reduce the EC of both low- and high-SES individuals, only those with lower education levels experience income losses. This result may indicate the presence of human capital externalities, where highly educated individuals benefit despite decreases in their social capital.

2 Related literature

While extensive research has explored the impact of immigrants on the social capital of destination regions in disciplines outside of economics, there remains a notable gap in economics addressing these effects. Political science research suggests that increased social diversity due to immigration can lead to a decline in social capital, particularly in areas such as interpersonal trust and participation in collective or political activities (Putnam, 2007; Kesler and Bloemraad, 2010; Dinesen et al., 2020). Although the economics literature examines the effects of immigration on various outcomes, studies on its impact on social capital are limited. Most existing research focuses on immigrants' decision-making processes (Glaeser et al., 2002), changes in social capital in the regions they emigrate from (Wahba and Zenou, 2012), and the influence of migration networks on immigrants' economic and educational outcomes. Consequently, there is a lack of research investigating how immigration affects social capital in receiving regions. However, recent work by Bailey et al. (2020) suggests that immigration may foster stronger social ties through historical migration patterns, with regions sharing links to the same foreign countries more likely to connect. This underscores the importance of past migration patterns in shaping social networks.

One of the central questions in the study of immigration is its potential impact on labor market competition, particularly for native-born workers. Empirical evidence on this matter has been mixed, while studies indicate a negative impact of immigration on native wages at the U.S. national level, particularly for lower-educated workers (Borjas, 2003), studies at the regional level find modest or negligible effects of immigration on native wages or employment (Card, 2001, 2009). By employing a robust theoretical model, Ottaviano and Peri (2012) investigate the wage effects of immigrants on natives across different levels of education and age. They find that the effect of immigrants can actually be positive for many native workers. It is also important to recognize the labor market adjustment over time and distinguish between short- and long-run effects. While immigration may initially put pressure on certain segments of the labor market, economies have demonstrated a remarkable capacity to adapt and reallocate resources efficiently, and thus it is also important to distinguish between short- and long-run effects (Borjas, 2014; Jaeger et al., 2018).

Beyond direct competition, the complementary effects of immigration on the local labor market have also been studied. Immigrants often have different skills and labor market characteristics compared to native-born workers, leading to potential complementarity rather than direct competition (Peri, 2016). An increase in low-skilled immigrant workers reduces the cost of services like housekeeping and gardening, likely due to lower wages. Low-skilled immigrants experience greater wage impacts than low-skilled natives, indicating they are not perfect substitutes in the labor market (Cortes, 2008), which aligns with (Moretti, 2004). Additionally, immigrants may contribute to entrepreneurship and innovation, creating new job opportunities and boosting local economies (Kerr and Kerr, 2020).

Understanding the relationship between social capital, particularly social networks, and labor market outcomes is crucial for employment and economic prosperity. Montgomery (1991) and Ioannides and Loury (2004) emphasize that social networks significantly enhance job search efficiency and employment probabilities, leading to better job matches and higher wages by facilitating information flow and reducing job search costs. Granovetter (1973) introduces the strength of weak ties theory, illustrating that acquaintances rather than close friends are more effective in job searches because they provide novel information, supported by case studies and surveys. Bayer et al. (2008) and Hellerstein et al. (2011) further investigate how neighborhood-based and geographic proximity networks positively influence employment outcomes and earnings, highlighting the role of local labor market networks. Calvó-Armengol and Jackson (2004) provide theoretical and empirical insights on how the structure and size of networks determine the efficiency of job information transmission, enhancing job matching. Dustmann et al. (2016) underscore the importance of ethnic networks in improving labor market integration and outcomes for immigrants, demonstrating the critical role of social networks in diverse labor markets.

While measuring social capital is challenging because it needs to accurately reflect real-world relationships, recent studies have tried to measure social capital and understand its economic impact more precisely. Using the SCI from Facebook friendship network data, Bailey et al. (2018) show significant correlations between social connectedness and economic outcomes, such as income levels and economic mobility. In another study, Bailey et al. (2020) find that these connections are influenced by access to public transit and past migration patterns. More recently, using Facebook data, Chetty et al. (2022a) provide a comprehensive measurement of social capital across three dimensions – economic connectedness, cohesiveness, and civic engagement – and show strong associations between social capital and economic mobility. In the companion paper, Chetty et al. (2022b) investigate the determinants of EC, specifically focusing on an individual's exposure to high-SES individuals and the friending rates of high-SES individuals. They emphasize the importance of understanding these determinants to develop effective policies, as the appropriate policy response depends on which factor is more problematic in a given context.

3 Data

We collect and combine data from two main sources. First, county-level data on EC and its two components, high-SES exposure and friending bias, are obtained from the SCI data (Chetty et al., 2022a,b). Second, data on other county characteristics, such as immigration shares and local average income are sourced from the U.S. Census and the ACS, all of which are accessible through the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2024).

Using data on individuals' friendship network, self-reported information, and group memberships from Facebook, Chetty et al. (2022a) develop three types of social capital measures at the county level: EC, cohesiveness, and civic engagement. In this paper, we focus only on EC because it captures the aspect of social capital that directly affects labor market outcomes. To measure EC, Chetty et al. (2022a) first predict each individual's SES using self-reported information, such as residential locations and schools. They classify a low-SES individual as someone whose SES is below the population median, and a high-SES individual as individuals whose SES is above the population median.

