

Supplemental Appendix to: “Labor Market Competition and the Assimilation of Immigrants”

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APPENDIX A: SAMPLE SELECTION AND VARIABLE DEFINITIONS

Our data are drawn from the U.S. Census and American Community Survey (ACS), downloaded from the Integrated Public Use Microdata Series database (IPUMS-USA, Ruggles et al., 2023). The sample includes data for the years 1970, 1980, 1990, and 2000 from the Census, and for the years 2009–2011 (labeled as “2010”) and 2018–2019 (labeled as “2020”) from the ACS using the largest available samples in each case. For the 1970 Census, we use the two samples that contain information about all relevant variables, including the state of residence (Form 1 Metro and State sample). In the 1970 Form 1 Metro sample, approximately 18% of respondents are missing information on the state of residence, which is for ensuring anonymity. For these observations, we impute the state by using the available information on the county group of residence (variable *cntygp97*). In particular, we identify the states of all the counties that comprise the county group of residence of a respondent and assign the state with the highest count of counties (in case of a tie, we select a state at random). Moreover, we reweight the Form 1 metro sample to keep representativeness across states by adjusting the Census weights such that the population share of each state is identical to that in the 1970 State sample.

Our sample comprises natives and immigrants aged 25 to 64 who are not self-employed, do not live in group quarters, are not enrolled in school (except for 1970, in which there is no information on school enrollment), work in the civilian sector, live in a known state,

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and report positive hours of work and earnings. We drop immigrants without information on their country of birth or year of arrival in the United States. We also drop immigrants who arrived in the United States at age 18 or before. The variables used in the analysis are defined as follows:

Immigrants. Are defined as foreign-born individuals with non-U.S. parents.

Wages. Hourly wages are computed combining information on annual wage and salary income, the number of weeks worked during the year, and the usual number of hours worked per week. In the 1970 Census and 2010 ACS, weeks worked are only available in intervals, so we impute the average number of weeks worked for individuals in each of the intervals in the census years in which detailed information is available. The imputed weeks worked in 1970 are 8, 20.8, 33.1, 42.4, 48.3 and 51.9 for the six intervals in 1970, and 7.4, 21.3, 33.1, 42.4, 48.2 and 51.9 for 2010. In the 1970 Census, usual hours worked are also unavailable, and hours worked last week are presented in intervals. Based on the other censuses, we impute the following hours per week to the eight available intervals: 8.7, 20.9, 31.1, 36.5, 40, 45.3, 51.8, and 68.1. All wages are deflated to U.S. dollars of 1999 using the Consumer Price Index for All Urban Consumers (CPI-U) from the Bureau of Labor Statistics. Top-coded observations (in the 1970 and 1980 Censuses) are multiplied by 1.5.

Education. We assign years of education using the following criteria: 0 for “no schooling”; 2 for “nursery school to grade 4”; 6.5 for “grade 5, 6, 7, 8”; the exact grade for 9 to 12th grade; 12 plus the reported years of college for immigrants with 4 or less years of college education; and 18 years for individuals with 5 or more years of college. Based on this mapping, we also define four educational levels: high school dropouts (<12 years of education), high school graduates (12), some college education (13–15), and college graduates (16+).

Immigrant cohorts. Based on the available information for the year of arrival in the different censuses, we group immigrant cohorts into seven groups: pre-1960, 1960–69, 1970–79, 1980–89, 1990–99, 2000–09, and 2010–20.

Years since migration. Years in the United States are constructed by subtracting the reported year of arrival in the census from the census reference year. When the year of arrival is reported in intervals, we use the midpoint of the interval. In the 1970 Census, year of arrival is reported in 10-year intervals until 1944 and in 5-year intervals thereafter. In the 1980 Census, immigrants are grouped into those that arrived before 1950, those that arrived during the 1950s, and into 5-year intervals thereafter. In the 1990 Census, the intervals are the same as in the 1980 Census, except that immigrants who arrived during the 1980s are grouped into the intervals 1980–1981, 1982–1984, 1985–1986 and 1987–1990. From the 2000 Census onward, the exact year of arrival is reported.

Region of birth. We consider five regions of birth for immigrants: Mexico; Other Latin

American Countries (Caribbean, Central America, South America); Western Countries (Western Europe, Israel, Australia, New Zealand, Canada); Asia; and Other.

English proficiency. The English proficiency variable is based on the “Speak English” variable included in the Census and ACS since 1980. We classify those individuals as proficient who declare speaking either only English or speaking English very well.

Immigrant networks. Two variables are created based on the country of birth variable included in IPUMS (bpl): the stock of immigrants from the same country of origin as the respondent living in that state and year, and the share that these immigrants represent of the total population in that state and year.

Undocumented immigrants. Following Borjas (2017), we first identify likely “legal” immigrants as those who fulfill at least one of the following conditions: hold U.S. citizenship, immigrated before 1982 (for immigrants observed after 1986), receive income from welfare programs, work or have worked for the armed forces or the government, were born in Cuba, work in an occupation that requires licensing, and/or are married to or the child of a legal resident. We then create a dummy for potentially undocumented immigrants, defined as those not satisfying any of these criteria.

Sample weights. Our baseline weights multiply the original sample weights by the predicted weeks worked divided by 52. We construct alternative weights for some of our robustness checks. To deal with the issue of undercounting, we divide the baseline weights of (potentially) undocumented immigrants by (1-40%) in the 1970 and 1980 Census, and (1-25%) in the 1990 Census, based on the undercount rates reported in Van Hook and Bean (1998). Similarly, we divide the baseline weights of 25–44 and 45–65 year-old Mexicans (whether undocumented or not) by (1-23%) and (1-21%) in the 2000 Census, and (1-12%) and (1+10%) in the 2010 ACS, based on the undercount rates reported in Van Hook, Bean and Tucker (2014). Finally, we divide the baseline weights of all potentially undocumented by (1-6%) in the 2018-2019 ACS, based on Passel and Cohn (2018).

For the robustness checks dealing with selective return migration, we use three different weighting schemes. In the first check based on Borjas and Bratsberg (1996), we multiply the baseline weights of immigrants who are observed in their first 10 years in the United States by $(1 - x)$, where x refers to one of the following country-specific return migration rates: 33.0 percent (Mexico), 22.7 percent (Other Latin America), 22.7 percent (Western Countries), 6.1 percent (Asia), and 11.5 percent (Rest of the World).

In the second check based on Rho and Sanders (2021), we obtained the following values from Figure 5 in their paper:

Education:	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
< 16 years	0	1	0	1	5	6	7	10	11	19
16 years	16	9	10	12	14	13	13	19	22	43
> 16 years	18	14	15	14	12	12	15	21	23	35

Each entry represents the percentage point difference between immigrants and natives in the probability of *not* being found in the 2010 Census, conditional on being observed in the 2000 Census, separately by decile of the self-reported 1999 earnings distribution. Interpreting a non-match in the 2010 Census as an indicator for having left the United States, these values can proxy for the return migration rates of immigrants, conditional on their observable (education) and unobservable (residual earnings decile) skill level. Similar to the first robustness check, we multiply the baseline weights of immigrants observed in their first 10 years in the United States by $(1 - x)$, where x is the percentage point difference that corresponds to their education level and position in the residual wage distribution (which we interpret as the percentiles of the predicted residuals from Equation (12)).

Finally, for the third return migration check, we divide our sample of immigrants into cells defined by cohort of entry, origin, education level and decile of the residual distribution from Equation (12). We do this separately for immigrants observed in their first 10 years in the United States and for immigrants observed after at least 10 years in the United States. We then adjust the weights of immigrants in the more recent arrival groups such that, when summed up, they reproduce the joint origin/education/residual distribution of the corresponding entry cohort observed after 10 years in the United States. In particular, let ω_i denote the baseline weight of an immigrant belonging to entry cohort c_i , origin o_i , education level e_i and residual wage decile d_i , $share_old_{c,o,e,d}$ denote the share of immigrants who belong to cell (o, e, d) among immigrants from entry cohort c who have lived in the United States for at least 10 years, and $share_recent_{c,o,e,d}$ denote the share of immigrants who belong to cell (o, e, d) among immigrants from entry cohort c who have lived in the United States for less than 10 years. The adjusted weight for immigrants belonging to the latter group is given by $\tilde{\omega}_i = \omega_i \times (share_old_{c_i,o_i,e_i,d_i} / share_recent_{c_i,o_i,e_i,d_i})$.

APPENDIX B: ADDITIONAL DESCRIPTIVE STATISTICS

TABLE B1—ADDITIONAL DESCRIPTIVES

	Census year:					
	1970	1980	1990	2000	2010	2020
Immigrant share (%)	3.8	5.0	6.9	10.7	14.4	16.3
Number (millions):						
Natives	47.0	62.5	76.5	87.6	89.8	97.7
Immigrants	1.8	3.1	5.3	9.4	13.0	15.9
Men (%):						
Natives	67.7	60.9	56.3	54.3	52.8	52.9
Immigrants	64.5	59.6	58.9	59.4	57.5	56.8
Age:						
Natives	43.2	41.3	40.7	42.3	44.1	43.6
Immigrants	44.0	42.2	42.4	42.4	44.2	45.6
Hourly wage:						
Natives	18.8	18.7	18.1	19.5	18.9	19.8
Immigrants	18.5	18.1	17.2	17.8	16.3	19.1
HS dropouts (%):						
Natives	38.1	21.7	10.4	6.6	4.6	3.7
Immigrants	48.0	39.6	30.9	28.6	26.0	21.2
HS graduates (%):						
Natives	36.4	39.9	35.3	40.4	35.2	32.8
Immigrants	24.2	24.3	24.8	28.6	28.1	28.2
Some college (%):						
Natives	11.6	17.6	29.0	23.7	25.8	24.9
Immigrants	11.4	12.9	18.1	13.8	13.9	13.5
College graduates (%):						
Natives	14.0	20.8	25.3	29.2	34.4	38.6
Immigrants	16.4	23.2	26.2	29.0	32.0	37.2

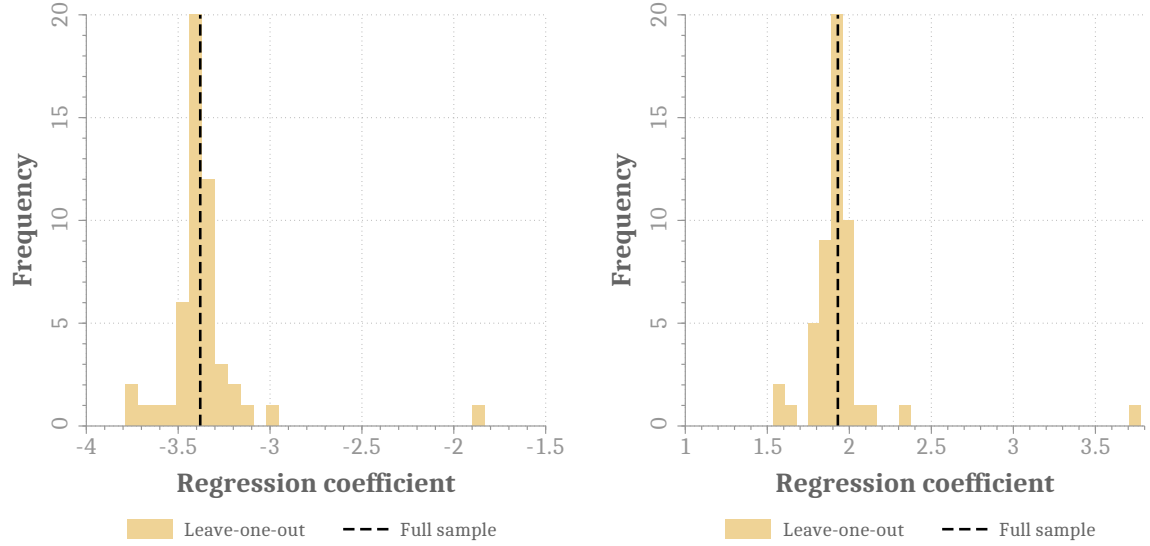
Note: The statistics are based on the sample of immigrants aged 25-64 reporting positive income (not living in group quarters) in the United States from the Census 1970, 1980, 1990, 2000, the pooled ACS 2009-2011 (labeled as 2010), and the ACS of 2018 and 2019 (labeled as 2020). Observations are weighted by the personal weights obtained from IPUMS, rescaled by annual hours worked.

APPENDIX C: ADDITIONAL DESCRIPTIVE EVIDENCE

FIGURE C1. LEAVE-ONE-OUT ANALYSIS FOR FIGURE 2

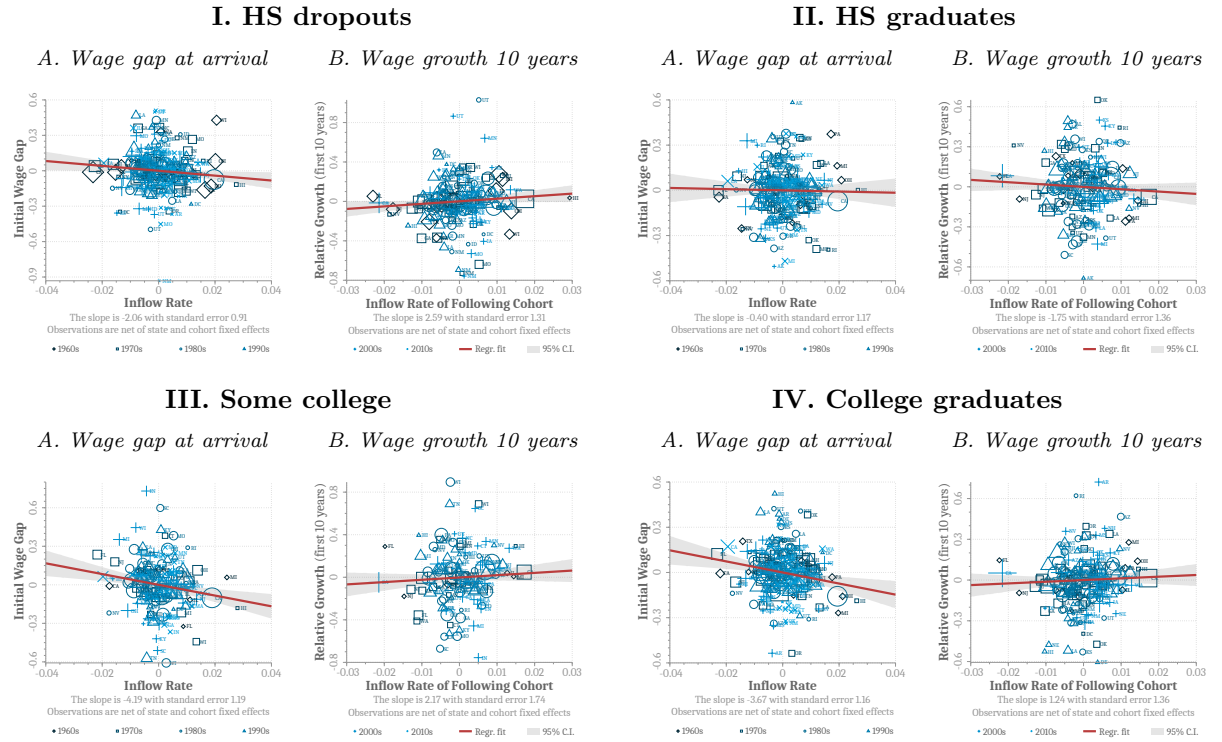
A. Wage gap at arrival

B. Relative wage growth first 10 years



Note: The figure plots a histogram of the regression coefficients obtained from repeating the estimation implemented in the corresponding panels of Figure 2 leaving one state out each time. The black line represents the point estimates in Figure 2. The height of the bars indicate the number of regressions that each bar represents.

FIGURE C2. COHORT SIZE, INITIAL WAGE GAP, AND RELATIVE WAGE GROWTH (BY EDUCATION)



Note: The figure replicates the analysis in Figure 2, breaking down the assimilation patterns by education group. State-year-education groups with fewer than 150 immigrants in the census year of arrival are not included. Scatter plots represent state-cohort observations, where size represents population, and lines represent linear regression fits (weighted by population size). Markers/shades distinguish different cohorts. Gray shaded areas represent 95% confidence intervals of the state regressions.

APPENDIX D: IMPERFECT SUBSTITUTABILITY ACROSS SKILL GROUPS

In this appendix, we consider an extension of our model that allows for imperfect substitutability between workers with different observable characteristics. Following the very general notation used in Ottaviano and Peri (2012, p. 159–160), let $k = 0, \dots, K$ denote the observable characteristic used to sequentially partition workers into skill groups (e.g. education at the highest level, experience at the second highest level, etc.), and let $\ell(k)$ denote the group of workers defined by common characteristics up to k (e.g. individuals with the same education level). Let $L_{\ell(k)t}$ denote the labor supply in skill cell $\ell(k)$ at time t , defined as:

$$L_{\ell(k)t} \equiv \left[\sum_{\ell(k+1) \in \ell(k)} \alpha_{\ell(k+1)} (L_{\ell(k+1)t})^{\frac{\phi_{k+1}-1}{\phi_{k+1}}} \right]^{\frac{\phi_{k+1}}{\phi_{k+1}-1}} \quad \forall \ell(k) \in \ell(0) \text{ and } k = 0, \dots, K, \quad (\text{D1})$$

where $\alpha_{\ell(k)}$ is the relative productivity of skill group $\ell(k)$, with $\sum_{\ell(k+1) \in \ell(k)} \alpha_{\ell(k+1)} \equiv 1$, and ϕ_k is the elasticity of substitution between any two labor inputs in the nest defined by characteristics up to k . Given this partition, consider the alternative production function $Y_t = A_t L_{\ell(0)t}$, where L_{0t} is recursively defined in (D1), and the lowest-level nest is always defined as the partition between general and specific skills within each skill group $\ell(K-1)$ (that is, $L_{\ell(K)t} \in \{G_{\ell(K-1)t}, S_{\ell(K-1)t}\}$). Given this alternative formulation of the production function, relative skill prices are determined by the relative quantities of general and specific skills supplied in each skill group:

$$\frac{r_{\ell(K-1)St}}{r_{\ell(K-1)Gt}} = \delta_t \left(\frac{G_{\ell(K-1)t}}{S_{\ell(K-1)t}} \right)^{\frac{1}{\sigma}}. \quad (\text{D2})$$

The comparison of wages of an immigrant and a comparable native defined in Equation (6) in the main text therefore still remains valid, with the modification that the relevant aggregate supplies of general and specific skills must now be defined within skill group $\ell(K-1)$ rather than, more broadly, for the overall labor market as in our baseline model.

In one of our robustness checks in Section VI, we adjust the production function to account for the possibility of imperfect substitutability between workers belonging to different education groups. This counterfactual requires a minor adjustment in the prediction of counterfactual wages that we explain below. To help build our argument, we first provide a detailed explanation of how the prediction of counterfactual wages works in our main decomposition, and then describe how these predictions need to be adjusted in the counterfactual with imperfect substitutability across education groups.

Counterfactual wages in the baseline model. Our counterfactual scenario without competition effects sets $\sigma = \infty$ in order to predict wages. While Equation (6) shows how this would affect relative wages of immigrants and observationally similar natives, a question remains as to whether or not the equilibrium effects on wage *levels* are relevant

for our counterfactual decomposition. Given our formulation of the model, any change in skill prices r_{Gt} and r_{St} that keeps their ratio constant would scale up or down native and immigrant wages in the same way, thus not affecting any relative wage comparisons, including that underlying our decomposition exercise. Wage level effects would therefore be innocuous for our wage decomposition.

