Human Capital, Immigration, and Skill Composition

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Abstract

The spatial correlation between worker skills and industry skill-intensity is amongst the best documented features of US economic geography. However, the causal impact of human capital on the industrial skill composition of US regions remains largely unknown. This paper studies how immigration-induced shifts in historical human capital affect the contemporary industrial skill composition of US counties. Leveraging quasi-random origin-by-destination immigration patterns from 1850 to 2010, I isolate exogenous variation in skill-specific local working-age population at the county level for 1970-2010. I find that an increase in medium- and high-skill worker shares raises employment and establishment shares in high-skill industries and reduces them in low-skill industries. The nontradable sector captures the major portion of the positive impacts, while the tradable sector absorbs the main fraction of the negative effects. The empirical findings are consistent with a CES model, in which representative firms with differentiated products employ labor of a certain skill type more intensively.

Keywords: Human Capital, Persistence, Immigrants, Workers, Establishments, Industries, Skills

JEL Codes: D22, F22, J21, J24, N91, N92, R12.

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1 Introduction

There exist significant differences in the skill composition of industries across the United States. These spatial variations are particularly noticeable at a more granular level, especially within local labor markets. The skill heterogeneity in industries can be partially attributed to technological change and job polarization along with local demand shocks and amenities.[1] Another likely channel causing the spatial sorting of skills and industries can be explained by human capital levels of individuals within localities. Importantly, the shifts in human capital can impact skills, workers, and firms across space and time. To the extent that education policymakers aim to improve the labor market outcomes of workers and spur firm creation opportunities in a given place, their policies might not be effective due to some underlying economic conditions in that area. For instance, if the policy targets building additional community colleges granting associate degrees in a particular city, which could potentially lead to higher wages and employment amongst the graduates, it might not produce the desired outcome. This could be due a certain historical event changing the path of development in that city over the long run, phenomena known as "persistence" and "path dependence."[2] Yet, despite this evidence, the causal effects of the exogenous shift in varying human capital levels of local population, induced by historical immigrant settlement patterns, on the industrial skill composition of employment and establishment shares in US counties remain largely unknown.

I study this question by providing systematic empirical evidence. The primary challenge in this examination pertains to the endogeneity concern stemming from human capital of local population, measured by individuals' educational attainment or years of schooling.[3] If, for example, a specific county is known for its large share of high-skill industries with high-paying jobs and entrepreneurial prospects, then it is reasonable to assume that individuals with college degrees would want to endogenously sort into this county. By attracting highly educated individuals, it would, consequently, result in spurious correlations between high-skill population share and employment alongside establishment shares of high-skill industries. To address this issue, I motivate three major facts as likely mechanisms to account for endogeneity in human capital.

First, the contemporary human-capital-related spatial differences can be ascribed to *persistence* through the effects of historical immigration. Notably, the historical settlement patterns of immi-

[1] See Acemoglu (2011), Autor and Dorn (2013), Moretti (2010), and Diamond (2016).

[2] For theoretical and empirical evidence on this front in various contexts, see Nunn (2014), Allen and Donaldson (2020), and Voth (2021).

[3] See Becker (1964) and Mincer (1974) for pioneering works on human capital.

grants have generated the heterogeneity in educational attainment amongst individuals in localities due the transmission of human capital (Abramitzky and Braggion, 2006; Sequeira et al., 2020). Second, one can observe the differential skill levels and specialization amongst immigrants arrived from various origin countries. This typical immigrant selection process (Borjas, 1987; Abramitzky et al., 2012; Clemens and Mendola, 2024) may shift the skill distribution of industries via the variation in immigrant human capital (Goldin, 1994; Abramitzky et al., 2014; Boberg-Fazlić and Sharp, 2024). Lastly, a well-established phenomenon in the literature is the fact that immigrants self-locate themselves to specific places due to the pre-existing "ethnic enclaves," underlining the non-random location choice of prospective immigrants (Altonji and Card, 1991; Card, 2001). The presence of "social networks" plays another key role in providing information about local economic conditions from past immigrants to newcomers (Munshi, 2003).

Directed by the potential mechanisms above, I proceed with my identification strategy in the following steps. Initially, I predict immigration stocks for each census year from 1850 to 2010 by leveraging historical origin-by-destination immigration patterns (*i.e.*, the "push" and "pull" factors) within an advanced version of the shift-share instrumental variable (SSIV) approach (Terry et al., 2021). This procedure generates the quasi-random variation in immigration, alleviating the endogeneity concern stemming from the non-random choice of destinations by immigrants. Later, utilizing this quasi-random variation in immigration, I isolate exogenous population of each skill type, measured by the number of individuals with varying educational attainment at the county level for the decennial 1970-2010 period.

I make two major contributions to the relevant literature. My first contribution is to generate skill-specific exogenous variation in working-age population at the county level by handling two main issues. The first problem is pertinent to the conventional use of a canonical shift-share approach. The concerns with this method include serial correlation in immigration patterns (Jaeger et al., 2018), levels or trends in economic outcomes being correlated with current immigration (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), and over-rejection problem (Adao et al., 2019). To this end, I employ a different approach, relying on the "leave-out push-pull" factors (Terry et al., 2021). This method generates granular variation in immigration that has exogenously occurred due to the timing of immigration from various origin countries (the "push" factor) and the timing of appealing characteristics of various US destination counties (the "pull" factor). For each decennial census year in 1850-2010, I predict the number of immigrants from a certain origin country to a certain destination county.[4] The predicting term is the interaction of the total number of immigrants from that country settled outside of a given census division in the US (the "leave-out push" element) with the share of immigrants from origin countries settled in that US county excluding immigrants from a continent where that country is located (the "leave-out pull" element). As opposed to the conventional shift-share techniques, adding the "leave-out" element to both "push" and "pull" factors tackles the concern that immigrant self-sorting into localities may be correlated with county-level labor market shocks and other country-county-level confounding factors.

The other issue relates to a challenge regarding the skill heterogeneity of local population. Individuals with varying educational attainment tend to relocate to places that offer employment and business activities requiring certain skills aligned with their human capital levels. For instance, the cluster of the high-tech jobs and firms in Palo Alto has likely attracted high-skill individuals to the area. If this local confounding factor is not corrected for, then it would result in a spurious correlation between high-skill population and employment and establishment shares in the high-tech sector within Palo Alto. To overcome this issue, I resume in the following steps. First, I classify working-age local population into low-, medium-, and high-skill cells corresponding to their educational attainment levels. Second, exploiting the predicted immigration stocks generated earlier, I isolate exogenous working-age population of each skill type at the county level. This procedure is driven by (*i*) the transmission of human capital from past immigrants ("ancestors") to new generations ("descendants") and (*ii*) the variation in immigrant human capital led by the immigrant selection process.

My second contribution pertains to quantifying the causal impact of the immigration-induced shift in exogenous human-capital-specific local population on the industrial skill composition of employment and establishment shares at the county level. The studies in the existing literature investigates the effects of immigration shocks on various outcomes within different contexts (Droller, 2018; Burchardi et al., 2019; Sequeira et al., 2020). These analyses examine how local labor market outcomes of natives and local economic development are shaped by exogenous immigration shocks. However, my focus is to seek an empirical answer to the question of how the industrial skill distribution of workers and establishments responds to skill-specific exogenous working-age population shifted by randomized historical immigrant settlement patterns. The classification of industries into skill cells closely follows the skill grouping of working-age individuals. To explore the heterogeneous

[4] Note that Terry et al. (2021) predict the number of individuals with reported ancestries at the county level for all census years. This difference in my technique is primarily due to the unavailability of the responses to the ancestry-related questions in the earlier census years.

responses of the outcomes of interest across industry tradability, I further classify industries into tradable and nontradable sectors.

To guide my empirical work, I utilize a CES model with two distinct representative firms (white and blue collar), each specializing in producing differentiated output sold in a perfectly competitive market. Each firm employs labor of a given skill type (high or low skill) more intensively (Autor et al., 1998). Moreover, the setup follows the literature using the imperfectly substitutable labor supplies of various education groups (Katz and Murphy, 1992; Card and Lemieux, 2001) within a CES framework. The model predicts that an increase in high-skill labor supply share raises labor demand share of white-collar firms, while a rise in low-skill labor supply share diminishes labor demand share in those firms. Furthermore, labor demand share of blue-collar firms increases as low-skill labor supply share rises, whereas it falls due to an increase in high-skill labor supply share.

In the baseline analysis, I find that, relative to low-skill population, an exogenous rise in medium- and high-skill population shares negatively affect employment and establishment shares of low-skill industries. This empirical result is in line with a model prediction, in which blue-collar firms utilize low-skill labor more intensively, while they employ high-skill labor less intensively. Additionally, the estimates show that, with respect to low-skill population, an exogenous increase in medium- and high-skill population shares raises employment and establishment shares of high-skill industries. This finding is supported by another model prediction, in that white-collar firms employ high-skill labor more intensively. My findings on establishment shares are comparable to Sequeira et al. (2020), while they are in contrast to Olney (2013), and the results on employment shares differ from Ottaviano et al. (2013).

The results on the heterogeneity across the industry tradability reveal the following patterns. The majority of the positive effects of a rise in population shares on employment and establishment shares originate from the nontradable sector, whereas the negative impacts predominantly arise from the tradable sector. The findings on employment shares are consistent with Moretti (2010), whereas they are different from Burstein et al. (2020).[5] Regarding the additional analysis along the establishment size domain, I document that the positive impacts are mainly captured by medium establishments in the tradable industries. The adverse impacts, on the other hand, are chiefly absorbed by large establishments in both tradable and nontradable industries along with small establishments in the tradable sector.

[5]Moretti explains an increase in the number of workers creating additional jobs in the nontradable sector through a rise in the demand for local goods and services. However, the tradable sector undergoes the opposite due to the increase in labor costs stemming from the labor demand shock.

Lastly, I carry out a set of robustness checks, which include the use of alternative instruments, various sample selections, and alternative tradability classification. Additionally, I implement randomization tests highlighted in Adao et al. (2019) to address an over-rejection problem typical in the SSIV designs. The results demonstrate that my main estimates are robust to all sensitivity checks.

Related Literature. My paper connects to several strands of literature. First, I contribute to the literature emphasizing the role of persistence of historical events in affecting the present-day economic outcomes (Nunn, 2014; Allen and Donaldson, 2020; Voth, 2021; Abramitzky and Braggion, 2006; Bleakley and Lin, 2012; Bazzi et al., 2020; Sequeira et al., 2020; Fulford et al., 2019; Rocha et al., 2017; Droller, 2018; Valencia Caicedo, 2019). Relative to these studies, I highlight the importance of the quasi-random variation in historical immigrant settlement patterns in shifting the varying human capital levels of local population. I show that historical immigration at the granular level is a powerful predictor of educational attainment of working-age population in US counties.

Second, I add to the large empirical literature that leverages the SSIV approach in various settings (Altonji and Card, 1991; Card, 2001; Borjas, 2003, 2005; Dustmann et al., 2017; Ottaviano and Peri, 2012; Foged and Peri, 2016; Pandey and Chaudhuri, 2017). These studies use a Card-type canonical SSIV method to tackle the endogeneity problem stemming from immigration, whereas I utilize an advanced SSIV design similar to Terry et al. (2021).[6] This new framework accounts for origin- and destination-specific confounding shocks by leaving out relevant geographic units in both push and pull factors.

Third, my study speaks the literature investigating the response of industries and establishments within quasi-experimental designs. The literature exploits immigration policies as local labor market shocks to analyze their impact on workers and firms (Kerr et al., 2015; Bound et al., 2017; Khanna et al., 2018; Doran et al., 2022; Mahajan et al., 2024; Clemens and Lewis, 2022; Amuedo-Dorantes et al., 2023).[7] In this light, I evaluate the impacts of the immigration-induced exogenous shift in local population on employment and establishment shares of distinct industry-skill types. I find that workers and establishments respond differentially to the exogenous shift in local population.

[6] This method expands on Burchardi et al. (2019). For other improved versions, see Burstein et al. (2020) and Caiumi and Peri (2024).

[7] Ulltveit-Moe et al. (2019) quantifies the industry and occupation adjustments to immigration-driven labor supply shocks.

Lastly, I complement the literature that utilizes a CES framework to model imperfectly substitutable labor supplies of various skill levels (Katz and Murphy, 1992; Card and Lemieux, 2001), in which each representative firm employs labor of a given skill level more intensively (Autor et al., 1998). The model predictions underscore the role of specialization of each firm in using labor of a certain skill type, which leads to changes in labor demand share of each firm.

The remainder of the paper is structured as follows. Section 2 discusses theoretical framework, setting up the model and deriving the comparative statics. Section 3 describes the empirical strategy, whereby I determine the issues arising from endogeneity in human capital and lay out my identification strategy. Section 4 highlights the sources of data and reports summary statistics. Section 5 presents the results along with their discussions. Section 6 provides robustness checks. Section 7 concludes.

2 Theoretical Framework

In this section, I introduce a theoretical framework that guides my subsequent empirical work. The model incorporates two distinct firm types with differentiated products, each employing labor of a certain skill type more intensively (Autor et al., 1998). This framework further follows the literature on labor supplies of different education groups (Katz and Murphy, 1992; Card and Lemieux, 2001) in a CES setting.

2.1 Setup

There exist two representative firms, blue and white collar, indexed by $i \in \{b, w\}$, each specializing in producing differentiated output, which they sell into a perfectly competitive market. Each type of firm produces output, Q_i, by combining labor of high-skill ($L_{i,h}$) and low-skill workers ($L_{i,l}$) according to a CES production function:

$$Q_i = \left(\beta_{i,h} L_{i,h}^{\frac{\sigma-1}{\sigma}} + \beta_{i,l} L_{i,l}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

Each firm utilizes labor of either high- or low-skill workers, $e \in \{h, l\}$ more intensively. The relative productivity parameters, $\beta_{i,h}$ and $\beta_{i,l}$, vary across firm types, in that $\beta_{w,h} > \beta_{b,h}$, but $\beta_{b,l} > \beta_{w,l}$, and $\beta_{i,h} + \beta_{i,l} = 1$, and σ represents the elasticity of substitution between labor types. Thus, the return of low-skill labor is relatively higher in blue-collar firms, and that of high-skill labor is relatively higher in white-collar firms. N_h and N_l represent labor supplies of high- and low-skill workers, respectively.

2.2 Comparative Statics

Each representative firm maximizes

$$\begin{aligned} \text{Max} \quad & \{Q_i - w_h L_{i,h} - w_l L_{i,l}\} \\ \text{s.t.} \quad & L_{b,h} + L_{w,h} = N_h, \\ & L_{b,l} + L_{w,l} = N_l. \end{aligned} \tag{2}$$

I assume that workers' wages in high-skill (w_h) and low-skill industries (w_l) are common across firms.

First-order conditions for both types of labor demanded by both types of firms yield

$$L_{b,l} = \frac{N_l B_w^{-1} - N_h Z^{-1}}{B_w^{-1} - B_b^{-1}}, \tag{3}$$

$$L_{w,l} = \frac{N_l B_b^{-1} - N_h Z^{-1}}{B_b^{-1} - B_w^{-1}}, \tag{4}$$

$$L_{b,h} = \frac{N_h B_w - N_l Z}{B_w - B_b}, \tag{5}$$

$$L_{w,h} = \frac{N_h B_b - N_l Z}{B_b - B_w}, \tag{6}$$

where

$$B_b = \left(\frac{\beta_{b,l}}{\beta_{b,h}}\right)^{\sigma}, \quad B_w = \left(\frac{\beta_{w,l}}{\beta_{w,h}}\right)^{\sigma}, \quad Z = \left(\frac{\beta_{b,l}^{\sigma} - \beta_{w,l}^{\sigma}}{\beta_{w,h}^{\sigma} - \beta_{b,h}^{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}.$$

Let industry-level labor demand shares, *i.e.*,, the share of workers employed in a given industry, be denoted by $s_w = \frac{L_{w,h}+L_{w,l}}{\sum_i L_{i,h}+\sum_i L_{i,l}}$ and $s_b = \frac{L_{b,l}+L_{b,h}}{\sum_i L_{i,l}+\sum_i L_{i,h}}$, and labor supply shares be given by $n_l = \frac{N_l}{N_h+N_l}$ and $n_h = \frac{N_h}{N_h+N_l}$. The differences in the relative productivity parameters and the fact that high- and low-skill labor is imperfectly substitutable ensure that $B_b > 0$, $B_w > 0$, $B_b > B_w$, and $Z > 0$. Therefore, the response of labor demand share of each firm type to labor supply share of each skill type becomes

$$\frac{\partial s_w}{\partial n_h} = \left(\frac{B_b}{B_b - B_w}\right)\left(\frac{Z + B_w}{Z}\right) > 0, \tag{7}$$

$$\frac{\partial s_w}{\partial n_l} = -\left(\frac{Z + B_w}{B_b - B_w}\right) < 0, \tag{8}$$

$$\frac{\partial s_b}{\partial n_l} = \left(\frac{Z + B_b}{B_b - B_w}\right) > 0, \tag{9}$$

$$\frac{\partial s_b}{\partial n_h} = -\left(\frac{B_w}{B_b - B_w}\right)\left(\frac{Z + B_b}{Z}\right) < 0. \tag{10}$$

An increase in labor supply share of high-skill workers leads to an increase in labor demand share of white-collar firms, whereas a rise in labor supply share of low-skill workers reduces labor demand share of those firms as shown in equations (7) and (8). Labor demand share of blue-collar firms increases in response to a rise in labor supply share of high-skill workers, while it declines due to an increase in labor supply share of those workers as demonstrated in equations (9) and (10).

