

Labor Market Competition and the Assimilation of Immigrants*

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This paper shows that the wage assimilation of immigrants is the result of the intricate interplay between individual skill accumulation and dynamic labor market equilibrium effects. When immigrants and natives are imperfect substitutes, rising immigrant inflows widen the wage gap between them. Using a production function framework in which workers supply both general and host-country-specific skills, we show that this labor market competition channel explains about one fifth of the large increase in the average immigrant-native wage gap across arrival cohorts in the United States since the 1960s. This figure increases to one third after also accounting for relative demand shifts due to technological change. The results further reveal substantial heterogeneity across different groups of immigrants.

Keywords: *Immigrant Assimilation, Labor Market Competition, Cohort sizes, Imperfect Substitution, General and Specific Skills*

JEL Codes: *J21, J22, J31, J61*

I. Introduction

The evolution of immigrants' wages over time relative to those of natives is widely used as a measure of successful integration. Documenting this process, and understanding its impediments and facilitators, is essential for migration policy design and has been the subject of an extensive literature in economics. Following the seminal work by Chiswick (1978) and Borjas (1985), most studies focus on two specific aspects of immigrants' wage assimilation: the initial immigrant-native wage gap and the way in which this wage gap changes as immigrants spend time in the host country. The first one is generally viewed as a proxy for the "quality" of immigrants in terms of their human capital upon arrival, the second one as reflecting immigrants' accumulation of host-country-specific skills, or the "speed of assimilation". For the United States, it has been documented that the initial wage

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gap between newly arriving immigrants and natives has widened significantly since the 1960s and that the speed of wage assimilation has simultaneously declined (Borjas, 2015), leading to the view that immigrants have become more negatively selected over time.

In this paper, we argue that changes in the quality of more recent cohorts are only part of the story. In particular, we show that the increasing size of immigrant arrival cohorts, and the resulting changes in labor market competition, have an important effect on relative wages in equilibrium. The intuition behind this new mechanism is straightforward. When immigrants and natives are imperfect substitutes in the labor market, for example because of a comparative advantage in different occupations, their relative wages are partly determined by the aggregate supply of foreign workers in the economy. Increasing immigrant inflows, such as those observed in the United States over the last half century, then raise labor market competition more for immigrants than for natives, driving their wages apart and thus directly affecting wage assimilation. This effect is further amplified if technological progress leads to an increase in the relative demand for those skills that are relatively more abundant among natives.

Our findings suggest that, in the United States, changes in labor market competition alone explain about one fifth of the observed increase in the average immigrant-native wage gap across arrival cohorts since the 1960s. This figure rises to about one third once shifts in relative skill demands are accounted for as well. These aggregate findings conceal substantial heterogeneity across different immigrant groups.

The theoretical basis of our empirical analysis is a production framework in which natives and immigrants supply two types of skills: general skills that are portable across countries, and specific skills that are particular to the host country. Upon arrival, immigrants are endowed with the same amount of general skills as observationally equivalent natives but only a fraction of their specific skills. Over time, immigrants accumulate further specific skills at a (usually) faster rate than natives, inducing wage convergence. The aggregate amounts of general and specific skills supplied in the economy are combined by a constant elasticity of substitution (CES) production technology. Technological change is allowed to increase the relative demand for either of the two types of skills. Equilibrium skill prices are competitively determined, which implies that relative skill prices depend on aggregate skill supplies, and workers are paid according to the skill bundle they supply. In our framework, imperfect substitutability between immigrants and natives arises as a consequence of their different skill sets. Since immigrants disproportionately supply general skills, increasing immigrant inflows shift relative prices in favor of specific skills, widening the wage gap between immigrants and natives. This effect is particularly pronounced in the early years after arrival when immigrants still have relatively few specific skills. In later years, in contrast, immigrants' skills are already more similar to those of natives, making their relative wages less responsive to changes in equilibrium skill prices. Whether immigration-induced changes in labor market competition increase

or decrease the speed of wage assimilation depends on the precise magnitude and timing of the immigrant inflows as well as the immigrants' skill accumulation profiles.

We fit our model by nonlinear least squares (NLS) using data from the U.S. Census and the American Community Survey (ACS) that cover the period 1970 to 2019. We exploit individual-level variation to estimate the parameters determining the skill accumulation process and identify the technology parameters of our production function from relative wage differences across labor markets (defined by states and time). Based on the results from this estimation, we then decompose the observed changes in the initial wage gap and relative wage growth between the 1960s and 1990s cohorts into three components: the labor market competition effect, a demand effect driven by skill-biased technological change, and a residual component that reflects changes in cohort quality, both due to changes in education and country of origin, and due to changes in unobservable skills.

Our results show that immigration-induced increases in labor market competition can explain 16.4 and 50.3 percent of the increase in the initial relative wage gap of the 1970s and 1980s cohorts relative to the 1960s cohort. Shifts in relative skill demand account for an additional 17.2 and 45.4 percent. With more years spent in the United States, these effects diminish since immigrants become closer substitutes to natives. Averaged over time, the competition effect alone accounts for 13.5 and 21.3 percent of the increase in wage gaps relative to the 1960s cohort. For the 1990s cohort, it accounts for 19.2 percent. When additionally considering the effects due to changes in relative skill demand, these figures increase to 24.3, 38.8 and 44.8 percent, respectively. The remaining differences can be attributed to decreasing cohort quality and fully explained by changes in immigrants' education and origin composition. Conditional on these two observable characteristics, our findings suggest that immigrants have become more positively selected in terms of unobservable skills. Through a series of robustness checks, we show that our findings are largely unaffected by selective return migration, undercounting of undocumented immigrants, network effects, alternative functional form assumptions, endogenous immigrant location choices, and alternative formulations of the production function.

We also find that these effects are highly heterogeneous across immigrant groups. For Mexican high school dropouts, for example, rising labor market competition increased the initial wage gap by more than 10 log points between the 1960s and 1990s arrival cohorts. For Western college graduates, in contrast, it had essentially no impact. Our results further show that rising labor market competition cannot explain the observed slowdown in average wage assimilation across cohorts, even though for some groups, such as Latin American high school graduates, it did inhibit long-run wage assimilation. Overall, we find that 33.5 percent of the total variation in the initial wage gaps across different types of immigrants and 29.5 percent of the variation in long-term assimilation rates can be attributed to changing labor market competition.

Our paper contributes first and foremost to the large literature that studies the wage

assimilation of immigrants. After the pioneering work by Chiswick (1978) and its crucial extension to repeated cross-sectional data by Borjas (1985, 1995), numerous studies have analyzed the wage assimilation of immigrants in different host-country settings and time periods (see Dustmann and Glitz, 2011, and Dustmann and Görlach, 2015, for surveys of the international literature). For the United States, an extensive body of research has documented the widening wage gaps across arrival cohorts as well as the declining speed of wage convergence between immigrants and natives (see Borjas, 2014, and Cadena, Duncan and Trejo, 2015, for surveys of the U.S. assimilation literature). Contrary to most of this literature, our paper shows that these empirical regularities are not driven by changing immigrant cohort quality alone but that an important part can be explained by increasing cohort sizes and labor market competition, as well as changes in the relative demand for host-country-specific skills.

Several papers in the literature have critically assessed some of the key assumptions underlying the estimation and interpretation of immigrants' wage assimilation profiles. Bratsberg, Barth and Raaum (2006) show that changing aggregate labor market conditions (measured by local unemployment rates) affect immigrants and natives differentially, leading to an upward bias in the assimilation rates obtained from the standard specification in the literature. To the extent that such changes in aggregate conditions are reflected in relative skill prices, our framework incorporates their differential effect on immigrant and native workers. Duleep and Regets (2013) document a strong inverse relationship between immigrants' earnings at entry and subsequent wage growth, which they explain by higher investment in human capital of immigrants that arrive with less transferable skills. Dustmann, Ku and Surovtseva (2024) show that variations in the real exchange rates between home and host countries are an important driver of immigrants' initial wage gaps and subsequent career trajectories. Lubotsky (2007) and, more recently, Akee and Jones (2019) and Rho and Sanders (2021), use longitudinal administrative data matched with U.S. survey information to show that selective return migration may significantly bias estimated relative wage profiles, a conclusion also supported by the findings in Hu (2000) and Abramitzky, Boustan and Eriksson (2014).¹ Due to the long period covered by our analysis, we cannot account for selective return migration as comprehensively as these studies do, but we show by means of three separate robustness checks that this issue is unlikely to affect our main conclusions.

Some papers in the literature highlight the importance of skill prices and occupational mobility for the wage assimilation of immigrants. LaLonde and Topel (1992) find that the relative earnings of immigrants are sensitive to persistent changes in wage inequality in the United States. In particular, since immigrants tend to be less skilled than natives, the rising returns to skills in the 1970s increased wages of the average native by more than those

¹ For a systematic treatment of the issue of selective return migration in the context of immigrants' wage assimilation, see Dustmann and Görlach (2015).

of the average immigrant. Lubotsky (2011) performs a similar analysis including more recent arrival cohorts using longitudinal social security data. Lessem and Sanders (2020) highlight the important role of occupational upgrading for immigrant wage growth and quantify the potential benefits from removing barriers to occupational mobility. Neither of these studies, however, considers labor market competition due to imperfect substitutability between immigrants and natives as a key driver of relative wage profiles.

Our work is also related to a small number of papers that emphasize the link between immigrants' labor market outcomes and the size of different arrival cohorts. Beaman (2012) analyzes the importance of social networks for immigrant wage dynamics, exploiting exogenous variation from a refugee resettlement policy in the United States. She finds that an increase in the number of contemporaneously resettled social network members worsens the labor market outcomes of immigrants, whereas an increase in the number of tenured network members improves them. These results are consistent with our finding that immigrants who arrive around the same time are relatively substitutable due to their similar skill sets, but that the substitutability between different cohorts declines the further apart their respective times of arrival. In line with this observation, D'Amuri, Ottaviano and Peri (2010) find evidence for imperfect substitutability between "new" (0–5 years since arrival) and "old" (more than 5 years since arrival) immigrants in Germany, suggesting that new immigrant inflows have larger wage impacts on more recent immigrants than on older immigrants, consistent with earlier results for the United States reported in LaLonde and Topel (1991). While our analysis does not focus on the wage impacts of immigration per se, our theoretical framework fully captures, and indeed generalizes, these patterns of imperfect substitutability across different arrival cohorts. It also builds on the idea that the wages of natives and immigrants with different tenure in the country are differentially affected by new immigration.

In contemporaneous work, Galeone and Görlach (2022) study immigrant wage progression through the lens of an asymmetric nested CES production function in which each nest represents either immigrant workers with a specific number of years of residence in the U.S. or natives. As immigrants move across nests, their skill efficiency and substitutability with other factor inputs change, which jointly determines their wage growth. Using Census and ACS data for the years 2000 to 2018, the authors show that, while immigrants' skill efficiency increases significantly over time, part of the associated wage gains are offset by immigrants becoming increasingly substitutable with natives and earlier immigrants. Similar to our paper, their analysis highlights that observed wage profiles of immigrants generally reflect both genuine skill accumulation and changes in aggregate factor supplies.

Finally, our analysis is closely linked to the large literature on the labor market impact of immigration (see e.g. Cadena et al., 2015, and Dustmann, Schönberg and Stuhler, 2016, for surveys of this literature). One important insight that has emerged over time in this research area is that immigrants and natives are often not perfect substitutes in the labor

market, even conditional on observable skills such as education and experience (see e.g. Peri and Sparber, 2009, Ottaviano and Peri, 2012, Manacorda, Manning and Wadsworth, 2012, and Llull, 2018). As a result, new immigrant inflows have a less detrimental impact on natives than on previous immigrants, with much of the literature seeking to estimate the magnitudes of these relative wage effects.² On closer inspection, however, the finding of imperfect substitutability generates a conceptual tension between the wage assimilation literature and the labor market impact literature. Even though both literatures study essentially the same outcome variable – the relative wages of immigrants and natives – they each account for its main determinants in very distinct and partial ways. While the traditional assimilation literature abstracts from aggregate factor supplies as possible drivers of relative wages, the impact literature usually does not, or only very rudimentarily, allow for immigrants’ skill accumulation and evolving substitutability with other factor inputs. Our theoretical framework synthesizes these two long-standing and influential literatures, showing in an intuitive way how aggregate factor supplies and individual skill accumulation interact to give rise to heterogeneous wage profiles across workers.

The rest of the paper is organized as follows. Section II provides a brief description of our data and illustrates the relationship between relative wage dynamics and the size of immigrant inflows. Section III presents our theoretical framework. Section IV discusses identification and estimation of the model. Section V reviews the baseline estimates for our model parameters. Section VI presents our simulation results and decomposition analysis. Section VII shows extensive robustness checks. Section VIII concludes the paper.

II. Data and Descriptive Evidence

In this section, we describe our main data sources and provide some key descriptive statistics of our sample. We then document the well-known immigrant wage assimilation profiles in the United States and present some spatial correlations that are indicative of our proposed labor market competition mechanism.