In practice, however, we estimate our model on 50 different U.S. states, which we treat as separate markets, and then perform our decomposition at the national level. If level effects differed across local labor markets, these effects would then not cancel out since the decomposition averages wage gaps across different states, thus generating composition effects due to the larger proportion of immigrants in some markets compared to others.

Given that our model has little to say about the interactions across local labor markets and is not well suited to speak about wage level effects, we make counterfactual predictions assuming that these level effects are the same across local labor markets. This assumption could be justified by spatial arbitrage across labor markets or as the result of capital adjustments. This normalization allows us to avoid contaminating our simulations with composition effects driven by the distribution of individuals across local labor markets. Our results can thus be interpreted as a population-weighted average of each state's competition effect.

Counterfactual wages in the imperfect substitutability scenario. In our robustness check with imperfect substitutability between workers with different education levels, there is a second reason why wage level effects may matter: the differences in level effects across education groups. In this counterfactual, while we take the same approach regarding differential level effects across states as in our main counterfactual, we internalize the different level effects across education groups in our simulations, given that our model explicitly accounts for these effects. In particular, without loss of generality, rewrite the wage function in Equation (5) as:

$$w_{gt}(n, y, o, c, E, x, \varepsilon) = (r_{G1t} + r_{S1t}) \frac{r_{Get} + r_{Set}}{r_{G1t} + r_{S1t}} \frac{[r_{Get} + r_{Set} s_g(n, y, o, c, E, x)]}{r_{Get} + r_{Set}} h_{gt}(E, x, \varepsilon). \quad (\text{D3})$$

Our approach assumes that the level effect on $r_{G1t} + r_{S1t}$ (or any normalizing level) is the same across states, but accounts for the change in the other two terms. The third term equals one for natives, and is evaluated in our central expression in Equation (6) for immigrants, whereas the change in $\frac{r_{Get} + r_{Set}}{r_{G1t} + r_{S1t}}$ is the new correction term we introduce here.

Given the modified production function in Equation (16) in the main text, general and specific skill prices for education group e are given, respectively, by:

$$r_{Get} = A_t \alpha_{et} \left[\frac{Y_t}{A_t L_{et}} \right]^{\frac{1}{\phi}} \left(\frac{L_{et}}{G_{et}} \right)^{\frac{1}{\sigma}} \quad \text{and} \quad r_{Set} = A_t \alpha_{et} \delta_t \left[\frac{Y_t}{A_t L_{et}} \right]^{\frac{1}{\phi}} \left(\frac{L_{et}}{S_{et}} \right)^{\frac{1}{\sigma}}, \quad (\text{D4})$$

where $L_{et} \equiv \left(G_{et}^{\frac{\sigma-1}{\sigma}} + \delta_t S_{et}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$. Thus, the second term in (D3) is given by:

$$\frac{r_{Get} + r_{Set}}{r_{G1t} + r_{S1t}} = \frac{\alpha_{et}}{\alpha_{1t}} \left[\frac{L_{et}}{L_{1t}} \right]^{\frac{1}{\sigma} - \frac{1}{\phi}} \left[\frac{G_{1t}}{G_{et}} \right]^{\frac{1}{\sigma}} \left(\frac{1 + \delta_t \left(\frac{G_{et}}{S_{et}} \right)^{\frac{1}{\sigma}}}{1 + \delta_t \left(\frac{G_{1t}}{S_{1t}} \right)^{\frac{1}{\sigma}}} \right). \quad (\text{D5})$$

In our counterfactual simulations, therefore, besides the analogous adjustments of immigrant wages relative to their native counterparts, both native and immigrant wages need to be further adjusted to account for the change in (D5). In particular, the recovered state-education-time fixed effects, which are in logs, are adjusted to account for the log-change in the above expression. This log-change is given by:

$$\Delta \ln \frac{r_{Get} + r_{Set}}{r_{G1t} + r_{S1t}} = \ln \frac{\left(\frac{r_{Get}^{(c)} + r_{Set}^{(c)}}{r_{G1t}^{(c)} + r_{S1t}^{(c)}} \right)}{\left(\frac{r_{Get}^{(b)} + r_{Set}^{(b)}}{r_{G1t}^{(b)} + r_{S1t}^{(b)}} \right)} = \ln \frac{\left[\frac{L_{et}^{(c)}}{L_{1t}^{(c)}} \right]^{-\frac{1}{\phi}}}{\left[\frac{L_{et}^{(b)}}{L_{1t}^{(b)}} \right]^{\frac{1}{\sigma} - \frac{1}{\phi}} \left[\frac{G_{1t}^{(b)}}{G_{et}^{(b)}} \right]^{\frac{1}{\sigma}} \left(\frac{1 + \delta_t \left(\frac{G_{et}^{(b)}}{S_{et}^{(b)}} \right)^{\frac{1}{\sigma}}}{1 + \delta_t \left(\frac{G_{1t}^{(b)}}{S_{1t}^{(b)}} \right)^{\frac{1}{\sigma}}} \right)}, \quad (\text{D6})$$

where superscript (c) denotes counterfactual and (b) denotes baseline. This adjustment needs to be made for both natives and immigrants. To implement it, we need to recover an estimate of ϕ . To obtain it, following the standard approach popularized in the immigration literature by Borjas (2003, eq.17, p.1364), we first recover $\{L_{et}\}_{e=1}^4$ given our estimates of σ and δ_t , and then estimate a linear regression of log wages on log labor aggregates at the education-time cell level, including education-specific linear trends.

APPENDIX E: THE ROLE OF CAPITAL

Unlike the popular CES formulations in the immigration literature (e.g. Borjas, 2003, or Ottaviano and Peri, 2012), our production function does not include capital. In this section, we show that the introduction of capital in the standard separable way is inconsequential for our analysis. Let K_t denote the aggregate stock of capital. Consider the following alternative formulation of Equation (1):

$$\begin{aligned} Y_t &= A_t K_t^\alpha L_t^{1-\alpha} \\ &= A_t K_t^\alpha \left(G_t^{\frac{\sigma-1}{\sigma}} + \delta_t S_t^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma(1-\alpha)}{\sigma-1}}, \end{aligned} \quad (\text{E1})$$

where α is the capital share. The marginal product of capital is given by:

$$\begin{aligned} \frac{\partial Y_t}{\partial K_t} &= A_t \alpha K_t^{\alpha-1} L_t^{1-\alpha} \\ &= A_t \alpha \left(\frac{K_t}{L_t} \right)^{\alpha-1}, \end{aligned} \quad (\text{E2})$$

which in a competitive equilibrium model without frictions is equal to the return to capital r_{K_t} . Consider the case in which interest rates are set in the world market, as in Ottaviano and Peri (2012), which implies that the capital-labor ratio in the economy is fixed, $K_t/L_t = k_{0t}$. Given constant returns to scale, the above production function can then be written as:

$$\begin{aligned} Y_t &= A_t K_t^\alpha L_t^{1-\alpha} \\ &= A_t \left(\frac{K_t}{L_t} \right)^\alpha L_t \\ &= A_t k_0^\alpha L_t = A_t^* L_t \end{aligned} \quad (\text{E3})$$

which is equivalent to our baseline model, given that A_t (or A_t^*) does not play any role in determining relative wages between natives and immigrants.

APPENDIX F: STANDARD ERROR FORMULAS

The standard error formulas derived in this appendix are obtained from a Generalized Method of Moments (GMM) representation of our two-step nonlinear estimation as an application of the general result presented in Newey and McFadden (1994, Section 6). Our least squares estimation of $\boldsymbol{\eta}$, $\boldsymbol{\theta}$, σ , and $\tilde{\delta}$, and the auxiliary parameters $\boldsymbol{\gamma}$, can be expressed as a GMM estimation with the moment conditions presented below in Equations (F3) and (F4), which are based on the ordinary and nonlinear least squares first order conditions of our estimating equations. To simplify notation in this derivation, let $\mathbf{x}$ denote the vector of all regressors included in the $s(\cdot)$ function, and $\mathbf{x}^N$ denote the regressors included in the $h(\cdot)$ function. Let also $R_i(\boldsymbol{\eta}, \boldsymbol{\theta}, \tilde{\delta}, \sigma)$, or sometimes simply R_i , denote the relative skill prices of general versus specific skills faced by an individual i who lives in market (j_i, t_i) , defined as $R_i(\boldsymbol{\eta}, \boldsymbol{\theta}, \tilde{\delta}, \sigma) \equiv \exp(\tilde{\delta} t_i) \left(\frac{G_{j_i t_i}(\boldsymbol{\eta})}{S_{j_i t_i}(\boldsymbol{\eta}, \boldsymbol{\theta})} \right)^{\frac{1}{\sigma}}$, where we expanded the notation in the main text to make the additional dependence of G and S on $\boldsymbol{\eta}$ explicit. Define by $d_{ijt} \equiv \mathbb{1}\{j_i = j, t_i = t\}$ a set of state-time dummies for all states $j \in \mathcal{J} \equiv \{1, \dots, J\}$ and periods $t \in \mathcal{T} \equiv \{1, \dots, T\}$ in the sample. Finally, define the native and immigrant least squares residuals, $\varepsilon_N(\boldsymbol{\eta}, \boldsymbol{\gamma})$ and $\varepsilon_I(\boldsymbol{\eta}, \boldsymbol{\gamma}, \boldsymbol{\theta}, \tilde{\delta}, \sigma)$, respectively as:

$$\varepsilon_i^N(\boldsymbol{\eta}, \boldsymbol{\gamma}) \equiv \ln w_i - \mathbf{x}_i^{N'} \boldsymbol{\eta} - \sum_{j \in \mathcal{J}, t \in \mathcal{T}} \gamma_{jt} d_{ijt}, \quad (\text{F1})$$

and:

$$\begin{aligned} \varepsilon_i^I(\boldsymbol{\eta}, \boldsymbol{\gamma}, \boldsymbol{\theta}, \tilde{\delta}, \sigma) \equiv & \ln w_i - \sum_{j \in \mathcal{J}, t \in \mathcal{T}} \gamma_{jt} d_{ijt} - \mathbf{x}_i^{N'} \boldsymbol{\eta} + \ln \left[1 + R_i(\boldsymbol{\eta}, \boldsymbol{\theta}, \tilde{\delta}, \sigma) \right] - \ln \left[1 + \mathbf{x}' \boldsymbol{\theta} R_i(\boldsymbol{\eta}, \boldsymbol{\theta}, \tilde{\delta}, \sigma) \right] \end{aligned} \quad (\text{F2})$$

The moment conditions (least squares FOCs) that identify all the parameters are:

$$\frac{1}{N} \sum_{i=1}^N \left[n_i \begin{pmatrix} \mathbf{x}_i^N \\ d_{i11} \\ \vdots \\ d_{iJT} \end{pmatrix} \varepsilon_i^N(\hat{\boldsymbol{\eta}}, \hat{\boldsymbol{\gamma}}) \right] = 0, \quad (\text{F3})$$

and:

$$\frac{1}{N} \sum_{i=1}^N \left[(1 - n_i) \begin{pmatrix} \frac{\partial \varepsilon_i^I(\cdot)}{\partial \boldsymbol{\theta}'} \\ \frac{\partial \varepsilon_i^I(\cdot)}{\partial \tilde{\delta}} \\ \frac{\partial \varepsilon_i^I(\cdot)}{\partial \sigma} \end{pmatrix} \varepsilon_i^I(\hat{\boldsymbol{\eta}}, \hat{\boldsymbol{\gamma}}, \hat{\boldsymbol{\theta}}, \hat{\tilde{\delta}}, \hat{\sigma}) \right] = 0. \quad (\text{F4})$$

Using the results in Theorem 6.1 of Newey and McFadden (1994):

$$\sqrt{N} \left[(\hat{\boldsymbol{\theta}}', \hat{\tilde{\delta}}, \hat{\sigma})' - (\boldsymbol{\theta}_0', \tilde{\delta}_0, \sigma_0)' \right] \xrightarrow{d} \mathcal{N}(\mathbf{0}, V_0), \quad (\text{F5})$$

where the zero subscripts denote true (population) values, and V_0 is given by:

$$V_0 = H^{-1} \mathbb{E} [(F + DM)(F + DM)'] H^{-1'}, \quad (\text{F6})$$

where H is the gradient of the NLS first order conditions relative to $\boldsymbol{\theta}$, $\tilde{\delta}$, and σ :

$$H \equiv \mathbb{E} \left[(1 - n) \begin{pmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{pmatrix} \right] \quad (\text{F7})$$

with:

$$\begin{aligned} H_{11} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}' \partial \boldsymbol{\theta}} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}'} \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}}, \\ H_{12} = H'_{21} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}' \partial \tilde{\delta}} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}'} \frac{\partial \varepsilon^I(\cdot)}{\partial \tilde{\delta}}, \\ H_{13} = H'_{31} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}' \partial \sigma} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}'} \frac{\partial \varepsilon^I(\cdot)}{\partial \sigma}, \\ H_{22} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial^2 \tilde{\delta}} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \left(\frac{\partial \varepsilon^I(\cdot)}{\partial \tilde{\delta}} \right)^2, \\ H_{23} = H'_{32} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \tilde{\delta} \partial \sigma} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \tilde{\delta}} \frac{\partial \varepsilon^I(\cdot)}{\partial \sigma}, \\ H_{33} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial^2 \sigma} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \left(\frac{\partial \varepsilon^I(\cdot)}{\partial \sigma} \right)^2, \end{aligned}$$

D is the gradient relative to $\boldsymbol{\eta}$ and $\boldsymbol{\gamma}$:

$$D \equiv \mathbb{E} \left[(1 - n) \begin{pmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \\ D_{31} & D_{32} \end{pmatrix} \right] \quad (\text{F8})$$

with:

$$\begin{aligned} D_{11} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}' \partial \boldsymbol{\eta}} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}'} \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\eta}}, \\ D_{12} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}' \partial \boldsymbol{\gamma}} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}'} \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\gamma}}, \\ D_{21} &\equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \tilde{\delta} \partial \boldsymbol{\eta}} \varepsilon^I(\boldsymbol{\eta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \tilde{\delta}} \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\eta}}, \end{aligned}$$

$$D_{22} \equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \tilde{\delta} \partial \gamma} \varepsilon^I(\boldsymbol{\eta}_0, \gamma_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \tilde{\delta}} \frac{\partial \varepsilon^I(\cdot)}{\partial \gamma},$$

$$D_{31} \equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \sigma \partial \boldsymbol{\eta}} \varepsilon^I(\boldsymbol{\eta}_0, \gamma_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \sigma} \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\eta}},$$

$$D_{32} \equiv \frac{\partial^2 \varepsilon^I(\cdot)}{\partial \sigma \partial \gamma} \varepsilon^I(\boldsymbol{\eta}_0, \gamma_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0) + \frac{\partial \varepsilon^I(\cdot)}{\partial \sigma} \frac{\partial \varepsilon^I(\cdot)}{\partial \gamma},$$

F is the vector of first order conditions of the NLS problem:

$$F \equiv (1 - n) \begin{pmatrix} \frac{\partial \varepsilon^I(\cdot)}{\partial \boldsymbol{\theta}'} \\ \frac{\partial \varepsilon^I(\cdot)}{\partial \tilde{\delta}} \\ \frac{\partial \varepsilon^I(\cdot)}{\partial \sigma} \end{pmatrix} \varepsilon^I(\boldsymbol{\eta}_0, \gamma_0, \boldsymbol{\theta}_0, \tilde{\delta}_0, \sigma_0), \quad (\text{F9})$$

and M is:

$$M \equiv -\mathbb{E} \left[n \begin{pmatrix} \mathbf{x}^N \\ d_{11} \\ \vdots \\ d_{JT} \end{pmatrix} (\mathbf{x}^{N'} \quad d_{11} \quad \dots \quad d_{JT}) \right]^{-1} n \begin{pmatrix} \mathbf{x}^N \\ d_{11} \\ \vdots \\ d_{JT} \end{pmatrix} \varepsilon^N(\boldsymbol{\eta}_0, \gamma_0). \quad (\text{F10})$$

After some algebra, the first derivatives that conform to the above expressions are:

$$\frac{\partial \varepsilon_i^I(\cdot)}{\partial \boldsymbol{\theta}'} = \frac{\partial R_i(\cdot)}{\partial \boldsymbol{\theta}'} \frac{1 - \mathbf{x}_i' \boldsymbol{\theta}_0}{(1 + \mathbf{x}_i' \boldsymbol{\theta}_0 R_i)(1 + R_i)} - \mathbf{x}_i \frac{R_i}{1 + \mathbf{x}_i' \boldsymbol{\theta}_0 R_i}, \quad (\text{F11})$$

with:

$$\frac{\partial R_i(\cdot)}{\partial \boldsymbol{\theta}'} = -\frac{1}{\sigma_0} \frac{R_i}{S_{j_i t_i}} \sum_{\ell=1}^N d_{\ell j_i t_i} (1 - n_\ell) \omega_i h_{g_{\ell t}}(E_\ell, x_\ell, \varepsilon_\ell) \mathbf{x}_\ell, \quad (\text{F12})$$

plus:

$$\frac{\partial \varepsilon_i^I(\cdot)}{\partial \tilde{\delta}} = \frac{t_i R_i (1 - \mathbf{x}' \boldsymbol{\theta}_0)}{(1 + \mathbf{x}_i' \boldsymbol{\theta}_0 R_i)(1 + R_i)}, \quad (\text{F13})$$

$$\frac{\partial \varepsilon_i^I(\cdot)}{\partial \sigma} = -\frac{(1 - \mathbf{x}' \boldsymbol{\theta}_0) R_i \ln \frac{G_{j_i t_i}}{S_{j_i t_i}}}{\sigma_0^2 (1 + \mathbf{x}_i' \boldsymbol{\theta}_0 R_i)(1 + R_i)}, \quad (\text{F14})$$

and:

$$\frac{\partial \varepsilon_i^I(\cdot)}{\partial \boldsymbol{\gamma}'} = - \begin{pmatrix} d_{i11} \\ \vdots \\ d_{iJT} \end{pmatrix} \quad \text{and} \quad \frac{\partial \varepsilon_i^I(\cdot)}{\partial \boldsymbol{\eta}'} = -\mathbf{x}_i^N. \quad (\text{F15})$$