EC specifically refers to cross-type interactions, indicating how low-SES individuals in a county are socially connected with high-SES individuals, regardless of the location of their interaction partners. Chetty et al. (2022b) specifically focus on six group memberships where friendships are commonly formed: high schools, colleges, recreational groups, religious groups, workplaces, and neighborhoods. They calculate an individual's EC within each group, and then take the average over those six groups. Each individual's EC in a group is calculated as the ratio of the individual's connections with high-SES individuals to the proportion of high-SES individuals within the group. Then, they take the average over those six groups to calculate the EC of an individual. The county-level EC is then obtained by averaging the EC of individuals within the county. Thus, the county-level EC measure reflects how well low-SES individuals in a county are connected to high-SES individuals through their social networks.[2]

Chetty et al. (2022b) decompose EC into two factors: exposure to high-SES individuals (hereafter, exposure) and the friending rates of high-SES individuals (hereafter, friending bias). Both exposure and friending bias are constructed exclusively from individuals who participate in the six group memberships. Once individuals' group memberships are identified, it becomes possible to differentiate between the opportunities for befriending high-SES individuals within these groups (exposure) and the actual rates at which friendships with high-SES individuals are formed (friending bias). Hence, exposure refers to the proportion of high-SES individuals within an individual's group memberships, indicating the extent to which someone is exposed to high-SES individuals through these groups. Friending bias, on the other hand, measures the likelihood of forming friendships with high-SES individuals, conditional on exposure. In other words, given a certain level of exposure within a group, friending bias represents the likelihood that an individual actually forms friendships with high-SES individuals in that group.

To construct county characteristics, we use the ACS data from years 2005 to 2021, which contains a 1% national sample of individuals and households in the U.S. Additionally, we utilize the full-count U.S. Census data for years 1920 and 1930 as well as the 1%

[2]The EC measure that we employ is a "group-based" EC by Chetty et al. (2022b). They also propose an EC based on the entire population, rather than groups. We also use the alternative EC measure (Chetty et al., 2022a), and our results remain almost identical. The results are available upon request.

metro sample for 1970, to construct the historical patterns of immigrants. We restrict our sample to individuals aged from 16 to 64 when constructing county-level variables, such as income and immigration shares. Given that county borders have changed throughout our sample period, we harmonize them to align with the baseline year 2010.[3]

There are three county-level outcome variables derived from the ACS data: the average annual wage, average earnings, and average total income. Wage refers to the total pre-tax income from salaries and wages earned as an employee. Earnings include income from wages, self-employment, or agricultural activities. Total income represents comprehensive pre-tax personal income or losses from all sources. All income variables are adjusted to 1999 U.S. dollars (USD) using the CPI multipliers provided by IPUMS. For heterogeneity analyses, we calculate these average income measures for three subgroups: 1) all individuals; 2) native-born individuals; and 3) foreign-born individuals. Each subgroup is then further divided based on education level into those without a college degree and those with a college degree or higher. We then compute the county-level average wage, earnings, and total income for each of these groups.

To construct the key explanatory variable, the immigration share, we define immigrants as individuals born outside of U.S. territory, identified through country-of-birth or birthplace information from the ACS or census data. Across the entire sample period, there are 87 distinct birthplaces recorded, but not all appear consistently. To address this, we consolidate the 87 birthplaces into 49 countries or regions based on ethnicity or geographic proximity. We then define the share of immigrants in a county as the number of immigrants in the current year divided by the total population of the county in the previous year. Additionally, we construct two control variables, the share of college graduates and the unemployment rate, as they are frequently used in previous studies on immigration (e.g., Sá, 2015).

Table 1 shows descriptive statistics for the primary variables in our final sample. In Panel A, the mean of the county-level average wage is 18,364 USD, with a range from 8,453 USD to 57,437 USD. There is a notable income disparity based on education level: Individuals with a college degree generally earn higher incomes than those without a college degree. Panel B shows that the average immigration share is 6.9%, ranging from 0.1% to 61.3%, reflecting substantial variation across counties. The county-level average EC for low-SES individuals is 0.849, implying that, within their social networks, low-SES

[3] Using the crosswalk from Eckert et al. (2020), we harmonize county boundaries from historical census years to align with the Federal Information Processing System (FIPS) code of 2010 census year. For the 1970 Census data, where geographic information is provided at the county-group level in IPUMS, we first converted these county-groups into the 1970 county FIPS codes before applying the historical crosswalk, following Wiltshire (2021). For the ACS data from 2005 to 2021, where geographic information is provided at the Public Use Microdata Areac (PUMA) level, we use the crosswalk from the National Historical Geographic Information System. Since the ACS data correspond to 2000 PUMAs, we first converted them to 2010 PUMAs and then matched each PUMA to its corresponding county FIPS code (Manson et al., 2023).

friends are 15.1% more common than high-SES friends. Additionally, the variation in EC across counties is wider for low-SES individuals compared to high-SES individuals. Low-SES individuals are generally less exposed to high-SES individuals, and individuals tend to form friendship within their own SES.

[Table 1]

4 Empirical strategy

4.1 Model

To examine the effects of immigration shares on EC, exposure, and friending bias, we consider the following model:

$$y_{is,2022} = \beta_1 ImmiShare_{i,2021} + \gamma X_{i,2021} + \rho_s + \epsilon_{i,2021}, \tag{4.1}$$

where $y_{is,2022}$ is one of those social capital measures – EC, exposure, or friending bias – of county i in state s in the year 2022. The key explanatory variable $ImmiShare_{i,2021}$ denotes the immigration share in county i for the year 2021. We use the social capital measures from 2022, but immigration shares from the 2021 ACS because the SCI data are cross-sectional, based on 2022, and the most recent county-level immigration from the ACS is available for 2021. We control for county-level socio-demographic characteristics X_i, such as the share of college graduates and the unemployment rate, and include state fixed effects ρ_s. The last term $\epsilon_{i,2021}$ is the county-level idiosyncratic error.

The immigration share, $ImmiShare_{i,2021}$, is calculated as the number of immigrants in county i in 2021, divided by the total population of the county in the previous year, 2020. Considering the diverse origin countries of immigrants, we define $Immi_{ijt}$ as the number of immigrants from origin country j living in county i in year t. Then, $ImmiShare_{it}$ can be written as follows:

$$ImmiShare_{it} = \frac{1}{Pop_{i,t-1}} \sum_{j=1}^{J} Immi_{ijt} \tag{4.2}$$

The key parameter β captures the effect of immigration share on EC, exposure, or friending bias. For a causal interpretation, there must be no correlation between the share of immigrants and any unobserved factors that influence the dependent variables. However, the choice of destination county by immigrants is inherently endogenous, driven by reverse causality and self-selection. For example, if the majority of immigrants are low-skilled, they may prefer to settle in areas where low-skilled individuals have greater opportunities to form connections with high-skilled individuals. If such patterns are systematically prevalent and not properly controlled for, the resulting estimates would be biased. To address this endogeneity concern, we adopt a shift-share IV approach, commonly applied in previous studies (Card, 2001; Sá, 2015).