A. Data

Our empirical analysis is based on U.S. Census data for the years 1970, 1980, 1990 and 2000, combined with observations from the American Community Survey (ACS) pooled across the years 2009–2011 (labeled as 2010) and the years 2018 and 2019 (labeled as 2020). All data are downloaded from the Integrated Public Use Microdata Series database (IPUMS-USA, Ruggles et al., 2018). Following previous work, the main sample comprises individuals aged 25–64 who are not self-employed, do not live in group quarters, are not enrolled in school (except for 1970, when there is no information on school enrollment), work in the civilian sector, and report positive hours of work and earnings. We drop

² In the context of internal migration in the United States, Boustan (2009) shows that, due to imperfect substitutability between black and white workers, the large black migration flows from the South to the North in the mid-20th century widened the racial wage gap in the North by 5 to 7 log points.

TABLE 1—DESCRIPTIVE STATISTICS OF IMMIGRANT COHORTS

	Cohort of entry:					
	1960-69	1970-79	1980-89	1990-99	2000-09	2010-19
Share of population (%)	3.0	4.2	5.5	7.6	9.0	7.3
Cohort size (millions)	0.8	1.4	2.3	3.8	4.7	4.2
Men (%)	64.9	61.9	62.5	61.8	60.2	59.6
Age	38.3	36.7	36.5	36.8	37.8	38.0
Hourly wage	16.6	16.0	14.5	15.9	14.2	18.1
HS dropouts (%)	46.6	41.0	31.4	28.1	26.2	15.2
HS graduates (%)	22.1	21.3	24.8	28.8	28.3	25.5
Some college (%)	11.0	11.8	17.2	12.0	11.8	11.7
College graduates (%)	20.3	25.9	26.6	31.1	33.7	47.6
Mexico (%)	8.5	20.0	18.6	25.8	27.4	13.4
Other Latin America (%)	30.3	21.4	26.9	22.0	26.6	28.0
Western countries (%)	37.0	17.2	11.1	9.7	6.6	8.3
Asia (%)	14.6	34.0	35.6	29.3	28.5	37.9
Other (%)	9.5	7.4	7.8	13.2	10.9	12.4

Note: The statistics are based on the sample of immigrants aged 25-64 reporting positive income (not living in group quarters) who entered the United States during the respective time intervals, measured in the first Census year following the arrival. Observations are weighted by the personal weights obtained from IPUMS, rescaled by annual hours worked.

immigrants without information on their country of birth or year of arrival in the United States. Further details on the variable definitions are provided in Online Appendix A.

Table 1 reports descriptive statistics on the size and composition of different immigrant arrival cohorts (which we aggregate by decades), measured in the first census year after arrival. With the exception of the most recent decade, cohort sizes increased steadily over time, from about 800,000 individuals in the 1960s to 2.3 million in the 1980s and 4.7 million in the 2000s. As shown in Table B1 in Online Appendix B, this led to a sizable increase in the foreign-born share of the population, from 3.8 percent in 1970 to 16.3 percent in 2020. This increase was accompanied by major shifts in the immigrants' educational attainment and origin composition. While most immigrants in the 1960s originated from Western source countries (37.0 percent) and only relatively few from Mexico (8.5 percent) and Asia (14.6 percent), this pattern reversed over the following decades, with the share of immigrants from Western countries (6.6 percent) decreasing and the shares from Mexico (27.4) and Asia (28.5) increasing rapidly until the early 2000s. In the last decade, there has been another meaningful shift in the origin composition, away from Mexican immigrants (13.4 percent) and toward Asian immigrants (37.9 percent).

Since the 1960s, the level of formal education of newly arriving immigrants improved significantly, with the share of high school dropouts decreasing from 46.6 percent in the 1960s to 15.2 percent in the 2010s, and the share of college graduates increasing from 20.3 percent in the 1960s to 47.6 percent in the 2010s. However, despite this considerable improvement in immigrants' educational attainment, the gap in formal education relative to natives widened during the last half century due to the even more rapid expansion of higher education in the United States (see Table B1).

The notable shifts in educational attainment and origin composition documented in Tables 1 and B1 are likely to explain at least part of the observed changes in immigrants' wage assimilation profiles documented below. In our empirical analysis, we will contrast the contribution of these compositional changes with the contribution due to labor market equilibrium effects and secular changes in the relative demand for specific skills.

B. Descriptive evidence on assimilation profiles

To set the stage for our main analysis, we start by documenting how immigrant wage assimilation profiles have changed over time, following the standard approach based on repeated cross-sectional data first advocated by Borjas (1985). To facilitate the comparison with earlier studies, and because selection effects due to changing labor force participation make female wage assimilation profiles more difficult to interpret, we focus on immigrant men and their assimilation profiles in the main text. All corresponding tables and figures for women can be found in Online Appendix N. In Figure 1, we depict two sets of results. The dashed lines are obtained from year-by-year regressions of log male wages on a third order polynomial in age and dummies for years since migration (which are all set to zero for native men). The plotted coefficients on these dummy variables thus reflect raw data averages (net of age effects). The solid lines are obtained from a single regression of log male wages on year fixed effects and their interaction with a third order polynomial in age, and cohort-of-entry fixed effects and their interaction with a third order polynomial in years since migration.³ While Figure 1A shows the estimated relative wage gaps and their evolution over time and across cohorts, Figure 1B highlights the relative wage growth by normalizing the initial wage gaps of each cohort to zero.

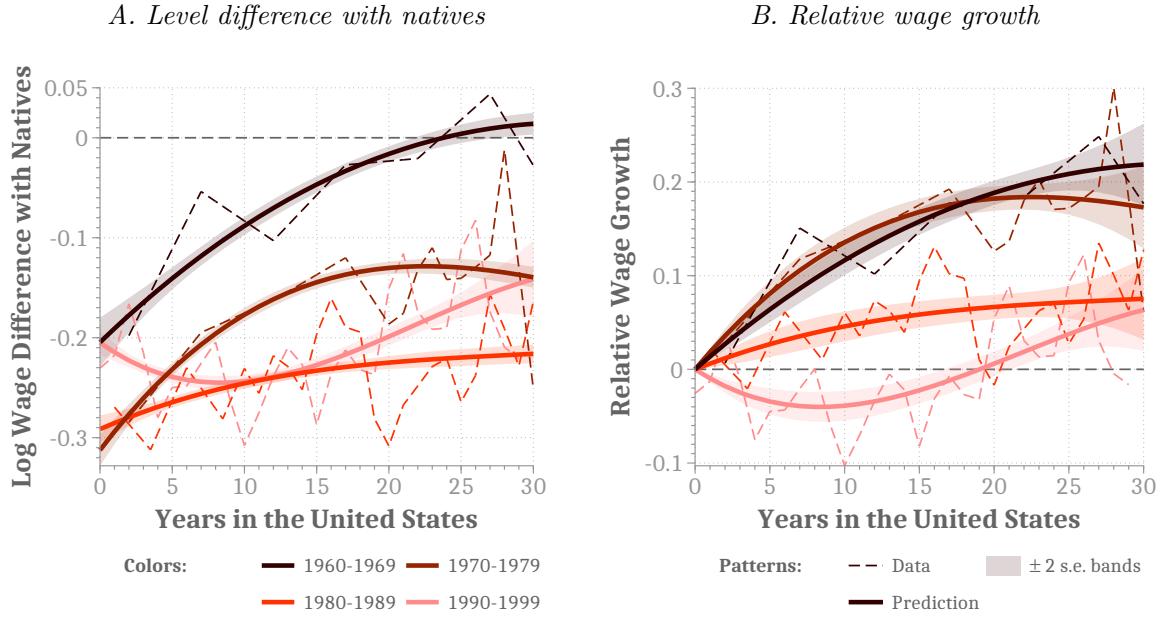
Figure 1 illustrates two major changes in immigrants' wage assimilation profiles during the period considered. First, the initial wage gap between newly arriving immigrants and natives widened substantially between the 1960s and 1980s. While the 1960s cohort arrived with an initial wage gap of about 20 log points, the 1970s and 1980s cohorts faced an initial wage gap of around 30 log points, which then narrowed once again to around 20 log points for the 1990s cohort. Second, the speed of wage convergence decreased significantly across cohorts, to the point that the relative wage gap of the 1990s cohort even widened initially before then starting to close after about 10 years in the country.⁴

Our central hypothesis is that the changing wage assimilation profiles across cohorts are

³ Cohorts are grouped in 10-year intervals. The pre-1960s and post-1990s cohorts are not plotted but included in all regressions. We exclude the cubic term for the 2000s cohort and both the quadratic and cubic terms for the 2010s cohort. The inclusion of these terms does not change the overall patterns in any significant way but makes the assimilation curves of those cohorts non-monotonic in an attempt to (over)fit the dispersion in the raw average wages over a shorter time window.

⁴ As we show below, our findings suggest that part of this initial divergence might be the result of competition and demand effects. Furthermore, we estimate the accumulation of skills for this cohort to be very close to zero over the first 10 years, consistent with only a moderate increase in language proficiency relative to other cohorts. The remaining divergence might be attributable to other elements such as positively selected return migration (Rho and Sanders, 2021) or to polynomial overfitting.

FIGURE 1. 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 men 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):

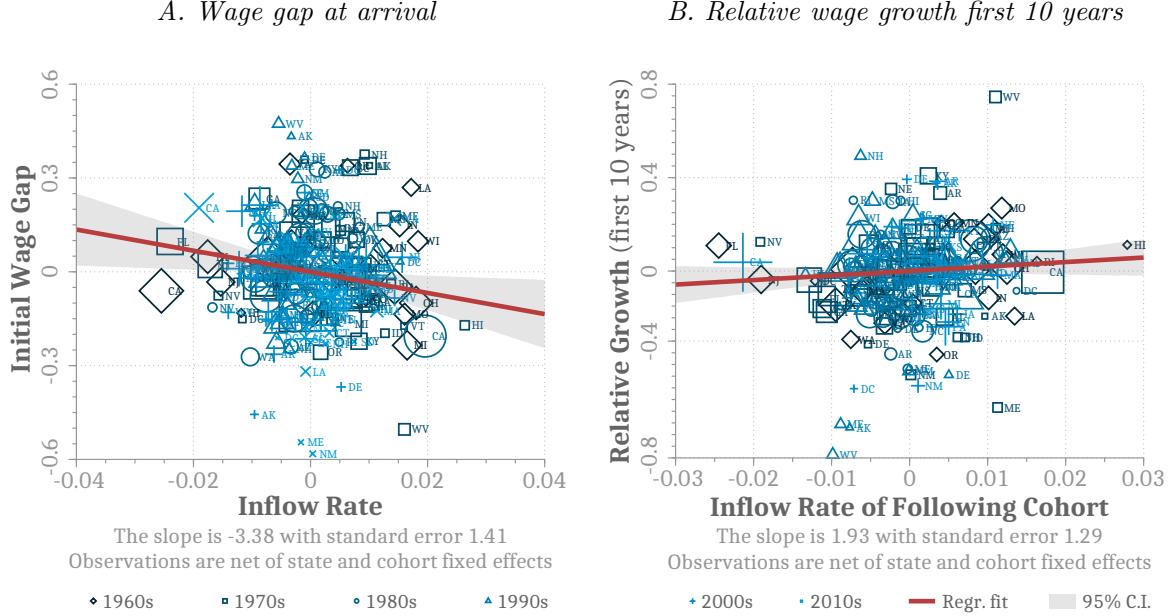
$$\ln w_i = \beta_{0c(i)} + \beta_{1t(i)} + \sum_{\ell=1}^3 \beta_{2\ell t(i)} \text{age}_i^\ell + \sum_{\ell=1}^3 \beta_{3\ell c(i)} y_i^\ell + \nu_i,$$

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.

partially driven by changes in relative aggregate skill supplies due to increasing immigrant inflows into the United States since the 1960s. To provide some *prima facie* evidence for this hypothesis, Figure 2 relates the predicted initial male wage gap (left panel) and relative wage growth over the first decade in the United States (right panel) to the size of the contemporary and subsequent immigrant arrival cohorts respectively, exploiting variation at the state-cohort level. The initial wage gaps and relative growth rates are predicted from regressions similar to those underlying the solid lines in Figure 1 but estimated for each state separately and then purged of cohort and state fixed effects.

According to Figure 2A, larger immigrant arrival cohorts are characterized by a more pronounced initial wage gap, as our theoretical framework below unambiguously predicts. The impact of growing cohort sizes on relative wage growth, in contrast, is theoretically ambiguous. Figure 2B shows that, in the data, the relationship between the size of future immigrant inflows and a given cohort's relative wage growth is positive, consistent with the findings of our main empirical analysis. Figure C1 in Online Appendix C shows that neither relationship is driven by any specific outliers by plotting a histogram of the slope estimates obtained after excluding one state at a time from the estimation sample.

FIGURE 2. COHORT SIZE, INITIAL WAGE GAP, AND RELATIVE WAGE GROWTH



Note: The figure plots the initial wage gap for men 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.