The factors that drive these predictions stem from the differences in relative productivity of each labor type employed by each representative firm. Since white-collar firms have a comparative advantage in employing high-skill labor, their labor demand share is positively affected by a rise in high-skill labor supply share. However, their labor demand share is inversely impacted by an increase in low-skill labor supply share. Similarly, labor demand share of blue-collar firms is positively affected by an increase in low-skill labor supply share because those firms specialize in producing output by using labor of low-skill workers more intensively. In contrast, blue-collar firms decrease their labor demand share in response to a rise in high-skill labor supply share.

3 Empirical Strategy

3.1 Estimating Equation and Potential Threats to Identification

Guided by the theoretical framework, I study the impact of population human capital shares on employment and establishment shares across all industrial skill types in US counties. The estimating equation is given by

$$y_{e,d,t} = \alpha_s + \alpha_t + \beta_e n_{e,d,t} + \varepsilon_{e,d,t}, \tag{11}$$

where $n_{e,d,t}$ is population human capital (e) share in county d at time t. For each decennial census year, I define this variable as the number of working-age individuals with certain educational attainment by county relative to entire working-age county population. I classify individuals with a high school degree and less as low skill, those with some college education as medium skill, and those with college degree and above as high skill. $y_{e,d,t}$ is the outcome of interest, which is employment and establishment shares of skill type e in county d at time t in separate specifications.

The classification of industries into skill cells closely follows the human capital classification. In particular, I classify industries with average years of education corresponding to a high-skill degree and less as low skill, those with mean education equivalent to some college as medium skill, and those with average education comparable to college degree and above as high skill.

I define the employment share variable for each skill type as the number of workers in industries of each skill type by county divided by the entire county workforce in each census year. I construct the establishment share variable of each skill type as the number of establishments in industries of each skill type by county relative to the total number of establishments by county in each census year. α_s and α_t represent state and time fixed effects controlling for any state- and time-specific trends in $y_{e,d,t}$, respectively. The error term $\varepsilon_{e,d,t}$ captures all omitted factors.

The OLS estimates of the coefficient of interest, β_e, however, are likely biased, since unobserved confounding factors may affect the industrial skill composition of both employment and establishments in counties despite the inclusion of state and time fixed effects. This problem may lead to reverse causality and omitted variable bias, which may emerge due to the local labor market and firm creation opportunities being likely correlated with local productivity shocks. Consequently, these opportunities may attract individuals with certain educational attainment to a specific locality. For instance, the major concentration of the oil and gas industry in Houston (Harris county) may draw in high-skill petroleum engineers. Furthermore, as this sector experiences a boom, it may result in an expansion of oil refineries (*i.e.*, establishments). Therefore, these local confounding shocks would generate spurious correlations between population human capital shares and the outcomes of interest. In the following subsection, I underline the mechanisms as motivating facts to account for this endogeneity concern.

3.2 What Explains Today's Varying Human Capital Levels across US Counties?

The first mechanism that contributes to the variation in the current economic conditions in US localities is *persistence*, the long-lasting impact of historical events (Nunn, 2014; Allen and Donaldson, 2020; Voth, 2021). From the human capital perspective, one likely channel through which the spatial differences in human capital levels exist at present can be attributed to historical immigration. In particular, settlements of earlier immigrants have induced varying degrees of educational attainment amongst local population via the transmission of human capital. For example, Sequeira et al. (2020) find that counties with a higher exposure to historical immigration have a larger level of educational attainment today.[8] Abramitzky and Braggion (2006) explain the comparative economic performance in the subsequent periods through the historical positive and negative selections amongst servants to mainland American colonies and those to West Indies, respectively.[9]

Building on the channel identified above, the second mechanism pertains to the heterogeneity in skills and occupational specialization of immigrants in both historical and modern times. To the extent that retrospective immigrant selection process (Borjas, 1987; Abramitzky et al., 2012) across different origins is instrumental in affecting future economic outcomes in destinations, one can illustrate shifts in the skill composition of industries through variation in immigrant human capital.[10] For instance, some immigrants historically provided unskilled labor (Bergquist, 2007; Goldin, 1994) and crucial skills for industries (Malone, 1935), while others provided knowledge and innovation in various industries (Wittke, 1939; Boberg-Fazlić and Sharp, 2024).

Findings in Abramitzky et al. (2014) reveal substantial heterogeneity in the 1900-level occupational distribution of immigrants. The similar patterns on the task specialization, innovation, comparative advantage, and skills can still be observed amongst the relatively recent immigrants (Peri and Sparber, 2009; Hunt and Gauthier-Loiselle, 2010; Chiquiar and Hanson, 2005; Chiswick and Taengnoi, 2007; Hanson and Liu, 2023; Clemens and Mendola, 2024).

The final mechanism connects to historical immigration leading to the emergence of "ethnic enclaves" (Altonji and Card, 1991; Card, 2001). The location choice of prospective immigrants is heavily dictated by pre-existing immigrant settlements in a certain location. This can be corroborated by the diverse historical ancestry compositions across regions of the US such as the prevalence of Mexican ancestry in the Southwest, Italian ancestry in the Northeast, and German ancestry in the Midwest (Abramitzky and Boustan, 2017). These "social networks" are another contributing factor in attracting immigrants to specific areas. The existence of these networks is pivotal to immigrants arriving in the succeeding periods, since they might receive job referrals or acquire information on local economic conditions from their fellow countrymen (Munshi, 2003).

[8] For the contributions of immigrants to the US educational system, see Faust (1916).

[9] Valencia Caicedo (2019) documents the role of eighteenth century Jesuit presence in places across South America. Rocha et al. (2017) demonstrate the importance of historical immigrant settlement policies in Brazilian municipalities in underpinning current higher educational attainment. Droller (2018) finds that counties with higher shares of historical European immigrants have higher GDP per capita today due to better educational attainment amongst immigrants in Argentina.

[10] The immigrant selection process is built upon the selection of workers into occupations pioneered in Roy (1951).

3.3 The Construction of Valid Instruments

Motivated by the mechanisms highlighted above, I generate the quasi-random variation in immigration relying on historical settlement patterns at the granular level within an enhanced version of the shift-share instrumental variable (SSIV) approach. Using this predicted immigration, I isolate plausibly exogenous working-age population with varying levels of educational attainment. These instruments correct for the previously identified endogeneity problem in human capital.

3.3.1 Predicting Immigration Stocks

First, I predict the total number of immigrants from origin o ("sending" country) settling in destination d ("receiving" county) at time t, $I_{o,d,t}$, by following the procedure described in Terry et al. (2021).[11] This method predicts immigration stocks via the interactions of the historical "push" and "pull" factors by also leaving out continents (where countries of origin of immigrants are located) and nine US census divisions, which helps identify variations in $I_{o,d,t}$ that are plausibly exogenous to both county-specific and origin-destination-specific factors.[12]

The following example provides some intuition. I predict a large stock of immigrants from Mexico relative to other immigrants from Americas to Los Angeles county in the Pacific census division relative to other census divisions in the West in 1880 if the following occur. First, a considerably large number of Mexicans migrate to the United States in 1880, into census divisions excluding the Pacific census division on the West. Second, Los Angeles county is an appealing destination to foreign immigrants from any origins excluding Americas in 1880, which coincides with the real estate boom and the expansion of railway system in Southern California. Thus, I generate granular quasi-random variation in immigration stocks at the county level from the simultaneous joint forces of the "push" and "pull" factors, by estimating the following equation:

$$I_{o,d,t} = \alpha_{o,r(d)} + \alpha_{c(o),d} + X'_{o,d}\phi + \sum_{\tau=1850}^{t} \gamma_{r(d),\tau} \left(I_{o,-r(d),\tau} \frac{I_{-c(o),d,\tau}}{I_{-c(o),\tau}} \right) + u_{o,d,t}, \qquad (12)$$

where $I_{o,d,t}$ is the total number of immigrants from origin/country o settled in destination/county d at time t. $I_{o,-r(d),\tau}$ is the "push" factor that is the total number of immigrants from o at time τ settled in counties *outside* of the census division where d is located. $\frac{I_{-c(o),d,\tau}}{I_{-c(o),\tau}}$ is the "pull" factor: that is, the denominator shows the total number of immigrants from o in the United States at time τ *outside* of the continent where o is located, whereas the numerator displays the total number of

[11] My specification is slightly different than theirs, in that I predict *immigration stocks*, whereas they predict *ancestry stocks* ($A_{o,d,t}$). Nevertheless, I show that predicted immigration stocks have a strong explanatory power.

[12] Appendix Table B1 displays the allocation of states to census divisions.

immigrants in d at time τ *outside* of the continent where o is located. $\alpha_{o,r(d)}$ and $\alpha_{c(o),d}$ represent a series of origin country $\times$ destination census division and continent of origin $\times$ destination county fixed effects. $X'_{o,d}$ is a vector of the time-invariant distance and difference in latitude controls between o and d. My identification strategy in this step allows me to estimate equation (12) separately for each decennial census year between 1970 and 2010 utilizing all 25 origin countries and all 3,141 destination counties in my sample. Finally, I obtain predicted immigration stocks as follows:

$$\hat{I}_{o,d,t} = \sum_{\tau=1850}^{t} \hat{\gamma}_{r(d),\tau} \left(I_{o,-r(d),\tau} \frac{I_{-c(o),d,\tau}}{I_{-c(o),\tau}} \right), \tag{13}$$

where $\hat{\gamma}_{r(d),\tau}$ are the coefficients that I estimate from equation (12).[13] If, on the other hand, I had used the observed or realized immigration stocks in the "push" and "pull" factors without the "leave-out" element (as in the canonical shift-share approach), this could have led to a spurious correlation between current immigration and employment as well as establishments owing to the persistent productivity shocks.[14]

3.3.2 Isolating Exogenous Population with Varying Levels of Educational Attainment

After predicting immigration stocks, I proceed to the second step to isolate human-capital-specific working-age population by county over the 1970-2010 period, which is a key contribution in my identification strategy. To this end, I predict the total number of individuals with varying levels of educational attainment, corresponding to low-, medium-, and high-skill types, in US counties by utilizing the quasi-random variation in immigration estimated in the previous step. Therefore, the estimating equation takes the following form:

$$N_{e,d,t} = \alpha_s + \alpha_t + \sum_{o=1}^{25} \mu_{e,o} \cdot \hat{I}_{o,d,t} + \nu_{e,o,d,t}, \tag{14}$$

where $N_{e,d,t}$ is the total number of individuals with educational attainment e residing in county d at time t. α_s and α_t represent state and time fixed effects, respectively. $\hat{I}_{o,d,t}$ is the predicted immigration stock obtained in equation (13) for each of 25 foreign origins (countries) in my sample.[15]

[13] Note that I take the residuals of the interactions of push and pull factors with respect to all of the fixed effects and controls included in equation (12) similar to Terry et al. (2021). This procedure is necessary to conclude that $\hat{I}_{o,d,t}$ hinges solely on local variations in relative predicted immigration stocks by eliminating any remaining confounding factors between large and small counties (arising from persistent productivity shocks) as well as countries. This addresses the first threat, reverse causality, highlighted above.

[14] Appendix Figure (C1) illustrates the binned scatter plot of predicted immigration, obtained in this step, against immigration stock in 2010.

[15] I choose to limit my sample to the top-25 "most-immigrant sending" origin countries, since the number and, thus, educational attainment of immigrants arrived from those origins is sufficiently large to induce variation in human capital of local population.

I estimate equation 14 for individuals with each educational attainment separately. Finally, I obtain main instruments for population human capital (e) share in county d at time t, $n_{e,d,t}$, in equation (11) as follows:

$$\hat{N}_{e,d,t} = \sum_{o=1}^{25} \hat{\mu}_{e,o} \cdot \hat{I}_{o,d,t}. \tag{15}$$

These instruments help address the endogeneity issue in human-capital-specific working-age population by integrating the channels influencing human capital of local population determined earlier. The channels are (i) the transmission of human capital from historical immigration to local population via persistence, (ii) heterogeneity in immigrants' skills, comparative advantages, along with occupational specialization, and (iii) forming of "ethnic enclaves" and "social networks" induced by immigration.[16]

Identifying Assumption. The advanced version of the SSIV design used in this study in the spirit of Terry et al. (2021) addresses one of the key critiques for the conventional Card-type instruments, which is serial correlation or autocorrelation amongst past and contemporaneous immigration stocks (Jaeger et al., 2018). As a remedy, this new method introduces the "leave-out" element for both "push" and "pull" factors as explained in detail above. Hence, a sufficient condition for the exogeneity of the constructed instruments rests on the assumption that the predicted immigration stock, $\hat{I}_{o,d,t}$, is exogenous in equation (11). Formally,

$$\left(I_{o,-r(d),\tau} \frac{I_{-c(o),d,\tau}}{I_{-c(o),\tau}} \right) \perp \varepsilon_{e,d,t} \quad \forall o, \tau \leq t. \tag{16}$$

In other words, any confounding factors that cause changes in the industrial skill composition of workers and establishments in a given county at time t ($\varepsilon_{e,d,t}$) do not systematically correlate with historical immigration from a certain origin to other census divisions at time τ ($I_{o,-r(d),\tau}$) interacted with the share of immigrants from other continents in that county in the same year $\left(\frac{I_{-c(o),d,\tau}}{I_{-c(o),\tau}}\right)$. The exogeneity condition for these instruments aligns with the "shock orthogonality" condition outlined in Goldsmith-Pinkham et al. (2020).[17]

The following example builds intuition for the plausibility of this assumption. Suppose that agriculture, a low-skill (LS) industry, experiences a productivity shock in Kern county at time

[16] Appendix Figures C2, C3, and C4 illustrate the bivariate maps of endogenous human-capital-specific working-age population shares, and Appendix Figures C5, C6, and C7 display the bivariate maps of exogenous skill-specific working-age population across US counties in 2010.

[17] Note that this is a sufficient, but not a necessary, condition for instrument validity within the SSIV framework. For both conditions, see Borusyak et al. (2022).

t ($\varepsilon_{LS,Kern,t}$), which draws in Mexican immigrants with a comparative advantage in agriculture ($I_{Mexico,Kern,t}$). A sufficient restriction for exogeneity to hold is that this confounding shock alongside any other country-county-specific factors that attract immigrants and shape changes in workers and establishments in low-skill industries witin that county does not affect the predicted Mexican immigration stock in Kern county at time t, $\hat{I}_{Mexico,Kern,t}$. The violation of this restriction would arise in the case, whereby the confounding shock: (i) systematically affected the settlement patterns of many immigrants excluding Americas such as Filipino immigrants, and (ii) drew a significant number of Mexicans to counties outside of the Pacific region such as Lancaster county in Pennsylvania. I probe this possibility using a variant of the "leave-out push-pull" instruments in Section 6 addressing another problem emphasized in Adao et al. (2019).

3.4 Instrument Validation Exercises and First-Stage Performance

To assess the validity of the identification strategy, I use the following reduced-form specification:

$$y^{std}_{e,d,1960} = \alpha_s + \alpha_t + \psi_e \hat{N}^{std}_{e,d,t} + \epsilon_{e,d,t}, \tag{17}$$

where $y^{std}_{e,d,1960}$ is a standardized measure of establishment share of each industry-skill type in 1960, and $\hat{N}^{std}_{e,d,t}$ is a standardized measure of exogenous population of each skill type over the 1970-2000 period. The regressions also include state (α_s) and time (α_t) fixed effects.

The rationale behind this specification is to examine whether human-capital-specific exogenous population, $\hat{N}^{std}_{e,d,t}$, is correlated with pre-study-period outcomes, *i.e.*, establishment shares of each industry-skill type in 1960. If the correlations between them exist, then they would point to the likely violations of the identifying assumption laid out above. In this light, $\hat{\psi}_e$ provide balance tests on pre-study-period estimates for establishment shares that probe whether these violations are present.