Finally, also with some algebra, the second derivatives are:

$$\begin{aligned} \frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \theta' \partial \theta} &= \frac{\partial^2 R_i(\cdot)}{\partial \theta' \partial \theta} \frac{1 - \mathbf{x}'_i \boldsymbol{\theta}_0}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)(1 + R_i)} \\ &\quad - \frac{\partial R_i(\cdot)}{\partial \theta'} \frac{\partial R_i(\cdot)}{\partial \theta} \frac{[1 - \mathbf{x}'_i \boldsymbol{\theta}_0][\mathbf{x}'_i \boldsymbol{\theta}_0(1 + R_i) + (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)]}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2(1 + R_i)^2} \\ &\quad - \left[\frac{\partial R_i(\cdot)}{\partial \theta'} \mathbf{x}'_i + \mathbf{x}_i \frac{\partial R_i(\cdot)}{\partial \theta} - \mathbf{x}_i \mathbf{x}'_i R_i^2 \right] \frac{1}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2}, \end{aligned} \quad (\text{F16})$$

with:

$$\frac{\partial^2 R_i(\cdot)}{\partial \theta' \partial \theta} = \frac{\partial R_i(\cdot)}{\partial \theta'} \frac{\partial R_i(\cdot)}{\partial \theta} \frac{1 + \sigma_0}{R_i}, \quad (\text{F17})$$

plus:

$$\frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \theta' \partial \tilde{\delta}} = t_i \left[\frac{\partial R_i}{\partial \theta'} \frac{(1 - \mathbf{x}'_i \boldsymbol{\theta}_0)(1 - \mathbf{x}'_i \boldsymbol{\theta}_0 R_i^2)}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2(1 + R_i)^2} - \mathbf{x}_i \frac{R_i}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2} \right], \quad (\text{F18})$$

$$\begin{aligned} \frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \theta' \partial \sigma} &= \frac{1}{\sigma_0^2} \ln \frac{G_{j_i t_i}}{S_{j_i t_i}} \left[\mathbf{x}_i \frac{R_i}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2} - \frac{\partial R_i}{\partial \theta'} \frac{(1 - \mathbf{x}'_i \boldsymbol{\theta}_0)(1 - \mathbf{x}'_i \boldsymbol{\theta}_0 R_i^2)}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2(1 + R_i)^2} \right] \\ &\quad - \frac{1}{\sigma_0} \frac{\partial R_i}{\partial \theta'} \frac{(1 - \mathbf{x}'_i \boldsymbol{\theta}_0)}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)(1 + R_i)}, \end{aligned} \quad (\text{F19})$$

$$\frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial^2 \tilde{\delta}} = \frac{t_i^2 R_i (1 - \mathbf{x}'_i \boldsymbol{\theta}_0)(1 - \mathbf{x}'_i \boldsymbol{\theta}_0 R_i^2)}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2(1 + R_i)^2}, \quad (\text{F20})$$

$$\frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \tilde{\delta} \partial \sigma} = - \frac{t_i R_i \ln \frac{G_{j_i t_i}}{S_{j_i t_i}} (1 - \mathbf{x}'_i \boldsymbol{\theta}_0)(1 - \mathbf{x}'_i \boldsymbol{\theta}_0 R_i^2)}{\sigma_0^2 (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2(1 + R_i)^2}, \quad (\text{F21})$$

$$\frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial^2 \sigma} = \frac{2(1 - \mathbf{x}' \boldsymbol{\theta}_0) R_i \ln \frac{G_{j_i t_i}}{S_{j_i t_i}}}{\sigma_0^3 (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)(1 + R_i)} + \frac{\left(\ln \frac{G_{j_i t_i}}{S_{j_i t_i}} \right)^2 (1 - \mathbf{x}'_i \boldsymbol{\theta}_0)(1 - \mathbf{x}'_i \boldsymbol{\theta}_0 R_i^2)}{\sigma_0^4 (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2(1 + R_i)^2}, \quad (\text{F22})$$

and:

$$\frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \theta' \partial \gamma} = \frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \tilde{\delta} \partial \gamma} = \frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \sigma \partial \gamma} = 0, \quad (\text{F23})$$

$$\begin{aligned} \frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \theta' \partial \boldsymbol{\eta}} &= \frac{\partial^2 R_i(\cdot)}{\partial \theta' \partial \boldsymbol{\eta}} \frac{1 - \mathbf{x}'_i \boldsymbol{\theta}_0}{(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)(1 + R_i)} \\ &\quad - \left[\frac{\partial R_i(\cdot)}{\partial \theta'} \frac{(1 - \mathbf{x}'_i \boldsymbol{\theta}_0)(1 + \mathbf{x}'_i \boldsymbol{\theta}_0 + 2\mathbf{x}'_i \boldsymbol{\theta}_0 R_i)}{(1 + R_i)^2} + \mathbf{x}_i \right] \\ &\quad \times \frac{R_i}{\sigma_0 (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2} \left(\frac{\partial G_{j_i t_i}}{\partial \boldsymbol{\eta}} \frac{1}{G_{j_i t_i}} - \frac{\partial S_{j_i t_i}}{\partial \boldsymbol{\eta}} \frac{1}{S_{j_i t_i}} \right), \end{aligned} \quad (\text{F24})$$

$$\frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \tilde{\delta} \partial \boldsymbol{\eta}} = \frac{t_i R_i (1 - \mathbf{x}' \boldsymbol{\theta}_0) (1 - \mathbf{x}'_i \boldsymbol{\theta}_0 R_i^2)}{\sigma_0 (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i)^2 (1 + R_i)^2} \left(\frac{\partial G_{j_i t_i}}{\partial \boldsymbol{\eta}} \frac{1}{G_{j_i t_i}} - \frac{\partial S_{j_i t_i}}{\partial \boldsymbol{\eta}} \frac{1}{S_{j_i t_i}} \right), \quad (\text{F25})$$

$$\begin{aligned} \frac{\partial^2 \varepsilon_i^I(\cdot)}{\partial \sigma \partial \boldsymbol{\eta}} = & - \frac{(1 - \mathbf{x}' \boldsymbol{\theta}_0) R_i}{\sigma_0^2 (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i) (1 + R_i)} \left[\frac{\ln \frac{G_{j_i t_i}}{S_{j_i t_i}} (1 - \mathbf{x}'_i \boldsymbol{\theta}_0 R_i^2)}{\sigma_0 (1 + \mathbf{x}'_i \boldsymbol{\theta}_0 R_i) (1 + R_i)} + 1 \right] \\ & \times \left(\frac{\partial G_{j_i t_i}}{\partial \boldsymbol{\eta}} \frac{1}{G_{j_i t_i}} - \frac{\partial S_{j_i t_i}}{\partial \boldsymbol{\eta}} \frac{1}{S_{j_i t_i}} \right), \end{aligned} \quad (\text{F26})$$

with:

$$\begin{aligned} \frac{\partial^2 R_i(\cdot)}{\partial \boldsymbol{\theta}' \partial \boldsymbol{\eta}} = & - \frac{1}{\sigma_0} \frac{R_i}{S_{j_i t_i}} \sum_{\ell=1}^N d_{\ell j_i t_i} (1 - n_\ell) \omega_i h_{g_{\ell t}}(E_\ell, x_\ell, \varepsilon_\ell) \mathbf{x}_\ell \mathbf{x}_\ell^{N'} \\ & - \frac{1}{\sigma_0^2 S_{j_i t_i}} \left(\sum_{\ell=1}^N d_{\ell j_i t_i} (1 - n_\ell) \omega_i h_{g_{\ell t}}(E_\ell, x_\ell, \varepsilon_\ell) \mathbf{x}_\ell \right) \left(\frac{R_i}{G_{j_i t_i}} \frac{\partial G_{j_i t_i}}{\partial \boldsymbol{\eta}} - (1 + \sigma_0) \frac{\partial S_{j_i t_i}}{\partial \boldsymbol{\eta}} \frac{R_i}{S_{j_i t_i}} \right), \end{aligned} \quad (\text{F27})$$

$$\frac{\partial G_{j_i t_i}}{\partial \boldsymbol{\eta}'} = \sum_{\ell=1}^N d_{\ell j_i t_i} (1 - n_\ell) \omega_i h_{g_{\ell t}}(E_\ell, x_\ell, \varepsilon_\ell) \mathbf{x}_\ell^N, \quad (\text{F28})$$

and:

$$\frac{\partial S_{j_i t_i}}{\partial \boldsymbol{\eta}'} = \sum_{\ell=1}^N d_{\ell j_i t_i} (1 - n_\ell) \omega_i \mathbf{x}'_i \boldsymbol{\theta}_0 h_{g_{\ell t}}(E_\ell, x_\ell, \varepsilon_\ell) \mathbf{x}_\ell^N. \quad (\text{F29})$$

Given that the first and the second step samples do not share observations in common (that is $n_i(1 - n_i) = 0$ for all individuals since an individual cannot be in the sample of natives and of immigrants at the same time), the inner product of the right hand side of Equation (F6) simplifies to the sum of squares, and the expression reduces to:

$$V_0 = H^{-1} \mathbb{E} [F F' + D M M' D] H^{-1'}. \quad (\text{F30})$$

Intuitively, $H^{-1} \mathbb{E} [F F'] H^{-1}$ is the variance-covariance matrix of the second step estimation when we ignore that some of the data come from a first step estimation. The term $M M'$ is the variance-covariance matrix of the first step estimation and the matrix D indicates how sensitive the second step parameter estimates are to changes in the first step parameters. Thus, the variance inflation term will be important if the second step estimates are sensitive to changes in the first step parameters and/or when the first step parameters are estimated with noise, and negligible when either the second step parameters are not very sensitive to the first step estimates and/or when the first step coefficients are precisely estimated.

APPENDIX G: ADDITIONAL DETAILS ON PARAMETER ESTIMATES

This appendix complements Section IV by providing additional information on the baseline parameter estimates. As in the main text, we focus on results for immigrant men ($g = 0$). Results for women ($g = 1$) are shown in Appendix N.

Productivity factor parameters. Table G1 reports the estimates for the productivity factor of men $h_{0t}(E, x, \varepsilon)$, with each column referring to a different census year. The parameter estimates are consistent with those in the literature (see e.g. Heckman, Lochner and Todd, 2006, for a survey). Beyond the wage returns to different education levels (1.3–5.4 log points for a high school diploma, 8.1–14.6 log points for some college education and 27.4–47.1 log points for a bachelor’s degree, depending on the census year), an extra year of education increases male wages by 4.2–6.3 log points. In general, returns to college education increased over time, in line with the findings of the wage inequality literature. The wage-experience profiles show the standard concave shape, flattening after around 25 years of experience.

Skill accumulation parameters Table G2 reports the parameter estimates that describe the process through which male immigrant workers accumulate specific skills, $s_0(0, y, o, c, E, x)$. The first column shows the coefficients of the non-interacted regressors along with the constant term. The constant represents the relative specific skills supplied upon entry by a male Mexican high school dropout who arrived with the 1970s cohort with zero years of experience. This constant term is estimated to be 0.804, in-

TABLE G1—PRODUCTIVITY FACTOR, $h_{0t}(E, x, \varepsilon)$

	Census year:					
	1970	1980	1990	2000	2010	2020
Years of education	0.045 (0.001)	0.044 (0.000)	0.047 (0.001)	0.052 (0.001)	0.063 (0.001)	0.051 (0.001)
Potential experience	0.057 (0.001)	0.070 (0.001)	0.052 (0.001)	0.061 (0.001)	0.072 (0.001)	0.066 (0.001)
Potential experience squared ($\times 10^2$)	-0.172 (0.004)	-0.191 (0.003)	-0.106 (0.003)	-0.174 (0.003)	-0.198 (0.004)	-0.165 (0.005)
Potential experience cube ($\times 10^3$)	0.016 (0.001)	0.016 (0.000)	0.005 (0.000)	0.016 (0.000)	0.017 (0.001)	0.014 (0.001)
High school graduate	0.015 (0.003)	0.050 (0.002)	0.052 (0.002)	0.055 (0.002)	0.045 (0.004)	0.024 (0.006)
Some college	0.085 (0.004)	0.089 (0.003)	0.146 (0.003)	0.150 (0.003)	0.147 (0.005)	0.140 (0.007)
College graduate	0.276 (0.005)	0.265 (0.004)	0.372 (0.004)	0.392 (0.005)	0.418 (0.008)	0.493 (0.009)

Note: The table presents parameter estimates for the productivity factor of men $h_{0t}(E, x, \varepsilon)$, including $\{\eta_{00et}\}_{e \in \mathcal{E}}$, η_{10t} , and $\{\eta_{2\ell 0t}\}_{\ell \in \{1,2,3\}}$ defined in Equation (4), estimated on native wages year by year. Each column represents a different census year. Labor markets for the computation of skill prices are defined at the state level, that is, state dummies are included in each regression. Sample weights, rescaled by annual hours worked are used in the estimation. Standard errors in parentheses.

TABLE G2—SPECIFIC SKILL ACCUMULATION, $s_0(0, y, o, c, E, x)$

	Interactions with years since migration:			
	Intercepts	Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Region of origin:				
Latin America	0.032 (0.009) [0.009]	0.004 (0.002) [0.002]	-0.001 (0.014) [0.014]	-0.003 (0.003) [0.003]
Western countries	0.616 (0.018) [0.018]	-0.008 (0.003) [0.003]	0.029 (0.021) [0.021]	-0.008 (0.004) [0.004]
Asia	0.189 (0.011) [0.011]	-0.006 (0.002) [0.002]	0.047 (0.016) [0.016]	-0.009 (0.003) [0.003]
Other	0.042 (0.012) [0.012]	0.010 (0.003) [0.003]	-0.004 (0.021) [0.021]	-0.004 (0.004) [0.004]
Education level:				
High school graduate	-0.229 (0.010) [0.010]	-0.007 (0.002) [0.002]	0.017 (0.013) [0.013]	-0.002 (0.002) [0.002]
Some college	-0.255 (0.012) [0.012]	-0.008 (0.003) [0.003]	0.022 (0.016) [0.017]	-0.003 (0.003) [0.003]
College graduate	-0.239 (0.011) [0.012]	-0.004 (0.003) [0.003]	-0.014 (0.017) [0.017]	0.002 (0.003) [0.003]
Cohort of arrival:				
Pre-1960s	0.300 (0.120) [0.121]	-0.019 (0.016) [0.016]	0.131 (0.064) [0.065]	-0.018 (0.008) [0.008]
1960s	-0.123 (0.016) [0.016]	0.049 (0.003) [0.003]	-0.164 (0.019) [0.019]	0.021 (0.003) [0.003]
1970s		0.031 (0.002) [0.002]	-0.089 (0.014) [0.014]	0.009 (0.002) [0.002]
1980s	0.062 (0.009) [0.010]	0.023 (0.002) [0.002]	-0.074 (0.014) [0.014]	0.010 (0.003) [0.003]
1990s	0.240 (0.010) [0.011]	-0.003 (0.002) [0.002]	0.056 (0.020) [0.021]	-0.010 (0.005) [0.005]
2000s ^a	0.188 (0.013) [0.014]	0.009 (0.005) [0.005]	0.024 (0.055) [0.056]	-0.009 (0.020) [0.020]
2010s ^a	0.297 (0.012) [0.012]	0.013 (0.004) [0.004]	0.024 (0.055) [0.056]	-0.009 (0.020) [0.020]
Experience at entry:				
Linear term	-0.025 (0.001) [0.001]			
Quadratic ($\times 10^2$)	0.074 (0.005) [0.005]			
Cubic ($\times 10^3$)	-0.009 (0.001) [0.001]			
Constant (skills of base individual):				
	0.812 (0.011) [0.011]			

Note: The table presents parameter estimates for the specific skill accumulation function of immigrant men, $\{\theta_{10o}, \{\theta_{2\ell 0o}\}_{\ell \in \{1,2,3\}}\}_{o \in \mathcal{O}}$, $\{\theta_{30e}, \{\theta_{4\ell 0e}\}_{\ell \in \{1,2,3\}}\}_{e \in \mathcal{E}}$, $\{\theta_{5\ell 0o}\}_{\ell \in \{1,2,3\}}$, and $\{\theta_{60c}, \{\theta_{7\ell 0c}\}_{\ell \in \{1,2,3\}}\}_{c \in \mathcal{C}}$ defined in Equation (3). All parameters refer to the baseline individual, who is a Mexican high school dropout man that arrived in the United States in the 1970s with zero years of potential experience. Parameters are estimated by NLS as described in Section III.C. Sample weights, rescaled by annual hours worked are used in the estimation. Standard errors in parentheses; corrected standard errors, which account for the error in the first stage estimation, in square brackets (see Online Appendix for details).

^a Quadratic and cubic interaction terms for the 2000s and 2010s cohorts are grouped in the estimation.

dicating that this reference immigrant supplied about 80 percent of the specific skills of an observationally equivalent native. All other estimates in the first column represent relative shifts at the time of arrival with respect to the reference individual. For example, relative to similarly educated natives, the amount of specific skills supplied by immigrants in the other three education groups is between 23.0 and 25.0 percentage points lower than for a high school dropout. Immigrants from other regions of origin are generally more skilled at arrival than Mexican immigrants. Yet, with the exception of immigrants from Western countries, all groups arrive with specific skills that are below those of comparable native workers.¹ Regarding the different arrival cohorts, apart from the pre-1960s cohorts (for whom the intercept is highly extrapolated), immigrants from earlier cohorts are less similar to natives upon arrival than immigrants from more recent cohorts, a key finding that we discuss in more detail below. Finally, the results in the first column show a negative and decreasing return to potential experience abroad, implying that, all else equal, older immigrants arrive with less host-country-specific skills than younger ones.

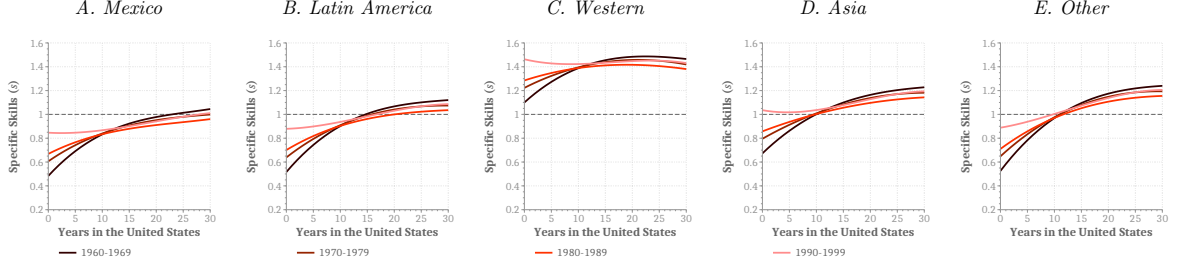
The remaining columns of Table G2 show the estimated coefficients for the interaction terms of each of the listed characteristics and a polynomial in years since migration. These coefficients correspond to the visualization displayed in Figure 4 in the main text.

Figure G1 below depicts the predicted skill accumulation profiles for all 80 immigrant groups that we distinguish in our analysis (4 arrival cohorts $\times$ 5 origin groups $\times$ 4 education levels), setting potential experience upon entry to its sample average.

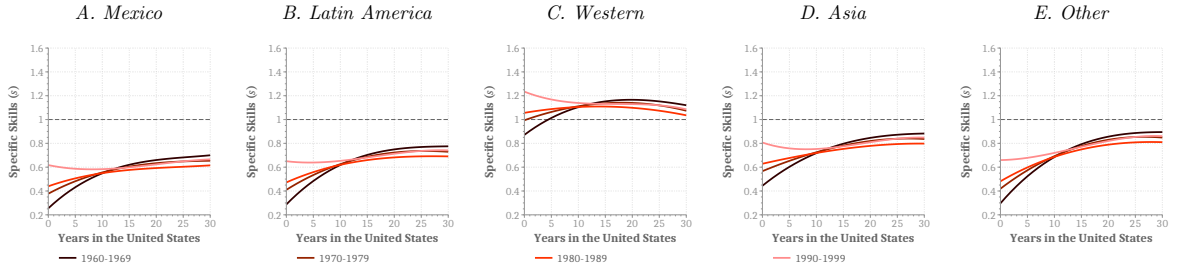
¹ Note that there are only very few immigrants from Western countries that are high school dropouts. We do not bound the specific skills of immigrants at a value of one, thus allowing their wages to exceed those of comparable natives, a feature we observe in the data for some immigrant groups.