III. Model

In this section, we propose a theoretical framework that highlights the importance of labor market competition for immigrants' wage assimilation profiles. The main building block is a production function that combines two types of imperfectly substitutable skills: "general" skills that are portable across countries and "specific" skills that are specific to the host country. The latter include local language proficiency but also, more generally, the ability to successfully navigate the institutional and cultural environment of the host country. Individuals are assumed to supply a bundle of both types of skills, which are shifted by an idiosyncratic productivity term that translates skills into efficiency units. This term is a function of education and potential experience, with returns that are allowed to vary over time, for example due to skill-biased technological change.⁵ Upon arrival in the host country, immigrants supply the same amount of general skills as comparable natives but (typically) only a fraction of their specific skills. This fraction then changes as immigrants spend time in the host country.

⁵ For a similar approach outside of the migration context, see Jeong, Kim and Manovskii (2015), who scale their skill supplies (there defined as labor and experience) by a similar Mincerian productivity term.

A. Theoretical framework

Let G_t denote the aggregate supply of general skills and S_t the aggregate supply of specific skills in year t . Output Y_t is produced according to the following constant returns to scale production function:

$$Y_t = A_t \left(G_t^{\frac{\sigma-1}{\sigma}} + \delta_t S_t^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad (1)$$

where σ denotes the elasticity of substitution between general and specific skills, A_t represents total factor productivity, and δ_t is a shifter for the relative demand of specific skills that is allowed to vary over time. The aggregate supplies of skills are obtained by summing up the individual supplies of all workers in the economy. The marginal products and, hence, equilibrium prices of general and specific skills r_{Gt} and r_{St} are equal to:

$$r_{Gt} = A_t \left(\frac{Y_t}{A_t G_t} \right)^{\frac{1}{\sigma}} \quad \text{and} \quad r_{St} = A_t \delta_t \left(\frac{Y_t}{A_t S_t} \right)^{\frac{1}{\sigma}}, \quad (2)$$

so that the relative skill prices are given by $r_{St}/r_{Gt} = \delta_t (G_t/S_t)^{\frac{1}{\sigma}}$.

As noted above, we normalize recent male high school dropouts to supply one general skill unit and a fraction s of a specific skill unit, where $s = 1$ for natives. Let $n \equiv \mathbb{1}\{\text{native}\}$ denote an indicator variable that equals one if the individual is a native and zero otherwise. For immigrants ($n = 0$), the fraction s depends on their gender g , the number of years in the host country y , national origin o , cohort of entry c , education level e (which are a function of years of education E , though we omit this dependence in our notation for simplicity), and potential experience at the time of arrival $x - y$, where x denotes current potential experience (age - years of education - 6). In particular:

$$s_g(n, y, o, c, E, x) \equiv \begin{cases} 1 & \text{if } n = 1 \\ \theta_{1go} + \sum_{\ell=1}^3 \theta_{2\ell go} y^\ell + \theta_{3ge} + \sum_{\ell=1}^3 \theta_{4\ell ge} y^\ell \\ + \sum_{\ell=1}^3 \theta_{5\ell g} (x - y)^\ell + \theta_{6gc} + \sum_{\ell=1}^3 \theta_{7\ell gc} y^\ell & \text{if } n = 0. \end{cases} \quad (3)$$

By including the interactions between cubic functions of y and the dummies indicating origin, cohort and education, the skill accumulation process is allowed to vary across different origin groups ($\theta_{2\ell go}$), education groups ($\theta_{4\ell ge}$), and cohorts of entry ($\theta_{7\ell gc}$). Furthermore, since all the θ parameters in the $s(\cdot)$ function are gender-specific, the skill accumulation profiles are allowed to differ between immigrant men and immigrant women.

Both general and specific skills are scaled by an idiosyncratic productivity term h_{gt} , which we model in the traditional Mincerian way (see e.g. Jeong et al., 2015) as:

$$h_{gt}(E, x, \varepsilon) \equiv \exp \left(\eta_{0gt} + \eta_{1gt} E + \sum_{\ell=1}^3 \eta_{2\ell gt} x^\ell + \varepsilon \right). \quad (4)$$

This productivity term measures efficiency units and depends on the education level of an individual (η_{0gt}), a term that is linear in the years of education ($\eta_{1gt} E$), a cubic function

in potential experience ($\sum_{\ell=1}^3 \eta_{2\ell gt} x^\ell$), and an unobservable (to the econometrician) individual productivity term (ε) that is assumed to be independent of the other regressors in the model.⁶ For natives, whose supply of specific skills is normalized to one and thus time-invariant, the term h_{gt} describes how they acquire skills over time. As in Equation (3), all the η parameters are gender-specific so that the returns to education and experience are allowed to differ between men and women.

Our model accounts for two forms of skill-biased technological change. The time-varying parameters η_{1gt} , $\{\eta_{0get}\}_{e \in \mathcal{E}}$ and $\{\eta_{2\ell gt}\}_{\ell \in \{1,2,3\}}$ in Equation (4) capture standard skill-biased technological change that increases the demand for high-skilled workers and workers with different levels of experience. The δ parameters in Equation (1), in turn, capture any additional changes in the relative demand for specific skills. There is ample evidence in the literature that routine-biased technological change has increased the relative demand for non-routine tasks which are often relatively communication intensive (see e.g. Acemoglu and Autor, 2011, or Goos, Manning and Salomons, 2014). As a result, occupations such as managers or personal care workers, which tend to require good language skills, have expanded substantially over the last few decades, whereas more routine task intensive occupations such as production workers or operators have contracted. The term δ_t captures these types of relative demand shifts.

Workers are paid according to the skill bundles they supply. Their wages are given by:

$$w_{gt}(n, y, o, c, E, x, \varepsilon) = [r_{Gt} + r_{St} s_g(n, y, o, c, E, x)] h_{gt}(E, x, \varepsilon). \quad (5)$$

The wages of immigrant workers relative to those of observationally equivalent natives are:

$$\begin{aligned} \frac{w_{gt}(0, y, o, c, E, x, \varepsilon)}{w_{gt}(1, \cdot, \cdot, \cdot, E, x, \varepsilon)} &= \frac{r_{Gt} + r_{St} s_g(0, y, o, c, E, x)}{r_{Gt} + r_{St}} \\ &= \frac{1 + s_g(0, y, o, c, E, x, \varepsilon) \delta_t (G_t/S_t)^{\frac{1}{\sigma}}}{1 + \delta_t (G_t/S_t)^{\frac{1}{\sigma}}}, \end{aligned} \quad (6)$$

where the second equality is obtained by substituting the equilibrium skill prices by their counterparts in Equation (2). Equation (6) serves as the basis for our estimation and counterfactual simulations.

B. The labor market competition effect

Equation (6) identifies the two key drivers of immigrant wage assimilation. The first one is the rate at which $s_g(0, y, o, c, E, x)$ evolves as immigrants spend time in the host country (y), which reflects their skill accumulation process. The second one is the competition effect due to changing aggregate skill supplies G_t/S_t , which affects relative wages if and only if general and specific skills are imperfect substitutes in the production process

⁶The linear term in years of education thus allows for a different number of efficiency units for individuals with the same broad education level but different years of education.

$(\sigma < \infty)$ and if immigrants differ from natives in terms of the skill bundles they supply ($s \neq 1$). As our results below suggest, this competition effect can be amplified by changes in the relative demand of specific skills depending on the evolution of δ_t .

Consider how a change in the size of immigrant inflows affects relative wages, holding the skill accumulation process constant. Since immigrants disproportionately supply general skills upon arrival (when typically $s \ll 1$), their inflow increases the relative supply of general skills G_t/S_t and thus widens the wage gap relative to natives:

$$\frac{d \left(\frac{w_{gt}(0, y, o, c, E, x, \varepsilon)}{w_{gt}(1, \cdot, \cdot, \cdot, E, x, \varepsilon)} \right)}{d(G_t/S_t)} = \frac{[s_g(0, y, o, c, E, x) - 1]\delta_t[G_t/S_t]^{\frac{1-\sigma}{\sigma}}}{\sigma \left[1 + \delta_t[G_t/S_t]^{\frac{1}{\sigma}} \right]^2} \leq 0. \quad (7)$$

Larger immigrant arrival cohorts therefore face bigger initial wage gaps relative to natives, all else equal. Furthermore, these larger arrival cohorts also widen the wage gap of previous cohorts, especially if those cohorts arrived relatively recently. This is because more recent immigrants have had less time to accumulate specific skills in the host country (s is still small) and therefore tend to be more similar to the new arrivals in terms of their skill supplies. Intuitively, closer arrival cohorts are more substitutable in the labor market than cohorts arriving many years apart.

The observation that, at a given point in time, new immigrant inflows affect the wage gap of previous cohorts differently depending on the latter's time of arrival suggests that such inflows also affect the speed of wage assimilation for a given cohort. To understand the underlying mechanism, it is instructive to first consider the hypothetical scenario of a permanent increase in the aggregate relative skill supply G_t/S_t . For a given cohort, such an increase has a larger (more negative) impact in the early years after arrival:

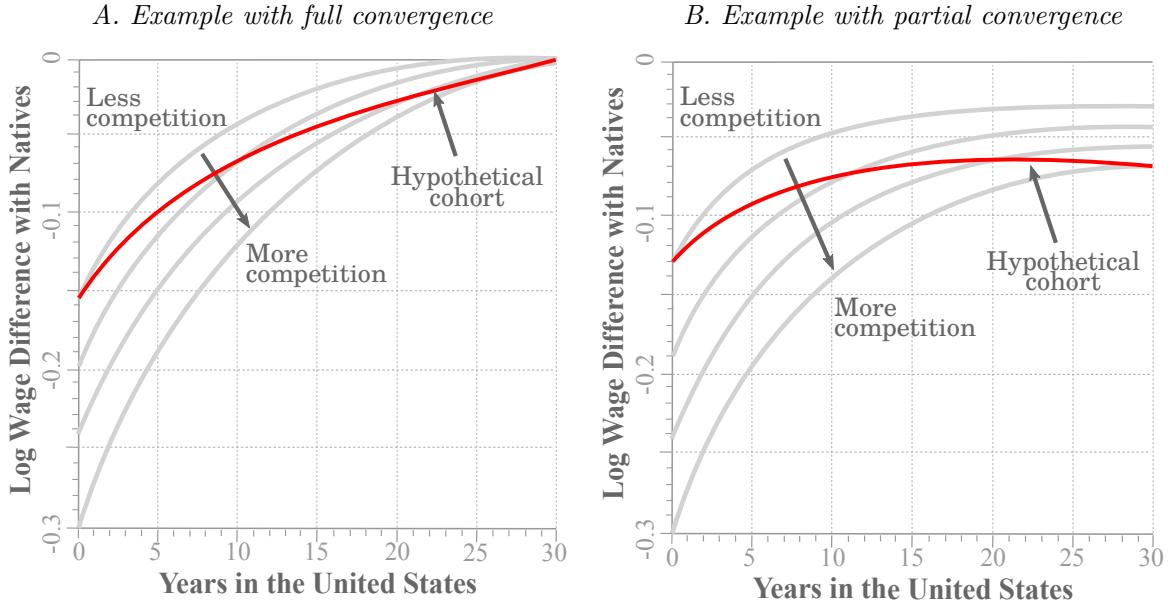
$$\frac{d}{dy} \left(\frac{d \left(\frac{w_{gt}(0, y, o, c, E, x, \varepsilon)}{w_{gt}(1, \cdot, \cdot, \cdot, E, x, \varepsilon)} \right)}{d[G_t/S_t]} \right) = \frac{d[s_g(0, y, o, c, E, x)]}{dy} \frac{\delta_t(G_t/S_t)^{\frac{1-\sigma}{\sigma}}}{\sigma \left[1 + \delta_t(G_t/S_t)^{\frac{1}{\sigma}} \right]^2} \geq 0, \quad (8)$$

which implies that the slope of the wage assimilation profile, and therefore the speed of wage convergence, increases for this particular cohort.

The gray lines in Figure 3 provide two examples of this hypothetical scenario. Figure 3A focuses on the case where immigrant wages eventually fully converge to those of natives ($s \rightarrow 1$), whereas Figure 3B depicts the case where, even in the long run, immigrant wages do not fully converge ($s \rightarrow < 1$). Each gray line represents the stylized wage assimilation profile for a different level of aggregate relative skill supplies, holding all other immigrant characteristics constant.