Next, to investigate the effects of immigration on local average income measures, we use the following fixed effects specification:

$$\log(Income)_{it} = \beta_2 ImmiShare_{it} + \gamma X_{it} + \delta_i + \alpha_t + \varepsilon_{it}, \tag{4.3}$$

where $\log(Income)_{it}$ represent one of the local income measures, such as the average wage, earnings, and total income in county i in year t. The key explanatory variable $ImmiShare_{it}$ is the immigration share of county i in year t, as described in equation (4.4), and X_{it} denotes the county-level control variables. The main difference between equations (4.1) and (4.3) lies in the time span of the data they cover. Equation (4.1) uses cross-section data, where the social capital measures are available only for 2022 and the immigration shares are from the 2021 ACS. In contrast, equation (4.3) is estimated using panel data from 2006 to 2021. By utilizing the panel data, we control for both county and year fixed effects, δ_i and α_t, respectively, whereas we control for state fixed effects in equation (4.1). While we can control for county and year fixed effects in the local income equation (equation (4.3)), to mitigate an endogeneity problem, we employ the shift-share IV approach as well.

4.2 Identification strategy

To address the potential endogeneity problems, we construct a set of shift-share IVs by fixing immigration shares based on three historical immigration patterns: the 1910s, 1920s, and 1960s with a particular shock of policy changes. Note that the immigration share in equation (4.4) can alternatively be written as follows.

$$ImmiShare_{it} = \frac{1}{Pop_{i,t-1}} \sum_{j=1}^{J} \frac{Immi_{ijt}}{Immi_{jt}} Immi_{jt}, \tag{4.4}$$

where $Immi_{jt}$ is the total number of immigrants from country j living in the U.S. in year t, and $\frac{Immi_{ijt}}{Immi_{jt}}$ is the share of immigrants from county j living in county i in year t. Let $M_{ijt} = \frac{Immi_{ijt}}{Immi_{jt}}$ denote this share. The shift-share IV for a given base year τ, denoted as Z_{it}^{τ} is constructed by replacing M_{ijt} with its counterpart $M_{ij\tau}$ from the baseline year τ. Specifically,

$$Z_{it}^{\tau} = \frac{1}{Pop_{i,t-1}} \sum_{j} M_{ij\tau} Immi_{jt} = \frac{1}{Pop_{i,t-1}} \sum_{j} \frac{Immi_{ij\tau}}{Immi_{j\tau}} Immi_{jt}, \tag{4.5}$$

where τ corresponds to the decades 1910s, 1920s, and 1960s. This IV predicts the share of immigrants in county i in current year t by interacting two main components: the historical shares and the current immigrants population. Because both $ImmiShare_{it}$ and Z_{it}^{τ} incorporate the current national-level stock of immigrants from each country of origin, $Immi_{jt}$, the relevance condition for a valid IV is likely satisfied.

More importantly, the identification of the key parameter relies on the exogeneity of the historical immigration patterns in 1910s, 1920s, and 1960s. First, following Tabellini (2020), we use the 1910s and 1920s immigration shares. During the Age of Mass Migration, spanning from 1850 to 1915, over 30 million Europeans migrated to the U.S. In this time, most of immigrants were from Northern and Western Europe. From the late 1880s, a gradual influx from Southern and Eastern Europe had shifted the composition of immigrants. And the fact that these newcomers were less skilled and had relatively low rate of literacy than those of Northern and Western Europeans leads to implementation of a literacy test in 1917 (Hatton and Williamson, 1998; Hatton et al., 2006; Goldin, 1994). This Age of Mass Migration abruptly ended with the outbreak of World War I in 1914, resulting in a sharp decline in European immigration between 1915 and 1919. Despite the literacy test in 1917, immigration flows rebounded to pre-war levels after WWI was over, by 1920. In response to this rebound, Congress passed the Immigration Acts of 1921 and 1924, introducing quotas that favored immigrants from established source regions. These changes in immigration policy led to a reversal of the composition of immigrants entering the U.S. (Tabellini, 2020).

Next, we use the 1960s shares, following Jaeger et al. (2018). The 1970s marked a pivotal period with a substantial change in the composition of immigrant inflows, making it well-suited for constructing an IV. The serial correlation of the national composition of immigrants' origin countries between the 1960s and 1970s was significantly lower compared to other decades. This transformation was primarily attributed to the Immigration and Nationality Act of 1965, which abolished quotas for Asian immigrants and marked a historical turning point in U.S. immigration policy. However, the serial correlation of national composition remained above 0.9 after the 1970s, indicating that the immigration patterns stabilized and persisted thereafter. Therefore, using the immigration shares in 1960s when constructing a shift-share IV is valid. These exogenous events and policy changes created significant variations in both the number and composition of immigrants arriving in U.S. counties over time, providing a valuable source of exogenous variation for our empirical analysis.[4]

[4] According to Mogstad et al. (2024), employing multiple IVs may potentially violate the monotonicity condition proposed by Imbens and Angrist (1994). Nonetheless, as shown in Tables A.1–A.6, the results remain broadly consistent when we use only a single instrument—particularly Z_{it}^{1960s}, which Jaeger et al. (2018) regard as the most reliable period.

5 Results

5.1 Effects of immigration on social capital

First, we examine the effect of immigration social capital. As a preliminary analysis, we use pooled ordinary least squares (OLS) estimation with and without state fixed effects.[5] It is important to note that neither of these methods fully addresses potential endogeneity problems. Table 2 presents the pooled OLS results for low-SES individuals' connections toward high-SES individuals in Panel A and those for high-SES individuals toward other high-SES individuals in Panel B. The pooled OLS results for both groups show a strong positive correlation between immigration shares and all three social capital measures. When we control for state fixed effects, the magnitudes of these correlations decrease but remain mostly positive and significant.