FIGURE G1. SKILL ACCUMULATION PROFILES FOR ALL EDUCATION AND ORIGIN GROUPS

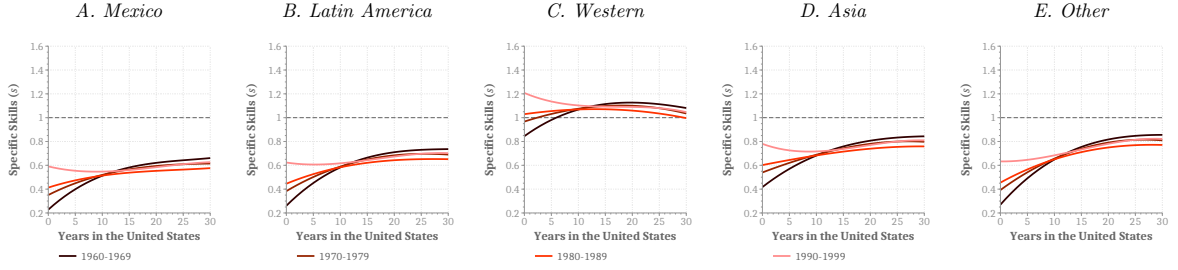
I. HS dropouts



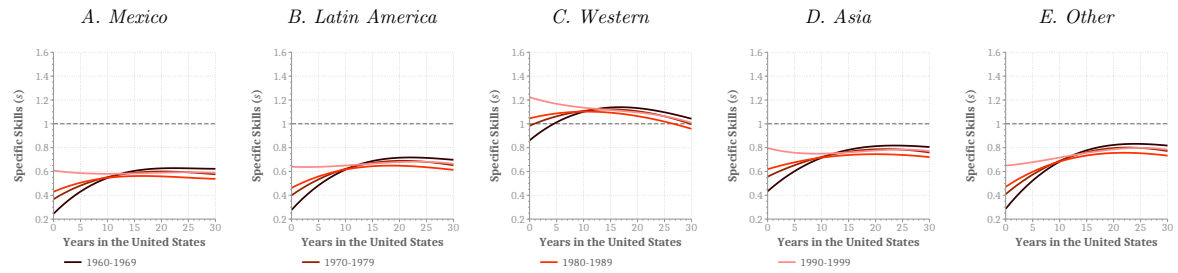
II. HS graduates



III. Some college



IV. College graduates



Note: The figure displays the predicted skill accumulation profiles by entry cohort for all the different origin and education groups we consider in our main specification based on the estimates for men reported in Table G2. Potential experience upon entry is set to its sample average.

APPENDIX H: DERIVATION OF THE ELASTICITY OF SUBSTITUTION BETWEEN NATIVES AND IMMIGRANTS

In this appendix, we derive an expression for the elasticity of substitution between natives and immigrants. Let N_ℓ denote the number of natives of type (or with characteristics) ℓ and let $I_{\ell'}$ denote the number of immigrants of type ℓ' . By definition, the total amount of general skill units is given by $G = \sum_\ell h_\ell N_\ell + \sum_{\ell'} h_{\ell'} I_{\ell'}$, and the total amount of specific skill units by $S = \sum_\ell h_\ell N_\ell + \sum_{\ell'} h_{\ell'} s_{\ell'} I_{\ell'}$, where h_ℓ , $h_{\ell'}$ and $s_{\ell'}$ denote the average idiosyncratic productivity and specific skill units of individuals of types ℓ and ℓ' .

The elasticity of substitution between natives and immigrants, holding constant each group's skill composition (that is, $d \ln N_\ell = d \ln N \forall \ell$, and $d \ln I_{\ell'} = d \ln I \forall \ell'$), is defined as $\varepsilon_{NI} \equiv \frac{d \ln(N/I)}{d \ln[(\partial Y / \partial I) / (\partial Y / \partial N)]}$. To derive an explicit formula for ε_{NI} , rewrite the general and specific skill units respectively as:

$$G = N \sum_\ell h_\ell \frac{N_\ell}{N} + I \sum_{\ell'} h_{\ell'} \frac{I_{\ell'}}{I} \equiv N \bar{h}_N + I \bar{h}_I, \quad (\text{H1})$$

and:

$$S = N \sum_\ell h_\ell \frac{N_\ell}{N} + I \sum_{\ell'} h_{\ell'} s_{\ell'} \frac{I_{\ell'}}{I} \equiv N \bar{h}_N + I \overline{h_I s_I}. \quad (\text{H2})$$

Note that, by assumption, N_ℓ/N and $I_{\ell'}/I$ for any ℓ and ℓ' are constant when we differentiate G and S relative to N or I . For example, in the case of N :

$$\begin{aligned} d \ln N_\ell &= \frac{d N_\ell}{N_\ell} = \frac{d N}{N} = d \ln N \\ \Rightarrow d N_\ell &= \frac{N_\ell}{N} d N \\ \Rightarrow d \frac{N_\ell}{N} &= \frac{N d N_\ell - N_\ell d N}{N^2} = \frac{N \frac{N_\ell}{N} d N - N_\ell d N}{N^2} = 0. \end{aligned} \quad (\text{H3})$$

The case of I is analogous.

The ratio of marginal productivity (i.e. the marginal rate of technical substitution, MRTS) of natives and immigrants is given by:

$$\frac{\partial Y / \partial I}{\partial Y / \partial N} = \frac{A \left(\frac{Y}{AG} \right)^{\frac{1}{\sigma}} \bar{h}_I + A \delta \left(\frac{Y}{AS} \right)^{\frac{1}{\sigma}} \overline{h_I s_I}}{A \left(\frac{Y}{AG} \right)^{\frac{1}{\sigma}} \bar{h}_N + A \delta \left(\frac{Y}{AS} \right)^{\frac{1}{\sigma}} \bar{h}_N} = \frac{\bar{h}_I + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \overline{h_I s_I}}{\left[1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \right] \bar{h}_N} \equiv \frac{1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \tilde{s}_I}{\left[1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \right]} \frac{\bar{h}_I}{\bar{h}_N}, \quad (\text{H4})$$

where $\tilde{s}_I \equiv \overline{h_I s_I} / \bar{h}_I = \sum_{\ell'} s_{\ell'} \frac{h_{\ell'} I_{\ell'}}{\sum_{\ell'} h_{\ell'} I_{\ell'}}$. Log-differentiating this expression yields:

$$\begin{aligned} d \ln \frac{\partial Y / \partial I}{\partial Y / \partial N} &= \frac{\frac{1}{\sigma} \tilde{s}_I \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} d \ln \frac{G}{S}}{1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \tilde{s}_I} - \frac{\frac{1}{\sigma} \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} d \ln \frac{G}{S}}{1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}}} \\ &= \frac{(\tilde{s}_I - 1) \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma} - 1}}{\sigma \left[1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \tilde{s}_I \right] \left[1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \right]} d \ln \frac{G}{S}. \end{aligned} \quad (\text{H5})$$

Rewrite now the ratio G/S as a function of N/I :

$$\frac{G}{S} = \frac{N\bar{h}_N + I\bar{h}_I}{N\bar{h}_N + I\bar{h}_I s_I} = \frac{\frac{\bar{h}_N}{\bar{h}_I} N/I + 1}{\frac{\bar{h}_N}{\bar{h}_I} N/I + \tilde{s}_I}. \quad (\text{H6})$$

Log-differentiating the previous expression gives:

$$d \ln \frac{G}{S} = \frac{\frac{\bar{h}_N}{\bar{h}_I} d(N/I)}{\frac{\bar{h}_N}{\bar{h}_I} N/I + 1} - \frac{\frac{\bar{h}_N}{\bar{h}_I} d(N/I)}{\frac{\bar{h}_N}{\bar{h}_I} N/I + \tilde{s}_I} = \left(\frac{N\bar{h}_N}{G} - \frac{N\bar{h}_N}{S} \right) d \ln \frac{N}{I}. \quad (\text{H7})$$

Substituting (H7) into (H5) and the resulting expression into the definition of the elasticity of substitution gives, after some rearranging:

$$\varepsilon_{NI} = \frac{\sigma \left[1 + \tilde{s}_I \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \right] \left[1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \right]}{(1 - \tilde{s}_I) \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \left(\frac{N\bar{h}_N}{S} - \frac{N\bar{h}_N}{G} \right)}, \quad (\text{H8})$$

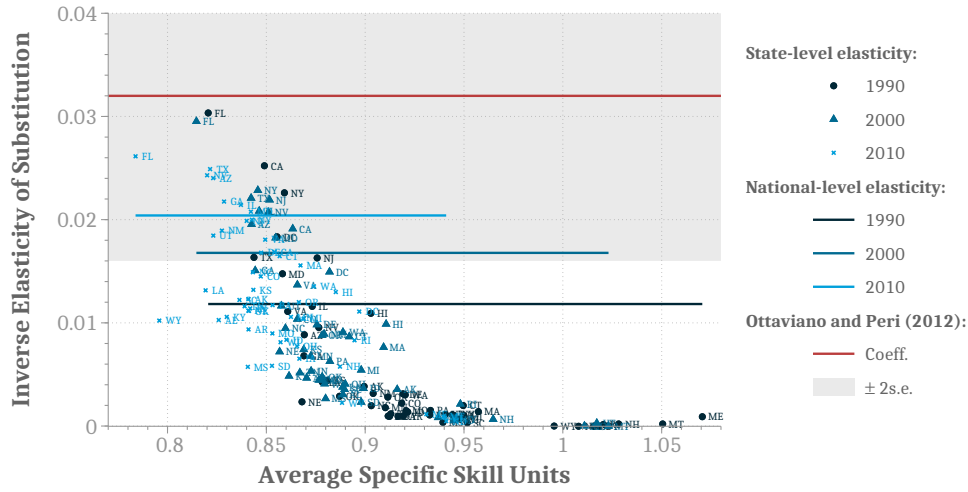
where $\bar{h}_N \equiv \sum_{\ell} h_{\ell} \frac{N_{\ell}}{N}$ is the average productivity of natives and $\tilde{s}_I \equiv \sum_{\ell'} s_{\ell'} \frac{h_{\ell'} I_{\ell'}}{\sum_{\ell'} h_{\ell'} I_{\ell'}}$ is the average of immigrants' specific skill units (weighted by their idiosyncratic productivity). Evaluated at market values δ , G and S , this elasticity tends to infinity when σ approaches infinity or $\tilde{s}_I$ converges to one. ■

APPENDIX I: ADDITIONAL RESULTS FOR THE ELASTICITY OF SUBSTITUTION BETWEEN NATIVES AND IMMIGRANTS

Evaluating Equation (15) at our parameter estimates, Figure I1 compares a set of (inverse) elasticities of substitution implied by our estimate of σ together with a benchmark elasticity taken from Ottaviano and Peri (2012).² The horizontal lines represent the elasticities of substitution for the years 1990, 2000 and 2010, computed at the national level after aggregating general and specific skills across states. These estimates are 0.012 for year 1990, 0.017 for 2000, and 0.020 for 2010, in the same ballpark as the estimate in Ottaviano and Peri (2012), which is 0.034 (s.e. 0.008) for the period 1990–2006.

Figure I1 also shows how our model predicts different elasticities of substitution for different markets, depending on the size and skill composition of their native and immigrant populations. In particular, the scatter of points depicted in the figure connects the implied elasticity of substitution of every state-year cell with the average specific skills of immigrants ($\tilde{s}_I$) in each cell. The figure shows that, while in some markets immigrants and natives are close to perfect substitutes, in others such as Florida, Texas and Arizona, their elasticity of substitution is substantially smaller (its inverse larger).

FIGURE I1. IMPLIED ELASTICITY OF SUBSTITUTION BETWEEN NATIVES AND IMMIGRANTS

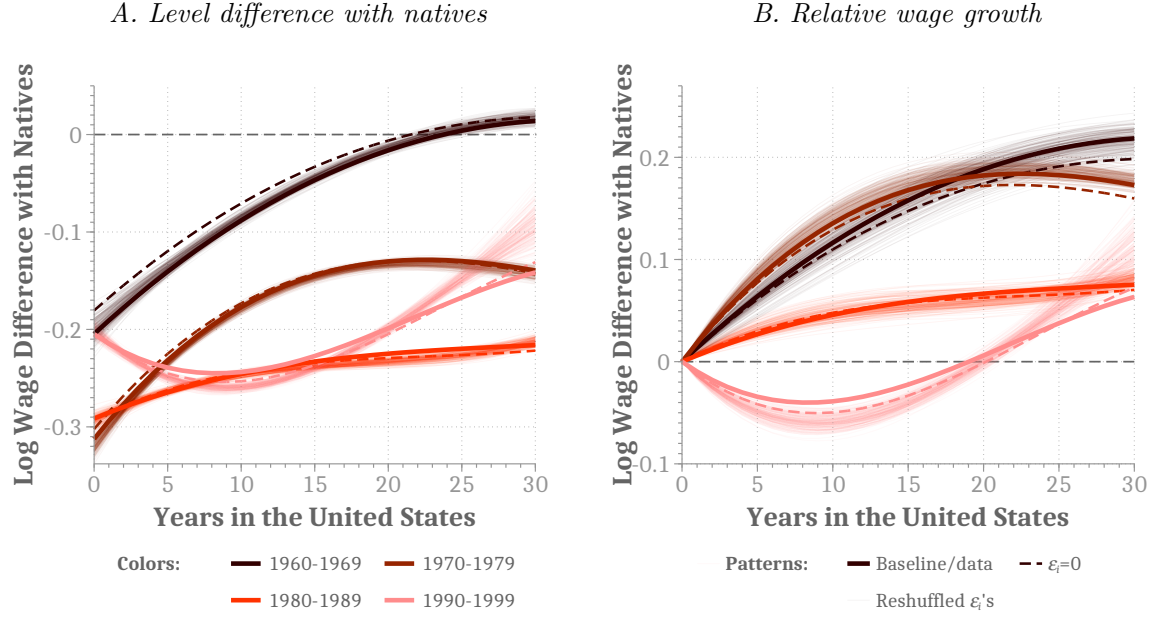


Note: The figure shows the implied inverse elasticity of substitution $1/\varepsilon_{NI}$ across different markets, where ε_{NI} is defined in Equation (15). The (short) blue lines represent our predicted values for 1990, 2000, and 2010 computing skill supplies and weighted average specific skills at the national level. The points in the scatter diagram are computed at the state-year level. The red (long) line and the shaded area represent the benchmark estimate and confidence band in Ottaviano and Peri (2012, Table 2, row 3, column 1, p. 171).

² The elasticities of substitution in Ottaviano and Peri (2012) are derived from a three-level CES production function in which immigrants and natives are allowed to be imperfect substitutes within narrowly defined education and experience cells. Among the many specifications the authors estimate, we select the one most directly comparable to our setting, which is based on a pooled sample of men and women, including full- and part-time workers weighted by hours worked, and that does not include fixed effects (specifically, Ottaviano and Peri, 2012, Table 2, row 3, column 1, p. 171). Since their estimates are obtained using data for years 1990 to 2006, we report predictions for the censuses of 1990, 2000, and 2010.

APPENDIX J: MODEL FIT

FIGURE J1. PREDICTED ASSIMILATION PATTERNS



Note: The figure compares, for men, the baseline predictions (which are identical to the solid lines of Figure 1), the predictions in which ε_i is assumed to be zero for all immigrants (dashed line), and the predictions from a set of 200 simulations in which ε_i 's are randomly reshuffled across observations (thin transparent lines).

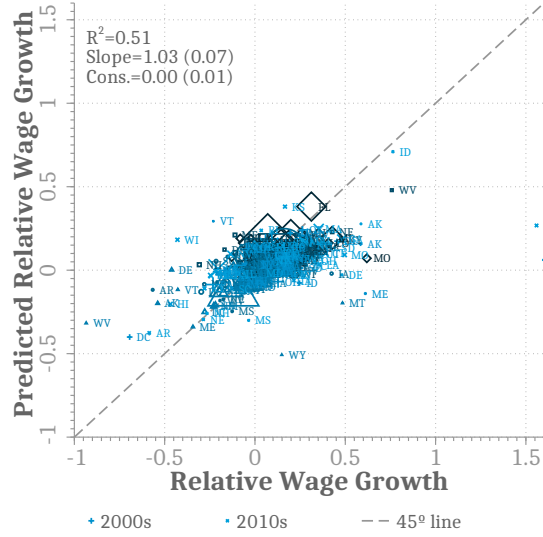
FIGURE J2. STATE-LEVEL PREDICTIONS: IN-SAMPLE AND OUT-OF-SAMPLE FITS

I. In sample

A. Wage gap at arrival

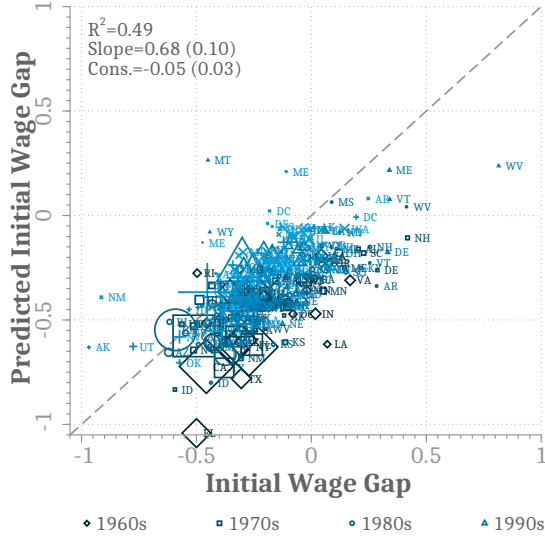


B. Relative wage growth first 10 years

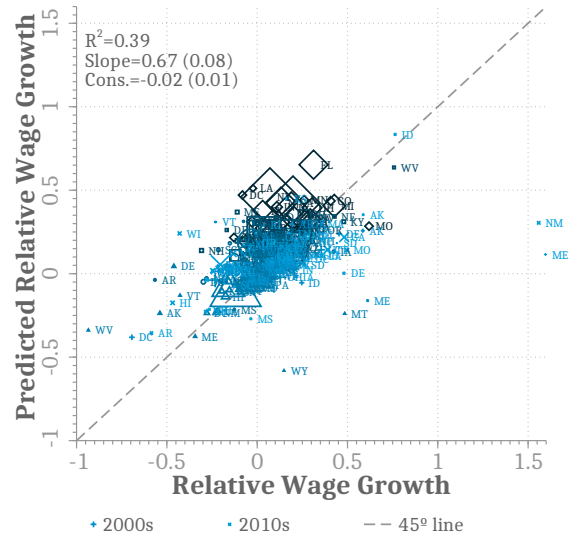


II. Out of sample

A. Wage gap at arrival



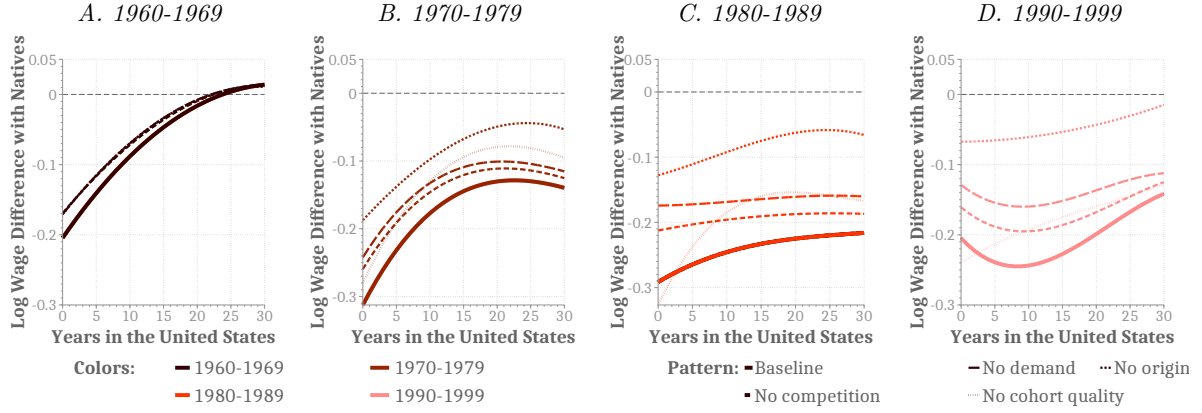
B. Relative wage growth first 10 years



Note: The figure plots the in-sample (Panel I) and out-of-sample (Panel II) model predictions for the initial wage gaps (Plots A) and relative wage growth rates (Plots B) of men in different state-cohort cells (obtained as in Figure 2) against the actual initial wage gaps and relative wage growth rates. The out-of-sample predictions are obtained from an estimated version of the model in which the state that is plotted is not used for the estimation in a leave-one-out type of approach. All plots include a 45-degree line for comparability. State-years with less than 150 immigrants in the census year of arrival are not included. Scatter plots represent state-cohort observations, where size represents population, and lines represent linear regression fits (weighted by population size). Markers/shades distinguish different cohorts.