In line with Equations (7) and (8), the larger the aggregate relative skill supply G_t/S_t , the larger the initial wage gap and the faster the subsequent relative wage growth. In the case of full convergence (Figure 3A), immigrant wages eventually fully catch up with those of natives, regardless of the aggregate skill supplies in the economy. This is because, when

FIGURE 3. DYNAMIC COMPETITION EFFECT: A STYLIZED EXAMPLE



Note: The figure plots hypothetical convergence paths for different levels of competition. The colored line that cuts across the hypothetical convergence paths represents the assimilation profile one would observe in the data for a hypothetical cohort that experienced rising levels of competition across decades. The light gray lines represent the hypothetical assimilation path for each level of competition. The left figure shows an example that exhibits full long-run wage convergence, the right figure one in which the hypothetical cohort only converges partially to native wages in the long run.

their level of specific skills s approaches one, immigrants provide the same skill bundles as natives and are therefore no longer differentially affected by changing aggregate supplies (the numerator of Equation (7) becomes zero). Increasing labor market competition thus delays the process of wage convergence in this case but does not prevent it. A different picture emerges when immigrants' level of specific skills only partially converges to that of natives (Figure 3B). In this case, even in the long run, immigrants supply relatively fewer specific skills than natives and are therefore more negatively affected by increases in G_t/S_t .

While helpful for understanding the main mechanism at work, the previous scenario misses an important point. If new immigrant arrival cohorts become larger over time, the level of competition faced by a given cohort increases simultaneously. As a result, the positive impact on the speed of convergence described in Equation (8) is counteracted by a continuous downward shift of that cohort's relative wage profile as implied by Equation (7). We refer to this combined effect as the *dynamic competition effect*. To illustrate this, assume competition levels increase monotonically over time and that each grey line in Figure 3 represents the prevailing competition level at the start of a given decade. Suppose a newly arriving immigrant starts off on the line representing the lowest level of competition. This immigrant would then be observed on the next lower line ten years later, the next lower line twenty years later, and so on. The red lines depict the actual assimilation profiles one would then observe for an immigrant in such a dynamic scenario. Comparing these profiles with the ones representing the lowest level of competition, one can see that the dynamic competition effect in this example slows down the wage conver-

gence process, and that this dynamic effect is more consequential when immigrants' wages do not fully converge to those of their native counterparts in the baseline (Figures 3B).

To summarize, our framework shows that immigrants' wage assimilation is not only driven by the accumulation of host-country-specific human capital as often implicitly assumed in the literature, but also directly affected by changing aggregate skill supplies. While these supply changes are primarily due to variation in the size of immigrant inflows, the composition of these inflows also matters as different types of immigrants provide different amounts of skills, both at arrival and over time. This makes a given cohort's wage assimilation profile a complex function of past, present, and future immigrant inflows. In the empirical analysis that follows, we estimate the skill accumulation process of different arrival cohorts and quantify the relative importance of changing labor market competition, secular demand changes, and composition effects in explaining the observed variation in immigrant wage assimilation over time.

C. Connection with other models in the literature

Our theoretical framework is consistent with key insights from the recent literatures on the labor market impact of immigration and immigrant wage assimilation. Peri and Sparber (2009) and Llull (2018) argue that natives and immigrants are imperfect substitutes in aggregate production because they specialize in different types of occupations. In Peri and Sparber (2009), this is because immigrants have a comparative advantage in occupations that are intensive in the use of manual tasks while natives have a comparative advantage in occupations that are communication-intensive. In Llull (2018), immigrants endogenously self-select into blue-collar occupations, in which they are found to have a comparative advantage. Through the lens of our model, manual tasks (and blue-collar occupations) primarily require general skills, as cleaning, building, or gardening, for example, are similar across countries. In contrast, communication tasks depend largely on host-country-specific skills, such as language proficiency.

Dustmann, Frattini and Preston (2013) highlight the widespread phenomenon of immigrant downgrading in the labor market: a surgeon from Venezuela is unlikely to be able to practice as such in the United States if she does not speak English sufficiently well. As a result, she has to work in a different, often lower-paying job in the early years after arrival before attaining the required English language proficiency to move up the occupational ladder. Our model captures such initial downgrading by allowing immigrants to lack specific skills at the time of arrival ($s \ll 1$) and to then accumulate these skills while living in the host country. To account for heterogeneity across immigrant groups, we allow the extent of the downgrading to vary with immigrants' observed characteristics, including their gender, education, and origin.

The production function in Equation (1) differs from the standard nested CES function popularized in the immigration literature by Borjas (2003), Ottaviano and Peri (2012) and

Manacorda et al. (2012), in which native and immigrant workers constitute distinct labor inputs within narrowly defined skill cells (usually based on education and experience). In line with Dustmann et al. (2013) and Llull (2018), our approach has the advantage of not having to define *ex ante* who competes with whom based on education, experience, or nativity status. Instead, we allow for imperfect substitutability between natives and immigrants to arise, in a flexible way, from differences in their underlying skill sets.⁷

Contrary to the standard nested CES production function, an implicit assumption in our framework is that workers with different education levels and experience but the same ratio of general to specific skills (e.g. two natives) are perfect substitutes. As we show in Online Appendix D, this assumption can be easily relaxed and the model extended to account for additional forms of imperfect substitutability across individuals with different observable characteristics. Assuming a standard nested CES production function (Borjas, 2003), we show that, as long as the lowest-level nest is defined as the partition between general and specific skills, relative skill prices will be determined by the relative quantities of general and specific skills that are supplied in each skill group. As a result, the comparison between the wages of an immigrant and a comparable native defined in Equation (6) remains valid, except that the relevant aggregate supplies of general and specific skills must now be defined within skill groups rather than, more broadly, for the overall labor market as in our baseline model. In Section VII, we test the robustness of our results to an alternative specification of the production function that allows for imperfect substitutability between workers with different education levels.

In contemporaneous work, Galeone and Görlach (2022) use an alternative nested CES formulation to investigate how immigrant wage growth is affected by the increasing substitutability between immigrants and natives as the former spend time in the United States. In their formulation, the lower levels of the nesting structure are themselves CES-nested aggregations of immigrants belonging to different arrival cohorts (from more to less recent) and, on the lowest level, natives in the same skill group. With this formulation, as immigrants move across nests, their skill efficiency and substitutability with other factor inputs change, which jointly determines their wage growth. Similar to our paper, their analysis highlights that observed wage profiles of immigrants generally reflect both genuine skill accumulation and changes in aggregate factor supplies. However, there are also important differences to our paper. Their analysis focuses primarily on the evolution of immigrants' productivity and substitutability with natives rather than the roles that skill accumulation and labor market competition played for actual wage assimilation profiles in the United States. Their CES formulation also restricts the degree of substitutability between any given worker, native or immigrant, and two immigrants belonging to the

⁷ Because of its focus on relative wages, our framework also allows us to abstain from explicitly modeling the role of capital. Under the standard assumption that capital is separable from the other inputs in the production function, it is effectively absorbed in the total factor productivity term A_t in Equation (1) and irrelevant for the relative wages between immigrants and natives (see Online Appendix E).

same arrival cohort and skill group to be the same (skill groups are defined in terms of low and high education for the most part, with some robustness also distinguishing Hispanic and non-Hispanic origin). Our framework is more flexible, allowing any pair of individuals with different observable characteristics (e.g. newly arrived Mexican and Canadian workers) to have different elasticities of substitution with other workers, and to also be imperfectly substitutable with each other.

Finally, our model (approximately) nests as a special case the standard wage assimilation regression that has been widely estimated in the existing literature (e.g. Borjas, 2015). In particular, under perfect substitutability between immigrants and natives ($\sigma = \infty$), and abstracting from secular changes in the relative demand for specific skills ($\delta_t = 1$), log wages in our framework are given by:

$$\begin{aligned} \ln w_{gt}(n, y, o, c, E, x, \varepsilon) &= \ln A_t + \ln[1 + s_g(n, y, o, c, E, x)] + \ln h_{gt}(E, x, \varepsilon) \quad (9) \\ &\approx \tau_t + \eta_{0get} + \eta_{1gt}E + \sum_{\ell=1}^3 \eta_{2\ell gt}x^\ell + (1 - n) \left[\begin{array}{l} \theta_{1go} + \sum_{\ell=1}^3 \theta_{2\ell go}y^\ell + \theta_{3ge} + \sum_{\ell=1}^3 \theta_{4\ell ge}y^\ell \\ + \sum_{\ell=1}^3 \theta_{5\ell g}(x - y)^\ell + \theta_{6gc} + \sum_{\ell=1}^3 \theta_{7\ell gc}y^\ell \end{array} \right] + \varepsilon, \end{aligned}$$

where $\tau_t \equiv \ln A_t + n \ln(2)$ and, in the second line, we use the approximation $\ln(1 + s) \approx s$. Our framework can thus be viewed as a generalization of the standard assimilation model that allows for the possibility that immigrants and natives are imperfect substitutes.

IV. Identification and Estimation

Our data set consists of repeated cross-sections of native and immigrant workers with individual information on gender, age and education as well as, for immigrants, age at the time of arrival, country of origin and cohort of entry. We parameterize $\delta_t \equiv \exp(\tilde{\delta}t)$.⁸ The parameters to estimate are the elasticity of substitution between general and specific skills σ , the demand shift parameter $\tilde{\delta}$, the parameters governing the speed at which immigrants acquire specific skills θ , and the period-specific parameters η of the productivity function.

The following subsections provide a detailed discussion of how the different parameters of the model are identified and estimated from these data. We begin this discussion by introducing our identifying equations, which build on Equations (5) and (6). These equations identify all the parameters of the model under our maintained assumption that ε is independent of all idiosyncratic and aggregate observable variables in the model. We then discuss potential threats to the validity of the independence assumption and their implications for our analysis. This discussion also provides the basis for the different robustness checks we implement in Section VII. Finally, we outline the two-step procedure that we implement to estimate the parameters of the model.

⁸ To be precise, we define t as years since 1970. In Section VII, we also estimate our model with alternative specifications for δ_t , in which we include either a full set of time dummies or region dummies.

A. Identifying equations

We begin with the identification of the η parameters of the productivity term $h_{gt}(E, x, \varepsilon)$. Let i index individuals observed in labor market j_i and year t_i , where labor markets are defined as U.S. states. From Equation (5), log wages of natives are given by:

$$\ln w_i = \ln [r_{Gj_i t_i} + r_{Sj_i t_i}] + \eta_{0g_i e_i t_i} + \eta_{1g_i t_i} E_i + \sum_{\ell=1}^3 \eta_{2\ell g_i t_i} x_i^\ell + \varepsilon_i. \quad (10)$$

Considering a separate regression for each census year and normalizing η_{0get} for one gender-education group (male high school dropouts), the remaining gender-specific parameters η are identified as linear-regression coefficients given the independence assumption for ε , while $\ln [r_{Gj_i t_i} + r_{Sj_i t_i}]$ is identified for each market-period as the coefficient on the corresponding year-specific state dummy. With these parameters in hand, the unobservable individual productivity $\hat{\varepsilon}_i$ is identified as a residual from (10), and the aggregate supply of general and specific skill units by natives in a given market-period, \hat{G}_{jt}^N and \hat{S}_{jt}^N , are identified as the aggregation of the predictions $\hat{h}_{gt}(E, x, \hat{\varepsilon})$ for every native individual in the sample working in market j in period t . That is:

$$\hat{G}_{jt}^N = \hat{S}_{jt}^N \equiv \sum_{\{i: n_i=1; (j_i, t_i)=(j, t)\}} \omega_i \hat{h}_{g_i t_i}(E_i, x_i, \hat{\varepsilon}_i), \quad (11)$$

where ω_i are sampling weights and the sum aggregates all native individual observations in market-period (j, t) .

The θ parameters of the specific-skills function $s_g(0, y, o, c, E, x)$, the elasticity of substitution σ , and the relative demand shifter $\tilde{\delta}$, are identified from Equation (6) as the coefficients from a nonlinear regression where the dependent variable is the difference between the observed log wage of immigrant i and the predicted log wage for the same individual if she was a native:⁹

$$\begin{aligned} \ln w_i - \ln [\widehat{r_{Gj_i t_i} + r_{Sj_i t_i}}] - \ln \hat{h}_{g_i t_i}(E_i, x_i, 0) &= -\ln \left[1 + \exp(\tilde{\delta} t_i) \left(\frac{\hat{G}_{j_i t_i}}{\hat{S}_{j_i t_i}(\boldsymbol{\theta})} \right)^{\frac{1}{\sigma}} \right] \\ &+ \ln \left[1 + s_{g_i}(n_i, y_i, o_i, c_i, E_i, x_i; \boldsymbol{\theta}) \exp(\tilde{\delta} t_i) \left(\frac{\hat{G}_{j_i t_i}}{\hat{S}_{j_i t_i}(\boldsymbol{\theta})} \right)^{\frac{1}{\sigma}} \right] + \varepsilon_i, \end{aligned} \quad (12)$$

where $\boldsymbol{\theta}$ is the vector of θ parameters, general and specific aggregate skill units are the sums of their native and immigrant counterparts, $\hat{G}_{jt} \equiv \hat{G}_{jt}^N + \hat{G}_{jt}^I$ and $\hat{S}_{jt} \equiv \hat{S}_{jt}^N + \hat{S}_{jt}^I$, immigrant general skills are aggregated as in Equation (11), and immigrants' specific skills

⁹ Given that ε_i is unobservable to the econometrician, we use the prediction $\hat{h}_{g_i t_i}(E_i, x_i, 0)$ instead of the unfeasible $\hat{h}_{g_i t_i}(E_i, x_i, \varepsilon_i)$ on the left hand side of the expression, which leaves ε_i as the additive error term on the right hand side of the nonlinear regression.

are given by:

$$\widehat{S}_{jt}^I(\boldsymbol{\theta}) \equiv \sum_{\{i:n_i=0;(j_i,t_i)=(j,t)\}} \omega_i s_{g_i}(n_i, y_i, o_i, c_i, E_i, x_i; \boldsymbol{\theta}) \widehat{h}_{g_i t}(E_i, x_i, \hat{\varepsilon}_i). \quad (13)$$

Equations (12) and (13) explicitly emphasize the dependence of $s_g(0, y, o, c, E, x)$ and \widehat{S}_{jt} on $\boldsymbol{\theta}$. More generally, the aggregate supply of specific skills S_{jt} also depends on the number of immigrants and natives in market-period (j, t) and their observables.