[Table 2]

In Table 3, we presents the impacts of immigration share on EC, exposure, and friending bias using the IV estimation approach with the three shift-share IVs. Panel A reports results for low-SES individuals' EC, exposure, and friending bias toward high-SES individuals, while Panel B presents the results for high-SES individuals toward other high-SES individuals. The first-stage estimation results, including the coefficients on the shift-share IV with 1960s immigration patterns, along with Cragg-Donald F-statistics, Anderson-Rubin F-statistics, and their corresponding p-values, indicate that the IVs we employ do not suffer from weak IV problems.

[Table 3]

We find that a one percentage point increase in the immigration share within a county leads to an approximately 0.011-point decrease in EC, a 0.013-point decrease in exposure for low-SES individuals. These negative effects are statistically significant. However, rising immigration shares do not have a significant effect on the friending bias of low-SES individuals toward high-SES individuals. Although these figures may appear small, the impacts become more pronounced when we consider a one-standard-deviation increase in immigration share, which is 6.73 percentage points. In this case, EC decreases by approximately 0.077 points, and exposure decreases by about 0.085 points. The mean and standard deviation of EC are 0.849 and 0.213, respectively, and those of exposure are 0.905 and 0.211. Compared to these values, the magnitudes of the effects of immigration are economically significant.

Similarly, Panel B of Table 3 shows that an increase in the immigration share within a county leads to a 1.155-points decrease in EC and a 0.732-points decrease in exposure

[5] Because the data for the EC analysis are cross-sectional at the county level, we use robust standard errors. When we apply cluster standard errors at the state level, the significance levels remain nearly the same.

of high-SES individuals to other high-SES individuals. When we consider a one-standard deviation increase in the immigration share (6.73 percentage points), EC decreases by 0.077 points, and exposure decreases by 0.049 points. These negative effects are statistically significant, whereas the impact of immigration on friending bias of high-SES individuals is insignificant.

Upon examining these negative effects in detail, it appears that immigration reduces exposure to high-SES individuals for both low- and high-SES groups, primarily because the majority of immigrants are low-skilled workers (Card, 2009; Ottaviano and Peri, 2006) in the US. The reduction in EC for both groups can be attributed to this reduced exposure to high-SES individuals following an increase in immigration shares. In contrast, the rising share of immigrants does not affect the friending bias of either group, and thus, does not contribute to the observed reduction in EC of both groups.

Our findings provide a few interesting observations. First, the results indicate that individuals with low SES tend to interact more within their own social groups, a phenomenon related to homophily as discussed in the social network literature (McPherson et al., 2001; Patacchini and Zenou, 2012; Kim et al., 2023). This tendency limits cross-SES social interactions and collaborations. This decreased EC could restrict access to work-related opportunities, potentially leading to a decline in their income (Granovetter, 1973; Chetty et al., 2014). Furthermore, as immigration shares increase, low-SES individuals appear to interact more within their own groups or communities, given that our EC is a group-based measure (Chetty et al., 2022b). Importantly, both existing and new immigrants tend to engage with individuals from their own ethnic or cultural background. Social, cultural, and language barriers further hinder interactions between low-SES individuals and those with high SES, reinforcing these divisions. This lack of cross-SES interactions may exacerbate economic disparities and impede upward mobility for low-SES individuals (Chetty et al., 2022a).

It is worth noting that a rise in the immigration share also reduces the EC of high-SES individuals, primarily due to greater exposure to low-SES individuals. Since EC is closely related to economic opportunities facilitated by social interactions, a decline in EC among high-SES individuals could potentially lead to negative effects on their economic outcomes, such as wages and earnings. However, the mechanisms through which immigration impacts individuals via social capital or EC may vary by their skill level or SES. In the next subsection, we will investigate the effects of immigration on local income to provide some evidence for this conjecture.

5.2 Immigration and local income

Table 4 shows the impacts of immigrants on the logarithm of the county-level average wages, earnings, and total incomes. The results are shown for three different estimation methods: pooled OLS, FE, and FE-IV, in Panels A, B, and C, respectively. Both the pooled OLS and FE estimates are positive and significant. While the results show positive associations between the share of immigrants and incomes in Panel A and B, they do not necessarily imply a causal link due to potential endogeneity in immigrant shares. For example, immigrants from a particular country of origin may choose to settle in areas with higher income. The pooled OLS and FE estimates cannot be used to assert that an increased share of immigrants directly causes a higher income levels within a county.

[Table 4]

In Panel C, we present the results from the FE-IV estimation. The first-stage estimation results, including Cragg-Donald F-statistics, Anderson-Rubin F-statistics, and their corresponding p-values, confirm that our IVs are valid predictors of current immigration shares. The FE-IV estimates show that there is a statistically significant negative impact of immigration on each measure of income. Specifically, a one-standard-deviation increase in the immigration share ($0.0673 = 6.73\%$) leads to decreases of approximately 5.1%, 4.9%, and 4.8% in wages, earnings, and total income, respectively. Compared to the positive estimates from both Pooled OLS and FE, these negative and significant FE-IV estimates suggest that the pooled OLS and FE results are likely biased.

Based on educational attainment, the majority of immigrants in our sample are categorized as low-skilled, about 78% being non-college-educated and 22% holding a college degree. Consequently, from the perspective of classical labor market competition, an increase in the immigration share intensifies competition in the local labor market, particularly in low-skilled sectors (Ottaviano and Peri, 2012). This heightened competition often results in lower incomes for low-skilled workers. However, we also argue another channel that as the immigration share increases, the EC of low-SES individuals toward high-SES individuals declines. This reduction in EC diminishes economic opportunities (Chetty et al., 2022a), ultimately leading to a decline in local income. It is important to note that the impact of immigrants on wages is the most pronounced among the three income measures, suggesting that salaries and wages for employees are primarily influenced by the proportion of immigrants in the area.

6 Heterogeneity analysis and robustness checks

6.1 Heterogeneity analysis by country of birth

Next, we conduct a heterogeneous analysis based on country of birth. Specifically, we separately construct the county-level average income measures for U.S.-born and foreign-born individuals and then run the FE-IV estimation, using each of these income measures as the outcome variable. In Table 5, we find that an increase in the immigration share significantly affects the income of foreign-born individuals only. The magnitudes of these effects are larger than those reported in Table 4. Specifically, a one-standard-deviation increase in the immigration share leads to decreases of 18.9%, 18.6%, and 18.7% in the average wage, earnings, and total income of foreign-born individuals, respectively. In contrast, the impacts on the average wage, earnings, and total income of native-born individuals are statistically insignificant.