Figure 1 displays the results of these balance tests. All estimated coefficients are small in magnitude and statistically insignificant conditional on state and time fixed effects in the pre-study-period of 1960. These findings provide reassuring evidence that the immigration-driven shift in human capital of local population is uncorrelated with short- and long-run economic outcomes, an issue raised in Jaeger et al. (2018). Figure 2 displays binned scatter plots of the first-stage estimates, whereby exogenous working-age population of each human capital level is plotted against endogenous working-age population of each human capital level.[18] Conditional on state and time fixed

[18]Formally, I estimate the following first-stage equation: $n_{e,d,t} = \alpha_s + \alpha_t + \kappa_e \hat{N}_{e,d,t} + \xi_{e,d,t}$

effects, binned scattered plots demonstrate that these variables are well-aligned.

4 Data

4.1 Sources

Immigration. I utilize data on immigration obtained from the individual decadal census files of the Integrated Public Use of Microdata Series (IPUMS USA and NHGIS: Ruggles et al., 2022; Manson et al., 2022) samples from 1850-2000 as well as the 2006-2010 five-year sample of the American Community Survey (ACS). I weigh observations by the person weights in these sources. My dataset on immigration covers 3,141 US counties, 25 foreign countries, and 15 census waves.[19] I provide additional details on the construction of immigration stock data in subsection A.1 of Data Appendix.

Working-Age Population, Employment, and Establishments. I acquire data on working-age population and employment at the county level using the individual census rounds from 1970-2000, and the 2006-2010 five-year waves. I define working-age population as individuals aged 16 to 64. As before, I weigh observations by the person weights. I obtain data on the number of establishments at the county level from the 1970-2010 extracts of the County Business Patterns (CBP) data published by the Census Bureau. I supplement these data with those compiled in Eckert et al. (2020a, 2022). The Census Bureau defines an establishment as a single physical location where services and production activities are undertaken.[20] I provide additional details on the constructions of working-age population, employment, and establishment data in subsections A.2, A.3, and A.4 of Data Appendix, respectively.

4.2 Skills, Human Capital, Tradability Classification, and Summary Statistics

A central component of my analysis is to allocate industries into skill cells. For this purpose, I construct the industry-based continuous skill measure in the following steps. First, I create an education variable and assign values to it based on the educational attainment (years of education) of each individual. Second, I aggregate the 1990-level census industry codes to a balanced panel of industries utilizing an industry concordance generated in Autor et al. (2019). Finally, I calculate mean education for workers employed by each industry in the balanced panel in each census year. I

[19] The complete list of 1990-level countries in my sample includes Austria, Canada, China, Colombia, Cuba, Czechoslovakia, Dominican Republic, El Salvador, Germany, Guatemala, Haiti, Hungary, India, Ireland, Italy, Jamaica, Japan, Republic of Korea, Mexico, Philippines, Poland, Sweden, USSR, UK, and Vietnam.

[20] An establishment is not necessarily identical to a firm or enterprise, which may own one or more establishments.

define industries with average years of education corresponding to a high school degree and less as low skill, those with average education corresponding to some college degree as medium skill, and those with mean education comparable to college degree and more as high skill. Appendix Table B2 presents the industry-skill classification. Classifying working-age individuals by human capital is identical to the procedure described above.

Moreover, I group industries into tradable and nontradable sectors. I classify agriculture, mining, and manufacturing industries as tradable, whereas I categorize all service industries as nontradable similar to the classification scheme in Burstein et al. (2020). Appendix Tables B3, B4, B5, and B6 display tradable and nontradable industries along with their skill types.

Table 1 reports summary statistics. It reveals substantial variation across the skill distribution of working-age population shares and mean education of working-age individuals at the county level in Panel A. The table presents employment and establishment shares as well as mean education of workers employed by each industry at the county level used in the baseline and tradability analyses in Panel B. Panel A shows that the majority of working-age population hold a high-school degree and less, while a quarter have some college education, and the remainder possess a college degree and higher. Panel B demonstrates that the distribution of employment and establishment shares in medium-skill industries is similar; however, a greater portion of workers are concentrated in low-skill industries, whereas a higher share of establishments is clustered in high-skill industries. The compositions of employment and establishment shares in low-skill industries across both tradable and nontradable sectors are comparable, but the majority of workers and establishments are predominantly concentrated in medium- and high-skill nontradable industries. While mean education of low- and medium-skill workers are similar across both sectors, workers employed by high-skill nontradable industries have, on average, 0.8 more years of schooling than those employed by high-skill tradable industries.

5 Results

In this section, I present my empirical findings by exploiting exogenous working-age population of each human capital level to explore the causal impacts of population shares on employment and establishment shares in the baseline and tradability analyses. Furthermore, I implement a heterogeneity analysis across major industries along with establishment size domains and probe the robustness of my baseline estimates on a series of checks. All regressions include state and time fixed effects, and standard errors are clustered by state in all specifications.

5.1 Baseline Analysis: Employment and Establishment Shares

Prior to the causal results, I report OLS estimates in Table 2 presenting the associations between population shares and employment shares in Panel A and establishment shares in Panel B based on estimating equation (11). The OLS estimates of medium- and high-skill population shares on employment shares of all industry-skill types are statistically significant. One can also notice the statistically significant estimated coefficients for the association between high-skill population share and establishment shares of all industry-skill types. However, the estimated coefficients for the association between medium-skill population share and establishment shares of all industry-skill types are statistically insignificant within the same specifications.

Table 3 reports IV estimates for the impacts of population shares on employment shares in Panel A and on establishment shares in Panel B. Endogenous medium- and high-skill population shares are instrumented with exogenous population of corresponding human capital levels as described in Section 3. Compared to the OLS results, most of the causal estimates for the effects of population shares on employment shares are larger in magnitude. Moreover, the coefficient estimates for the impacts of population shares on establishment shares are large and statistically significant. All Anderson-Rubin Wald F-test p-values for the statistically significant point estimates are around 0%, suggesting that endogenous population shares are jointly significant, and that my instruments, exogenous population of given human capital levels, are valid.

In particular, I find that, relative to low-skill population share, a one-percentage-point increase in medium- and high-skill population shares leads to a decrease in employment share of low-skill industries by 0.91 and 0.52 percentage points, respectively. By contrast, this increase results in a rise in employment share of high-skill industries by corresponding 0.15 and 0.55 percentage points. Additionally, a one-percentage-point rise in medium-skill population share boosts employment share of medium-skill industries by 0.76 percentage points. One can observe similar patterns across the estimates for establishment shares. Specifically, establishment share of low-skill industries drops by 1.67 and 0.34 percentage points as medium- and high-skill population shares rise by a one percentage point. Conversely, establishment share of high-skill industries grows by 1.54 and 0.40 percentage points in response to a one-percentage-point increase in medium- and high-skill population shares.

To compare the establishment estimates, Sequeira et al. (2020) show that an aggregate establishment share increased in response to a rise in average immigrant share during the Age of Mass

Migration. Olney (2013) finds that a 1 percent increase in low-skill immigrant employment share raises the number of establishments by 0.2 percent within a city. Regarding the comparison of the employment estimates, Ottaviano et al. (2013) demonstrate that overall employment grows by 3.9 percent as immigrant share of employment increases by 1 percent. They do not conduct a skill-based analysis, but do consider the task complexity carried out by native, immigrant, and offshore workers.[21]

Taken together, these empirical findings are in line with the model predictions introduced in Section 2. First, both employment and establishment shares of high-skill industries respond positively to a rise in medium- and high-skill population shares. This is equivalent to white-collar firms increasing their labor demand share for high-skill labor supply share due to their comparative advantage in employing high-skill labor more intensively.[22] Second, a rise in medium- and high-skill population shares reduces employment and establishment shares of low-skill industries. This corresponds to blue-collar firms having comparative advantage in using low-skill labor more intensively while employing high-skill labor less intensively.

5.2 Tradability Analysis: Employment and Establishment Shares

The theory and empirical evidence in the existing literature suggest that the exposure to immigration-induced local labor supply shocks affects firms, occupations, and industries differently. At the more granular level, the adjustment to these shocks varies within and across firms producing tradable or nontradable goods as well as workers employed in tradable or nontradable occupations or industries (Ottaviano et al., 2013; Dustmann and Glitz, 2015; Burstein et al., 2020). In this subsection, I present my results pertinent to the effects of working-age population shares of all human capital levels, instrumented similarly as before, on the outcomes of interest in the tradable and nontradable sectors. I further aim to implement this exercise to disentangle the heterogeneous estimates from the aggregate ones. This effectively helps determine which sector and skill types absorb the impacts of the immigration-induced exogenous shift in local population. I include state and time fixed effects and cluster standard errors by state in all specifications.

Table 4 reports the regression results of how population shares affect employment shares in the tradable and nontradable sectors in Panels A and B, respectively. The estimates demonstrate that

[21] Admittedly, the findings of these studies do not provide direct comparisons with those of mine, since they rely on immigration-led local labor supply shocks, but they nevertheless offer relevant context for my analysis.

[22] Although the theoretical framework introduces only two types of labor—low and high skills—the model predictions can be extended to a setting that includes a third type, medium skill, in addition to the existing two.

the main portion of the positive effects found in the baseline results stems from the nontradable sector, whereas the large fraction of the adverse impacts is captured by the tradable sector. Notably, medium- and high-skill population shares have large negative effects on employment share of low-skill tradable industries, while they have sizable positive impacts on that of high-skill nontradable industries. Medium-skill population share has a moderate positive effect on employment shares of medium-skill industries in both sectors. High-skill population share has a modest adverse impact on employment share of medium-skill tradable industries, whereas it has a small positive effect on that of high-skill tradable industries.

Table 5 presents the regression results for the effects of population shares on establishment shares in the tradable and nontradable sectors in Panel A and Panel B, respectively. As regards the comparison with the baseline estimates, the following is worth noting. The negative effects are chiefly borne by the tradable sector, while the positive impacts arise from the nontradable sector. More specifically, medium- and high-skill population shares have considerable negative effects on establishment share of low-skill industries, whereas the magnitudes of their negative impacts on that of high-skill industries are moderate in the tradable sector. However, they have substantial positive effects on establishment share of high-skill nontradable industries. The sizes of the positive impacts of medium-skill population share on establishment share of low-skill industries are also large, while the adverse effect of high-skill population share on establishment share of medium-skill industries is modest in magnitude in the nontradable sector.

My findings on employment shares are consistent with Moretti (2010). In particular, Moretti illustrates that an increase in the number of workers can generate jobs, especially for high-skill workers in the nontradable sector, due to a rise in the demand for local goods and services. On the other hand, the tradable sector can endure the adverse effects because of the increase in labor costs on account of the labor demand shock. Although not directly comparable, in contrast to Burstein et al. (2020), I find that employment shares of high-skill industries in both sectors respond positively to an increase in population shares. However, they show that the impact of immigration shock on high-skill workers is negative across both sectors. Relative to the effect of low-skill population share, I document that a rise in medium- and high-skill population shares adversely affect establishment share of low-skill tradable sector aligning with the positive impact of low-skill immigrant share on establishments in that sector found in Olney (2013). By contrast, my results reveal positive effects in the nontradable sector, while Olney finds statistically insignificant estimates in the same sector.

5.3 Employment Heterogeneity by Nativity

I isolate exogenous human-capital-specific local population using the quasi-random variation in historical immigrant settlement patterns. It should be noted that apart from the transmissions of human capital and knowledge emphasized in Section 3 as a likely channel, earlier immigrants (*i.e.*, "ancestors") can pass some other traits on to next generations (*i.e.*, "descendants") due to cultural ties as documented in the relevant literature (Sequeira et al., 2020; Alesina and Tabellini, 2024). Furthermore, immigrant assimilation can contribute to the changes in economic outcomes (Abramitzky et al., 2014; Gagliarducci and Tabellini, 2022).

While the design of my instruments does not directly permit separating individuals by nativity, my objective is to test whether the immigration-driven shift in exogenous population affects both native and immigrant workers. To this end, Appendix Table B7 presents the regression results of this assessment for native employment shares in Panel A and immigrant employment shares in Panel B. The estimated coefficients show that both native and employment shares are impacted by changes in population shares, with the effects being more pronounced for native employment shares. These findings provide suggestive evidence that the constructed instruments affect the industrial skill composition of local areas most strongly via their impact on native employment shares. Although the exogenous variation derives from historical immigration, the assimilation and eventual naturalization of immigrants enabled them to become part of the "native" population over time.

5.4 Employment and Establishment Heterogeneity by Industry

The historical events can have both short-run and long-run effects on sectoral shifts, industrialization, and structural transformation in the local labor markets (Peters, 2022; Droller, 2018; Rocha et al., 2017). To the extent that these changes occur, I aim to investigate the sectoral reallocation of employment and establishment shares due to the exogenous shift in human capital of local population. Therefore, I present additional results across several major industries in this subsection, except I do not disaggregate them by skill types.[23] As before, I add state and time fixed effects and cluster standard errors by state in all specifications.

Appendix Table B8 reports these estimates for employment and establishment shares in Panels A and B, respectively. The findings reveal that an increase in medium- and high-skill population shares negatively affect employment share in agriculture, while it positively impacts employment share

[23] Given the limitations in the coverage of agricultural establishments in the CBP data during the study period, I exclude this category from the analysis.

in services sector. The mining and manufacturing, wholesale and retail trade, and transportation sectors experience an increase in their employment shares in response to a rise in medium-skill population share. However, an increase in high-skill population share adversely affects the mining and manufacturing along with transportation sectors. The coefficient estimates for employment share in construction are statistically insignificant. A rise in medium- and high-skill population shares raise establishment share in services sector similar to employment share in that sector. In contrast, mining and manufacturing, construction, and transportation sectors undergo a reduction in their establishment share as a result of an increase in medium-skill population share. Wholesale and retail trade alongside transportation sectors are also negatively affected by a rise in high-skill population share.

Overall, considering the signs and magnitudes of the estimated coefficients, these findings are in line with those found in the tradability analysis. In parallel to my results, Peters (2022) shows that the change in local population induced by the inflows of refugees from East to West Germany raises manufacturing employment share, whereas it reduces agricultural employment share in German counties. Additionally, he finds a positive effect on firm entry, but does not decompose it by sectors. Contrary to his estimates, my results demonstrate an increase in employment share in services as population shares rise. It conforms to the positive findings across the nontradable sector demonstrated above, which practically consists of services.

5.5 Establishment Heterogeneity by Size

In this subsection, I provide further heterogeneity across establishment size for all industries as well as tradable and nontradable sectors. This analysis helps identify which establishments are affected the most by the immigration-induced exogenous shift in human capital of local population resulting in additional industry-skill compositional changes across establishments of various sizes. Following the existing literature, I define small establishments as those employing fewer than 20 workers, medium establishments as those employing between 20 and 500 workers, and large establishments as those employing more than 500 workers.[24] I instrument endogenous population shares of given skill types with exogenous population of corresponding human capital levels as before. All specifications include state and time fixed effects, and standard errors are clustered by state.

Establishments in All Industries. Appendix Table B9 reports the regression results of how population shares affect small, medium, and large establishment shares across all skill types in Pan-

[24] For a similar classification scheme, see Olney (2013).

els A, B, and C, respectively. The estimates demonstrate that the negative impacts of medium- and high-skill population shares are mainly absorbed by small and large establishments. The effects are stronger on small establishments in low-skill industries along with large establishments in medium- and high-skill industries. However, medium establishments in medium- an high-skill industries capture the positive effects of medium- and high-skill population shares with more marked impacts on medium-skill establishments. As opposed to Olney (2013), I find that small and large establishment shares in low-skill industries are adversely affected, while small and medium establishment shares in high-skill industries are positively impacted by the immigration-driven exogenous shift in human capital.[25]

Establishments in the Tradable and Nontradable Sectors. Appendix Tables B10 and B11 present the results of the responses of small, medium, and large establishment shares in the tradable and nontradable sectors to population shares in Panels A, B, and C, respectively. The estimates in Appendix Table B10 for the tradable sector show that the negative effects of population shares on establishment share of low-skill industries reported in the baseline findings are predominantly captured by small followed by large and medium establishments. Their positive effects on establishment share of medium-skill industries are fully borne by medium establishments of medium-skill industries. The estimated coefficients in Appendix Table B11 for the nontradable sector reveal that the adverse effects of population shares on establishment share of low-skill industries displayed in the baseline estimates emanate from small and large establishments with the impact on the latter being much sharper. One can notice a similar trend across small and large establishments of medium-skill industries. By contrast, the positive impacts of population shares on establishment share of medium-skill industries can be entirely attributed to medium establishments of medium-skill industries.[26]

6 Robustness

I implement a battery of robustness checks and show that my results are robust to (i) an alternative construction of the shift-share instruments using various time periods and a different method, (ii)

[25] Olney explains the positive and negative impacts of immigration shocks on establishment counts through the fast and slow capital adjustment channels, respectively.