APPENDIX K: EXTENDED DECOMPOSITION: COMPETITION, DEMAND, AND COMPOSITION EFFECTS

FIGURE K1. WAGE GAP DECOMPOSITION: COMPETITION, DEMAND, AND COMPOSITION EFFECTS



Note: The figure adds to the baseline decomposition in Figure 6 the counterfactual assimilation profiles holding unobservable cohort quality (dotted lines) and country of origin (short-dashed lines) composition constant. In particular, taking the counterfactual predictions without competition and demand effects, assimilation profiles without changes in cohort quality are estimated on predicted wages in which specific skill units of immigrants are predicted replacing the cohort-related coefficients of the $s(\cdot)$ function with the values for the 1960s cohort. Taking these predictions as a base, assimilation profiles holding country of origin composition constant are computed replacing the baseline weights by corrected weights adjusted so that, for each cohort, the relative weight of each region of origin is held constant at the level of the 1960s cohort, keeping the total weight of the cohort fixed as in the baseline. Each plot represents one cohort. The depicted lines are predicted assimilation profiles obtained from regressions analogous to those underlying Figure 1, estimated on the predicted wages under the different counterfactual scenarios. Due to the small number of observations of Western immigrants from the 1990s cohort in the 2020 Census, we only include a quadratic and not a third order polynomial in years of experience to determine the final assimilation profile that holds the country of origin composition constant.

TABLE K1—WAGE GAP DECOMPOSITION: COMPETITION, DEMAND, AND COMPOSITION EFFECTS

	Competition	Demand	Cohort quality	Origin	Education
1970-1979	13.5	10.8	4.4	39.0	32.2
1980-1989	21.3	17.5	-23.9	71.6	13.5
1990-1999	19.2	25.6	-42.9	117.4	-19.3

Note: The table presents the fraction of the wage gap of each cohort's assimilation profile relative to the 1960s cohort that is explained by each mechanism (in percentages) averaged across all years since migration. These results summarize the information provided in Figure K1.

APPENDIX L: GENERALIZED METHOD OF MOMENTS (GMM) ESTIMATION

We deal with the potential endogeneity of immigrant stocks across states by reestimating our model using GMM, building on the NLS first order conditions, but replacing endogenous variables by exogenous predictions. In our nonlinear setting, the first order conditions of the NLS estimation are given by the derivatives of the right-hand side of the nonlinear regression, Equation (12), with respect to the individual model parameters. After some algebra, these derivatives are given by the following expressions:

$$\frac{\partial \text{Eq.}(12)}{\partial \boldsymbol{\theta}'} = \frac{1}{\frac{r_{Gt}}{r_{St}} + s(\cdot)} \mathbf{x} - \frac{s(\cdot) - 1}{\sigma S_{jt} \left[\frac{r_{Gt}}{r_{St}} + s(\cdot) \right] \left[1 + \frac{r_{St}}{r_{Gt}} \right]} \sum_i \omega_i \mathbf{x}_i h_t(E_i, x_i), \quad (\text{L1})$$

where $\boldsymbol{\theta}$ denotes the vector of parameters of $s(\cdot)$ and $\mathbf{x}$, the associated regressors:

$$\frac{\partial \text{Eq.}(12)}{\partial \tilde{\delta}} = t \frac{s(\cdot) - 1}{\left[\frac{r_{Gt}}{r_{St}} + s(\cdot) \right] \left[1 + \frac{r_{St}}{r_{Gt}} \right]}, \quad (\text{L2})$$

and:

$$\frac{\partial \text{Eq.}(12)}{\partial \sigma} = \ln \left(\frac{G_{jt}}{S_{jt}} \right) \frac{s(\cdot) - 1}{\left[\frac{r_{Gt}}{r_{St}} + s(\cdot) \right] \left[1 + \frac{r_{St}}{r_{Gt}} \right]}. \quad (\text{L3})$$

If immigrants were randomly assigned across states conditional on observables, so that $E(\varepsilon_i | \mathbf{x}_i, t_i, G_{jt}/S_{jt}) = 0$, the GMM estimation using these first order conditions as moments, which would be equivalent to our NLS estimation, would provide consistent (and efficient) estimates. In this robustness check, we deal with the case where ε_i and G_{jt}/S_{jt} are potentially correlated, replacing the potentially endogenous regressor G_{jt}/S_{jt} by an exogenous prediction in the spirit of the widely used shift-share instrument proposed by Card (2001). In particular, we generate our instruments by replacing the original sample weights ω_i (which appear implicitly in r_{Gt}/r_{St} and G_{jt}/S_{jt} and explicitly in the first set of instruments) by $\tilde{\omega}_i$, defined as:

$$\tilde{\omega}_i \equiv \omega_i \frac{\tilde{I}_{j_i, t_i}}{I_{j_i, t_i}} = \omega_i \frac{1}{I_{j_i, t_i}} \sum_{q=1}^Q \frac{I_{j_i, q, 1970}}{I_{q, 1970}} I_{q, t_i}, \quad (\text{L4})$$

where $I_{j, q, t}$ is the stock of immigrants from origin country q living in state j at time t , $I_{qt} \equiv \sum_{j=1}^J I_{jq, t}$ the total stock of immigrants from country q living in the United States at time t , and $I_{j, t} \equiv \sum_{q=1}^Q I_{j, q, t}$ is the total stock of immigrants living in state j at time t . The weights $\tilde{\omega}_i$ thus generate aggregates based on exogenously predicted immigrant stocks. Note that these generated instruments depend on the true parameter values and are therefore unfeasible. In practice, we evaluate the derivatives at our baseline estimates, which is not efficient, but does not affect their validity as instruments even if these estimates were biased. In order to provide additional variation to ensure convergence of our nonlinear estimation, in practice, we estimate our model using both the instruments described above and their squares.

APPENDIX M: ROBUSTNESS CHECKS PARAMETERS AND RESULTS

Table M1 reports the key parameters estimates associated with each of our robustness checks. Panel A refers to the two specifications related to the networks robustness check and the specification that allows for different wage assimilation profiles for potentially undocumented and legal immigrants. Panel B shows the parameters for the alternative specifications of the relative demand shifts. Panel C reports the estimate of the parameter related to the elasticity of substitution across education groups.

Table M2 reports, for the baseline model and each of the robustness checks, the shifts in the relative wage profiles that can be attributed to the competition effect and the competition plus demand effects. The shifts are expressed in log points (counterfactual minus baseline multiplied by 100) and averaged over all years since migration.

TABLE M1—SELECTED PARAMETER ESTIMATES FROM ROBUSTNESS CHECKS

A. Additional elements of assimilation profiles from some of the checks (men)				
		Interaction with years since migration:		
	Direct effect	Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Potentially undocumented	-0.012 (0.007)	0.003 (0.002)	-0.090 (0.016)	0.021 (0.004)
Share of state's population	-1.117 (0.161)	0.013 (0.037)	-0.126 (0.244)	0.022 (0.045)
Stock in the state ($\times 10^6$)	-0.091 (0.013)	-0.003 (0.003)	0.013 (0.018)	-0.002 (0.003)
B. Alternative specifications of the demand shifters for relative skill prices				
		Region dummies specification		
Time dummies specification		Linear term	0.038	(0.002)
		Region dummies:		
1980	-0.835 (0.041)	New England	-0.476	(0.049)
1990	-0.270 (0.039)	Middle Atlantic	-0.653	(0.028)
2000	0.065 (0.044)	East North Central	-0.818	(0.040)
2010	1.289 (0.122)	West North Central	-1.088	(0.103)
2020	0.822 (0.096)	South Atlantic	-0.962	(0.034)
		East South Atlantic	-0.848	(0.101)
		West South Central	-0.869	(0.042)
		Mountain	-0.866	(0.054)
C. Elasticity of substitution across groups ($-1/\phi$)				
		Point estimate	Standard error	
By education		-0.136	(0.011)	

Note: Panel A of the table presents estimates for the additional parameters of the $s(\cdot)$ function associated with the two specifications of the networks robustness check and for the specification that allows for heterogeneous convergence between potentially undocumented and legal immigrants (each row corresponds to one specification) for men. Panel B shows the parameters for the alternative specifications of the relative demand shifts. Panel C presents the parameter estimates for the elasticity of substitution across education groups or genders for the counterfactual that allows for imperfect substitutability across these groups. Least squares standard errors, not corrected for multi-step estimation error, in parentheses.

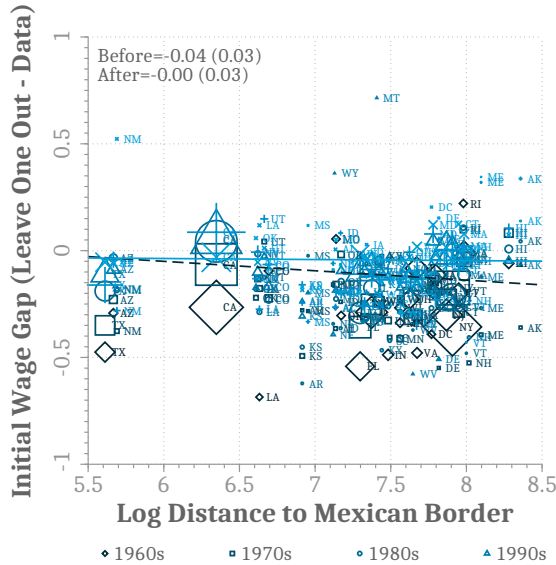
TABLE M2—WAGE GAP DECOMPOSITION: ROBUSTNESS

	Competition effect				Competition+demand effect:			
	1960s	1970s	1980s	1990s	1960s	1970s	1980s	1990s
Baseline estimate:	1.3	2.7	4.7	3.7	1.4	4.0	7.5	6.8
Selective return migration:								
Borjas and Bratsberg (1996)	1.3	2.6	4.3	3.3	1.4	4.0	7.6	6.7
Rho and Sanders (2021)	2.2	4.1	6.4	5.6	2.4	5.2	8.8	8.3
Synthetic cohorts	1.5	3.2	4.9	3.9	1.6	4.3	7.3	6.5
Undocumented migrants:								
Reweighted only	0.0	1.4	3.5	2.2	0.2	2.8	6.6	5.5
Reweighted and heterogeneous	0.0	1.5	3.6	2.3	0.2	2.8	6.5	5.4
Networks:								
Share of state's population	0.8	1.2	1.8	1.2	1.1	4.0	7.6	7.0
Stock in the state	0.7	1.1	1.6	1.0	1.1	4.1	7.8	7.1
Alternative specifications of δ_t , $s(\cdot)$ and the production function:								
Demand δ_t : Time dummies	1.5	4.0	5.0	3.3	0.7	0.3	5.6	6.0
Demand δ_t : Region dummies	1.0	1.5	2.3	1.8	1.5	5.1	9.4	8.5
Skills $s(\cdot)$: Pairwise interactions	2.1	3.5	5.5	4.3	2.2	4.8	8.3	7.3
Skills $s(\cdot)$: Quartic polynomials	1.3	2.7	4.6	3.7	1.4	4.0	7.5	6.8
Imperfect substitution by education	1.8	2.3	4.4	5.0	3.1	5.8	10.1	10.8
Endogenous immigrant location:								
GMM instruments based on Card (2001)	2.1	4.0	6.4	5.1	2.1	4.8	8.1	7.0

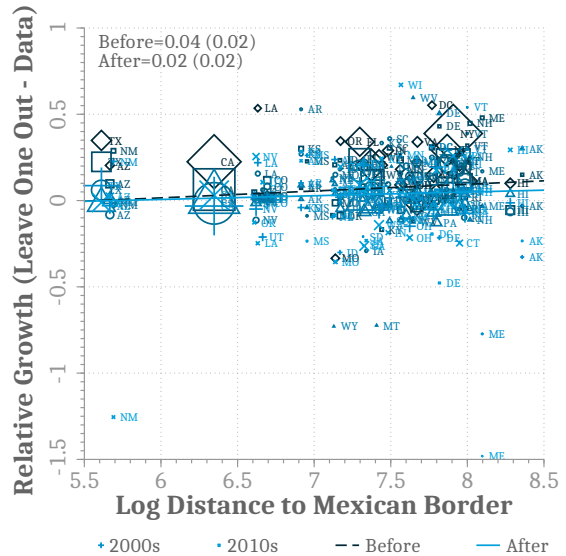
Note: The table shows, for each robustness check, the competition and competition plus demand effects for each cohort (counterfactual minus baseline multiplied by 100) for men, averaged across years in the United States.

FIGURE M1. STATE-LEVEL PREDICTIONS AND THE PESO CRISIS

A. Initial wage gap



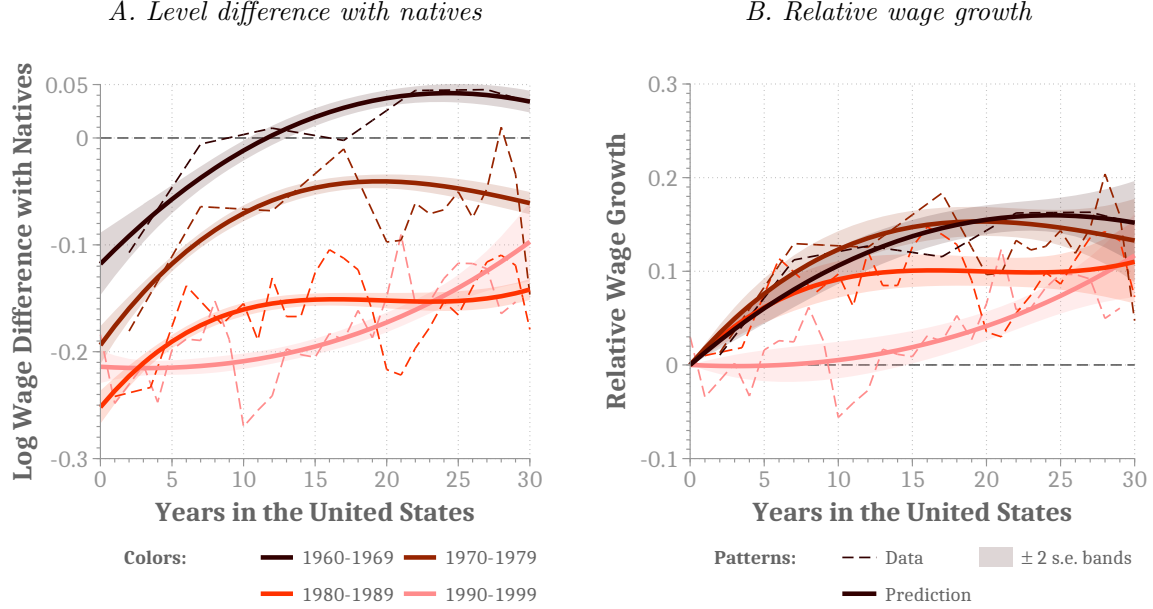
B. Relative wage growth first 10 years



Note: The figure correlates the gap between the leave-one-out predictions and their data counterparts shown in Panel II of Figure J2 with the distance to the Mexican border. The distance to the Mexican border is computed using data from the U.S. Census Bureau (2018) and the Humanitarian Data Exchange (2021). The two regression lines represent the predictions from (weighted) linear regressions estimated using all the state-cohort observations of the 1990s cohort and earlier and all the state-cohort observations of the 2000s cohort and later, respectively, to capture the pre- and post-peso crisis episodes (slopes and standard errors reported in the top-left corner). State-years with less than 150 immigrants in the census year of arrival are not included. Scatter plots represent state-cohort observations, where size represents population, and lines represent linear regression fits (weighted by population size). Markers/shades distinguish different cohorts.

APPENDIX N: RESULTS FOR WOMEN

FIGURE N1. WAGE GAP BETWEEN NATIVES AND IMMIGRANTS AND YEARS IN THE U.S.