[Table 5]

As discussed in the previous section, an increase in the number of immigrants in a county can intensify job competition, particularly in low-skilled or entry-level positions. Moreover, factors, such as language barriers, unfamiliarity with local workplace norms, and limited access to professional networks, may reduce immigrants' economic connectedness with high-SES individuals (Dustmann and Fabbri, 2003; Hellerstein et al., 2011). Consequently, immigrants compete more among themselves rather than with native-born residents (Card, 2001). As a result, the average income of the foreign-born population in the county with increased immigrants could decrease (Ottaviano and Peri, 2012). In contrast, native-born individuals benefit from well-established networks and social connections, which provide them better access to job opportunities (Borjas, 1992). As a result, they are less directly impacted by changes in the immigration share compared to immigrant populations.

6.2 Heterogeneity analysis by education level

Next, we further examine heterogeneity in the effects of immigration by education level. We divide individuals into two subgroups based on their level of education: those without a four-year college degree (non-college graduates) and those with a four-year college degree (college graduates). We then construct the county-level average income measures again for non-college graduates and college graduates separately. Table 6 presents the results. Panel A shows the difference in the effects of immigration shares on local income for the entire population, while Panels B and C show the results for native-born and foreign-born individuals, respectively. In Panel A, we find that the effects of immigration shares on the local income exhibit opposite signs between the two groups. Specifically, for non-college graduates, a one-standard-deviation increase in the immigration share leads to declines of 11.4%, 10.2%, and 10% in the average wage, earnings, and total income, respectively. In contrast, for college graduates, a one-standard-deviation increase in the immigration share results in increases of 7.3%, 9.2%, and 9.8% in the average wage, earnings, and total income, respectively.

[Table 6]

It is worth noting that the magnitudes of the effects differ substantially between the two groups. Non-college graduates experience the largest negative effect on wages, followed by earnings and total income. In contrast, for college graduates, the largest positive effect is observed on total income, followed by earnings and wages. An inflow of immigrants into an area can increase greater competition for jobs, particularly in low-skilled sectors (Ottaviano and Peri, 2012). This increased competition may drive down wages for non-college graduates (Card, 2001). Immigrants often face barriers such as limited English proficiency and unfamiliarity with American workplace norms, making it difficult for them to access high-paying jobs, which may contribute to lower incomes. Alternatively, college graduates typically work in different segments of the labor market, such as information technology, finance, healthcare, and professional services. In these sectors, immigrants may complement rather than compete with the skills of college graduates, resulting in higher average incomes for college graduates (Ottaviano and Peri, 2006; Peri, 2012). Additionally, college graduates may benefit from the presence of low-skilled workers, who can be hired at lower wages, due to increased immigration. This dynamic can enhance productivity and increase income from sources beyond wages through a more efficient division of labor (Peri and Sparber, 2009).

The overall impact of an increase in the share of immigrants on the income of native-born residents appears insignificant, as shown in Table 5. However, in Panel B of Table 6, when we further divide native-born individuals by educational attainment, the effects become distinct. Specifically, native-born individuals also exhibit varying income responses based on their educational level. As the immigration share in a county rises, native-born non-college graduates experience a negative impact on their income, while the average income of native-born college graduates increases.

Finally, although the increase in immigrants negatively affects the income of foreign-born individuals, the impact differs substantially by educational attainment. Panel C of Table 6 shows that a one-standard-deviation increase in the immigration share results in declines of 19%, 21.4%, and 22% in the average wage, earnings, and total income of foreign-born non-college graduates, respectively. These effects are slightly larger than those estimated for all foreign-born individuals. As new immigrants and existing foreign-born residents often compete in similar industries, heightened market competition may reduce their earnings and total income, even more so than their wages. Conversely, foreign-born college graduates experience statistically significant increases in average earnings and total income. Similarly to their native-born counterparts, foreign-born college graduates may benefit from lower costs of low-skilled services (Peri and Sparber, 2009), driven by the increased inflow of immigrants without college degrees.

6.3 Robustness checks

Recent literature has highlighted potential threats to identification in the context of shift-share IVs. To test the robustness of our results, we construct an alternative version of the shift-share IVs. In this version, we exclude immigrants from each origin country residing in a given county, from the national total of immigrants from that origin country when predicting the current immigration share based on historical patterns. This "leave-out" version of shift-share IV is commonly used in previous studies (Goldsmith-Pinkham et al., 2020). Tables 7 and 8 demonstrate that our results remain almost identical when we employ the alternative leave-out shift-share IVs.

[Table 7]

[Table 8]

7 Concluding remarks

This study investigates the impact of immigration on social capital and local income. We employ an IV estimation approach with shift-share IVs using historical immigration patterns. We find a statistically significant negative impact of immigration on social capital, specifically on the EC of both low- and high-SES individuals. We suggest that, beyond the traditional view of labor market competition, the decrease in EC can be another significant channel through which immigration influences economic outcomes. To examine this mechanism, we investigate the impact of immigration on local income. We find a statistically significant negative impact of immigration on income, suggesting that the decline in EC is a plausible channel explaining the negative effect of immigration.

Furthermore, through heterogeneity analyses, we find a negative but insignificant impact of immigration on local income of U.S.-born individuals. Additionally, individuals without a college degree experience a significantly negative impact on local income, whereas individuals with a college degree have a significantly positive impact. These findings suggest that the mechanisms operate primarily for low-SES individuals, while high-SES individuals benefit from potential human capital externalities, regardless of changes in their social capital.

We suggest that policies could focus on promoting socioeconomic integration. The decrease in EC appears to be driven largely by limited exposure to high-SES individuals within each group. This lack of exposure may reduce economic opportunities for low-SES individuals, contributing to lower local income levels. Approaches such as school busing programs or creating shared public spaces and community centers could help foster socioeconomic diversity and potentially mitigate some of the negative impacts of immigration. However, for these approaches may not fully address issues related to friending bias, continuous monitoring or direct matching program between different SES individuals may also have to be considered.