[26] Mahajan (2024) provides an explanation through the firm productivity mechanism. Olney (2013) and Dustmann and Glitz (2015) delineate a change in establishment counts via the "production" channel in the tradable sector, whereas Olney (2013) offers an implication for a decrease in the number of establishments through the "consumption" channel in the nontradable sector. Note that these studies examine how firms and establishments respond to immigration shocks in various contexts.

various sample selections, (*iii*) an alternative tradability classification, and (*iv*) randomization tests.

Alternative Instruments/Exogenous Population of Different Human Capital Levels. Initially, I want to assess whether the immigration-induced exogenous shift in human capital levels of local population has had long-run effects on the industrial skill composition of workers and establishments in counties. This exercise further contributes to our understanding of the persistence of particular historical events in local labor markets. For this purpose, while predicting immigration stocks from 1970 to 2010, I restrict the push and pull factors to the 1850-1900 and 1850-1950 periods in separate specifications.[27] Afterwards, I proceed to isolate human-capital-specific exogenous local population using these predicted immigration stocks as in the baseline instruments. Appendix Tables B12 and B13 report the regression results of this exercise for employment and establishment shares in Panels A and B, respectively. The coefficient estimates for both outcomes across these two different time periods closely match those documented in the main analysis utilizing the baseline instruments. These findings confirm two ideas. First, historical episodes do have long-lasting impacts on local labor markets. In this context, it attests to the effects of the exogenous population shifts due to the randomized historical immigrant settlement patterns across space and time on the industrial skill distribution of workers and establishments in counties. Second, to a lesser extent, limiting the time periods in generating instruments does not alter my main results.

Furthermore, I address the potential threat to my identification strategy specified in Section 3. If, for instance, some historical confounding shock arising from agricultural productivity drew Filipino and Mexican immigrants to Kern and Lancaster counties, and if later agricultural productivity shocks persistently had large similar effects, then my instruments may be contaminated with endogenous immigration stocks that may be correlated with productivity. I use an alternative leave-out strategy in building my instruments to tackle this potential threat as follows: while predicting immigration stocks from o (Mexico) to d (Kern county), rather than leaving out o's immigrants who have settled in the census division where d is located (Pacific), I exclude immigrants from o who have settled in counties with immigration stocks that are serially correlated with those to d (Lancaster county).[28] Similar to the baseline analysis, I include state and time fixed effects in the regressions of employment and establishment shares on population shares as reported in Panels A and B of Appendix Table B14, respectively. The table demonstrates that the estimated coefficients across both specifications are highly comparable to the baseline estimates. Moreover, the p-values

[27] The time periods roughly correspond to the Age of Mass Migration.

[28] Terry et al. (2021) implement the same strategy to address this concern potentially stemming from productivity shock to innovation.

for the Anderson-Rubin Wald F-tests are around 0% for all statistically significant estimates. These results provide evidence that my baseline findings do not suffer from the county-country-specific omitted factors.

Various Sample Selections. Another concern would be that the baseline estimates might be driven by large immigrant-sending countries and immigrant-receiving counties. To ensure that the estimates do not vary upon the exclusion of these large geographic units to a noticeable degree, I carry out the following exercise. First, I leave out those five largest origins in isolating the human-capital-specific exogenous population and run regressions for employment and establishment shares. Second, I exclude five largest destinations in constructing the instruments and run the same regressions as before.[29] I introduce the regression results in Appendix Tables B15 and B16. The estimated coefficients remain consistent with the baseline ones in both cases.

Alternative Tradability Classification. Next I employ an alternative measure of tradability, in that I classify industries to different tradable and nontradable sectors. My goal is to check whether there would be considerable variations compared to the baseline estimates. I utilize the industry tradability measure outlined in Mian and Sufi (2014). This measure is based on geographical Herfindahl-Hirschman Indices (HHIs) through which industries become more tradable if they are more geographically concentrated.[30] I tabulate the effects on employment and establishment shares using the alternative tradability measure in Appendix Tables B17 and B18, respectively. On the whole, the results suggest that using a different classification method does not alter the baseline estimates to a considerable extent, and that the estimated coefficients, in large part, remain robust to this measure.

Randomization Inference. An over-rejection problem originating from conventional shift-share instruments has been discussed in Adao et al. (2019). If two counties with similar historical immigration distribution also experience similar exposure to other unobservable economic forces, the isolation of population instruments for all skill types may not be exogenous. This may be because conventional clustered standard errors may not capture a dependency across regression residuals. Hence, I follow the procedure described in Adao et al. (2019) and randomly construct a placebo population instrument for each skill type as follows. First, I randomly generate predicted immigration stocks for each country-region-time triplet (instead of each country-county-time triplet as

[29] In my sample, the five largest origins (i.e., the most immigrant-sending countries) include Canada, China, Germany, Mexico, and Philippines, and the five largest destinations (i.e, the most immigrant-receiving counties) are Los Angeles, Cook, Harris, Miami-Dade, and Kings counties.

[30] See Appendix Table I in the online appendix of their paper for this classification scheme.

in the main instruments). Later, I isolate human-capital-specific population relying on randomly generated predicted immigration stocks. I then run 1,000 placebo first-stage regressions of endogenous population share of each skill type on a randomly generated placebo instrument of each skill type. I also run the relevant reduced-form regressions. Appendix Table B19 presents the results and reports the fraction for which I reject the null hypothesis of "no effect" at the 1% level of statistical significance. Since I find a false rejection rate of 0%, I conclude that my skill-specific population instruments are orthogonal to any confounding forces, and confirm that my inferences based on conventional clustered standard errors are valid.

7 Conclusion

One can notice sizable differences in the skill distribution of industries across the United States. These variations can be due to a number of factors including technological change, job polarization, and local demand shocks. However, the role of human capital is largely unknown. In this paper, I study how the immigration-induced exogenous shift in the varying human capital levels of local population affects the industrial skill composition of employment and establishment shares in US counties. To this end, I overcome the endogeneity challenge in human capital using a two-step procedure. Initially, leveraging the recent developments in the literature on the use of the shift-share instrumental variables (SSIV) approach, I predict the immigration stocks via the "leave-out push-pull" technique by relying on 160 years of historical granular immigration data. Afterwards, using this quasi-random variation in immigration, I isolate skill-specific working-age local population. To rationalize my empirical findings, I utilize a model incorporating two distinct firm types that specialize in producing differentiated output by employing imperfectly substitutable either low- or high-skill labor more intensively. The model predicts that due to differences in specialization, each firm type experiences differential impacts in their labor demand shares in response to a rise in labor supply shares of given skill types.

I find that, relative to low-skill population share, an exogenous increase in medium- and high-skill population shares leads to a decline in employment and establishment shares of low-skill industries. This empirical finding corresponds to a model prediction, whereby blue-collar firms undergo a decrease in labor demand share, since they employ high-skill labor less intensively. However, relative to low-skill population shares, a rise in medium- and high-skill population shares raises employment and establishment shares of high-skill industries. This finding is supported by another model prediction, in which white-collar firms experience an increase in their labor demand share due to employing high-skill labor more intensively. Furthermore, the results reveal that the nontradable sector absorbs the majority of the positive effects, while the tradable sector captures the sizable fraction of the adverse impacts.

A potential research avenue in the future could involve exploring how county-level local economic development is shaped by exogenous changes in local population. These changes can be isolated by using the instruments that exploit past immigrant settlement patterns similar to those in this study. The question can potentially shed light on the path of local economic development at the granular level, furthering the literature on persistence and path dependence.

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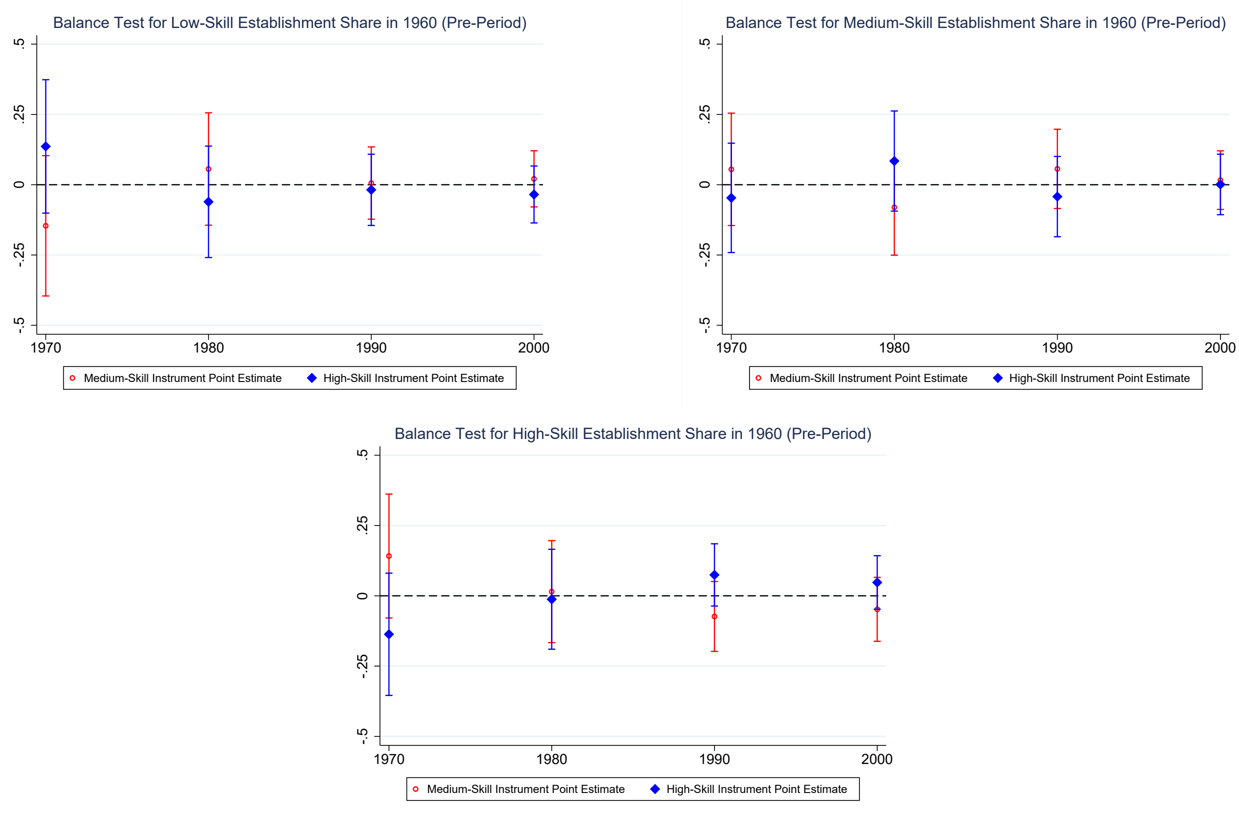

Figure 1: Balance Tests

Notes: These figures display the results of the balance tests specified in equation (17). Coefficients report the effect of a one-standard-deviation increase in each instrument, human-capital-specific exogenous population, over the 1970-2000 period on a standardized measure of establishment share of each skill type in 1960. All regressions include state and time fixed effects. Whiskers indicate 95% confidence intervals computed using standard errors clustered by state.

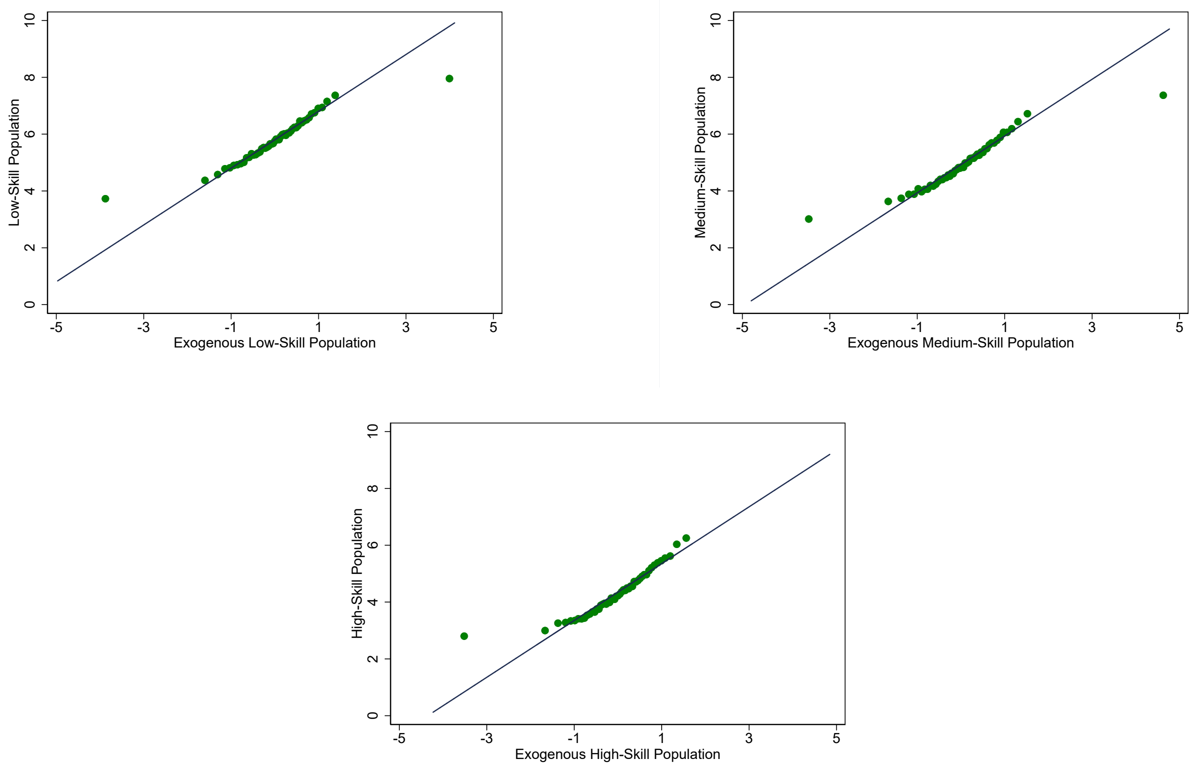

Figure 2: First-Stage Relationship

Notes: These figures display binned scatter plots of the first-stage estimates, whereby exogenous working-age population of each human capital level obtained in equation (15) is plotted against endogenous working-age population of each human capital level. The number of bins is fixed at 500. All regressions include state and time fixed effects, and standard errors are clustered by state for all specifications. The figures have been plotted using the "`binsreg`" package in Stata (Cattaneo et al., 2024).

Table 1: SUMMARY STATISTICS

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Population Human Capital			
$Working-Age\ Population\ Share_{e,d,t}$ (%)	59.60	25.64	14.76
	(13.21)	(7.97)	(6.69)
$Mean\ Education_{e,d,t}$	10.80	13.55	16.77
	(0.63)	(0.11)	(0.19)
Panel B: Industrial Skill Composition			
Baseline			
$Employment\ Share_{e,d,t}$ (%)	31.79	45.99	22.22
	(25.53)	(17.13)	(11.75)
$Establishment\ Share_{e,d,t}$ (%)	25.09	43.15	31.76
	(19.87)	(14.93)	(16.04)
$Mean\ Education_{e,d,t}$	11.41	12.76	14.82
	(0.46)	(0.14)	(0.14)
Tradable Sector			
$Employment\ Share_{e,d,t}$ (%)	17.68	10.36	2.71
	(13.75)	(6.72)	(2.91)
$Establishment\ Share_{e,d,t}$ (%)	11.14	9.58	2.43
	(20.06)	(13.61)	(5.35)
$Mean\ Education_{e,d,t}$	11.27	12.51	13.68
	(0.55)	(0.17)	(0.27)
Nontradable Sector			
$Employment\ Share_{e,d,t}$ (%)	15.15	22.84	31.25
	(13.20)	(7.25)	(13.27)
$Establishment\ Share_{e,d,t}$ (%)	14.67	31.56	30.62
	(11.55)	(14.05)	(16.85)
$Mean\ Education_{e,d,t}$	11.56	12.55	14.49
	(0.39)	(0.11)	(0.15)
N	15,705	15,705	15,705

Notes: This table presents the mean, standard deviation (in parentheses), and the number of observations for both independent and dependent variables of all skill types (e) at the county (d) level for the decennial 1970-2010 period (t). Panel A displays the human-capital-specific variables. The working-age population share variable of each skill type at the county level in a certain decennial census year equals the number of working-age individuals with a given mean education level by county relative to total county population in that year. The employment share variable of each skill type at the county level in a given census year represents the number of workers of each skill type by county relative to the entire workforce in that county and census year. The establishment share variable of each skill type at the county level in a certain year is normalized by the total number of establishments by county in that year. Panel B reports the industry-skill-specific variables utilized in the baseline and tradability analyses. The determinant of the continuous skill measure corresponds to mean education of workers employed by each industry in each year. The measure of tradability is based on Burstein et al. (2020). The tradable sector includes the agriculture, mining, and manufacturing industries, whereas the nontradable sector covers all services industries. The employment share variable of each skill type in each sector and census year is normalized by the entire workforce in each sector and year. The establishment share of each skill type in each sector and year is normalized by the total number of establishments in each sector and year.