These two equations identify $\boldsymbol{\theta}$, σ , and $\tilde{\delta}$ from cross-sectional variation on immigrants distributed across labor markets and census years, up to a set of normalizations of some θ parameters that avoid collinearity across the different terms included in $s(\cdot)$. Given our independence assumption on ε , the different parameters are identified as nonlinear least squares regression coefficients. Intuitively, $\boldsymbol{\theta}$ is identified off the wage differences between immigrants with different characteristics working in a given labor market, whereas σ and $\tilde{\delta}$ are identified off the variation across markets and over time. To see this more clearly, let us divide the nonlinear least squares estimation into two hypothetical steps. First, replace the aggregate terms of (12) by state-time dummies, namely $\exp(\tilde{\delta}t_i) \left(\widehat{G}_{j_i t_i} / \widehat{S}_{j_i t_i}(\boldsymbol{\theta}) \right)^{\frac{1}{\sigma}} \equiv \gamma_{j_i t_i}$. By inspection, $\boldsymbol{\theta}$ and the coefficients of these state-time dummies would be identified from (12) as nonlinear least squares coefficients.¹⁰ The unobservable individual productivities $\hat{\varepsilon}$ of the immigrants are also identified as the predicted residuals from this same equation. Given $\hat{\varepsilon}$, $\boldsymbol{\theta}$, and $\boldsymbol{\eta}$, the aggregate skill units are trivially identified from the aggregation of the predicted individual skill units of all individuals in the sample as in Equations (11) and (13). Armed with these identified terms, the second step then identifies σ and $\tilde{\delta}$ from the variation across states and time as regression coefficients of the following expression:

$$\ln \widehat{\gamma}_{j_i t_i} = \tilde{\delta}t_i + \frac{1}{\sigma} \ln \frac{\widehat{G}_{j_i t_i}}{\widehat{S}_{j_i t_i}}. \quad (14)$$

This equation shows that, with our baseline parameterization, variation from two state-time periods is enough to identify σ and $\tilde{\delta}$, and more state-time periods would allow us to identify richer parameterizations, as we do in our robustness checks. In our application, our available state-time periods provide us with many additional degrees of freedom, which we use to increase precision in our (single-step) NLS estimation of Equation (12).

B. Identifying assumptions and potential threats to their validity

Identification of the model parameters using the equations described above hinges on the crucial assumption of independence of ε with respect to G_{jt}/S_{jt} as well as the different covariates included in the $h(\cdot)$ and $s(\cdot)$ functions. It also relies on the model being correctly specified and the accurate measurement of the different aggregates. Since the implications and plausibility of these assumptions may not seem immediately obvious

¹⁰ By the same arguments, the $s(\cdot)$ function would be non-parametrically identified up to a constant.

given the structure of our model, we now provide additional intuition by discussing how relatively standard issues and concerns raised in the literature may or may not affect the validity of our estimates. While there are theoretical reasons to believe that the covariates in $h(\cdot)$ may be correlated with ε , several decades of estimating Mincer equations have shown that, in practice, the least squares estimation of the returns to education and experience from repeated cross-sections provides similar results as other instrumental variable approaches (Heckman, Lochner and Todd, 2006). Furthermore, as apparent from Equation (6), a biased estimation of our idiosyncratic productivity term would have a limited impact on assimilation profiles. We therefore focus our attention on deviations from our assumptions that could jeopardize the validity of our estimates of $\boldsymbol{\theta}$, σ and $\tilde{\delta}$.

Selective return migration. A large literature has discussed the implications of selective return migration for the estimation of immigrant wage assimilation profiles (see Dustmann and Görlach, 2015, for a survey). Selective return migration can bias the estimation of $\boldsymbol{\theta}$ in a similar way as regression coefficients are biased in the standard Roy model popularized by Heckman (1979).¹¹ To deal with this challenge, the ideal study would use longitudinal data that follow immigrants over time from their moment of entry (see Akee and Jones, 2019, and Rho and Sanders, 2021, for two very recent examples). Alternatively, one could try to address this problem by using stock-sampled data, where retrospective longitudinal data are obtained for immigrants who remained in the United States for a given minimum duration (see e.g. Lubotsky, 2007). Since neither of the two types of longitudinal data are available for the long time period covered by our analysis, we cannot fully account for the issue of selective return migration using the approaches of these earlier studies. Instead, we provide a battery of robustness checks in Section VII that show that selective return migration does not seem to have any appreciable influence on our results. These robustness checks involve sensitivity analyses based on estimates of return migration rates by Borjas and Bratsberg (1996), Rho and Sanders (2021), and our own calculations.

Undocumented migrants. While the Census is considered to offer one of the best systematic counts of immigrants in the United States, it is also known to undercount undocumented immigrants, many of which are low-skilled Mexicans (see e.g. Passel, 2007). The underrepresentation of these immigrants could affect our estimation results in two ways. First, the relative supply of general skills G_t/S_t would be understated. Given the identification arguments surrounding Equation (14), such measurement error would tend to affect the estimation of σ and $\tilde{\delta}$ more than the estimation of $\boldsymbol{\theta}$. Second, undocumented immigrants may accumulate skills at different rates than legal immigrants. Ignoring this

¹¹ In particular, $\mathbb{E}[\varepsilon|d = 1] = \lambda(\Pr[d = 1|n, y, o, c, E, x, \mathbf{z}])$, where \mathbf{z} is a vector of other potential determinants of the return migration decision, and $\lambda(\cdot)$, following the general formulation in Das, Newey and Vella (2003), is an unknown function. Return migration may induce a bias if $\lambda(\cdot)$ is a non-trivial function of any of the covariates included in Equation (12).

heterogeneity would imply that we identify a weighted average of the true differential effects of each variable (the θ parameters) on assimilation. Additionally, the undercounting of undocumented migrants may bias this weighted average towards the assimilation profiles of documented migrants, potentially overestimating skill assimilation. In Section VII, we provide several robustness checks that use the method proposed by Borjas (2017) to identify potentially undocumented migrants. This information, in combination with estimates in the literature on the number of undercounted undocumented immigrants in each Census, allows us to assess the importance of each of these two channels.

Networks. A larger concentration of immigrants in a given market may not only affect relative skill prices as predicted by our model but also directly reduce the speed at which immigrants accumulate specific skills (see e.g. Borjas, 2015, or Battisti, Peri and Romiti, 2021). This may happen, for example, because of the formation of immigrant employment networks or residential ghettos that make learning English and other U.S.-specific skills expendable. In terms of our model, this specification issue would call for the inclusion of a variable that directly accounts for the size of the relevant network inside the $s(\cdot)$ function. Not including such a variable could generate an omitted variable bias if the network size were correlated with the aggregate skill supplies, potentially leading to an overestimation of the importance of labor market competition. We provide several tests for the sensitivity of our results to such an omission in Section VII by including different proxies for the relevant network size in the $s(\cdot)$ function.

Endogenous location of immigrants. It is well known that immigrants do not settle randomly across geographical areas (e.g., see Card, 2001). The type of endogeneity that is often discussed in the immigration literature refers to the possibility that immigrants tend to cluster in areas where wages are relatively high. In our model, this would be reflected by immigrants sorting into regions with high total factor productivity, A_t . Such endogenous sorting would not affect our estimation since we are interested in relative wages (rather than wage levels) which do not depend on A_t (as apparent from Equation (12)). A second type of concern could be that immigrants sort into places where there is less relative demand for U.S.-specific skills. In terms of our model, this situation would occur if δ_t was state-specific, as in $\delta_{jt} \equiv \tilde{\delta}_t + \xi_{jt}$. If state-periods with low ξ_{jt} attract more immigrants, this would generate a negative correlation between ξ_{jt} and G_{jt}/S_{jt} . Given the identification discussion around Equation (14) above, this would lead to a downward bias in the estimation of $1/\sigma$, and hence an overestimation of σ . In that case, our results would underestimate the importance of the competition effects, and, therefore, be conservative. In Section VII, we explore the robustness of our findings to the use of common shift-share instrumental variables as proposed by Card (2001).

Other model specification issues. Even if $s(\cdot)$ is non-parametrically identified from Equation (12) up to a constant, as noted in Footnote 10, the correct specification of

the model is an important assumption in any structural estimation. In Section VII, we provide additional analyses of the sensitivity of our results to different specifications of the model. In particular, we consider alternative parameterizations of δ_t and $s(\cdot)$ and an alternative nesting structure that allows for imperfect substitutability between individuals with different education levels, as discussed at the end of Section III.

C. Estimation

Our estimation proceeds in two steps. In the first step, we obtain the parameters of the productivity term $h_{gt}(E, x, \varepsilon)$ by estimating the wage regressions described in Equation (10) using observations for native men and women only. We estimate a separate regression for each census year, thus allowing the returns to education and experience to vary over time. Since labor markets are defined as U.S. states, we include state dummies in each of the regressions to identify the relevant skill prices. In the second step, we first compute \widehat{G}_{jt}^N and \widehat{S}_{jt}^N using the expression in Equation (11) and the worker-specific left-hand-side terms of Equation (12) using the estimated parameters from the first step. We then estimate the remaining parameters by nonlinear least squares, fitting Equation (12) to the subsample of immigrant workers. For each candidate parameter vector at which the criterion function is evaluated during the execution of the NLS estimation algorithm, we use Equation (13) to update \widehat{S}_{jt}^I , and an expression analogous to Equation (11) to update \widehat{G}_{jt}^I . We report both regular standard errors and standard errors that account for the estimation error in the first step of the analysis (see Online Appendix F for details).

V. Estimation Results

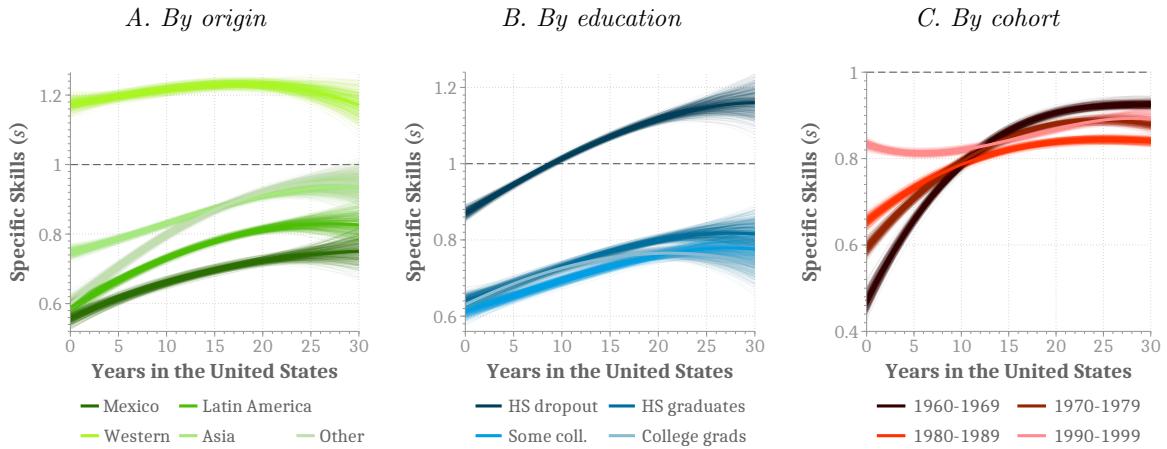
This section presents an overview of our baseline estimation results. Since most of the earlier literature relevant to our findings has examined the wage assimilation profiles of immigrant men ($g = 0$), we focus on this particular group in the following sections. The corresponding tables and figures for women ($g = 1$) are provided in Online Appendix N.

Table G1 in Online Appendix G reports the parameter estimates for the Mincerian productivity function $h_{0t}(E, x, \varepsilon)$. The estimates are consistent with previous findings in the literature (see e.g. Heckman, Lochner and Todd, 2006, for a survey), with the returns to college education increasing over time and the experience profiles showing the standard concave pattern, flattening after around 25 years of experience.