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Tables

Table 1: Descriptive Statistics

Variables	Mean	St. Dev	Min	Max	Obs
Panel A. Income					
Wages	18,364	4,604	8,453	57,437	48,896
Earnings	19,874	4,852	8,929	64,737	48,896
Total Incomes	22,249	4,989	10,848	72,998	48,896
Non-College Graduates					
Wages	14,365	2,689	6,471	27,687	48,896
Earnings	15,645	2,976	6,956	29,180	48,896
Total Incomes	17,676	2,988	8,009	33,624	48,896
College Graduates					
Wages	34,468	6,729	17,697	84,216	48,896
Earnings	36,970	6,907	19,007	95,337	48,896
Total Incomes	40,836	7,105	22,810	106,128	48,896
Panel B. Demographics					
Share of immigrants	0.069	0.067	0.001	0.613	48,896
Unemployment rate	0.069	0.032	0.002	0.251	48,896
Share of college graduates or more	0.189	0.077	0.052	0.745	48,896
Panel C. Economic connectedness					
Low-SES Individuals					
Economic Connectedness	0.849	0.213	0.187	1.476	2,981
Exposure to High-SES	0.905	0.211	0.270	1.486	2,981
Friending Bias	0.065	0.051	-0.108	0.335	2,981
High-SES Individuals					
Economic Connectedness	1.271	0.199	0.623	1.766	2,981
Exposure to High-SES	1.078	0.210	0.510	1.666	2,981
Friending Bias	-0.189	0.064	-0.536	-0.043	2,981

Table 2: The effects of immigration share on economic connectedness: pooled OLS estimation

	(1) Economic Connectedness	(2) Exposure to high-SES	(3) Friending Bias
Panel A. EC of low-SES individuals			
Pooled OLS			
Immigration share	0.283***	0.470***	0.168***
	(0.057)	(0.057)	(0.016)
State fixed effects	No	No	No
Control variables	No	No	No
Observations	2981	2981	2981
Pooled OLS with state fixed effects			
Immigration share	-0.037	0.085*	0.121***
	(0.053)	(0.050)	(0.021)
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981
Panel B. EC of high-SES individuals			
Pooled OLS			
Immigration share	0.881***	1.009***	0.261***
	(0.055)	(0.059)	(0.016)
State fixed effects	No	No	No
Control variables	No	No	No
Observations	2981	2981	2981
Pooled OLS with state fixed effects			
Immigration share	0.308***	0.411***	0.144***
	(0.037)	(0.038)	(0.016)
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981

Robust standard errors are in parentheses. Control variables are the share of college graduates and unemployment rate. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: The effects of immigration share on economic connectedness: IV estimation

	(1) Economic Connectedness	(2) Exposure to high-SES	(3) Friending Bias
Panel A. EC of low-SES individuals			
Second stage			
Immigration share	-1.146***	-1.257***	0.033
	(0.408)	(0.375)	(0.124)
First stage			
1910s shift share IV	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
1920s shift share IV	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)
1960s shift share IV	0.040**	0.040**	0.040**
	(0.020)	(0.020)	(0.020)
Cragg-Donald F-statistic	24.122	24.122	24.122
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	1.449	1.863	1.116
Anderson-Rubin p-value	[0.227]	[0.134]	[0.341]
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981
Panel B. EC of high-SES individuals			
Second stage			
Immigration share	-1.155***	-0.732**	0.161
	(0.413)	(0.357)	(0.098)
First stage			
1910s shift share IV	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
1920s shift share IV	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)
1960s shift share IV	0.040**	0.040**	0.040**
	(0.020)	(0.020)	(0.020)
Cragg-Donald F-statistic	24.122	24.122	24.122
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	1.926	1.113	2.816
Anderson-Rubin p-value	[0.123]	[0.343]	[0.038]
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981

Robust standard errors are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: The effects of immigrants on local income

	(1)	(2)	(3)
	$\ln Wage$	$\ln Earn$	$\ln Total$
A. Pooled OLS			
Immigration share	1.060***	1.045***	0.898***
	(0.022)	(0.021)	(0.020)
County fixed effects	No	No	No
Year fixed effects	No	No	No
Control variables	No	No	No
B. FE estimation			
Immigration share	0.103***	0.067**	0.020
	(0.033)	(0.030)	(0.028)
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
C. FE-IV estimation			
Immigration share	-0.865***	-0.725**	-0.712***
	(0.322)	(0.296)	(0.274)
First stage			
1910s shift share IV	0.010**	0.010**	0.010**
	(0.005)	(0.005)	(0.005)
1920s shift share IV	0.019**	0.019**	0.019**
	(0.010)	(0.010)	(0.010)
1960s shift share IV	0.063	0.063	0.063
	(0.045)	(0.045)	(0.045)
Cragg-Donald F-statistic	238.92	238.92	238.92
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	2.958	3.566	3.320
Anderson-Rubin p-value	[0.031]	[0.014]	[0.019]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Heterogeneity analysis: Native-born and foreign-born individuals

FE-IV estimation	Native-born			Foreign-born		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln Wage$	$\ln Earn$	$\ln Total$	$\ln Wage$	$\ln Earn$	$\ln Total$
Immigration share	-0.418	-0.145	-0.137	-2.806***	-2.763***	-2.782***
	(0.329)	(0.281)	(0.261)	(0.563)	(0.592)	(0.573)
Cragg-Donald F-statistic	238.923	238.923	238.923	238.960	238.960	238.960
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	3.060	0.623	0.574	2.557	2.905	2.908
Anderson-Rubin p-value	[0.027]	[0.600]	[0.632]	[0.054]	[0.033]	[0.033]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,896	48,896	48,896	48,892	48,892	48,892

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: The heterogeneous effects of immigrants on local income