Table 2: OLS Estimates of Employment and Establishment Shares

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Employment Shares			
$Population\ Share^{t}_{MS,d}$	-0.627***	0.539***	0.088***
	(0.044)	(0.051)	(0.032)
$Population\ Share^{t}_{HS,d}$	-0.357***	-0.234***	0.591***
	(0.027)	(0.036)	(0.028)
R^2	0.973	0.912	0.944
Panel B: Establishment Shares			
$Population\ Share^{t}_{MS,d}$	-0.101	0.047	0.054
	(0.088)	(0.075)	(0.062)
$Population\ Share^{t}_{HS,d}$	-0.272***	-0.289***	0.561***
	(0.035)	(0.028)	(0.039)
R^2	0.355	0.056	0.465
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table reports the OLS results of estimating equation (11). The dependent variables are employment and establishment shares of each industrial skill type at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are medium- and high-skill working-age population shares at the county level. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: IV Estimates of Employment and Establishment Shares

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Employment Shares			
$Population\,Share^{t}_{MS,d}$	-0.907***	0.755***	0.152**
	(0.103)	(0.093)	(0.065)
$Population\,Share^{t}_{HS,d}$	-0.519***	-0.033	0.552***
	(0.048)	(0.055)	(0.045)
AR Wald F-Test P-value	0.000	0.000	0.000
Panel B: Establishment Shares			
$Population\,Share^{t}_{MS,d}$	-1.668***	0.125	1.543***
	(0.375)	(0.184)	(0.309)
$Population\,Share^{t}_{HS,d}$	-0.344***	-0.057	0.401***
	(0.087)	(0.054)	(0.091)
AR Wald F-Test P-value	0.000	0.457	0.000
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table reports the IV results of estimating equation (11). The dependent variables are employment and establishment shares of each industrial skill type at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with medium- and high-skill exogenous working-age population at the county level. Each specification presents the p-value for the Anderson-Rubin Wald F-test. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: EMPLOYMENT ESTIMATES IN THE TRADABLE AND NONTRADABLE SECTORS

	Employment Shares			
	All	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)	(4)
Panel A: Tradable Sector				
$Population\ Share^{t}_{MS,d}$	-0.774***	-1.064***	0.239***	0.051
	(0.137)	(0.128)	(0.066)	(0.044)
$Population\ Share^{t}_{HS,d}$	-0.732***	-0.524***	-0.272***	0.064***
	(0.051)	(0.058)	(0.035)	(0.019)
AR Wald F-Test P-value	0.000	0.000	0.000	0.005
Panel B: Nontradable Sector				
$Population\ Share^{t}_{MS,d}$	0.774***	0.020	0.308***	0.447***
	(0.137)	(0.050)	(0.052)	(0.081)
$Population\ Share^{t}_{HS,d}$	0.732***	-0.043*	-0.036	0.811***
	(0.051)	(0.025)	(0.034)	(0.047)
AR Wald F-Test P-value	0.000	0.145	0.000	0.000
N	15,705	15,705	15,705	15,705
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports the IV results of estimating equation (11). The dependent variables are employment shares of each industrial skill type in the tradable and nontradable sectors at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with medium- and high-skill exogenous working-age population at the county level. Each specification presents the p-value for the Anderson-Rubin Wald F-test. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Establishment Estimates in the Tradable and Nontradable Sectors

	Establishment Shares			
	All	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)	(4)
Panel A: Tradable Sector				
$Population\ Share^{t}_{MS,d}$	-2.444***	-2.150***	0.065	-0.359***
	(0.475)	(0.498)	(0.123)	(0.087)
$Population\ Share^{t}_{HS,d}$	-0.407***	-0.340***	0.057	-0.125***
	(0.134)	(0.103)	(0.056)	(0.040)
AR Wald F-Test P-value	0.000	0.001	0.537	0.000
Panel B: Nontradable Sector				
$Population\ Share^{t}_{MS,d}$	2.444***	0.460***	0.004	1.981***
	(0.475)	(0.161)	(0.216)	(0.324)
$Population\ Share^{t}_{HS,d}$	0.407***	0.001	-0.214***	0.620***
	(0.134)	(0.046)	(0.058)	(0.106)
AR Wald F-Test P-value	0.000	0.006	0.000	0.000
N	15,705	15,705	15,705	15,705
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports the IV results of estimating equation (11). The dependent variables are employment shares of each industrial skill type in the tradable and nontradable sectors at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with medium- and high-skill exogenous working-age population at the county level. Each specification presents the p-value for the Anderson-Rubin Wald F-test. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendices

A Data Appendix

A.1 Construction of Immigration Stock Data

I construct county-level data on immigration utilizing the individual census files of the IPUMS USA and NHGIS samples of the 1850 (full sample), 1860 (full sample), 1870 (10% sample), 1880 (10% sample), 1890 (10% sample), 1900 (5% sample), 1910 (1% sample), 1920 (10% sample), 1930 (5% sample), 1940 (1% sample), 1950 (1% sample), 1960 (5% sample), 1970 (1% Form 1 Metro sample), 1980 (5% State sample), 1990 (5% State sample), and 2000 (5% sample) waves, as well as the 2006-2010 five-year sample of the ACS. I define immigrants as "foreign-born" individuals born outside of the US and its territories in each decennial wave beginning from 1850 to 2000 in the census and the 2006-2010 five-year sample of the ACS. I define the measure of immigration stock, $I_{o,d,t}$, as the number of immigrants (foreign-born people) from origin (country) o, who resides in US destination (county) d in census year t. Countries of origin are based on the detailed birthplace variable in the census.

Both origins and destinations are either historical (prior to 1990) or modern (post-1990) geographical units. Therefore, to have consistent geographic units of countries and counties, I follow the method highlighted in Burchardi et al. (2019), in that I transform non-1990-level foreign countries of origin or detailed birthplaces to 1990-level foreign countries as well as non-1990-level counties, county groups, and PUMAs to 1990-level counties. Initially, I transition non-1990-level counties, county groups, and PUMAs to 1990-level counties in each census year utilizing the transition matrices created in Burchardi et al. (2019) and complementing it with county crosswalk files generated in Eckert et al. (2020b).[31] Afterwards, I generate a country crosswalk file and transform non-1990-level countries to 1990-level countries in each census wave. All transition matrices and crosswalk files rely on population-based weights.

A.2 Construction of Working-Age Population Data

I construct variables for human-capital-specific working-age population shares using each decennial census wave in 1970, 1980, 1990, 2000, and the 2006-2010 five-year sample of the ACS in the following steps. First, I restrict the sample to individuals aged 16-64. Second, I allocate them

[31] The additional details on the construction of county crosswalk files and the weighting scheme can be found in those papers alongside the following websites: (1) and (2).

into skill cells based on their educational attainment (*i.e.*, years of schooling). Finally, I take the number of individuals with a given human capital level by county relative to the entire working-age population by county. To have consistent geographic units of counties, I follow the procedure described above.

A.3 Construction of Employment Data

I construct variables for all, native, and immigrant employment shares of each industry-skill type utilizing each decennial census wave in 1970, 1980, 1990, 2000, and the 2006-2010 five-year sample of the ACS. The measure of employment is the number of individuals employed, and the continuous skill measure corresponds to average years of education of workers employed by each industry. I further distinguish employment shares by industry tradability and discuss how I generate these shares below.

Initially, I restrict the sample to only households and drop individuals working in the military occupations along with those classified as "unemployed" and "not in the labor force." Afterwards, I aggregate the 1990-level census industry codes to a balanced panel of industries utilizing an industry concordance outlined in Autor et al. (2019).[32] Then I allocate workers to three industry-skill cells based on mean education of workers in industries. Later, I take the number of workers by county and industry-skill types relative to the entire workforce by county. I proceed with the construction of immigrant and native employment shares similarly, in that I take the number of workers by county, industry-skill types, and nativity relative to the entire workforce by county. Lastly, I generate the employment shares for workers of all industry-skill types in the tradable and nontradable sectors through distinguishing them by industry tradability.

A.4 Construction of Establishments Data

I construct establishment share of each industry skill type by county along with industry tradability using the 1970, 1980, 1990, 2000, and 2010 extracts of the County Business Patterns (CBP) data published by the Census Bureau and supplement them with those assembled in Eckert et al. (2020a, 2022).[33] The data provide further important details on establishment size, defined as the number of workers employed in a given establishment, and industry, in which an establishment operates.

[32]For additional details, see their paper and David Dorn's website. The crosswalk file I utilize is "[C4] Census *ind*1990 to *ind*1990*dd*."

[33]For further details on digitization, cleaning, imputation on employment counts, and consolidation of these panels under consistent industry codes, see their papers, and Fabian Eckert's website.

Apart from establishment and industry characteristics, they also provide employment figures during the pay period including March 12, first-quarter payroll, and annual payroll. Consistent with the literature, I define small establishments as those employing fewer than 20 workers, medium establishments as those employing between 20 and 500 workers, and large establishments as those employing more than 500 workers. I carry out the following steps to create establishment shares.

First, using the industry concordance files generated in Eckert et al. (2020a, 2022), I crosswalk all industry codes to a unique industry classification, $SIC87$. Afterwards, I map the $SIC87$ industry codes to a balanced panel of industries compiled in Autor et al. (2019).[34] This step is necessary for not only making them compatible with the census industry codes but also identifying the industry-skill rankings discussed in the text. Next I take the number of establishments by county and industry-skill types relative to the total number of establishments by county. I further differentiate establishment share of each industry-skill type by the industry tradability.

[34] See David Dorn's website for additional details. The crosswalk file I utilize is "[C8] $SIC87$ to $ind1990ddx$."

B Appendix Tables

Table B1: Allocation of States to Census Divisions

Census Division	**State**
New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
Middle Atlantic	New Jersey, New York, Pennsylvania
East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin
West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
South Atlantic	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia
East South Central	Alabama, Kentucky, Mississippi, Tennessee
West South Central	Arkansas, Louisiana, Oklahoma, Texas
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Pacific	Alaska, California, Hawaii, Oregon, Washington

Table B2: Industry Skill Classification

Low Skill	Medium Skill		High Skill	
Agricultural production, crops	Agricultural production, livestock	Apparel and accessory stores, except shoe	Agricultural chemicals	Accounting, auditing, and bookkeeping services
Apparel and accessories, except knit	Bakery products	Auto and home supply stores	Aircraft and parts	Advertising
Carpets and rugs	Blast furnaces, steelworks, rolling, and finishing mills	Automobile parking and carwashes	Beverage industries	Air transportation
Logging	Canned, frozen, and preserved fruits, and vegetables	Automotive rental and leasing, without drivers	Computers and related equipment	Alcoholic beverages
Meat products	Cement, concrete, gypsum, and plaster products	Automotive repair and related services	Construction and material handling machines	Apparel, fabrics, and notions
Private households	Coal mining	Barber shops	Drugs	Banking
Scrap and waste materials	Cutlery, handtools, and general hardware	Beauty shops	Electrical machinery, equipment, and supplies, n.e.c	Book and stationery stores
Services to dwellings and other buildings	Cycles and miscellaneous transportation equipment	Bowling centers	Engines and turbines	Business services, n.e.c
	Dairy products	Bus service and urban transit	Forestry	Catalog and mail order houses
	Dyeing and finishing textiles, except wool and knit goods	Department stores	Guided missiles, space vehicles, and parts	Child day care services
	Fabricated structural metal products	Detective and protective services	Industrial and misc. chemicals	Colleges and universities
	Farm machinery equipment	Eating and drinking places	Machinery, n.s	Computer and data processing services
	Fishing, hunting, and trapping	Farm-product raw materials	Medical, dental, and optical instruments and supplies	Credit agencies, n.e.c
	Food industries, n.s	Food stores, n.e.c	Metal mining	Direct selling establishments
	Footwear, except rubber and plastic	Fuel dealers	Miscellaneous petroleum and coal products	Drug stores
	Furniture and fixtures	Gasoline service stations	Newspaper publishing and printing	Drugs, chemicals, and allied products
	Glass and glass products	Groceries and related products	Oil and gas extraction	Educational services, n.e.c
	Grain mill products	Grocery stores	Ordnance	Electric and gas, and other combinations
	Household appliances	Hardware stores	Paints, varnishes, and related products	Electric light and power
	Iron and steel foundries	Hotels and motels	Petroleum refining	Electrical goods
	Knitting mills	Laundry, cleaning, and garment services	Pottery and related products	Electrical repair shops
	Landscape and horticultural services	Lodging places, except hotels and motels	Printing, publishing, and allied industries, except newspapers	Elementary and secondary schools
	Leather products, except footwear	Lumber and building material retailing	Radio, TV, and communication equipment	Engineering, architectural, and surveying services
	Machinery, except electrical, n.e.c	Lumber and construction materials	Scientific and controlling instruments	Farm supplies
	Manufacturing industries, n.s	Misc. entertainment and recreation services	Soaps and cosmetics	Funeral service and crematories
	Metalworking machinery	Misc. general merchandise stores	Tobacco manufactures	Furniture and home furnishings
	Misc. food preperations and kindred products	Misc. repair services	Furniture and home furnishings stores	Gas and steam supply systems
	Misc. nonmetallic mineral and stone products	Misc. vehicle dealers	Gift, novelty, and souvenir shops	Hardware, plumbing and heating supplies
	Misc. fabricated metal products	Motor vehicles and equipment	Health services, n.e.c	Hospitals
	Misc. fabricated textile products	Nursing and personal care facilities	Household appliance stores	Insurance
	Misc. manufacturing industries	Railroads	Labor unions	Legal services
	Misc. paper and pulp products	Retail bakeries	Liquor stores	Libraries
	Misc. plastics products	Retail florists	Machinery, equipment, and supplies	Management and public relations services
	Motor vehicles and motor vehicle equipment	Retail nurseries and garden stores	Membership organizations, n.e.c	Metals and minerals, except petroleum
	Nonmetallic mining and quarrying, except fuels	Sanitary services	Misc. personal services	Misc. professional and related services
	Other primary metal industries	Shoe stores	Misc. retail stores	Misc. wholesale, durable goods
	Other rubber products, and plastics footwear and belting	Taxicab service	Misc. wholesale, nondurable goods	Museums, art galleries, and zoos
	Paperboard containers and boxes	Trucking service	Jewelry stores	Job training and vocational rehabilitation services
	Plastics, synthetics, and resins	Vending machine operators	Music stores	Offices and clinics of chiropractors
	Primary aluminum industries	Warehousing and storage	Offices and clinics of dentists	Offices and clinics of optometrists
	Pulp, paper, and paperboard mills	Railroad locomotives and equipment	Offices and clinics of physicians	Paper and paper products
	Sawmills, planing mills, and millwork	Ship and boat building and repairing	Personnel supply services	Professional and commercial equipment and supplies
	Structural clay products	Sugar and confectionery products	Radio and television broadcasting and cable	Radio, tv, and computer stores
	Tires and inner tubes	Toys, amusement, and sporting goods	Real estate, including real estate-insurance offices	Religious organizations
	Veterinary services	Wood buildings and mobile homes	Research, development, and testing services	Residential care facilities, without nursing
	Yarn, thread, and fabric mills	All construction	Retail trade, n.s	Savings institutions, including credit unions
	Metal forgings and stampings		Security, commodity brokerage, and investment companies	Services incidental to transportation
			Sewing, needlework, and piece goods stores	Social services, n.e.c
			Sporting goods, bicycles, and hobby stores	Telephone communications
			Theaters and motion pictures	U.S. postal service
			Utilities, n.s	Video tape rental
			Water supply and irrigation	Water transportation
			Wholesale trade, n.s	Administration of economic programs
			Administration of human resources programs	Administration of environmental quality and housing programs
			General government, n.e.c	Justice, public order, and safety
			National security and international affairs	Public finance, taxation, and monetary policy

Notes: This detailed industry-skill classification is based on mean education of workers employed by a given industry as described in the text. Since this classification is a continuous measure of industry-skill types varying over time, I present the skill types for only the 2010-level data. Workers in low-skill, medium-skill, and high-skill industries have average years of education corresponding to a high-school degree and less, some college education, and college education and above, respectively.

Table B3: Tradable and Nontradable Industries

Tradable Industries	**Nontradable Industries**
Agriculture, forestry and fisheries	Retail trade
Mining	Personal services
Transportation equipment	Professional and related services
Professional and photographic equipment and watches	Transportation
Petroleum and coal products	Wholesale trade, durables
Toys, amusement, and sporting goods	Wholesale trade, nondurables
Printing, publishing and allied industries	Communications
Apparel and other finished textile products	Business and repair services
Manufacturing industries, others	Finance, insurance, and real estate
Machinery and computing equipment	Entertainment and recreation services
Rubber and miscellaneous plastics products	Utilities and sanitary services
Textile mill products	
Chemicals and allied products	
Leather and leather products	
Electrical machinery, equipment, and supplies	
Furniture and fixtures	
Tobacco manufactures	
Food and kindred products	
Lumber, woods products (except furniture)	
Paper and allied products	
Stone, clay, glass and concrete products	

Notes: This broad industry tradability classification is based on Burstein et al. (2020). I classify all goods industries (agriculture, mining, and manufacturing) as tradable and all services industries as nontradable. I also drop the construction industry from the analysis.