Table G2 reports the parameter estimates describing the process through which male immigrants accumulate specific skills, $s_0(0, y, o, c, E, x)$. Since these estimates are difficult to interpret in isolation, we plot the predicted skill accumulation profiles of different types of immigrants in Figure 4. The baseline type in all figures is a synthetic individual with the average characteristics of all immigrant men in the sample, except for the characteristic that is varied in each panel.¹² Figure 4A shows the evolution of specific skills by region

¹² Figure G1 in Online Appendix G (men) and Figure N6 in Online Appendix N (women) show separate

FIGURE 4. SKILL ACCUMULATION PROFILES, $s_0(0, y, o, c, E, x)$



Note: The figure displays predicted skill accumulation profiles for different groups based on the estimates reported in Table G2. The baseline individual in all figures is a synthetic individual with the average characteristics of all immigrant men 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 the first-step estimation error as derived in the Online Appendix.

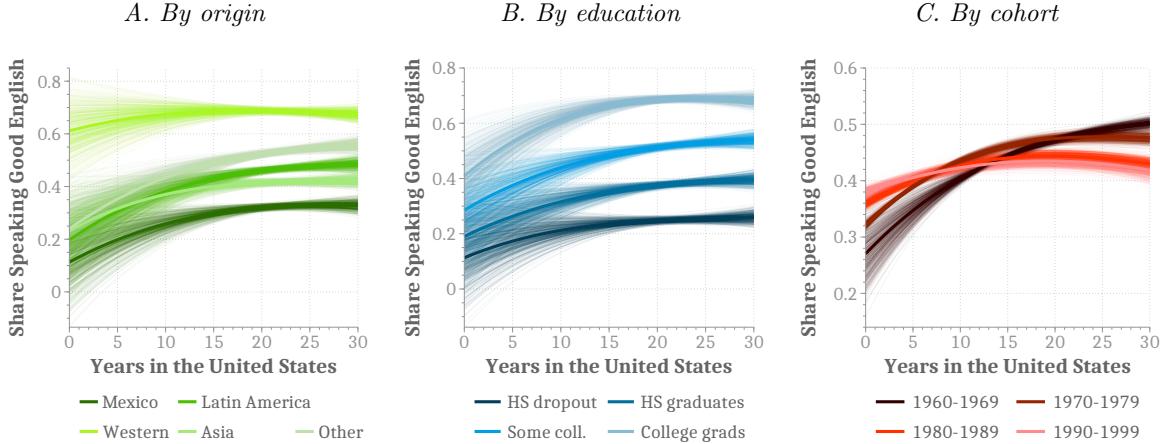
of origin. Except for Western immigrants, all groups arrive with specific skills that are significantly lower than those of comparable natives. Over time, all groups then accumulate additional skills so that the gap relative to natives shrinks significantly. Figure 4B depicts the corresponding profiles by level of education. Relative to similarly educated natives, immigrant high school dropouts arrive with the highest level of specific skills, suggesting that they are more similar to native dropouts than, for example, immigrant college graduates are to their native counterparts.¹³ Figure 4C plots the skill accumulation profiles by arrival cohort.¹⁴ While the 1960s cohort faced a substantial initial skill gap of around 53.0 percent, this gap narrowed to 40.8 percent for the 1970s cohort, 34.6 percent for the 1980s cohort, and 16.8 percent for the 1990s cohort. Conditional on origin and education, more recent immigrant cohorts are thus more positively selected in terms of unobservable skills than earlier cohorts. However, Figure 4C also shows that the speed of specific skill accumulation declined for more recent cohorts, which could reflect diminishing returns to investments in specific skills. After 20–30 years, all arrival cohorts perform similarly well, having accumulated 84.4–92.5 percent of the specific skills of comparable natives.

skill accumulation profiles for each of the 80 immigrant groups distinguished in our analysis (4 arrival cohorts x 5 origin groups x 4 education levels).

¹³ Contrary to all other education groups who only reach about 70–80 percent of their native counterparts' specific-skill levels, immigrant high school dropouts manage to not only reach but surpass the native level of specific skills after about 10 years in the country. This could be due to differential selection into the immigrant and native high school dropout populations. However, note that the synthetic average immigrant has a higher weight of Western immigrants and lower weight of Mexican immigrants than the average high school dropout in the data. Since Western immigrants perform particularly well, this explains to some extent the high specific-skill levels of the high school dropout group in Figure 4B. The same applies to Western immigrants in Figure 4A since they are more educated than the average immigrant.

¹⁴ We omit the pre-1960s and post-2000s cohorts in Figure 4C since we only observe them partially in the data. They are, however, both accounted for in the estimation (as shown in Table G2).

FIGURE 5. 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 $s_0(\cdot)$ and year dummies on a sample of men. The baseline individual in all figures is a synthetic individual with the average characteristics of all immigrant men 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.

The finding of a narrowing gap in specific skills at the time of arrival could be a reflection of an increasingly more selective U.S. immigration policy (see e.g. Llull, 2023, and Rho and Sanders, 2021) or an intensifying globalization process that makes U.S.-specific skills, in particular English language skills, more abundant among potential migrants. Using information about English language proficiency available in the Census data from 1980 onward, we provide additional evidence supporting this interpretation. Following Borjas (2015), we define a dummy variable that equals one if immigrants declare to either speak English very well or only speak English, and regress this dummy on all the elements included in the skill accumulation function $s(\cdot)$ as well as year fixed effects. The predicted language profiles from this regression, depicted in Figure 5, show a close correspondence with the estimated skill accumulation profiles in Figure 4, suggesting that the latter indeed reflect changes in the specific skills of immigrant workers.¹⁵

The estimates of the remaining parameters σ and $\tilde{\delta}$ are reported in Table 2. Our finding for $\tilde{\delta}$ indicates a secular shift in the relative demand for specific skill, which raises relative skill prices, $\ln(r_{St}/r_{Gt})$, by 1.7 log points per year. These demand shifts further amplify the relative wage impacts generated by immigration-induced increases in the relative supply of general skills (see Equation (6)). Our baseline estimate of the elasticity of substitution between general and specific skills σ is a precisely estimated 0.021. Interpreting this value

¹⁵ Note that the results by education level in Figure 5B are not directly comparable to those in Figure 4B since the latter represent the U.S.-specific skills of an immigrant relative to a native worker with the same level of education whereas the former depicts the average English proficiency of immigrants by education level. Not surprisingly, individuals with higher levels of education are more proficient in English at arrival and also accumulate further language skills at a faster rate. This does not contradict the patterns shown in Figure 4B. Given that language-specific skills tend to be more important in high-skill occupations, the difference in specific skills relative to natives with the same level of education may very well be smaller for low-educated than high-educated immigrants.

TABLE 2—ELASTICITY OF SUBSTITUTION σ , AND RELATIVE DEMAND SHIFT δ_t

	Point estimate	Standard error	Corrected standard error	Confidence interval
Elasticity of substitution (σ)	0.021	(0.002)	[0.002]	[0.018,0.026]
Trend in relative demand ($\tilde{\delta}$)	0.017	(0.002)	[0.002]	

Note: The table presents parameter estimates for the elasticity of substitution between general and specific skills σ , and for the demand shift parameter $\tilde{\delta}$. Both parameters are defined in Equation (1) and are estimated by NLS as described in Section IV.C. Corrected standard errors account for the additional error introduced in the first stage and are derived in Online Appendix F.

is not straightforward given the absence of comparable estimates in the literature. To get a sense of the plausibility of this magnitude, we link our estimate to the more familiar elasticity of substitution between natives and immigrants that has been estimated in the prior migration literature. As shown in Online Appendix H, within our framework, the elasticity of substitution between an average native and immigrant can be expressed as:

$$\varepsilon_{NI} = \frac{\sigma \left[1 + \tilde{s}_I \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \right] \left[1 + \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \right]}{(1 - \tilde{s}_I) \delta \left(\frac{G}{S} \right)^{\frac{1}{\sigma}} \left(\frac{N\bar{h}_N}{S} - \frac{N\bar{h}_N}{G} \right)}, \quad (15)$$

where \bar{h}_N is the average idiosyncratic productivity of natives and \tilde{s}_I is the (weighted) average of immigrants' specific skill units. This elasticity tends to infinity when σ approaches infinity or \tilde{s}_I converges to one, i.e. when general and specific skills are perfectly substitutable or when immigrants have the same specific skills as natives.

Aggregating general and specific skills across all states to the national level and evaluating Equation (15) at our baseline parameter estimates, we obtain (inverse) elasticities of substitution of 0.012 for the year 1990, 0.017 for 2000, and 0.020 for 2010. These elasticities are comparable in magnitude to the estimate of 0.034 (s.e. 0.008) that Ottaviano and Peri (2012) obtain for the period 1990-2006.¹⁶ Contrary to their estimates, however, the implied elasticity of substitution between natives and immigrants in our framework is not unique but depends on the size and skill composition of the native and immigrant populations considered. In Figure I1 in Online Appendix I, we illustrate this by documenting the significant variation in immigrant-native substitutability across U.S. states and periods. While in many states, immigrants and natives are close to perfect substitutes, in some large states such as Florida, Texas and Arizona, the inverse elasticity of substitution is substantially larger, reaching values of around 0.03.

¹⁶ The elasticities of substitution reported 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.

VI. Labor Market Competition and Immigrant Wage Assimilation

Our estimated model provides us with a useful tool to quantify the importance of the labor market competition channel using simulations. Before we do that, we evaluate the ability of our framework to reproduce the well-known wage assimilation profiles shown in Section II.B. For this purpose, we repeat the type of analysis that underlies Figure 1 but now use individuals' *predicted wages* from our model as the dependent variable rather than their actual wages. Since we consider the residuals ε_i as part of an individual's productivity, the baseline model-based wage predictions are, by construction, identical to the actual wages observed in the data. To show that our model performs well in predicting relative wage profiles even without relying on this particular treatment of the residuals, we set those residuals equal to zero for all immigrants in the sample, predict their wages using our model estimates, and then plot the resulting assimilation profiles as dashed lines in Figure J1 in Online Appendix J.¹⁷ Reassuringly, these profiles are very similar to the solid lines that reproduce the benchmark profiles presented in Figure 1, indicating that our model does a very good job in fitting the key features of the data. We also depict the predicted assimilation profiles obtained after 200 random reshuffles across individuals of the estimated residuals $\hat{\varepsilon}_i$. With the exception of some minor deviations for the 1990s cohort, all the resulting profiles are located closely around their benchmark profiles, lending further support to our estimated model. We also investigate the ability of our model to predict wage gaps and relative growth across states in and out of our sample. Figure J2 in Online Appendix J contrasts the actual initial wage gaps and the relative wage growth rates over the first 10 years across state-cohort cells (presented in Figure 2) with their predicted counterparts based on our model estimates. Panel I depicts in-sample predictions, Panel II out-of-sample predictions, which we obtain from estimated versions of the model in which we exclude the specific state for which we make the predictions from the estimation sample following a leave-one-out approach. Both in-sample and out-of-sample, we find a good fit between our model predictions and the data.

With the knowledge that our model can reproduce the observed assimilation profiles in the data very well, we now quantify the importance of the labor market competition effect in shaping these profiles. We start with an aggregate assessment of the role of labor market competition before we then document, in Section VI.B, the significant heterogeneity in the extent to which competition effects have impacted different types of immigrants.

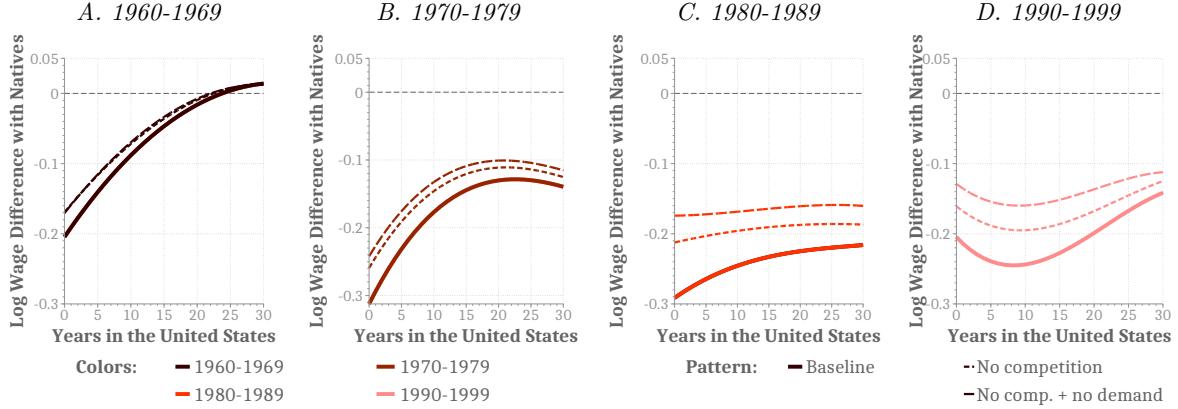
A. The role of labor market competition

To evaluate the extent to which changing labor market competition can explain the unconditional wage assimilation profiles depicted in Figure 1, we simulate each individual's

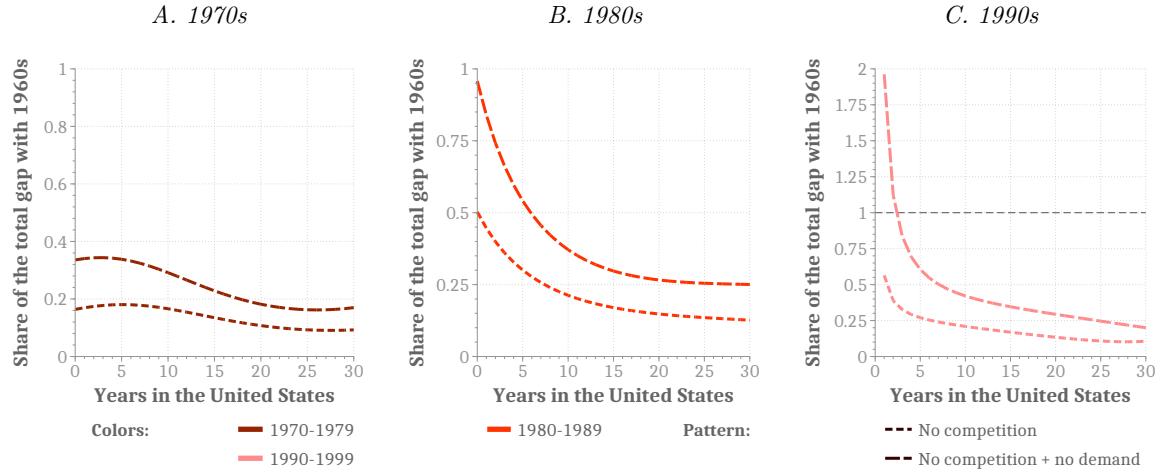
¹⁷In particular, for both the observed and predicted wages, we regress wages on cohort and year dummies, a third order polynomial in age interacted with year dummies, and a third order polynomial in years since migration interacted with cohort dummies.