FE-IV estimation	Non-college graduates			College graduates		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln Wage$	$\ln Earn$	$\ln Total$	$\ln Wage$	$\ln Earn$	$\ln Total$
Panel A. All						
Immigration share	-1.693***	-1.514***	-1.493***	1.080***	1.370***	1.456***
	(0.459)	(0.426)	(0.401)	(0.268)	(0.265)	(0.266)
Cragg-Donald F-statistic	238.923	238.923	238.923	238.923	238.923	238.923
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	5.829	7.702	7.266	5.597	8.427	11.714
Anderson-Rubin p-value	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,896	48,896	48,896	48,896	48,896	48,896
Panel B. Native-born						
Immigration share	-1.303***	-0.941**	-0.908**	0.956***	1.163***	1.219***
	(0.491)	(0.425)	(0.407)	(0.278)	(0.241)	(0.219)
Cragg-Donald F-statistic	238.923	238.923	238.923	238.923	238.923	238.923
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	9.969	7.125	7.455	3.227	4.830	7.255
Anderson-Rubin p-value	[0.000]	[0.000]	[0.000]	[0.022]	[0.002]	[0.000]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,896	48,896	48,896	48,896	48,896	48,896
Panel C. Foreign-born						
Immigration share	-2.817***	-3.177***	-3.274***	0.454	2.186**	1.906*
	(0.732)	(0.832)	(0.810)	(0.962)	(1.046)	(0.978)
Cragg-Donald F-statistic	238.795	238.797	238.931	235.457	235.612	238.056
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	3.169	3.855	4.044	0.689	1.898	2.215
Anderson-Rubin p-value	[0.023]	[0.009]	[0.007]	[0.558]	[0.128]	[0.084]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,842	48,843	48,878	47,987	48,051	48,194

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Robustness checks with leave-one-out IV - economic connectedness

	(1) Economic Connectedness	(2) Exposure to high	(3) Friending Bias
Panel A. Low- to high-SES			
Second stage			
Immigration share	-1.161***	-1.276***	0.031
	(0.419)	(0.386)	(0.126)
First stage			
1910s leave-one-out SSIV	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
1920s leave-one-out SSIV	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)
1960s leave-one-out SSIV	0.039**	0.039**	0.039**
	(0.019)	(0.019)	(0.019)
Cragg-Donald F-statistic	23.006	23.006	23.006
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	1.438	1.847	1.101
Anderson-Rubin p-value	0.230	0.136	0.347
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981
Panel B. High- to high-SES			
Second stage			
Immigration share	-1.191***	-0.760**	0.165*
	(0.426)	(0.367)	(0.100)
First stage			
1910s leave-one-out SSIV	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
1920s leave-one-out SSIV	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)
1960s leave-one-out SSIV	0.039**	0.039**	0.039**
	(0.019)	(0.019)	(0.019)
Cragg-Donald F-statistic	23.006	23.006	23.006
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	1.911	1.115	2.770
Anderson-Rubin p-value	0.126	0.342	0.040
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981

Robust standard errors are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Robustness checks with leave-one-out IV - local income

FE-IV estimation	(1) $\ln Wage$	(2) $\ln Earn$	(3) $\ln Total$
Panel A. All			
Second stage			
Immigration share	-0.864***	-0.725**	-0.711**
	(0.325)	(0.299)	(0.277)
First stage			
1910s leave-one-out SSIV	0.010**	0.010**	0.010**
	(0.005)	(0.005)	(0.005)
1920s leave-one-out SSIV	0.019**	0.019**	0.019**
	(0.010)	(0.010)	(0.010)
1960s leave-one-out SSIV	0.061	0.061	0.061
	(0.045)	(0.045)	(0.045)
Cragg-Donald F-statistic	235.415	235.415	235.415
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	2.923	3.524	3.282
Anderson-Rubin p-value	[0.033]	[0.014]	[0.020]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896
Panel B. Non-college graduates			
Second stage			
Immigration share	-1.697***	-1.518***	-1.497***
	(0.464)	(0.431)	(0.406)
First stage			
1910s leave-one-out SSIV	0.010**	0.010**	0.010**
	(0.005)	(0.005)	(0.005)
1920s leave-one-out SSIV	0.019**	0.019**	0.019**
	(0.010)	(0.010)	(0.010)
1960s leave-one-out SSIV	0.061	0.061	0.061
	(0.045)	(0.045)	(0.045)
Cragg-Donald F-statistic	235.415	235.415	235.415
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	5.781	7.660	7.216
Anderson-Rubin p-value	[0.001]	[0.000]	[0.000]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896
Panel C. College graduates			
Second stage			
Immigration share	1.091***	1.382***	1.468***
	(0.269)	(0.267)	(0.269)
First stage			
1910s leave-one-out SSIV	0.010**	0.010**	0.010**
	(0.005)	(0.005)	(0.005)
1920s leave-one-out SSIV	0.019**	0.019**	0.019**
	(0.010)	(0.010)	(0.010)
1960s leave-one-out SSIV	0.061	0.061	0.061
	(0.045)	(0.045)	(0.045)
Cragg-Donald F-statistic	235.415	235.415	235.415
Stock-Yogo 10% CV	[22.3]	[22.3]	[22.3]
Anderson-Rubin F-statistic	5.598	8.420	11.700
Anderson-Rubin p-value	[0.001]	[0.000]	[0.000]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Tables

Table A.1: The effects of immigration share on economic connectedness with single instrument

	(1) Economic Connectedness	(2) Exposure to high	(3) Friending Bias
Panel A. Low- to high-SES			
Second stage			
Immigration share	-1.312***	-1.328***	0.146
	(0.377)	(0.352)	(0.125)
First stage			
1960s shift share IV	0.054**	0.054**	0.054**
	(0.021)	(0.021)	(0.021)
Cragg-Donald F-statistic	54.016	54.016	54.016
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	3.670	4.006	0.894
Anderson-Rubin p-value	0.055	0.045	0.345
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981
Panel B. High- to high-SES			
Second stage			
Immigration share	-1.018***	-0.638*	0.064
	(0.382)	(0.326)	(0.098)
First stage			
1960s shift share IV	0.054**	0.054**	0.054**
	(0.021)	(0.021)	(0.021)
Cragg-Donald F-statistic	54.016	54.016	54.016
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	2.624	1.937	0.286
Anderson-Rubin p-value	0.105	0.164	0.593
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.2: The effects of immigrants on local income with single instrument