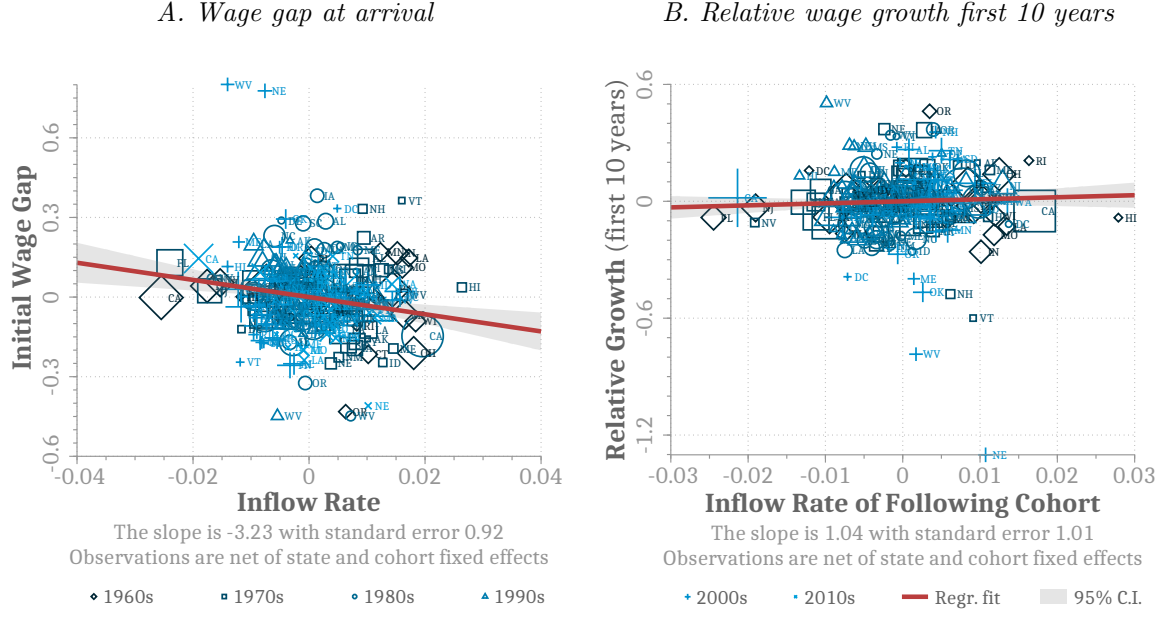


Note: The figure shows the prediction of the wage gap between native and immigrant women of different cohorts as they spend time in the United States. The dashed lines represent the raw data and are the result of year-by-year regressions of log wages on a third order polynomial in age and dummies for the number of years since migration. Solid lines represent fitted values of a regression that includes cohort and year dummies, a third order polynomial in age interacted with year dummies, and a (up to a) third order polynomial in years since migration interacted with cohort dummies (in particular, we include the first term of the polynomial for all cohorts, the second term for all cohorts that arrived before 2010, and the third order term for all cohorts that arrived before 2000):

$$\ln w_i = \beta_{0c(i)} + \beta_{1t(i)} + \sum_{\ell=1}^3 \beta_{2\ell t(i)} age_i^\ell + \sum_{\ell=1}^3 \beta_{3\ell c(i)} y_i^\ell + \nu_i,$$

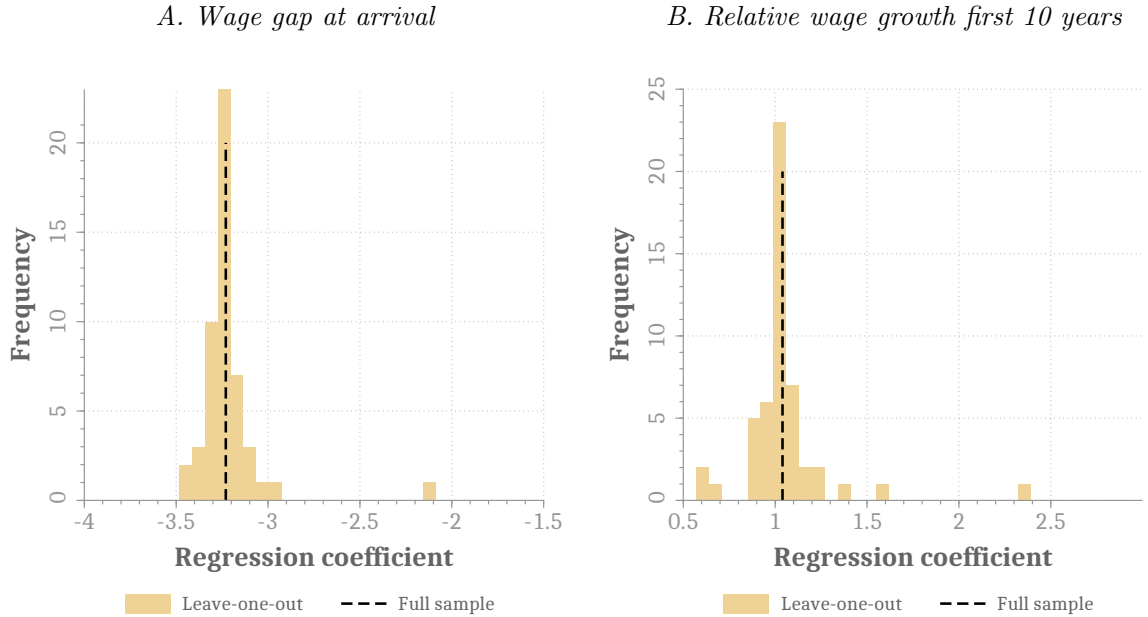
where $c(i)$ and $t(i)$ indicate the immigration cohort and the census year in which individual i is observed, age_i indicates age, and y_i indicates years since migration. Cohorts are grouped in the following way: before 1960, 1960-69, 1970-79, 1980-89, 1990-99, 2000-09, and 2010 or later. Colors represent cohorts, and shapes represent data or regression predictions as indicated in the legend. Shaded areas represent two-standard-error confidence bands.

FIGURE N2. COHORT SIZE, INITIAL WAGE GAP, AND RELATIVE WAGE GROWTH



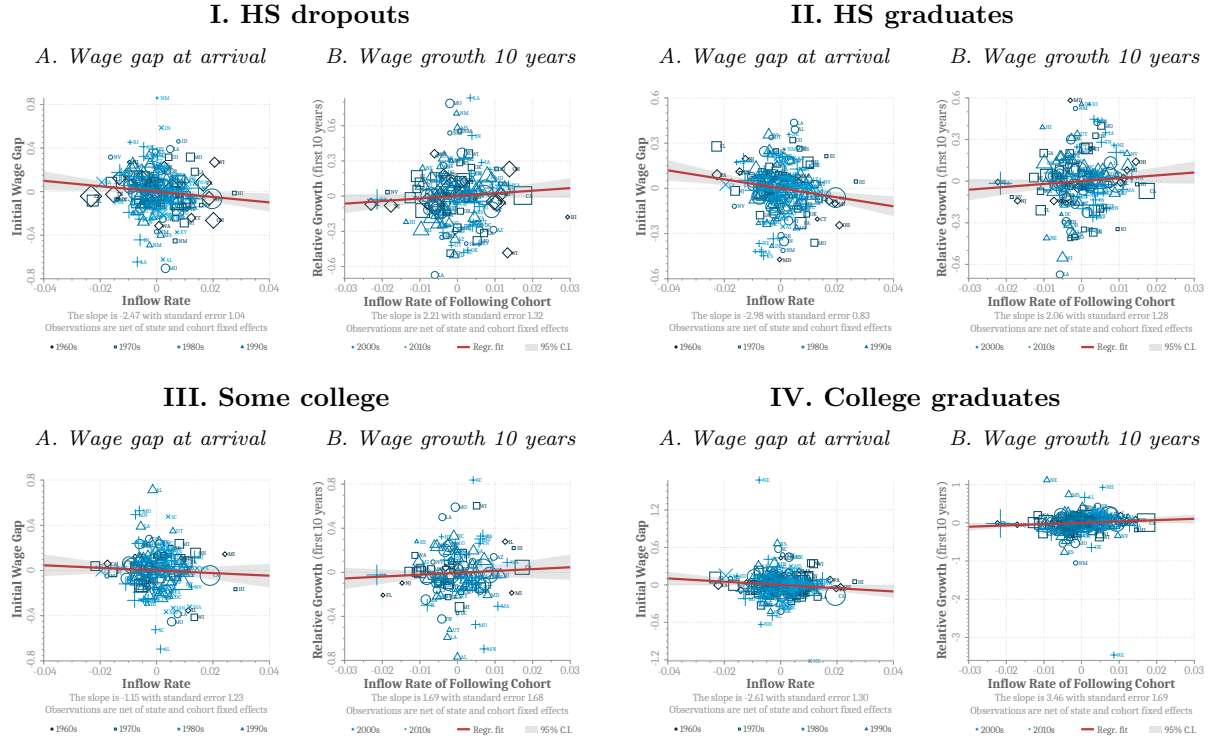
Note: The figure plots the initial wage gap for women in different state-cohort cells against the size of the own arrival cohort (left panel) and the relative wage growth over the first 10 years against the size of the following immigrant cohort (right panel). The initial wage gap and relative wage growth are computed based on state-by-state regressions analogous to those underlying Figure 1. The initial wage gap is measured as the state-specific cohort fixed effect ($\beta_{0c(i)}$) and the relative wage growth as the change in the wage gap over the first 10 years, calculated based on the polynomial in years since migration interacted with cohort dummies ($\{\beta_{3\ell c(i)}\}_{\ell \in \{1,2,3\}}$). Immigrant inflows are computed as the state population of the respective cohort (including men and women) divided by the native population in the state in the first census year the cohort is observed. The depicted observations are net of cohort and state fixed effects. State-years with less than 150 immigrants in the census year of arrival are not included. Scatter plots represent state-cohort observations, where size represents population, and lines represent linear regression fits (weighted by population size). Markers/shades distinguish different cohorts. Gray shaded areas represent 95% confidence intervals of the state-regressions.

FIGURE N3. LEAVE-ONE-OUT ANALYSIS FOR FIGURE N2



Note: The figure plots a histogram of the regression coefficients obtained from repeating the estimation implemented in the corresponding panels of Figure N2 leaving one state out each time. The black line represents the point estimates in Figure N2. The height of the bars indicate the number of regressions that each bar represents.

FIGURE N4. COHORT SIZE, INITIAL WAGE GAP, AND RELATIVE WAGE GROWTH (BY EDUCATION)



Note: The figure replicates the analysis in Figure 2, breaking down the assimilation patterns by education group. State-year-education groups with fewer than 150 immigrants in the census year of arrival are not included. Scatter plots represent state-cohort observations, where size represents population, and lines represent linear regression fits (weighted by population size). Markers/shades distinguish different cohorts. Gray shaded areas represent 95% confidence intervals of the state regressions.

TABLE N1—PRODUCTIVITY FACTOR, $h_{1t}(E, x)$

	Census year:					
	1970	1980	1990	2000	2010	2020
Female	-0.033 (0.014)	0.009 (0.009)	-0.080 (0.009)	-0.078 (0.010)	-0.131 (0.015)	-0.129 (0.017)
Years of education	0.043 (0.001)	0.042 (0.001)	0.048 (0.001)	0.056 (0.001)	0.076 (0.001)	0.069 (0.001)
Potential experience	0.003 (0.001)	0.023 (0.001)	0.030 (0.001)	0.033 (0.001)	0.043 (0.001)	0.044 (0.001)
Potential experience squared ($\times 10^2$)	0.000 (0.006)	-0.074 (0.003)	-0.091 (0.003)	-0.092 (0.002)	-0.125 (0.003)	-0.126 (0.004)
Potential experience cube ($\times 10^3$)	-0.001 (0.001)	0.008 (0.000)	0.009 (0.000)	0.008 (0.000)	0.012 (0.000)	0.012 (0.001)
High school graduate	0.075 (0.004)	0.061 (0.002)	0.068 (0.002)	0.077 (0.003)	0.057 (0.004)	-0.032 (0.007)
Some college	0.153 (0.006)	0.127 (0.003)	0.203 (0.003)	0.195 (0.003)	0.161 (0.005)	0.057 (0.008)
College graduate	0.418 (0.008)	0.308 (0.005)	0.412 (0.005)	0.390 (0.005)	0.338 (0.007)	0.311 (0.010)

Note: The table presents parameter estimates for the productivity factor of women $h_{1t}(E, x)$, including $\{\eta_{01et}\}_{e \in \mathcal{E}}$, η_{11t} , and $\{\eta_{2\ell 1t}\}_{\ell \in \{1,2,3\}}$ defined in Equation (4), estimated on native wages year by year. Each column represents a different census year. Labor markets for the computation of skill prices are defined at the state level, that is, state dummies are included in each regression. Sample weights, rescaled by annual hours worked are used in the estimation. Standard errors in parentheses.

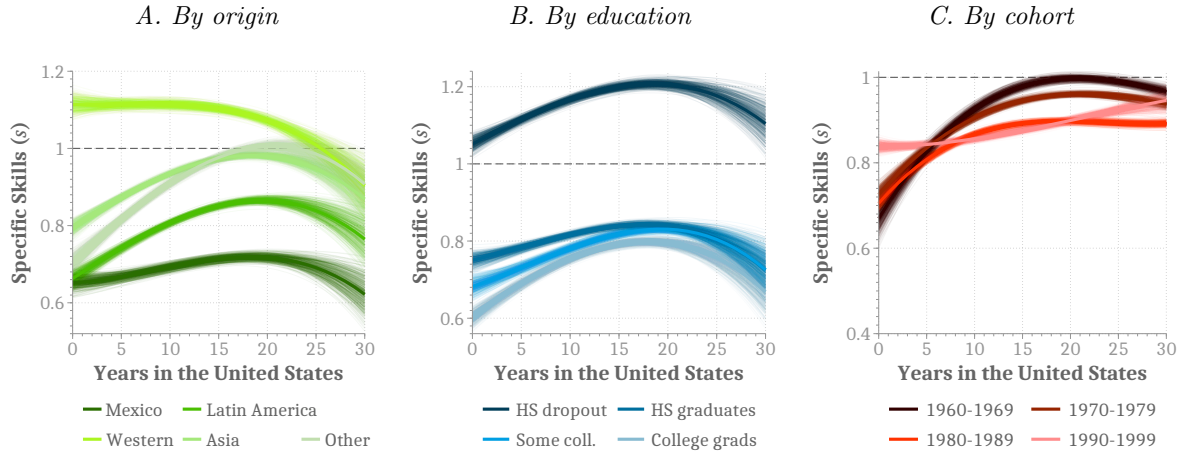
TABLE N2—SPECIFIC SKILL ACCUMULATION, $s_1(0, y, o, c, E, x)$

	Interactions with years since migration:			
	Intercepts	Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Region of origin:				
Latin America	0.011 (0.013) [0.013]	0.015 (0.003) [0.003]	-0.052 (0.018) [0.018]	0.006 (0.003) [0.003]
Western countries	0.462 (0.019) [0.019]	-0.002 (0.004) [0.004]	-0.023 (0.023) [0.023]	0.003 (0.004) [0.004]
Asia	0.142 (0.013) [0.014]	0.015 (0.003) [0.003]	-0.061 (0.019) [0.019]	0.007 (0.003) [0.003]
Other	0.053 (0.016) [0.016]	0.022 (0.004) [0.004]	-0.058 (0.024) [0.024]	0.003 (0.004) [0.004]
Education level:				
High school graduate	-0.301 (0.014) [0.014]	-0.008 (0.003) [0.003]	0.032 (0.017) [0.017]	-0.005 (0.003) [0.003]
Some college	-0.369 (0.017) [0.017]	-0.005 (0.003) [0.003]	0.036 (0.021) [0.021]	-0.007 (0.004) [0.004]
College graduate	-0.449 (0.016) [0.017]	0.006 (0.003) [0.003]	-0.022 (0.020) [0.020]	0.001 (0.003) [0.003]
Cohort of arrival:				
Pre-1960s	0.330 (0.146) [0.147]	-0.032 (0.018) [0.018]	0.139 (0.072) [0.073]	-0.017 (0.009) [0.009]
1960s	-0.056 (0.024) [0.025]	0.028 (0.004) [0.004]	-0.101 (0.024) [0.024]	0.012 (0.004) [0.004]
1970s		0.017 (0.003) [0.003]	-0.053 (0.019) [0.020]	0.006 (0.003) [0.003]
1980s	-0.020 (0.013) [0.013]	0.016 (0.003) [0.003]	-0.078 (0.019) [0.019]	0.013 (0.003) [0.003]
1990s	0.112 (0.013) [0.014]	-0.009 (0.003) [0.003]	0.055 (0.025) [0.025]	-0.006 (0.006) [0.006]
2000s ^a	0.088 (0.017) [0.017]	-0.021 (0.006) [0.006]	0.313 (0.068) [0.068]	-0.105 (0.024) [0.024]
2010s ^a	0.157 (0.015) [0.015]	-0.019 (0.005) [0.005]	0.313 (0.068) [0.068]	-0.105 (0.024) [0.024]
Experience at entry:				
Linear term	-0.026 (0.001) [0.001]			
Quadratic ($\times 10^2$)	0.090 (0.006) [0.006]			
Cubic ($\times 10^3$)	-0.010 (0.001) [0.001]			
Constant (skills of base individual):				
	1.076 (0.016) [0.016]			

Note: The table presents parameter estimates for the specific skill accumulation function of immigrant women, $\{\theta_{11o}, \{\theta_{2\ell 1o}\}_{\ell \in \{1,2,3\}}\}_{o \in \mathcal{O}}$, $\{\theta_{31e}, \{\theta_{4\ell 1e}\}_{\ell \in \{1,2,3\}}\}_{e \in \mathcal{E}}$, $\{\theta_{5\ell 1o}\}_{\ell \in \{1,2,3\}}$, and $\{\theta_{61c}, \{\theta_{7\ell 1c}\}_{\ell \in \{1,2,3\}}\}_{c \in \mathcal{C}}$ defined in Equation (3). All parameters refer to the baseline individual, who is a Mexican high school dropout woman that arrived in the United States in the 1970s with zero years of potential experience. Parameters are estimated by NLS as described in Section III.C. Sample weights, rescaled by annual hours worked are used in the estimation. Standard errors in parentheses; corrected standard errors, which account for the error in the first step estimation, in square brackets (see Online Appendix for details).

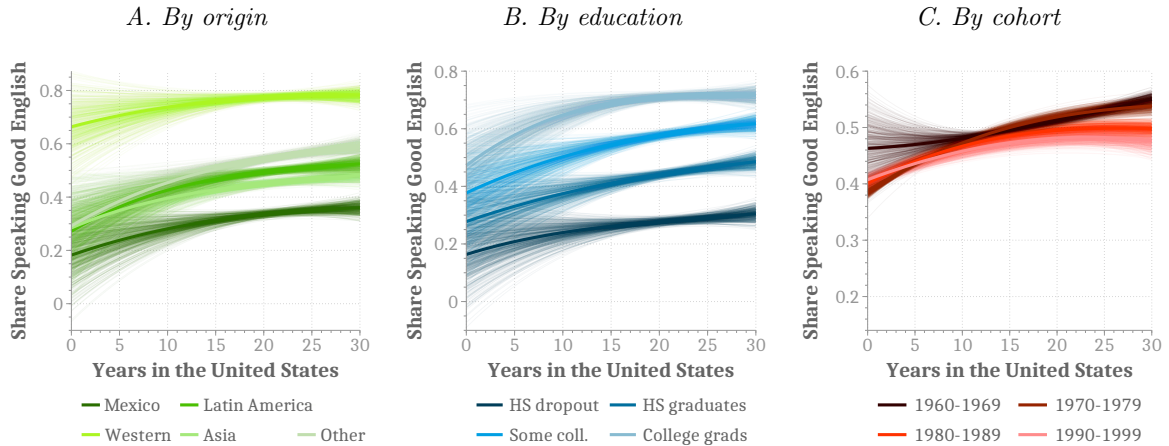
^a Quadratic and cubic interaction terms for the 2000s and 2010s cohorts are grouped in the estimation.

FIGURE N5. SKILL ACCUMULATION PROFILES, $s_1(0, y, o, c, E, x)$



Note: The figure displays predicted skill accumulation profiles for different groups based on the estimates reported in Table N2. The baseline individual in all figures is a synthetic individual with the average characteristics of all women in the sample, except for the characteristic that is being plotted in each graph. The characteristics observed in the data are region of origin, level of education, year of arrival, and potential experience upon entry. Thin lines around each main line are counterparts obtained from each of 500 draws from the asymptotic distribution of the estimated parameters, and are plotted to represent confidence bands. The variance-covariance matrix of such distribution accounts for first step estimation error as derived in the Online Appendix.