FIGURE 6. WAGE GAP DECOMPOSITION: COMPETITION AND DEMAND EFFECTS

I. Assimilation profiles under different scenarios



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



Note: The figure shows baseline and counterfactual predictions of the unconditional wage gaps between native and immigrant men 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 1, estimated on the predicted wages under the different counterfactual scenarios. The baseline profiles (solid) correspond to the solid lines in Figure 1. 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 wage gap of each cohort relative to that of the 1960s cohort that is closed in each counterfactual scenario.

wage under two counterfactual scenarios. In the first, we assume there is no competition effect ($\sigma = \infty$). In the second, we additionally hold the relative demand for specific skills constant at the 1970 level (i.e. we set $\tilde{\delta} = 0$) to see how these demand shifts interacted with the competition effect. For both sets of predicted wages, we then run regressions like those underlying Figure 1 and present the resulting assimilation profiles in Figure 6.

Panel I in Figure 6 presents the assimilation profiles estimated using the baseline wage predictions (solid lines), the predicted wages without the competition effects (short-dashed lines), and the predicted wages without both the competition and the demand effects (long-dashed lines). Each graph represents one cohort and therefore corresponds to one of the solid lines plotted in Figure 1. To quantify the role of the competition and demand effects, Panel II depicts the fraction of the baseline gap between each cohort's assimilation profile and the profile of the 1960s cohort that is closed in each of the two counterfactual

TABLE 3—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	-20.5	-8.8	-1.6	1.4	-6.4	
1970-1979	-31.2	-17.7	-13.0	-14.0	-17.3	
1980-1989	-29.1	-24.6	-22.5	-21.6	-24.0	
1990-1999	-20.5	-24.4	-19.9	-14.2	-20.8	
<i>ii. No competition effect</i>						
1960-1969	-16.9	-7.2	-0.9	1.4	-5.1	
1970-1979	-25.9	-14.6	-11.1	-12.5	-14.6	
1980-1989	-21.2	-19.6	-18.7	-18.7	-19.4	
1990-1999	-16.1	-19.5	-16.8	-12.5	-17.1	
<i>iii. No competition and no demand effects</i>						
1960-1969	-17.1	-7.0	-0.8	1.2	-5.0	
1970-1979	-24.2	-13.3	-10.1	-11.5	-13.4	
1980-1989	-17.4	-16.9	-16.1	-16.0	-16.5	
1990-1999	-12.9	-16.0	-13.7	-11.2	-14.1	
B. Percent of the baseline wage gap with the 1960s cohort closed by each channel						
<i>i. No competition effect</i>						
1970-1979	16.4	16.6	10.7	9.3	13.5	
1980-1989	50.3	21.3	14.8	12.6	21.3	
1990-1999	—	20.9	13.4	10.7	19.2	
<i>ii. No competition and no demand effects</i>						
1970-1979	33.6	29.2	18.2	17.0	24.3	
1980-1989	95.7	37.1	26.6	25.0	38.8	
1990-1999	—	42.1	29.4	20.0	44.8	

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 6.

scenarios. Table 3 summarizes the information in Figure 6, reporting the wage gaps for each cohort and counterfactual scenario at the time of arrival and after 10, 20 and 30 years in the United States, with the last column showing the average across all years.

The results in Figure 6 and Panel B of Table 3 show that the competition effect alone can explain 16.4 and 50.3 percent of the increase in the *initial* wage gap of the 1970s and 1980s cohorts relative to the 1960s cohort. In combination with shifts in relative skill demands, these numbers increase further to 33.6 and 95.7 percent, respectively.¹⁸ More labor market competition and rising demand for specific skills thus explain almost the entire increase in the initial wage gap between the 1960s cohort and the 1980s cohort. For the 1990s cohort, the initial wage gap is estimated to be even smaller than that of the 1960s cohort once competition and demand effects are accounted for. This improvement relative to previous cohorts could be due to more selective immigration policies at the time, which raised the education level of immigrants and shifted their origin composition,

¹⁸ Since the difference in initial wage gaps between the 1960s and the 1990s cohort is essentially zero (both cohorts face an initial wage gap of 20.5 log points), the corresponding estimate for the 1990s cohort is very large in magnitude and would be difficult to graph in Panel II of Figure 6. We therefore exclude this particular data point from Plot C of Panel II and Panel B of Table 3.

and increased globalization, which may have improved English language proficiency and other U.S.-specific skills among immigrants of a given education and origin.

Turning to the full shape of the assimilation profiles, it is clear that neither the competition effect nor the changes in relative demand can explain the flattening of the assimilation profiles across cohorts. In fact, once these effects are netted out, the slope of the assimilation profiles is largely unchanged for the 1970s cohort but smaller for the 1980s and 1990s cohorts relative to the baseline. Figure 4, in conjunction with Figure 5, provides a plausible explanation. Conditional on education and origin, recent cohorts arrive in the United States with better English language proficiency (and other specific skills) which is likely to have slowed down their skill accumulation given that returns to human capital investments are known to be diminishing. In addition, the education and origin composition shifted towards groups that have a harder time accumulating specific skills.

As shown in the last column of Panel B in Table 3, averaged across years since migration, the competition effect explains roughly one fifth of the increase in the native-immigrant wage gap across cohorts. When evaluated in conjunction with the shifting demand effects, this magnitude increases to about one third, suggesting an important role for these two mechanisms in explaining variation in immigrant wage assimilation profiles across cohorts.

The remaining differences in wage gaps across cohorts can be attributed to changes in immigrants' origin composition, educational attainment and quality in terms of unobservables. To get a sense of the relative importance of these three channels, we extend our decomposition in Panel I of Figure 6 in two steps. In the first, after shutting down the competition effect and holding demand constant, we additionally fix unobservable cohort quality at the level of the 1960s cohort. In the second step, we then also hold the origin composition of immigrants constant at the 1960s level. The respective predicted assimilation profiles are depicted as dotted and short-dashed lines in Figure K1 in Online Appendix K. Since cohort quality in terms of unobservables improved over time according to our estimates (see Figure 4), holding it constant at the 1960s level generally leads to a downward adjustment in the predicted assimilation profiles, especially for the 1980s and 1990s cohorts and the initial years after arrival. Holding the origin composition constant, in contrast, leads to large upward shifts in the profiles, indicating that changes in origin composition are an important driver of the deterioration in immigrant assimilation profiles. As shown in Table K1, averaged across years since arrival, changes in the origin composition of immigrants explain 39.0 and 71.6 percent of the increase in the native-immigrant wage gap across cohorts for the 1970s and 1980s cohort, while changes in the educational attainment of immigrants explain another 32.2 and 13.5 percent.¹⁹

¹⁹ Note that the fixing of the origin composition at the level of the 1960s cohorts already accounts to a large extent for the shifts in educational attainment across immigrants cohorts. By weighting up Western immigrants and weighting down Mexican and Asian immigrants, we already give more weight to highly educated immigrants in the estimations underlying the "no origin" counterfactual profiles in Figure K1. The remaining contribution of education referred to in the final column of Table K1 is therefore due to

B. Heterogeneity across individuals

The results from the previous section show that increasing labor market competition and rising demand for specific skills had an important impact on average cohort-specific assimilation profiles. We now show that these average impacts conceal substantial heterogeneity across different types of immigrants. We first illustrate this through a few meaningful examples. Figure 7 shows wage assimilation profiles under different counterfactual scenarios for three specific groups of immigrants: Mexican high school dropouts, Latin American high school graduates, and Western college graduates. We select these groups because they each represent an important contingent of the U.S. immigrant population, and because they are characterized by very distinct assimilation profiles. To focus attention on the role of labor market competition, we consider for each group a representative immigrant who arrived with the unobservable skills of the 1960s cohort, was exposed to the demand effects (δ) experienced by that cohort, and had potential experience upon arrival equal to the average of all immigrant men in the sample (11.2 years).

In all plots of Figure 7, the thick dashed line represents predicted wage assimilation profiles in the absence of any competition effects, i.e. when $\sigma = \infty$. The remaining colored lines show how the relative wages of the respective immigrants would have evolved if they had faced the same dynamic labor market competition as the corresponding arrival cohorts listed in the legend.²⁰ Plots A depict the relative wage profiles under these counterfactual scenarios. For example, a Mexican high school dropout, would initially earn 26.6 log points less than an equivalent native if relative skill supplies were irrelevant for skill prices, and would fully assimilate within about 25 years (Plot A, Panel I, thick dashed line). Plots B display the relative wage growth, similar to Panel B of Figure 1. Plots C show the difference between the counterfactual profiles and the no-competition benchmark, as well as (in gray), the hypothetical assimilation profiles had the level of competition observed in each census year remained constant across all subsequent years.²¹

Panel I of Figure 7 documents a sizable impact of labor market competition on the wage assimilation profiles of Mexican high school dropouts. If the reference individual (who belongs to the 1960s cohort) had faced the same level of competition as, for example, the 1990s cohort, his initial wage gap would have been 9.3 log points bigger (the difference

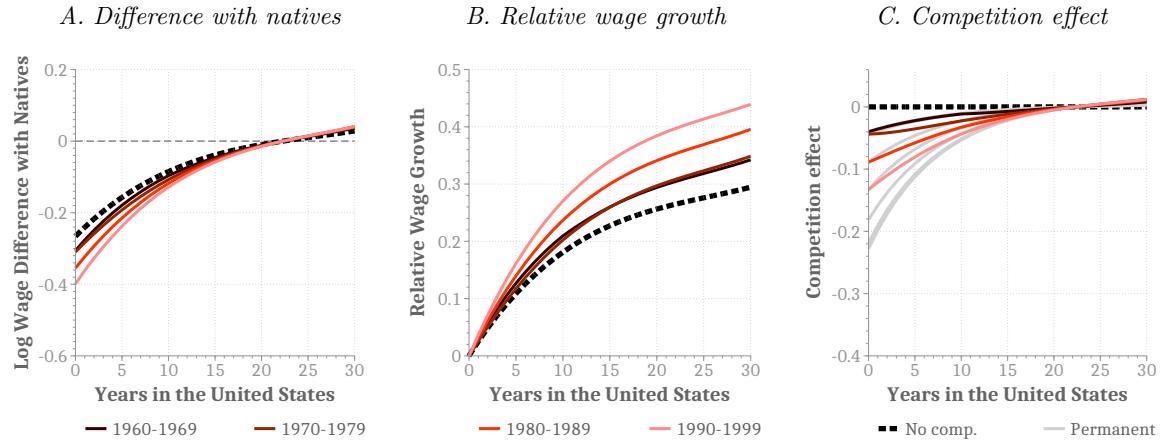
changes in educational attainment within the different origin groups over time.

²⁰ In practice, we simulate these assimilation profiles based on Equation (6) and our estimated parameters, using the corresponding cohort-specific sequence of $(G_t/S_t)^{1/\sigma}$, which is the yearly weighted average of all state-specific relative skill supplies using immigrant stocks as weights. For example, to simulate the counterfactual assimilation profile “1980–1989”, we assume that the relevant relative skill supplies at arrival were those prevailing in 1980, after 10 years in the United States those prevailing in 1990 and so on. For the intermediate years, the census-specific relative supplies are linearly interpolated.