Table B4: Low-Skill Tradable and Nontradable Industries

Tradable Industries	**Nontradable Industries**
Agricultural production, crops	Private households
Apparel and accessories, except knit	Scrap and waste materials
Carpets and rugs	Services to dwellings and other buildings
Logging	
Meat products	

Notes: This detailed industry-skill classification across tradability is based on mean education of workers employed by a given industry as described in the text. Since this classification is a continuous measure of industry-skill types varying over time, I present the skill types for only the 2010-level data. In this case, workers in low-skill industries have average years of education corresponding to a high-school degree and less.

Table B5: Medium-Skill Tradable and Nontradable Industries

Tradable Industries	**Nontradable Industries**
Agricultural production, livestock	Apparel and accessory stores, except shoe
Bakery products	Auto and home supply stores
Blast furnaces, steelworks, rolling, and finishing mills	Automobile parking and carwashes
Canned, frozen, and preserved fruits, and vegetables	Automotive rental and leasing, without drivers
Cement, concrete, gypsum, and plaster products	Automotive repair and related services
Coal mining	Barber shops
Cutlery, handtools, and general hardware	Beauty shops
Cycles and miscellaneous transportation equipment	Bowling centers
Dairy products	Bus service and urban transit
Dyeing and finishing textiles, except wool and knit goods	Department stores
Fabricated structural metal products	Detective and protective services
Farm machinery equipment	Eating and drinking places
Fishing, hunting, and trapping	Farm-product raw materials
Food industries, n.s	Food stores, n.e.c
Footwear, except rubber and plastic	Fuel dealers
Furniture and fixtures	Gasoline service stations
Glass and glass products	Groceries and related products
Grain mill products	Grocery stores
Household appliances	Hardware stores
Iron and steel foundries	Hotels and motels
Knitting mills	Laundry, cleaning, and garment services
Landscape and horticultural services	Lodging places, except hotels and motels
Leather products, except footwear	Lumber and building material retailing
Machinery, except electrical, n.e.c	Lumber and construction materials
Manufacturing industries, n.s	Misc. entertainment and recreation services
Metalworking machinery	Misc. general merchandise stores
Misc. food preperations and kindred products	Misc. repair services
Misc. nonmetallic mineral and stone products	Misc. vehicle dealers
Misc. fabricated metal products	Motor vehicles and equipment
Misc. fabricated textile products	Nursing and personal care facilities
Misc. manufacturing industries	Railroads
Misc. paper and pulp products	Retail bakeries
Misc. plastics products	Retail florists
Motor vehicles and motor vehicle equipment	Retail nurseries and garden stores
Nonmetallic mining and quarrying, except fuels	Sanitary services
Other primary metal industries	Shoe stores
Other rubber products, and plastics footwear and belting	Taxicab service
Paperboard containers and boxes	Trucking service
Plastics, synthetics, and resins	Vending machine operators
Primary aluminum industries	Warehousing and storage
Pulp, paper, and paperboard mills	
Railroad locomotives and equipment	
Sawmills, planing mills, and millwork	
Ship and boat building and repairing	
Structural clay products	
Sugar and confectionery products	
Tires and inner tubes	
Toys, amusement, and sporting goods	
Veterinary services	
Wood buildings and mobile homes	
Yarn, thread, and fabric mills	

Notes: This detailed industry-skill classification across tradability is based on mean education of workers employed by a given industry as described in the text. Since this classification is a continuous measure of industry-skill types varying over time, I present the skill types for the 2010-level data. In this case, workers in medium-skill industries have average years of education corresponding to some college education.

Table B6: High-Skill Tradable and Nontradable Industries

Tradable Industries	Nontradable Industries	
Agricultural chemicals	Accounting, auditing, and bookkeeping services	Furniture and home furnishings stores
Aircraft and parts	Advertising	Gas and steam supply systems
Beverage industries	Air transportation	Gift, novelty, and souvenir shops
Computers and related equipment	Alcoholic beverages	Music stores
Construction and material handling machines	Apparel, fabrics, and notions	Personnel supply services
Drugs	Banking	Professional and commercial equipment and supplies
Electrical machinery, equipment, and supplies, n.e.c	Book and stationery stores	Hardware, plumbing and heating supplies
Engines and turbines	Business services, n.e.c	Health services, n.e.c
Forestry	Catalog and mail order houses	Household appliance stores
Guided missiles, space vehicles, and parts	Child day care services	Hospitals
Industrial and misc. chemicals	Colleges and universities	Insurance
Machinery, n.s	Computer and data processing services	Jewelry stores
Medical, dental, and optical instruments and supplies	Credit agencies, n.e.c	Job training and vocational rehabilitation services
Metal mining	Direct selling establishments	Labor unions
Miscellaneous petroleum and coal products	Drug stores	Liquor stores
Newspaper publishing and printing	Drugs, chemicals, and allied products	Libraries
Oil and gas extraction	Educational services, n.e.c	Machinery, equipment, and supplies
Ordnance	Electric and gas, and other combinations	Management and public relations services
Paints, varnishes, and related products	Electric light and power	Membership organizations, n.e.c
Petroleum refining	Electrical goods	Metals and minerals, except petroleum
Pottery and related products	Electrical repair shops	Misc. personal services
Printing, publishing, and allied industries, except newspapers	Elementary and secondary schools	Misc. professional and related services
Radio, TV, and communication equipment	Engineering, architectural, and surveying services	Misc. retail stores
Scientific and controlling instruments	Farm supplies	Misc. wholesale, durable goods
Soaps and cosmetics	Funeral service and crematories	Misc. wholesale, nondurable goods
Tobacco manufactures	Furniture and home furnishings	Museums, art galleries, and zoos
	Offices and clinics of chiropractors	Offices and clinics of dentists
	Offices and clinics of optometrists	Offices and clinics of physicians
	Paper and paper products	Radio and television broadcasting and cable
	Radio, tv, and computer stores	Real estate, including real estate-insurance offices
	Religious organizations	Research, development, and testing services
	Residential care facilities, without nursing	Retail trade, n.s
	Savings institutions, including credit unions	Security, commodity brokerage, and investment companies
	Services incidental to transportation	Sewing, needlework, and piece goods stores
	Social services, n.e.c	Sporting goods, bicycles, and hobby stores
	Telephone communications	Theaters and motion pictures
	U.S. postal service	Utilities, n.s
	Video tape rental	Water supply and irrigation
	Water transportation	Wholesale trade, n.s

Notes: This detailed industry-skill classification across tradability is based on mean education of workers employed by a given industry as described in the text. Since this classification is a continuous measure of industry-skill types varying over time, I present the skill types for only the 2010-level data. In this case, workers in high-skill industries have average years of education corresponding to college education and above.

Table B7: Employment Estimates by Nativity

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Native Employment Shares			
$Population\ Share^{t}_{MS,d}$	-0.717***	0.541***	0.541***
	(0.135)	(0.108)	(0.084)
$Population\ Share^{t}_{HS,d}$	-0.359***	-0.453***	0.699***
	(0.048)	(0.060)	(0.052)
AR Wald F-Test P-value	0.000	0.000	0.000
Panel B: Immigrant Employment Shares			
$Population\ Share^{t}_{MS,d}$	-0.237*	-0.059	-0.069
	(0.131)	(0.041)	(0.054)
$Population\ Share^{t}_{HS,d}$	-0.008	0.023**	0.098***
	(0.035)	(0.010)	(0.023)
AR Wald F-Test P-value	0.159	0.005	0.000
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are native and immigrant employment shares of each industrial skill type at the county level in separate regressions as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population at the county level. Each specification presents the p-value for the Anderson-Rubin Wald F-test. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B8: Employment and Establishment Estimates by Industry

	Agriculture	Mining & Manufac.	Construction	Services	Wholesale & Retail Trade	Transportation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Employment Shares						
Population Share$^{t}_{MS,d}$	-0.898***	0.334**	-0.035	0.333**	0.328***	0.116**
	(0.138)	(0.153)	(0.053)	(0.138)	(0.065)	(0.047)
Population Share$^{t}_{HS,d}$	-0.308***	-0.349***	0.009	0.669***	0.011	-0.026*
	(0.076)	(0.097)	(0.020)	(0.055)	(0.021)	(0.014)
Panel B: Establishment Shares						
Population Share$^{t}_{MS,d}$	-	-1.922***	-0.380***	3.322***	0.163	-1.182***
	-	(0.475)	(0.115)	(0.319)	(0.228)	(0.166)
Population Share$^{t}_{HS,d}$	-	-0.194	-0.016	0.811***	-0.255***	-0.345***
	-	(0.138)	(0.047)	(0.150)	(0.061)	(0.087)
N	15,705	15,705	15,705	15,705	15,705	15,705
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11), but the outcome variables are not disaggregated by industrial skill types. The dependent variables are employment and establishment shares of major industries at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population at the county level. The "Services" sector also includes "Finance, Insurance, and Real Estate" along with "Public Administration," and the "Transportation" sector includes "Communications" and "Other Public Utilities." Since the CBP data do not provide the full coverage of establishments operating in agriculture during the study period, I exclude them from the analysis. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B9: Establishment Estimates by Size

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Small Establishments			
$Population\ Share^{t}_{MS,d}$	-0.820***	-0.380	1.607***
	(0.179)	(0.230)	(0.244)
$Population\ Share^{t}_{HS,d}$	-0.307***	-0.196***	0.456***
	(0.059)	(0.064)	(0.085)
Panel B: Medium Establishments			
$Population\ Share^{t}_{MS,d}$	-0.463	0.640***	0.239***
	(0.303)	(0.143)	(0.081)
$Population\ Share^{t}_{HS,d}$	0.062	0.215***	0.032
	(0.075)	(0.051)	(0.031)
Panel C: Large Establishments			
$Population\ Share^{t}_{MS,d}$	-0.353***	-0.203***	-0.268***
	(0.057)	(0.050)	(0.048)
$Population\ Share^{t}_{HS,d}$	-0.105***	-0.073***	-0.085***
	(0.023)	(0.025)	(0.027)
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are small, medium, and large establishment shares of each industrial skill type at the county level in separate regressions as displayed in Panels A, B, and C, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population at the county level. Consistent with the literature, small establishments are defined as those employing fewer than 20 workers, medium establishments are defined as those employing between 20 and 500 workers, and large establishments are defined as those employing more than 500 workers. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B10: Establishment Estimates by Size in the Tradable Sector

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Small Establishments			
$Population\ Share^{t}_{MS,d}$	-0.679***	-0.136***	-0.139***
	(0.168)	(0.046)	(0.032)
$Population\ Share^{t}_{HS,d}$	-0.187***	-0.048*	-0.050***
	(0.040)	(0.027)	(0.015)
Panel B: Medium Establishments			
$Population\ Share^{t}_{MS,d}$	-1.258***	0.261**	-0.072*
	(0.365)	(0.106)	(0.041)
$Population\ Share^{t}_{HS,d}$	-0.087	0.130***	-0.032**
	(0.082)	(0.046)	(0.013)
Panel C: Large Establishments			
$Population\ Share^{t}_{MS,d}$	-0.214***	-0.059*	-0.150***
	(0.038)	(0.033)	(0.028)
$Population\ Share^{t}_{HS,d}$	-0.054***	-0.022	-0.041***
	(0.014)	(0.013)	(0.015)
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are small, medium, and large establishment shares of each industrial skill type in the tradable sector in separate regressions as displayed in Panels A, B, and C, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population at the county level. Consistent with the literature, small establishments are defined as those employing fewer than 20 workers, medium establishments are defined as those employing between 20 and 500 workers, and large establishments are defined as those employing more than 500 workers. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B11: ESTABLISHMENT ESTIMATES BY SIZE IN THE NONTRADABLE SECTOR

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Small Establishments			
$Population\ Share^{t}_{MS,d}$	-0.212	-0.237	1.764***
	(0.129)	(0.208)	(0.259)
$Population\ Share^{t}_{HS,d}$	-0.121***	-0.276***	0.570***
	(0.041)	(0.052)	(0.099)
Panel B: Medium Establishments			
$Population\ Share^{t}_{MS,d}$	0.812***	0.428***	0.315***
	(0.094)	(0.066)	(0.070)
$Population\ Share^{t}_{HS,d}$	0.173***	0.107***	0.082***
	(0.034)	(0.021)	(0.027)
Panel C: Large Establishments			
$Population\ Share^{t}_{MS,d}$	-0.147***	-0.147***	-0.130***
	(0.026)	(0.026)	(0.026)
$Population\ Share^{t}_{HS,d}$	-0.053***	-0.049***	-0.043***
	(0.014)	(0.014)	(0.014)
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are small, medium, and large establishment shares of each industrial skill type in the nontradable sector in separate regressions as displayed in Panels A, B, and C, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population at the county level. Consistent with the literature, small establishments are defined as those employing fewer than 20 workers, medium establishments are defined as those employing between 20 and 500 workers, and large establishments are defined as those employing more than 500 workers. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B12: Employment and Establishment Estimates Using Instruments for the 1850-1900 Period

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Employment Shares			
$Population\ Share^{t}_{MS,d}$	-0.875***	0.715***	0.160**
	(0.101)	(0.094)	(0.065)
$Population\ Share^{t}_{HS,d}$	-0.507***	-0.047	0.554***
	(0.049)	(0.056)	(0.044)
AR Wald F-Test P-Value	0.000	0.000	0.000
Panel B: Establishment Shares			
$Population\ Share^{t}_{MS,d}$	-1.554***	0.055	1.499***
	(0.361)	(0.177)	(0.305)
$Population\ Share^{t}_{HS,d}$	-0.305***	-0.083	0.388***
	(0.090)	(0.056)	(0.093)
AR Wald F-Test P-Value	0.001	0.347	0.000
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are employment and establishment shares of each industrial skill type at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenou medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population. Exogenous working-age population of each skill type has been generated using the predicted immigration stocks based on the immigrant leave-out push-pull variables for only the 1850-1900 period. Each specification reports the p-value for the Anderson-Rubin Wald F-Test. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B13: Employment and Establishment Estimates Using Instruments for the 1850-1950 Period

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Employment Shares			
$Population\ Share^{t}_{MS,d}$	-0.903***	0.746***	0.156**
	(0.104)	(0.098)	(0.063)
$Population\ Share^{t}_{HS,d}$	-0.515***	-0.041	0.555***
	(0.049)	(0.056)	(0.044)
AR Wald F-Test P-Value	0.000	0.000	0.000
Panel B: Establishment Shares			
$Population\ Share^{t}_{MS,d}$	-1.603***	0.094	1.509***
	(0.372)	(0.184)	(0.303)
$Population\ Share^{t}_{HS,d}$	-0.314***	-0.071	0.385***
	(0.091)	(0.054)	(0.093)
AR Wald F-Test P-Value	0.001	0.385	0.000
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are employment and establishment shares of each industrial skill type at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population. Exogenous working-age population of each skill type has been generated using the predicted immigration stocks based on the immigrant leave-out push-pull variables for only the 1850-1950 period. Each specification reports the p-value for the Anderson-Rubin Wald F-Test. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B14: Robustness: Alternative "Leave-Out" Instruments

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Employment Shares			
$Population\ Share^{t}_{MS,d}$	0.899***	0.749***	0.150**
	(0.103)	(0.094)	(0.065)
$Population\ Share^{t}_{HS,d}$	-0.505***	-0.043	0.549***
	(0.049)	(0.056)	(0.046)
AR Wald F-Test P-Value	0.000	0.000	0.000
Panel B: Establishment Shares			
$Population\ Share^{t}_{MS,d}$	-1.652***	0.134	1.518***
	(0.372)	(0.181)	(0.308)
$Population\ Share^{t}_{HS,d}$	-0.333***	-0.054	0.387***
	(0.088)	(0.055)	(0.091)
AR Wald F-Test P-Value	0.000	0.447	0.000
N	15,701	15,701	15,701
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are employment and establishment shares of each industrial skill type at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population based on alternative "leave-out" strategy. Utilizing equation (12), this alternative leave-out method relies on excluding all destination counties from the push factor whose overall time series of immigration stocks are correlated with those of d (instead of excluding counties that are in the same census division, $r(d)$, as d). Each specification reports the p-value for the Anderson-Rubin Wald F-Test. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B15: Robustness - Excluding the Top-Five Countries