	(1) ln $Wage$	(2) ln $Earn$	(3) ln $Total$
FE-IV estimation			
Immigration share	-1.124***	-0.893***	-0.861***
	(0.347)	(0.310)	(0.287)
First stage			
1960s shift share IV	0.11**	0.11**	0.11**
	(0.047)	(0.047)	(0.047)
Cragg-Donald F-statistic	415.796	415.796	415.796
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	5.010	4.871	5.079
Anderson-Rubin p-value	[0.025]	[0.027]	[0.024]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A.3: Heterogeneity analysis: Native-born and foreign-born individuals with single instrument

FE-IV estimation	Native-born			Foreign-born		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln $Wage$	ln $Earn$	ln $Total$	ln $Wage$	ln $Earn$	ln $Total$
Immigration share	-0.684	-0.336	-0.306	-3.188***	-3.052***	-3.120***
	(0.421)	(0.379)	(0.364)	(0.965)	(0.952)	(0.915)
Cragg-Donald F-statistic	415.796	415.796	415.796	415.764	415.764	415.764
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	6.161	1.455	1.299	2.993	3.073	3.294
Anderson-Rubin p-value	[0.013]	[0.228]	[0.254]	[0.084]	[0.080]	[0.070]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,896	48,896	48,896	48,892	48,892	48,892

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A.4: The heterogeneous effects of immigrants on local income with single instrument

FE-IV estimation	Non-college graduates			College graduates		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln Wage$	$\ln Earn$	$\ln Total$	$\ln Wage$	$\ln Earn$	$\ln Total$
Panel A. All						
Immigration share	-2.138***	-1.785***	-1.785***	0.994**	1.245***	1.484***
	(0.593)	(0.525)	(0.501)	(0.432)	(0.420)	(0.412)
Cragg-Donald F-statistic	415.796	415.796	415.796	415.796	415.796	415.796
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	11.560	11.212	12.020	3.365	4.338	5.808
Anderson-Rubin p-value	[0.001]	[0.001]	[0.001]	[0.067]	[0.037]	[0.016]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,896	48,896	48,896	48,896	48,896	48,896
Panel B. Native-born						
Immigration share	-1.750**	-1.229*	-1.201*	0.731*	0.888**	1.084***
	(0.742)	(0.655)	(0.636)	(0.415)	(0.388)	(0.355)
Cragg-Donald F-statistic	415.796	415.796	415.796	415.796	415.796	415.796
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	24.014	17.562	20.169	1.732	2.346	3.440
Anderson-Rubin p-value	[0.000]	[0.000]	[0.000]	[0.188]	[0.126]	[0.064]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,896	48,896	48,896	48,896	48,896	48,896
Panel C. Foreign-born						
Immigration share	-3.455***	-3.840***	-4.283***	1.636	3.430**	3.678**
	(0.977)	(1.050)	(1.067)	(1.457)	(1.538)	(1.512)
Cragg-Donald F-statistic	415.732	415.730	415.664	412.971	412.741	415.370
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	5.761	6.212	6.850	1.571	5.070	6.169
Anderson-Rubin p-value	[0.016]	[0.013]	[0.009]	[0.210]	[0.024]	[0.013]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,842	48,843	48,878	47,987	48,051	48,194

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.5: Robustness checks with leave-out IV - economic connectedness

	(1) Economic Connectedness	(2) Exposure to high	(3) Friending Bias
Panel A. Low- to high-SES			
Second stage			
Immigration share	-1.345***	-1.361***	0.150
	(0.389)	(0.363)	(0.128)
First stage			
1960s leave-one-out SSIV	0.039**	0.039**	0.039**
	(0.019)	(0.019)	(0.019)
Cragg-Donald F-statistic	51.688	51.688	51.688
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	3.710	4.052	0.904
Anderson-Rubin p-value	0.054	0.044	0.342
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981
Panel B. High- to high-SES			
Second stage			
Immigration share	-1.065***	-0.674**	0.064
	(0.394)	(0.337)	(0.101)
First stage			
1960s leave-one-out SSIV	0.039**	0.039**	0.039**
	(0.019)	(0.019)	(0.019)
Cragg-Donald F-statistic	51.688	51.688	51.688
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	2.682	2.003	0.279
Anderson-Rubin p-value	0.102	0.157	0.597
State fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	2981	2981	2981

Robust standard errors are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.6: Robustness checks with leave-out IV - local income with single instrument

FE-IV estimation	(1) $\ln Wage$	(2) $\ln Earn$	(3) $\ln Total$
Panel A. All			
Second stage			
Immigration share	-1.131***	-0.898***	-0.865***
	(0.325)	(0.299)	(0.277)
First stage			
1960s leave-one-out SSIV	0.050**	0.050**	0.050**
	(0.020)	(0.020)	(0.020)
Cragg-Donald F-statistic	403.904	403.904	403.904
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	4.910	4.774	4.974
Anderson-Rubin p-value	[0.027]	[0.029]	[0.026]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896
Panel B. Non-college graduates			
Second stage			
Immigration share	-2.161***	-1.803***	-1.802***
	(0.464)	(0.431)	(0.406)
First stage			
1960s leave-one-out SSIV	0.050**	0.050**	0.050**
	(0.020)	(0.020)	(0.020)
Cragg-Donald F-statistic	403.904	403.904	403.904
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	11.393	11.059	11.833
Anderson-Rubin p-value	[0.001]	[0.001]	[0.001]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896
Panel C. College graduates			
Second stage			
Immigration share	1.011**	1.264***	1.508***
	(0.269)	(0.267)	(0.269)
First stage			
1960s leave-one-out SSIV	0.050**	0.050**	0.050**
	(0.020)	(0.020)	(0.020)
Cragg-Donald F-statistic	403.904	403.904	403.904
Stock-Yogo 10% CV	[16.38]	[16.38]	[16.38]
Anderson-Rubin F-statistic	3.357	4.302	5.744
Anderson-Rubin p-value	[0.067]	[0.038]	[0.017]
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	48,896	48,896	48,896

Robust standard errors clustered at the county level are in parentheses. Control variables are the share of college graduates and unemployment rate. CV refers to the critical value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$