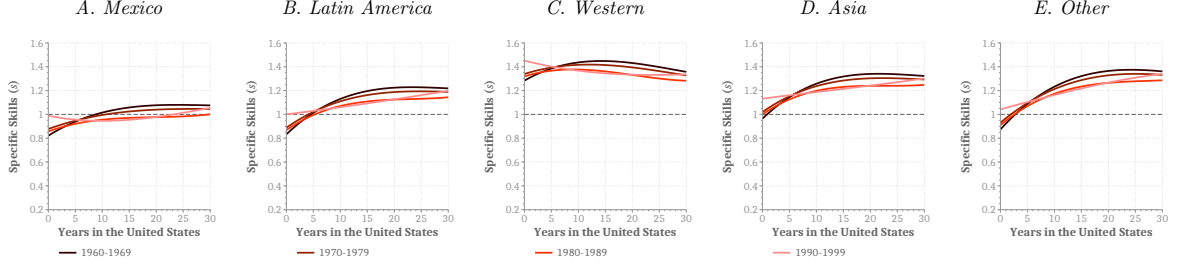
FIGURE N6. ENGLISH PROFICIENCY



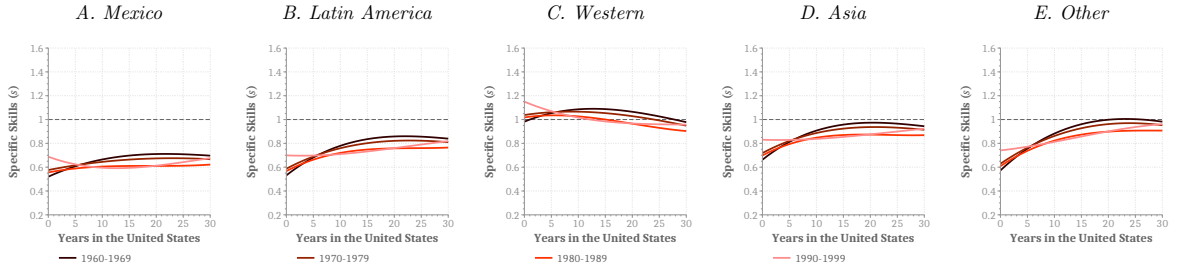
Note: The figure displays English language proficiency profiles predicted from a linear regression of an indicator for “speaking English very well” or “only speaking English” on all the variables included in the specific-skills function $s_1(\cdot)$ and year dummies on a sample of women. The baseline individual in all figures is a synthetic individual with the average characteristics of all women in the sample except for the characteristic that is plotted in each graph. Thin lines around main plotted lines are counterparts obtained from the regression coefficients from each of 500 draws from the asymptotic distribution of estimated parameters, and are plotted to represent confidence bands.

FIGURE N7. SKILL ACCUMULATION PROFILES FOR ALL EDUCATION AND ORIGIN GROUPS

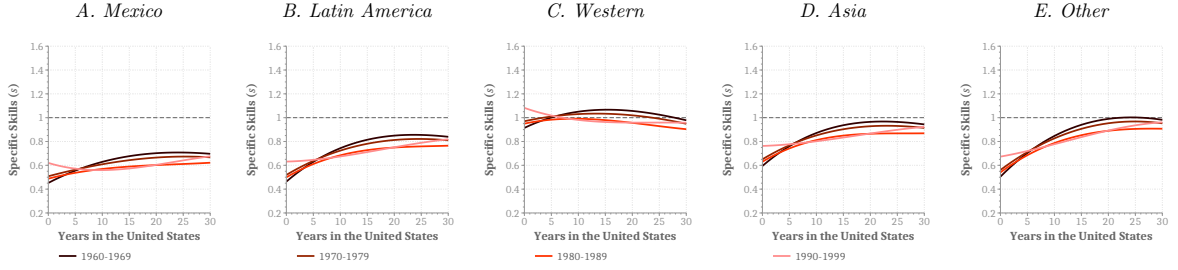
I. HS dropouts



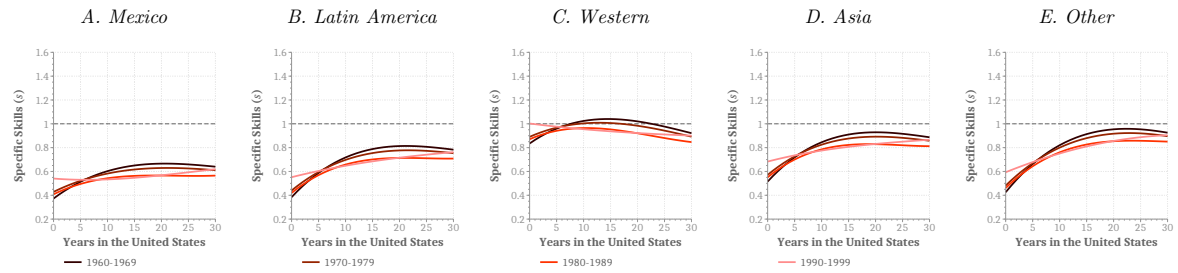
II. HS graduates



III. Some college



IV. College graduates

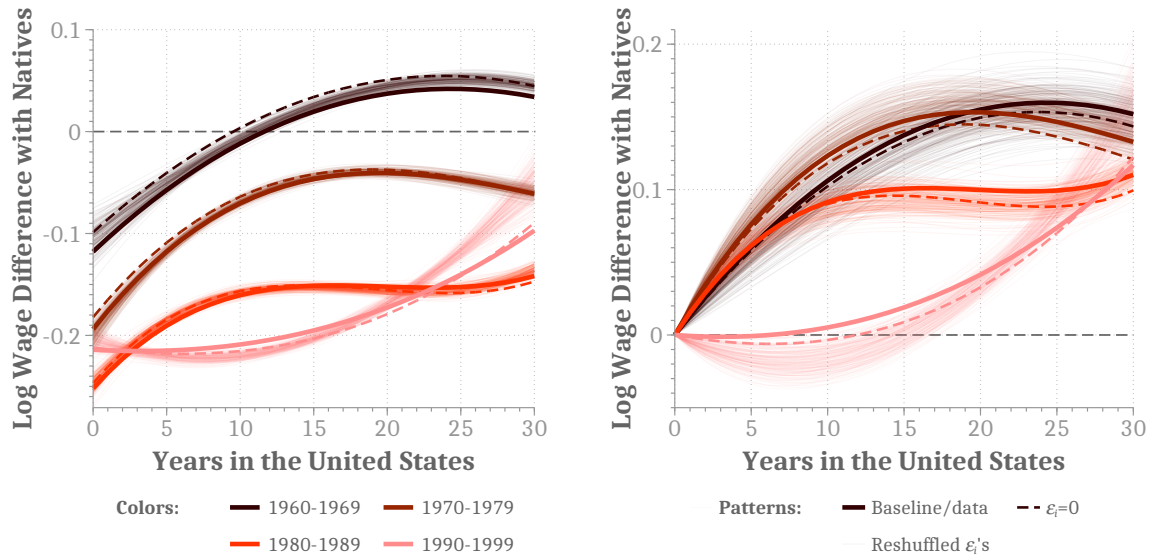


Note: The figure displays the predicted skill accumulation profiles by entry cohort for all the different origin and education groups we consider in our main specification based on the estimates for women reported in Table N2. Potential experience upon entry is set to its sample average.

FIGURE N8. PREDICTED ASSIMILATION PATTERNS

A. Level difference with natives

B. Relative wage growth

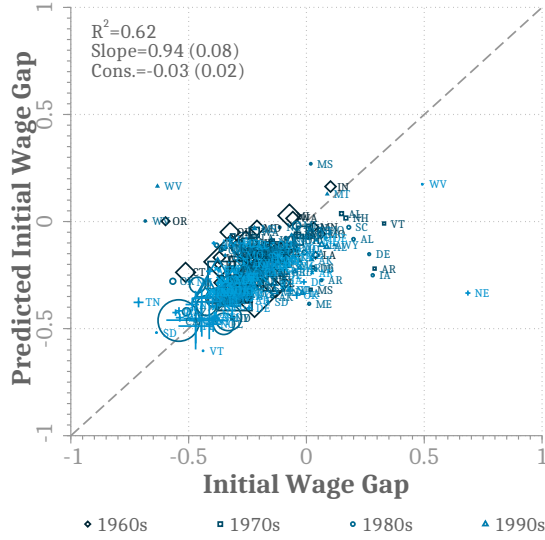


Note: The figure compares, for women, the baseline predictions (which are identical to the solid lines of Figure N1), the predictions in which ε_i is assumed to be zero for all immigrants (dashed line), and a set of 200 predictions in which ε_i 's are randomly reshuffled across observations (thin transparent lines).

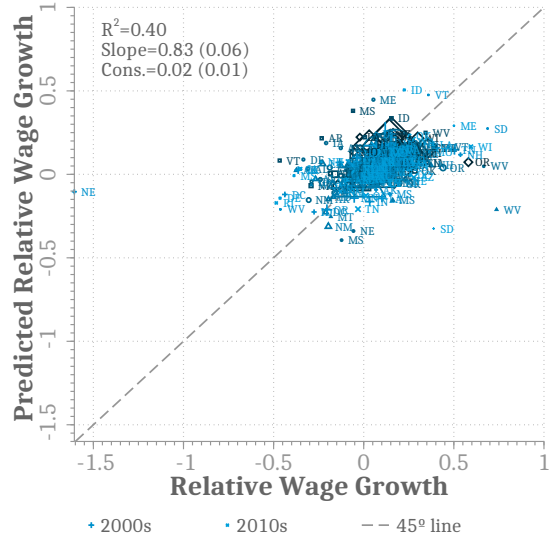
FIGURE N9. STATE-LEVEL PREDICTIONS: IN-SAMPLE AND OUT-OF-SAMPLE FITS

I. In sample

A. Wage gap at arrival

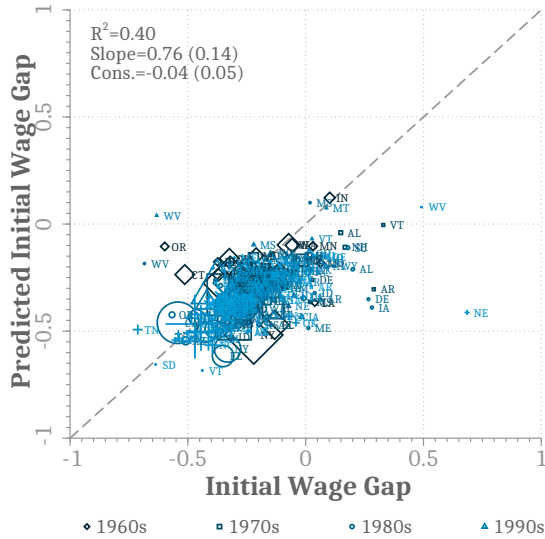


B. Relative wage growth first 10 years

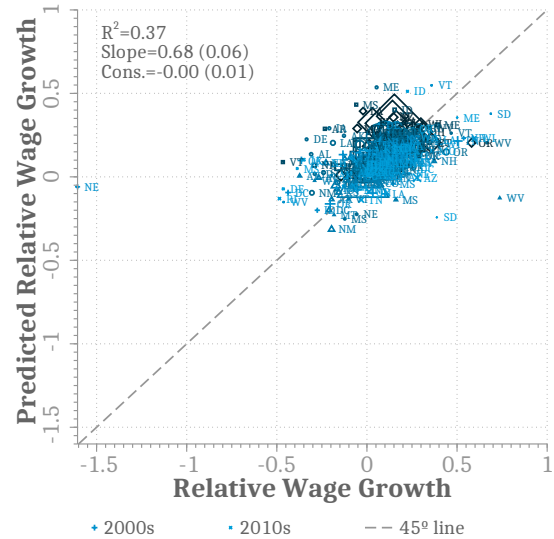


II. Out of sample

A. Wage gap at arrival



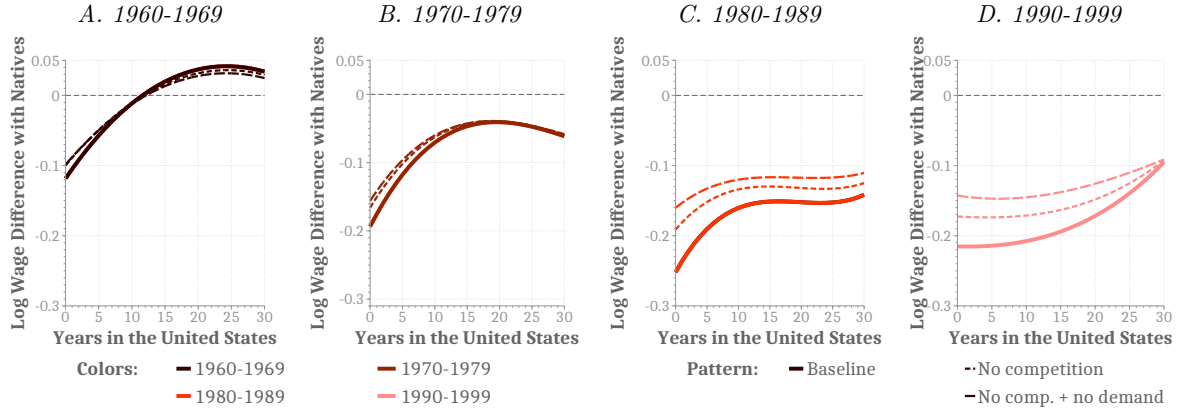
B. Relative wage growth first 10 years



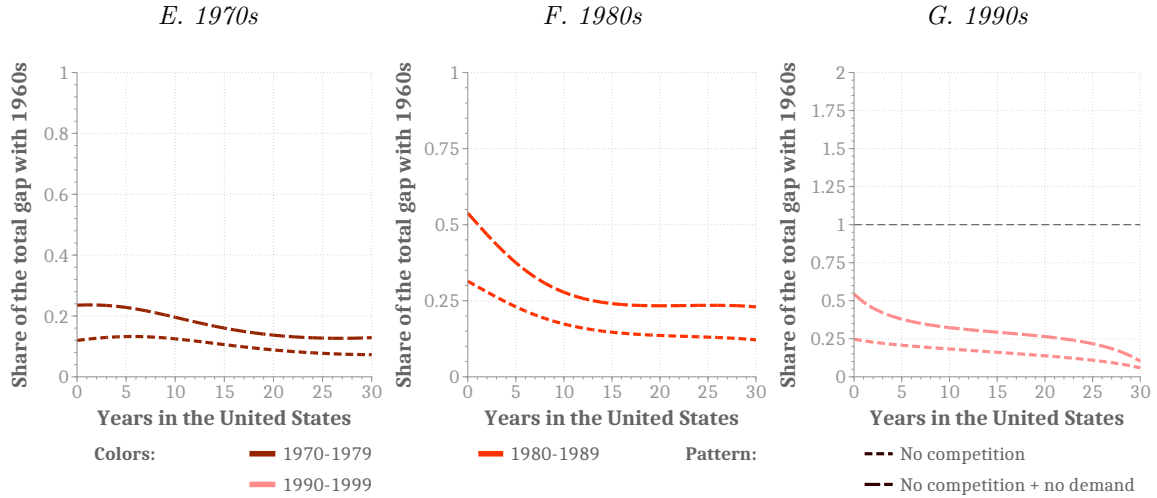
Note: The figure plots the in-sample (Panel I) and out-of-sample (Panel II) model predictions for the initial wage gaps (Plots A) and relative wage growth rates (Plots B) of women in different state-cohort cells (obtained as in Figure N1) against the actual initial wage gaps and relative wage growth rates. The out-of-sample predictions are obtained from an estimated version of the model in which the state that is plotted is not used for the estimation in a leave-one-out type of approach. All plots include a 45-degree line for comparability. State-years with less than 150 immigrants in the census year of arrival are not included. Scatter plots represent state-cohort observations, where size represents population, and lines represent linear regression fits (weighted by population size). Markers/shades distinguish different cohorts.

FIGURE N10. WAGE GAP DECOMPOSITION: COMPETITION AND DEMAND EFFECTS

I. Assimilation profiles under different scenarios



II. Share of the increase in the wage gaps relative to 1960 closed by each channel



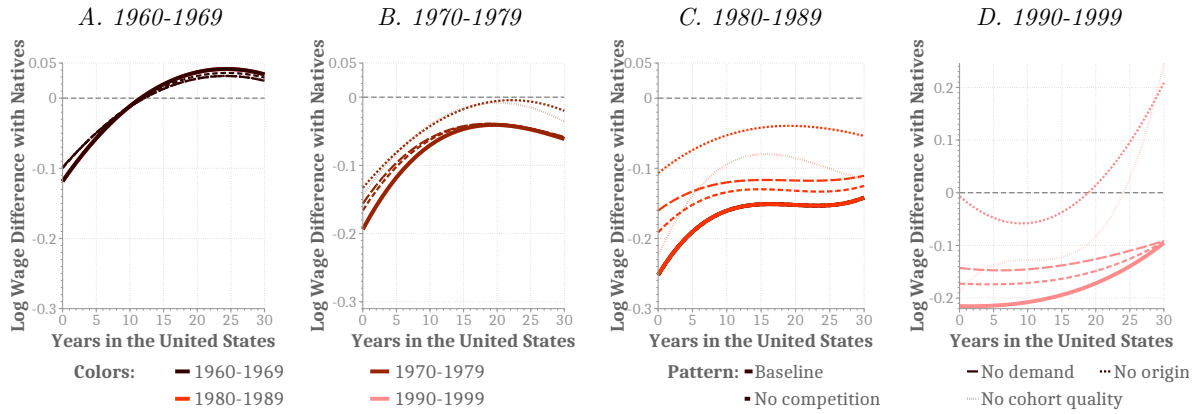
Note: The figure shows baseline and counterfactual predictions of the unconditional wage gaps between native and immigrant women for different cohorts as they spend time in the United States. Each plot represents one cohort. The depicted lines in Panel I are predicted assimilation profiles obtained from regressions analogous to those underlying Figure N1, estimated on predicted wages under the different counterfactual scenarios. The baseline profiles (solid) correspond to the solid lines in Figure N1. The counterfactuals represent assimilation profiles in the absence of competition effects (short-dashed line), and in the absence of competition and demand effects (long-dashed line). Figures in Panel II show the fraction of the gap of each cohort relative to 1960s that is closed in each counterfactual.

TABLE N3—WAGE GAP DECOMPOSITION: COMPETITION AND DEMAND EFFECTS

Cohort	Years in the United States:				Average across years in the U.S.
	0 years	10 years	20 years	30 years	
A. Wage gap with natives (in log points difference)					
<i>i. Baseline</i>					
1960-1969	-11.9	-1.1	3.7	3.4	-0.2
1970-1979	-19.4	-7.1	-4.1	-6.1	-7.5
1980-1989	-25.2	-16.0	-15.2	-14.2	-16.7
1990-1999	-21.5	-20.8	-17.2	-9.5	-18.0
<i>ii. No competition effect</i>					
1960-1969	-10.0	-1.1	3.2	2.9	-0.2
1970-1979	-16.6	-6.3	-3.9	-5.9	-6.8
1980-1989	-19.1	-13.4	-13.2	-12.5	-14.0
1990-1999	-17.3	-17.1	-14.8	-9.2	-15.2
<i>iii. No competition and no demand effects</i>					
1960-1969	-9.9	-1.2	2.8	2.5	-0.5
1970-1979	-15.6	-6.0	-3.9	-5.8	-6.5
1980-1989	-16.0	-12.0	-11.7	-11.1	-12.3
1990-1999	-14.3	-14.5	-12.6	-9.1	-13.1
B. Percent of the baseline wage gap with the 1960s closed by each channel					
<i>i. No competition effect</i>					
1970-1979	12.0	12.5	8.8	7.3	10.4
1980-1989	31.4	17.4	13.6	12.1	17.3
1990-1999	24.7	18.3	13.8	5.9	15.9
<i>ii. No competition and no demand effects</i>					
1970-1979	23.5	19.6	13.7	12.9	17.2
1980-1989	53.8	27.8	23.3	23.0	29.2
1990-1999	54.4	32.3	26.5	10.3	29.9

Note: The table presents the wage gap with natives (in log points) and the fraction of the gap of each cohort's assimilation profile relative to the 1960s cohort that is explained by each mechanism (in percentages) at different points in time. These results summarize the information provided in Figure N10.