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Employment Shares			
$Population\ Share^{t}_{MS,d}$	-0.906***	0.754***	0.152**
	(0.103)	(0.093)	(0.066)
$Population\ Share^{t}_{HS,d}$	-0.494***	-0.066	0.560***
	(0.048)	(0.054)	(0.043)
Panel B: Establishment Shares			
$Population\ Share^{t}_{MS,d}$	-1.668***	0.121	1.547***
	(0.378)	(0.185)	(0.311)
$Population\ Share^{t}_{HS,d}$	-0.378***	-0.051	0.429***
	(0.085)	(0.053)	(0.091)
N	15,705	15,705	15,705
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are employment and establishment shares of each industrial skill type in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population. While isolating exogenous working-age population of each skill type, I exclude the top-five (i.e., most "immigrant-sending") origin countries from the list of predicted immigration stocks. These countries are Canada, China, Germany, Mexico, and Philippines. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B16: Robustness - Excluding the Five Largest Counties

	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)
Panel A: Employment Shares			
$Population\ Share^{t}_{MS,d}$	-0.896***	0.740***	0.156**
	(0.103)	(0.094)	(0.065)
$Population\ Share^{t}_{HS,d}$	-0.515***	-0.037	0.552***
	(0.049)	(0.056)	(0.045)
Panel B: Establishment Shares			
$Population\ Share^{t}_{MS,d}$	-1.628***	0.128	1.501***
	(0.370)	(0.182)	(0.307)
$Population\ Share^{t}_{HS,d}$	-0.330***	-0.057	0.388***
	(0.088)	(0.054)	(0.090)
N	15,680	15,680	15,680
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variables are employment and establishment shares of each industrial skill type at the county level excluding the five most "immigrant-receiving" counties in separate regressions as reported in Panels A and B, respectively. The excluded counties are Los Angeles, Cook, Harris, Miami-Dade, and Kings counties. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population. All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B17: Robustness - Alternative Tradability Classification

	Employment Shares			
	All	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)	(4)
Panel A: Tradable Sector				
$Population\ Share^{t}_{MS,d}$	0.181	-0.462**	0.631***	0.012
	(0.229)	(0.200)	(0.131)	(0.073)
$Population\ Share^{t}_{HS,d}$	-0.334***	-0.331***	-0.304***	0.301***
	(0.110)	(0.119)	(0.053)	(0.042)
Panel B: Nontradable Sector				
$Population\ Share^{t}_{MS,d}$	-0.181	-0.004	-0.340***	0.164***
	(0.229)	(0.123)	(0.122)	(0.059)
$Population\ Share^{t}_{HS,d}$	0.334***	-0.111	-0.036	0.481***
	(0.110)	(0.075)	(0.044)	(0.036)
N	15,705	15,705	15,705	15,705
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variable is employment share of each industrial skill type in the tradable and nontradable sectors at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population. In classifying workers by the tradability domain, I use an alternative tradability measure highlighted in Mian and Sufi (2014) based on geographical Herfindahl-Hirschman Indices (HHIs). All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B18: Robustness - Alternative Tradability Classification

	Establishment Shares			
	All	Low Skill	Medium Skill	High Skill
	(1)	(2)	(3)	(4)
Panel A: Tradable Sector				
$Population\ Share^{t}_{MS,d}$	-1.752***	-2.159***	0.566***	-0.160
	(0.439)	(0.559)	(0.164)	(0.103)
$Population\ Share^{t}_{HS,d}$	-0.241*	-0.402***	0.190***	-0.029
	(0.137)	(0.124)	(0.069)	(0.041)
Panel B: Nontradable Sector				
$Population\ Share^{t}_{MS,d}$	1.752***	-0.471	-0.234	2.457***
	(0.439)	(0.281)	(0.233)	(0.284)
$Population\ Share^{t}_{HS,d}$	0.241*	-0.155	-0.248***	0.645***
	(0.137)	(0.094)	(0.076)	(0.117)
N	15,705	15,705	15,705	15,705
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: This table presents the IV results of estimating equation (11). The dependent variable is establishment share of each industrial skill type in the tradable and nontradable sectors at the county level in separate specifications as displayed in Panels A and B, respectively. The independent variables are endogenous medium- and high-skill working-age population shares instrumented with exogenous medium- and high-skill working-age population. In classifying establishments by the tradability domain, I use an alternative tradability measure highlighted in Mian and Sufi (2014) based on geographical Herfindahl-Hirschman Indices (HHIs). All regressions include state and time fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B19: Placebo Analysis

	(1)	(2)	(3)	(4)
	Coefficient		Standard Error	Rejection Rate
	(Mean)	(Std. Dev)	(Median)	(%)
Panel A: Low Skill				
First Stage	0.00000855	0.00050030	0.00048280	0
Reduced Form (1)	0.00000353	0.00033170	0.00032130	0
Reduced Form (2)	0.00000626	0.00031400	0.00030530	0
Panel B: Medium Skill				
First Stage	0.00000136	0.00024300	0.00023160	0
Reduced Form (1)	0.00001240	0.00036310	0.00036370	0
Reduced Form (2)	0.00000788	0.00033890	0.00033840	0
Panel C: High Skill				
First Stage	0.00000717	0.00030300	0.00030000	0
Reduced Form (1)	-0.00001590	0.00023660	0.00025100	0
Reduced Form (2)	-0.00001410	0.00022900	0.00024190	0

Notes: This table displays the results of the placebo analysis. Following Adao et al. (2019), I first randomly generate predicted immigration stocks for each country-region-time triplet (instead of country-county-time triplet as in the baseline case) and then construct placebo instruments by regressing working-age population of each human capital level on these randomly generated predicted immigration stocks. Next I run 1,000 placebo first-stage regressions of endogenous working-age share of each skill type on each of this skill-specific placebo instrument. Additionally, I run the relevant reduced-form regressions, in which the dependent variable is employment share of each industrial skill type, and the independent variables are medium- and high-skill placebo instruments. Reduced Form (1) and Reduced Form (2) represent the reduced-form estimates of medium- and high-skill placebo instruments in each randomization test separately. Column 1 presents the mean value of the coefficient across all placebo regressions, and Column 2 reports the standard deviation. Column 3 presents the median standard error for the coefficient across all placebo regressions, and Column 4 reports the fraction of placebo regressions for which I reject the null hypothesis of "no effect" at the 1% level of statistical significance. The alternative instruments generated for all skill types have a false rejection rate of 0% for both first-stage and reduced-form estimates, meaning my instruments do not suffer from the over-rejection problem identified in Adao et al. (2019) for conventional shift-share instruments. Standard errors are clustered by state for all specifications similar to the baseline analysis.

C Appendix Figures

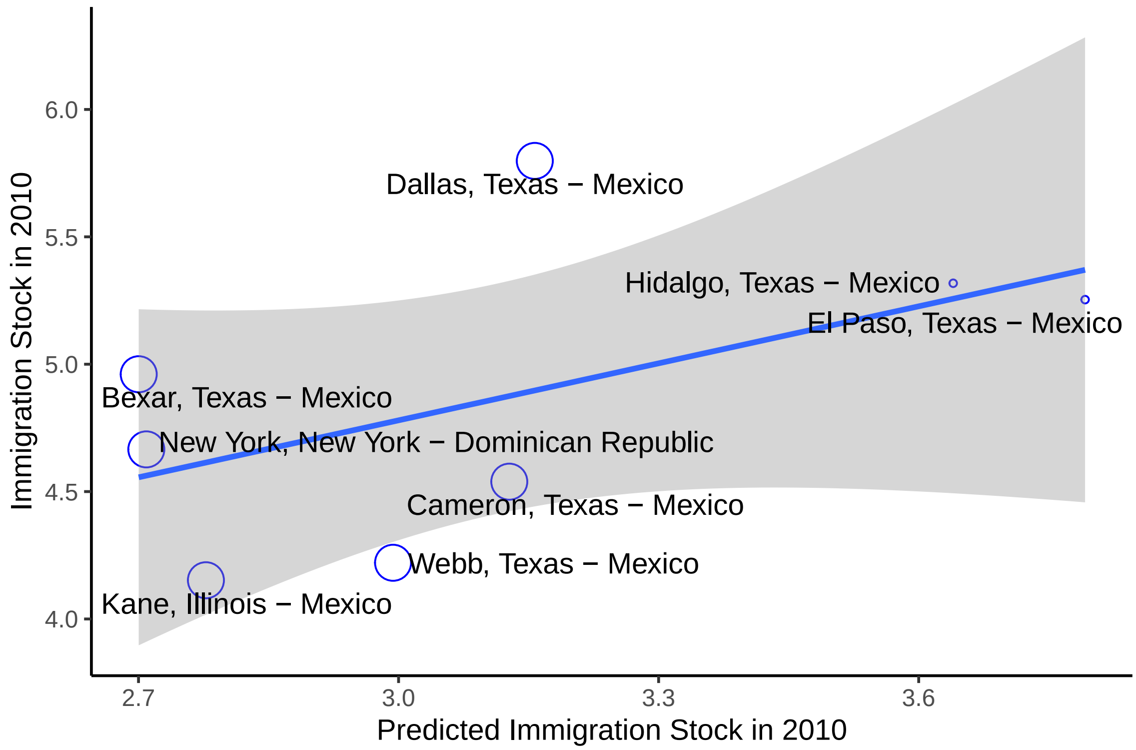

Figure C1: PREDICTED VS. ACTUAL IMMIGRATION STOCKS IN 2010

Notes: This figure displays a binned scatter plot of the predicted immigration stock obtained in equation (13) against the log of actual immigration stock in 2010. It illustrates the first step in instrument construction, whereby the quasi-random variation in immigration is generated. The fixed bins are based on predicted immigration stock, and the size of each circle indicates the number of observations in a given bin. The labeled county-country pairs denote the primary destinations with the highest immigrant populations from specific countries in 2010.

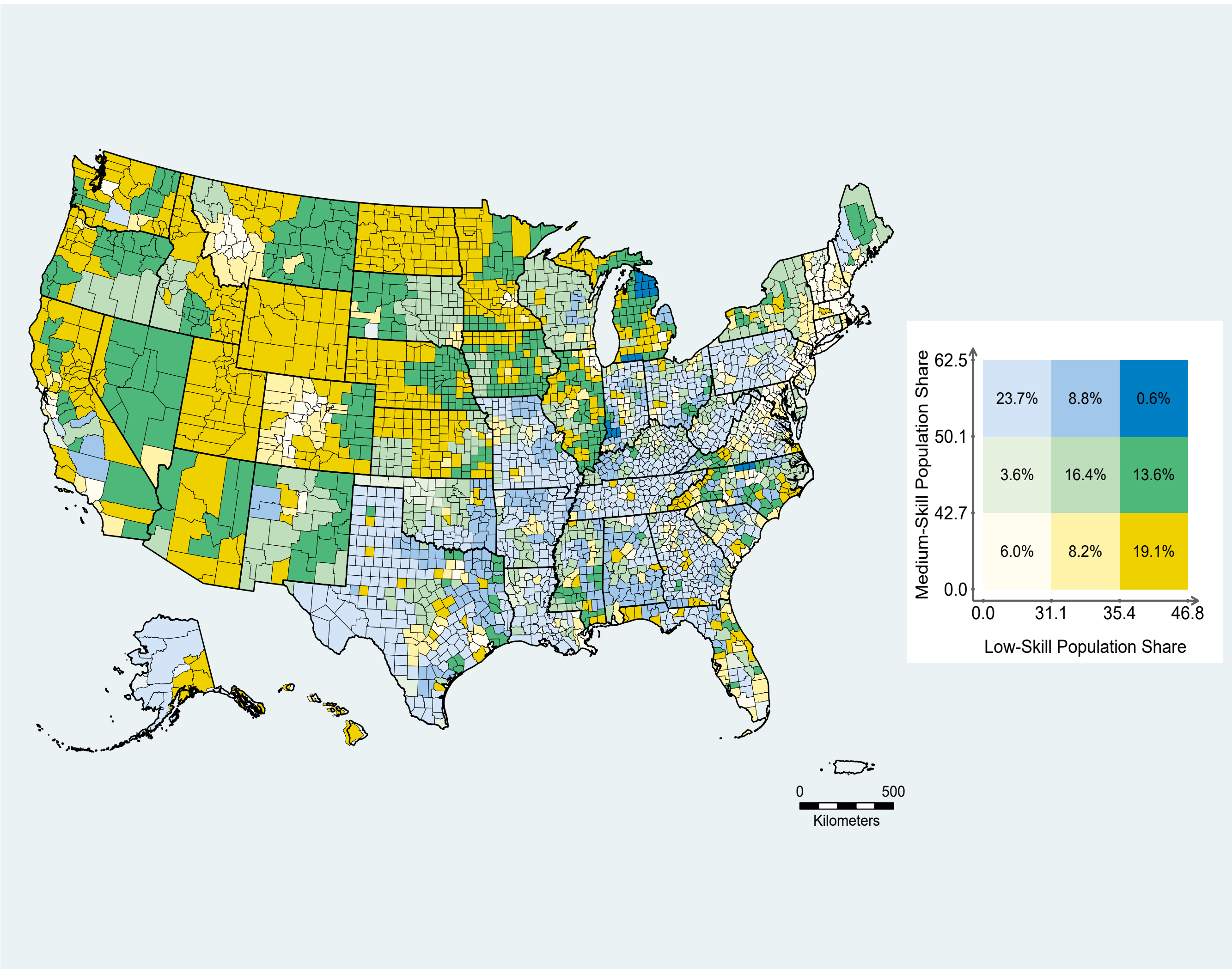

Figure C2: The Bivariate Map of Low- and Medium-Skill Working-Age Population Shares in 2010

Notes: This bivariate map illustrates the distribution of low- and medium-skill working-age population shares across US counties in 2010. Lighter colors indicate lower concentrations, while darker colors represent higher concentrations for each respective skill type The map has been plotted using the "`bimap`" package in Stata (Naqvi, 2024).

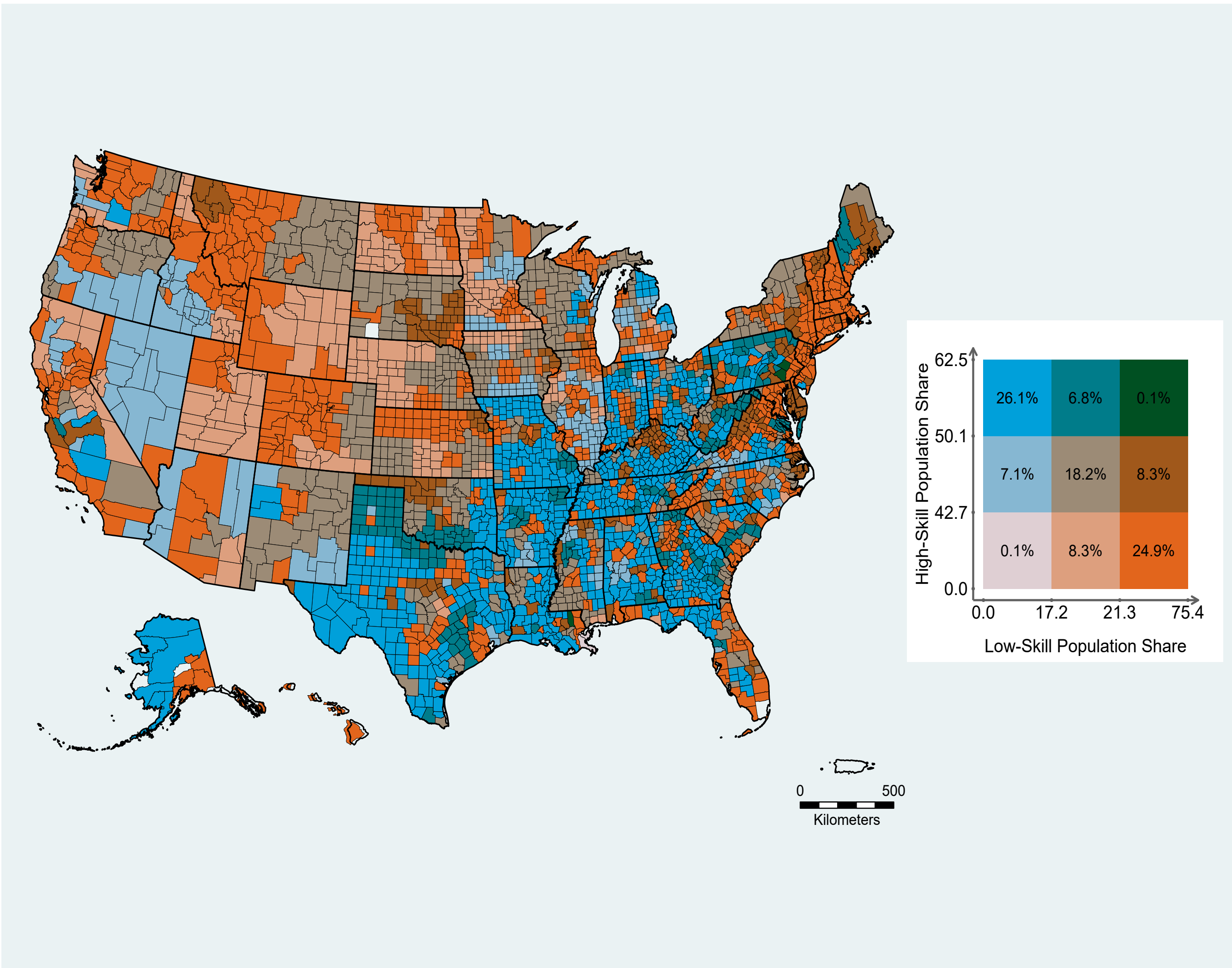

Figure C3: The Bivariate Map of Low- and High-Skill Working-Age Population Shares in 2010

Notes: This bivariate map illustrates the distribution of low- and high-skill working-age population shares across US counties in 2010. Lighter colors indicate lower concentrations, while darker colors represent higher concentrations for each respective skill type. The map has been plotted using the "`bimap`" package in Stata (Naqvi, 2024).