FIGURE N11. WAGE GAP DECOMPOSITION: COMPETITION, DEMAND, AND COMPOSITION EFFECTS



Note: The figure adds to the baseline decomposition in Figure N10 the counterfactual assimilation profiles holding unobservable cohort quality (dotted lines) and country of origin (short-dashed lines) composition constant. In particular, taking the counterfactual predictions without competition and demand effects, assimilation profiles without changes in cohort quality are estimated on predicted wages in which specific skill units of immigrants are predicted replacing the cohort-related coefficients of the $s(\cdot)$ function with the values for the 1960s cohort. Taking these predictions as a base, assimilation profiles holding country of origin composition constant are computed replacing the baseline weights by corrected weights adjusted so that, for each cohort, the relative weight of each region of origin is held constant at the level of the 1960s cohort, keeping the total weight of the cohort fixed as in the baseline. Each plot represents one cohort. The depicted lines are predicted assimilation profiles obtained from regressions analogous to those underlying Figure N1, estimated on the predicted wages under the different counterfactual scenarios. Due to the small number of observations of Western immigrants from the 1990s cohort in the 2020 Census, we only include a quadratic and not a third order polynomial in years of experience to determine the final assimilation profile that holds the country of origin composition constant.

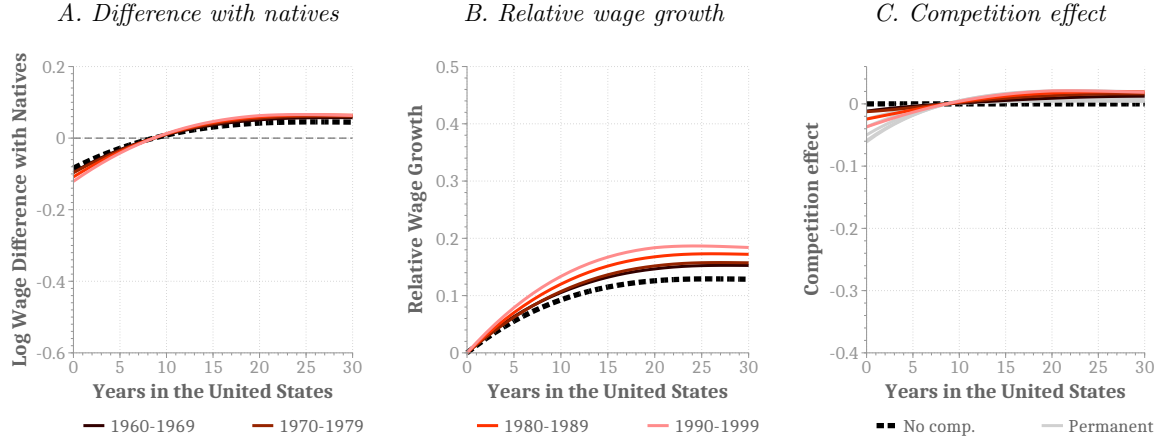
TABLE N4—WAGE GAP DECOMPOSITION: COMPETITION, DEMAND, AND COMPOSITION EFFECTS

	Competition	Demand	Cohort quality	Origin	Education
1970-1979	10.4	6.8	31.6	4.2	47.0
1980-1989	17.3	11.9	5.5	35.7	29.6
1990-1999	15.9	14.1	37.3	48.6	-15.9

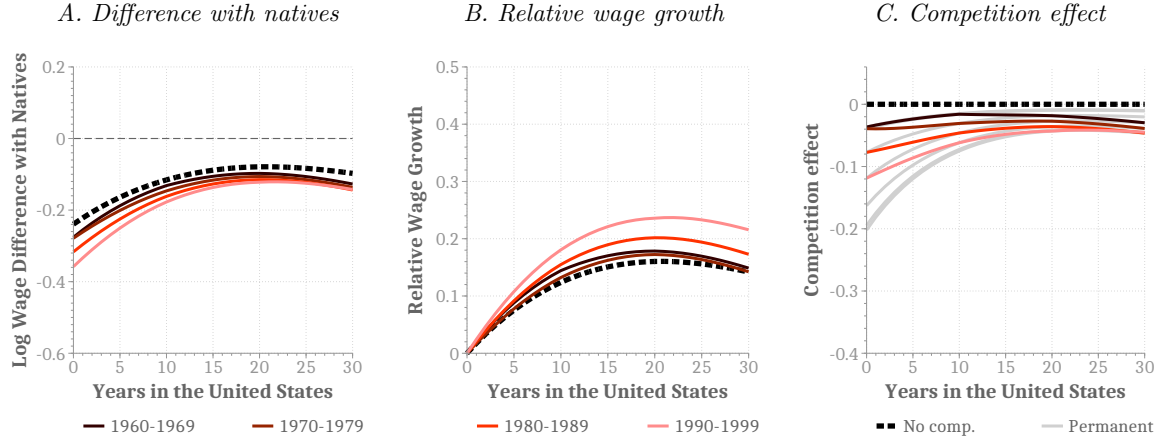
Note: The table presents the fraction of the wage gap of each cohort's assimilation profile relative to the 1960s cohort that is explained by each mechanism (in percentages) averaged across all years since migration for women. These results summarize the information provided in Figure N11.

FIGURE N12. HETEROGENEOUS LABOR MARKET COMPETITION EFFECTS: EXAMPLES

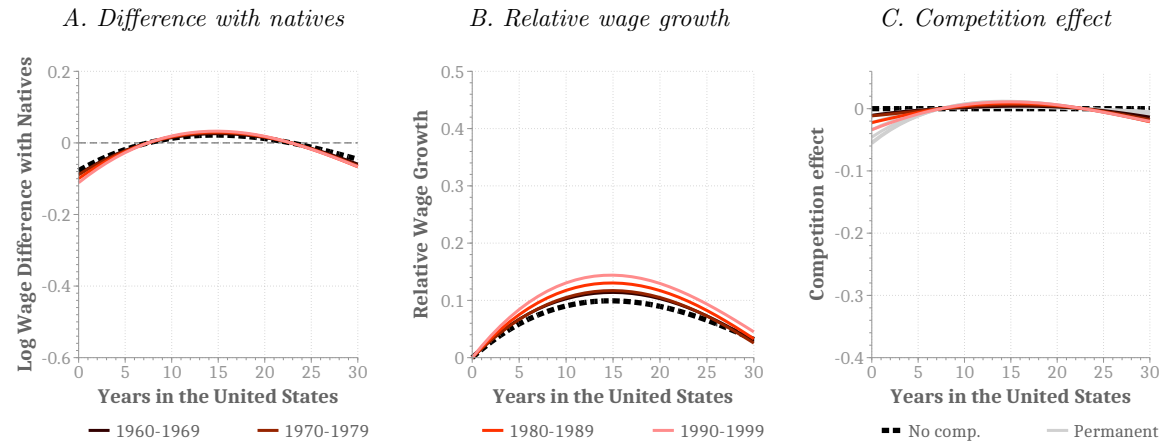
I. Mexican high school dropouts



II. Latin American high school graduates



III. Western college graduates

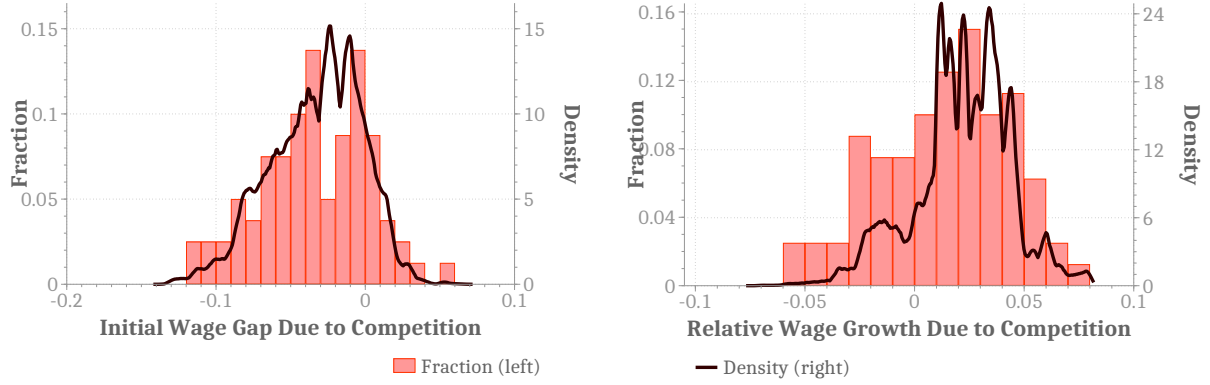


Note: The figure shows wage assimilation profiles of selected immigrant groups (as indicated by each panel's header) under different counterfactual scenarios. All profiles assume that the individual arrived with the skills of the 1960s cohort, was exposed to the demand effects experienced by this cohort, and arrived with potential experience equal to the average of all women in the sample. The thick dashed line assumes no competition effects ($\sigma = \infty$). The colored solid lines represent assimilation profiles under the competition level (weighted average across states) experienced by each cohort (dynamic effect). The gray lines in Plots C represent the assimilation curves under the competition level of each calendar year (one-time permanent effect). Plots A and B in each panel show the wage gap relative to natives and the relative wage growth as in Figure 1. Plots C show the difference between the assimilation profiles in each counterfactual scenario and the no-competition benchmark.

FIGURE N13. HETEROGENEOUS LABOR MARKET COMPETITION EFFECTS

A. Initial wage gap

B. Relative wage growth

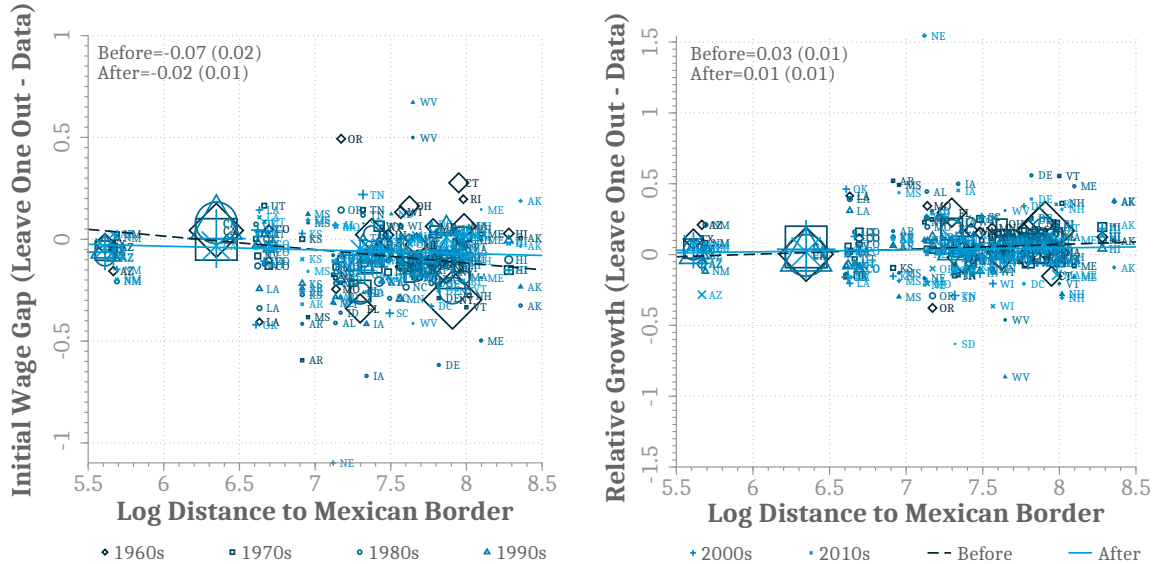


Note: The histograms show by how much labor market competition changed the initial wage gap (Panel A) and relative wage growth over the first 30 years (Panel B) for the 80 immigrant groups distinguished in our analysis (4 arrival cohorts $\times$ 5 origin groups $\times$ 4 education levels, computed on the average potential experience abroad), relative to a scenario without competition effects. The solid lines represent the kernel density of the population-weighted predictions of the effects for all women in the sample. Estimated effects are expressed in log differences.

FIGURE N14. STATE-LEVEL PREDICTIONS AND THE PESO CRISIS

A. Initial wage gap

B. Relative wage growth first 10 years



Note: The figure correlates the gap between the leave-one-out predictions and their data counterparts shown in Panel II of Figure N9 with the distance to the Mexican border. The two regression lines represent the predictions from (weighted) linear regressions estimated using all the state-cohort observations of the 1990s cohort and earlier and all the state-cohort observations of the 2000s cohort and later, respectively, to capture the pre- and post-peso crisis episodes (slopes and standard errors reported in the top-left corner). State-years with less than 150 immigrants in the census year of arrival are not included. Scatter plots represent state-cohort observations, where size represents population, and lines represent linear regression fits (weighted by population size). Markers/shades distinguish different cohorts.

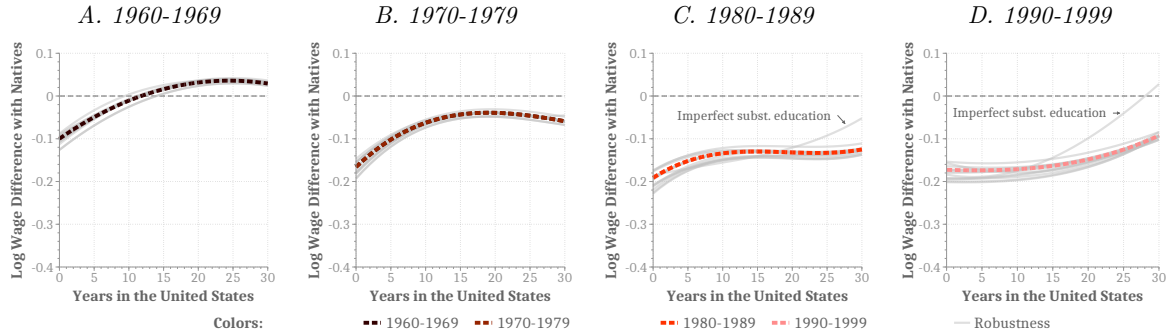
TABLE N5—ADDITIONAL ELEMENTS OF $s(\cdot)$ FOR SOME OF THE ROBUSTNESS CHECKS

	Direct effect	Interaction with years since migration:		
		Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Potentially undocumented	-0.064 (0.009)	0.006 (0.003)	-0.086 (0.020)	0.018 (0.004)
Share of state's population	-0.483 (0.228)	-0.133 (0.052)	0.731 (0.325)	-0.111 (0.058)
Stock in the state ($\times 10^6$)	-0.056 (0.020)	-0.009 (0.004)	0.041 (0.025)	-0.006 (0.004)

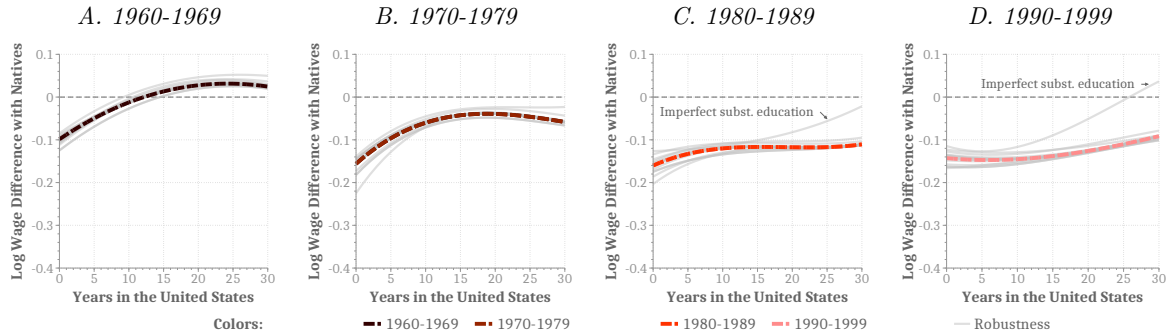
Note: The table presents estimates for the additional parameters of the $s(\cdot)$ function associated with the two specifications of the networks robustness check and for the specification that allows for heterogeneous convergence between potentially undocumented and legal immigrants (each row corresponds to one specification) for women.

FIGURE N15. ASSIMILATION PROFILES UNDER ALTERNATIVE SPECIFICATIONS

I. No competition effect



II. No demand and no competition effects



Note: The figure reproduces the counterfactual assimilation profiles described in Figure 6 (Panel I) for the different scenarios (colored lines) and the different robustness checks described in the text for women (gray lines).

TABLE N6—WAGE GAP DECOMPOSITION: ROBUSTNESS

	Competition effect				Competition+demand effect:			
	1960s	1970s	1980s	1990s	1960s	1970s	1980s	1990s
Baseline estimate:	0.0	0.8	2.8	2.8	-0.2	1.0	4.4	5.0
Selective return migration:								
Borjas and Bratsberg (1996)	0.0	0.7	2.5	2.5	-0.2	1.0	4.5	5.0
Rho and Sanders (2021)	0.5	1.6	4.1	4.3	0.5	2.0	5.7	6.4
Synthetic cohorts	0.1	1.0	2.9	2.8	-0.1	1.2	4.2	4.7
Undocumented migrants:								
Rewighted only	-1.2	-0.5	1.6	1.6	-1.5	-0.2	3.5	4.0
Rewighted and heterogeneous	-1.2	-0.5	1.7	1.7	-1.5	-0.2	3.5	4.0
Networks:								
Share of state's population	0.1	0.4	1.1	0.9	-0.3	1.0	4.5	5.1
Stock in the state	0.1	0.4	0.9	0.8	-0.4	1.0	4.6	5.2
Alternative specifications of δ_t , $s(\cdot)$ and the production function:								
Demand δ_t : Time dummies	-0.1	1.2	3.0	2.5	0.4	-0.2	3.3	4.4
Demand δ_t : Region dummies	0.1	0.5	1.4	1.4	-0.5	1.3	5.6	6.3
Skills $s(\cdot)$: Pairwise interactions	0.1	1.0	3.2	3.2	-0.1	1.2	4.9	5.4
Skills $s(\cdot)$: Quartic polynomials	0.0	0.7	2.7	2.8	-0.2	1.0	4.4	5.0
Imperfect substitution by education	0.9	0.7	3.5	6.0	1.6	2.8	7.6	10.9
Endogenous immigrant location:								
GMM instruments based on Card (2001)	-0.0	0.4	2.3	2.7	-0.2	0.6	3.6	4.3

Note: The table shows, for each robustness check, the competition and competition plus demand effects for each cohort (counterfactual minus baseline multiplied by 100) for women, averaged across years in the United States.