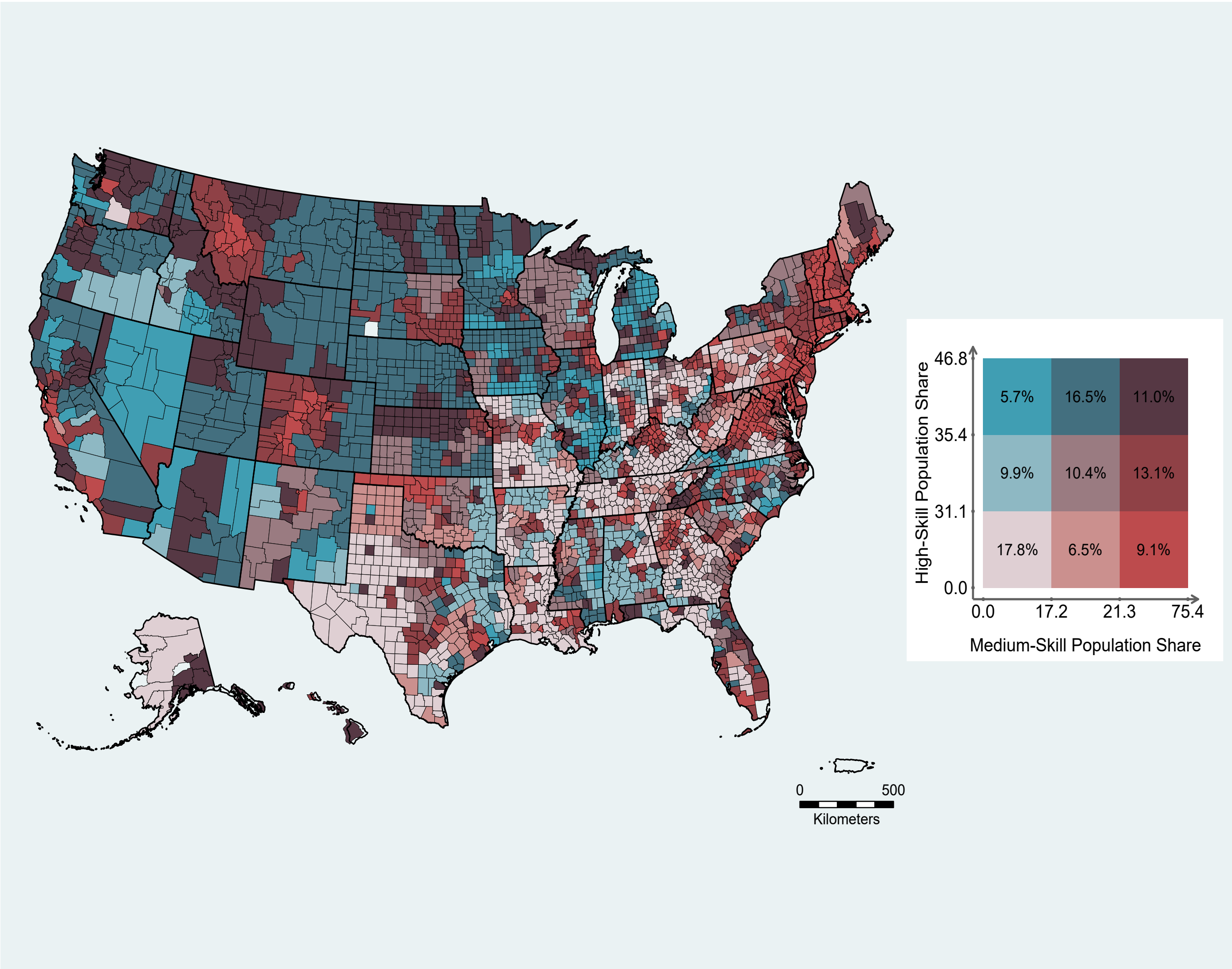

Figure C4: The Bivariate Map of Low- and High-Skill Working-Age Population Shares in 2010

Notes: This bivariate map illustrates the distribution of medium- and high-skill working-age population shares across US counties in 2010. Lighter colors indicate lower concentrations, while darker colors represent higher concentrations for each respective skill type. The map has been plotted using the "`bimap`" package in Stata (Naqvi, 2024).

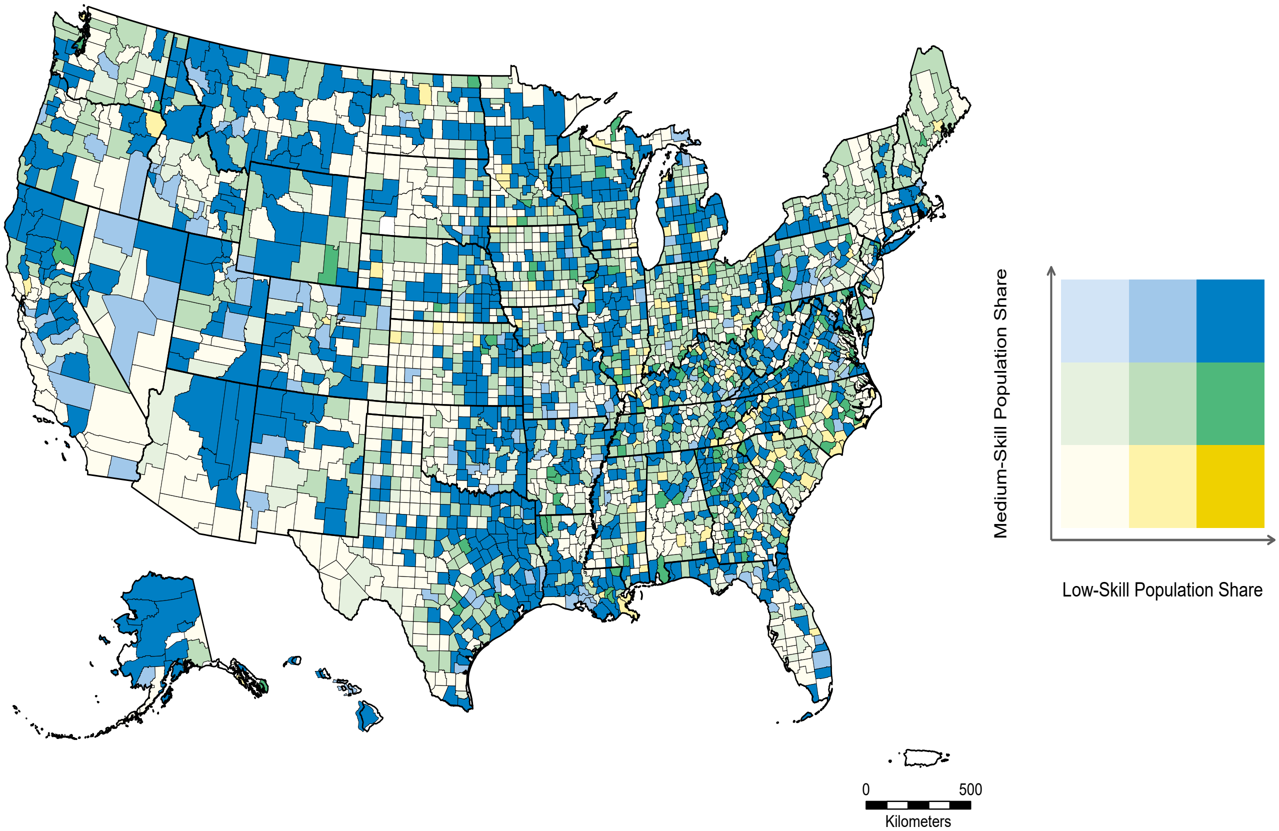

Figure C5: The Bivariate Map of Low- and Medium-Skill Exogenous Population in 2010

Notes: This bivariate map illustrates the distribution of low- and medium-skill exogenous population across US counties in 2010. I regress each instrument on county and time fixed effects and obtain the residuals. The color coding visualizes the 200 quantiles of the residuals across counties. Lighter colors indicate lower quantiles, while darker colors represent higher quantiles for each respective skill type. The map has been plotted using the "`bimap`" package in Stata (Naqvi, 2024).

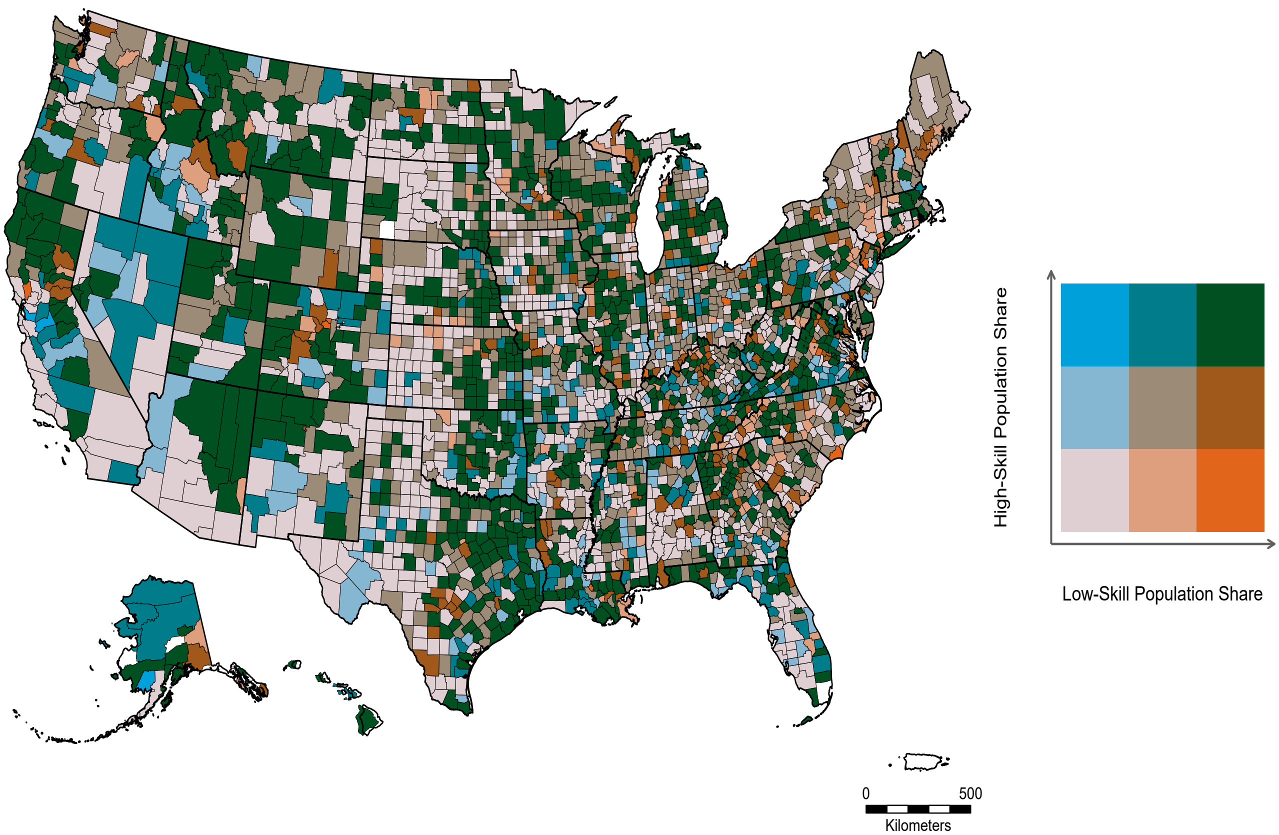

Figure C6: The Bivariate Map of Low- and High-Skill Exogenous Population in 2010

Notes: This bivariate map illustrates the distribution of low- and high-skill exogenous population across US counties in 2010. I regress each instrument on county and time fixed effects and obtain the residuals. The color coding visualizes the 200 quantiles of the residuals across counties. Lighter colors indicate lower quantiles, while darker colors represent higher quantiles for each respective skill type. The map has been plotted using the "`bimap`" package in Stata (Naqvi, 2024).

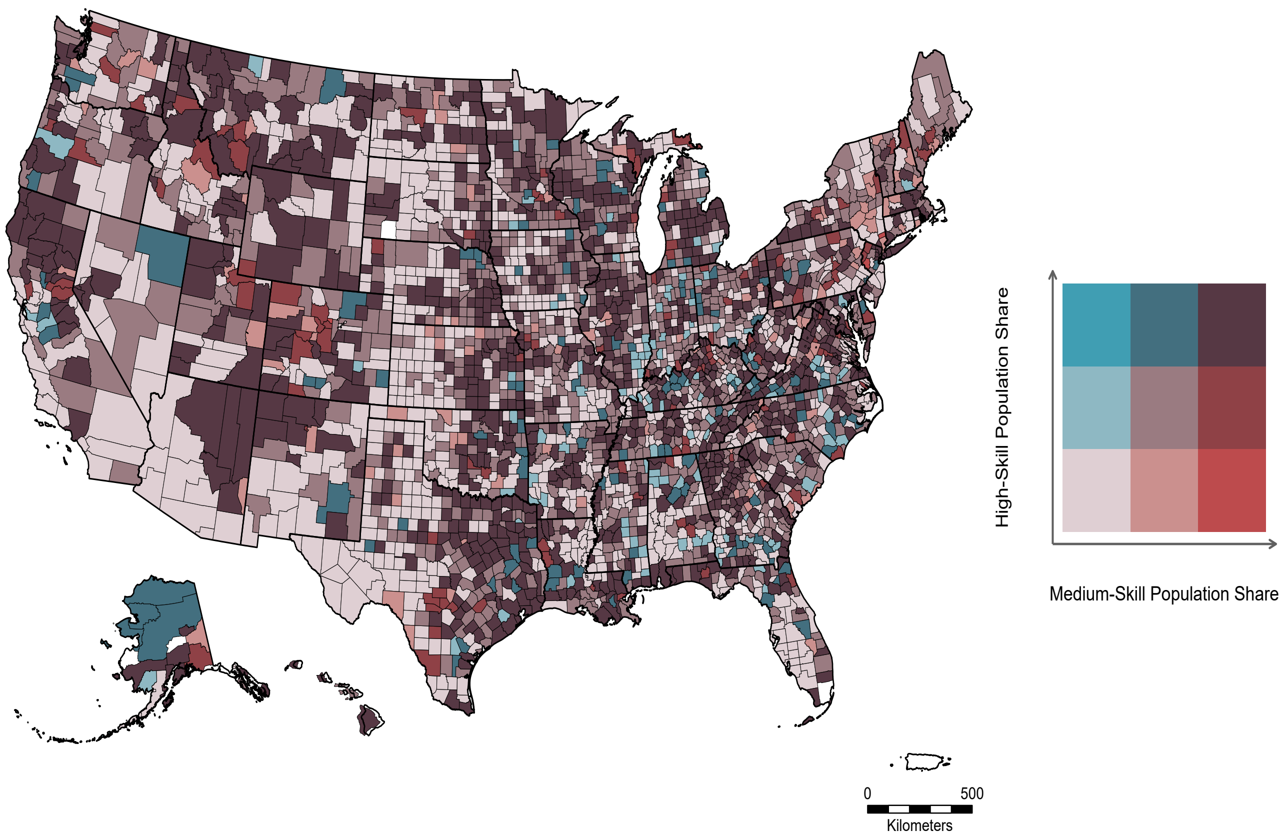

Figure C7: The Bivariate Map of Medium- and High-Skill Exogenous Population in 2010

Notes: This bivariate map illustrates the distribution of medium- and high-skill exogenous population across US counties in 2010. I regress each instrument on state and time fixed effects and obtain the residuals. The color coding visualizes the 200 quantiles of the residuals across counties. Lighter colors indicate lower quantiles, while darker colors represent higher quantiles for each respective skill type. The map has been plotted using the "`bimap`" package in Stata (Naqvi, 2024).