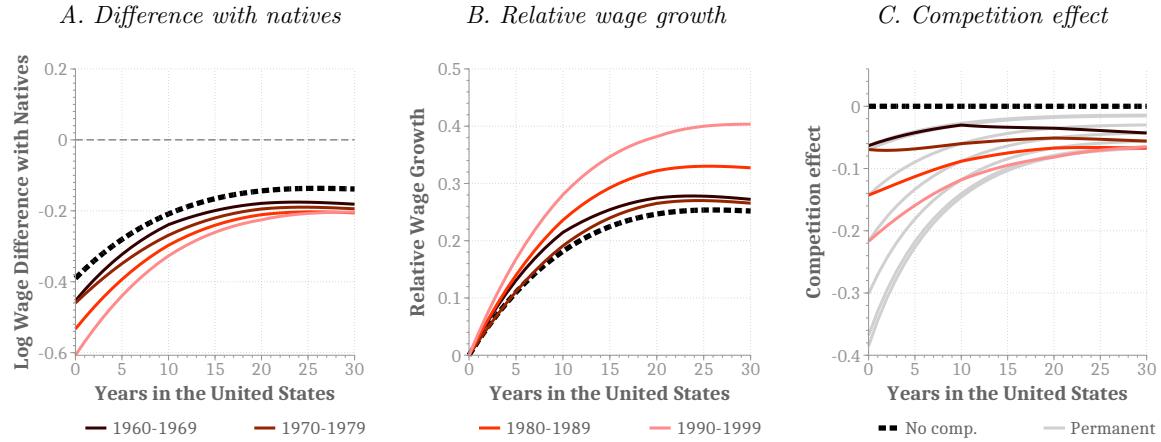
²¹ The gray lines thus represent the case of a permanent increase in relative skill supplies (as discussed in Section III.B) and correspond to the gray lines in Figure 3. Note that, from top to bottom, the three lowest gray lines in Plots C of Figure 7 represent the hypothetical profiles under the level of competition prevailing in the years 2000, 2020, and 2010 respectively. The small reversal between 2010 and 2020 reflects the fact that the competition level slightly declined during that decade, consistent with the well-known slowdown in migration to the United States over those years (see Table 1).

FIGURE 7. HETEROGENEOUS LABOR MARKET COMPETITION EFFECTS: EXAMPLES

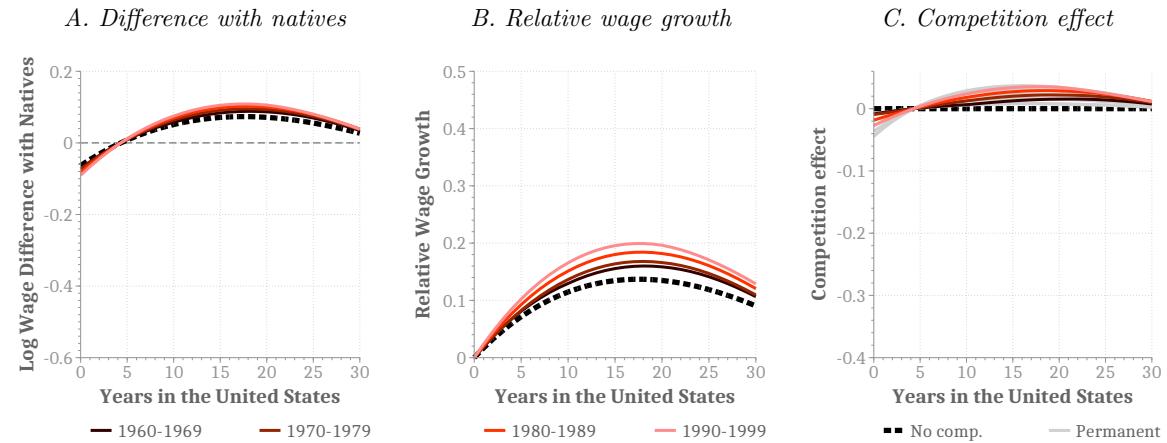
I. Mexican high school dropout



II. Latin American high school graduate



III. Western college graduate



Note: The figure shows wage assimilation profiles of selected immigrants (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 that cohort, and arrived with potential experience equal to the average of all immigrant men 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 fixed competition level prevailing at the time of arrival (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.

between the lines labeled “1960–1969” and “1990–1999” in Plot C). If he had faced the competition level of 2010, the impact would have been even larger, with the initial wage gap widening by 18.8 log points (the difference between the line “1960–1969” and the bottom gray line in Plot C). As shown in Plot B, however, the competition effect would also have increased the speed of wage convergence for the Mexican high school dropout, which would have completely offset the large negative impact at the time of arrival after around 25 years. In the long run, labor market competition effects do not prevent this particular type of immigrant from fully converging to his native counterpart.

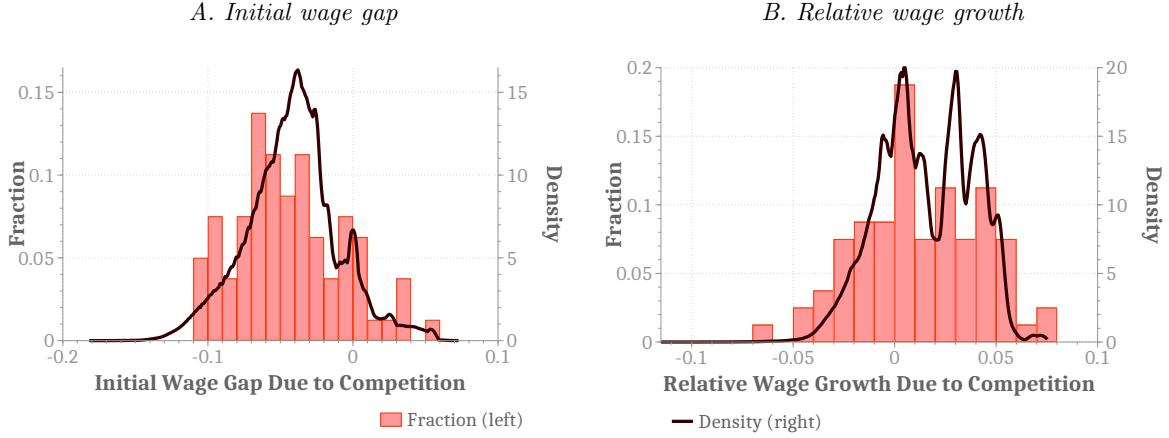
Panel II shows the corresponding profiles for a representative Latin American high school graduate. The key difference between this immigrant and the Mexican high school dropout of Panel I is that Latin American high school graduates never fully assimilate ($s \rightarrow < 1$). This has important consequences in the context of rising labor market competition since these immigrants’ relative wages will then continue to be affected by changing relative skill prices even in the long run. As shown in Plot C of Panel II, if the reference Latin American high school graduate had faced the same level of competition as the 1990s cohort, not only would his initial wage gap have increased by 15.4 log points, but he would also have ended up with a 2.2 log-point larger wage gap in the long run (the difference between the lines labeled “1960–1969” and “1990–1999” at the time of arrival and after 30 years, respectively). Consistent with our stylized example in Figure 3B, for this particular type of immigrant, the dynamic competition effect therefore inhibits overall wage assimilation.

Panel III depicts the counterfactual assimilation profiles for a representative Western college graduate. The key feature of this specific immigrant is that his skills closely resemble those of natives already at the time of arrival. As a result, changes in skill prices have little impact on his relative wage profile, both in the short and in the long run.

Figure 8 illustrates the full heterogeneity in the extent to which different types of immigrants are affected by the competition effect. The vertical bars show, for the 80 immigrant groups distinguished in the analysis (4 arrival cohorts \times 5 origin groups \times 4 education levels), the impact of the competition effect on each group’s initial wage gap (Panel A) and 30-year assimilation rate (Panel B), defined as the difference between the wage gap to natives in the initial period and the wage gap to natives after 30 years. We also plot the kernel density of the corresponding impacts obtained separately for each individual immigrant in the sample, who also differ in their potential experience abroad.

With few exceptions, labor market competition had a negative effect on the initial wage gap of immigrants, in some cases widening it by more than 10 log points. The impact on the 30-year assimilation rate is more varied, with some groups experiencing faster relative wage growth due to the competition effect, others experiencing slower wage growth. Overall, our findings suggest that 33.5 percent of the total variation in the initial wage gaps and 29.5 percent of the total variation in the 30-year assimilation rates across all immigrants can be explained by the heterogeneous impact of labor market competition

FIGURE 8. HETEROGENEOUS LABOR MARKET COMPETITION EFFECTS



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 at 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 men in the sample. Estimated effects are expressed in log differences.

on different types of individuals.²²

VII. Robustness Checks

In this section, we show that our main results in Section VI.A are robust to alternative specifications that deal with various potential concerns regarding our baseline model. Before presenting our results, we explain each of the robustness checks in more detail.

Selective return migration. While it is unlikely to produce a significant direct bias in the quantification of the competition effect, as explained in Section IV.B, selective return migration may have an indirect effect by biasing the estimation of the skill accumulation profiles (θ) due to standard self-selection arguments. To assess the importance of these concerns, we implement three robustness checks that evaluate the extent to which selective return migration may affect our results. In all three checks, we adjust our estimation sample (by adjusting the population weights) such that the resulting estimation (but not the computation of the aggregate supplies of skill units) uses a sample that resembles the stock-sampled longitudinal data often used in the related literature (e.g., see Lubotsky, 2007, or Dustmann and Görlach, 2015).

In the first check, we build our adjustment factor relying on results by Borjas and Bratsberg (1996). Using data for the 1970s arrival cohort, these authors estimate country-of-origin-specific return migration rates over the first 10 years in the United States.²³ For

²² To obtain these numbers, we use our model estimates to predict the assimilation profile for each immigrant in the sample relative to observationally equivalent natives. Based on these profiles, we calculate the variances of the predicted initial wage gaps and the 30-year assimilation rates. We then repeat this process after shutting down the competition effect in the model ($\sigma = \infty$). The share of the variance in the initial wage gaps and assimilation rates that is explained by the competition effect is then given by one minus the ratio between the variance without and the variance with the competition effect.

²³ To obtain estimates for the regions of origin distinguished in our analysis, we take a weighted average of the country-specific estimates in Borjas and Bratsberg (1996), weighting by the size of the respective

the second check, we rely on recent results by Rho and Sanders (2021), who estimate return migration rates separately by education group and earnings percentile for immigrants arriving between 1995 and 1999, using newly-assembled longitudinal data matched with Census information. Contrary to Borjas and Bratsberg (1996), who find the highest return migration rates for the least-skilled group of immigrants, Rho and Sanders (2021) show that, if anything, return migrants are positively selected in terms of both observed education levels and unobservable skills conditional on education (see Figures 1 and 5 in their paper).²⁴ Since the findings from these two studies point in opposite directions, and since they deal with different dimensions of selective return migration (country of origin in the case of Borjas and Bratsberg, 1996, education and unobserved skills in the case of Rho and Sanders, 2021), we use them in two separate robustness checks.

For both checks, we reestimate our model after multiplying the original sample weights of immigrants that we observe during their first 10 years in the United States by one minus the corresponding estimated return migration rate (see Online Appendix A for details). This reweighting approach implicitly mimics what studies based on stock-sampled data do by holding the composition of immigrants in terms of origin (or education and unobservable skills) constant across the first and subsequent decades after arrival. Note that, in these robustness checks, we use the new sample weights to weight observations in the estimation but the original weights to compute the aggregate relative skill supplies G_t/S_t as these depend on the workers who are actually present in the labor market.

In the third robustness check, we adjust the weights to keep the size of different synthetic cohorts constant. For this, we first divide our sample of immigrants into cells defined by cohort of arrival, origin, education level, and quartile of the distribution of wage residuals from Equation (12). We then further divide the sample into immigrants observed within the first 10 years after arrival and immigrants observed after at least 10 years in the United States. Within cohort, we finally adjust the baseline sample weights of the first group (those with less than 10 years in the United States) so that, on aggregate, they reproduce the joint distribution of origin, education, and residual wage quartile observed in the second group (more than 10 years in the United States), thus holding the distribution of these characteristics within our synthetic cohorts constant over time.

stock of immigrants from each origin. The resulting return migration rates 10 years after arrival are 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).

²⁴ Rho and Sanders (2021) infer return migration rates from the inability to “find” immigrant workers from the considered arrival cohort in the full 2010 population census, conditional on observing them in the 2000 Census. Since match rates may not amount to 100 percent for other reasons than return migration, only the differences between the match rates of immigrants and comparable natives are interpreted as proxies for return migration rates. To assess return migration rates in terms of unobservable skills, Rho and Sanders (2021) divide the sample of workers with a given education into deciles based on their self-reported earnings in the 2000 Census, and then compute the corresponding return migration rates within each decile (once again subtracting the non-match rate for similar natives to net out other reasons for not finding a match).

Undocumented migrants. To assess how the undercounting of undocumented immigrants in the Census data may affect our results, we implement two robustness checks in which we explicitly account for the underestimation of the total number of undocumented immigrants competing in the labor market. In the second one, we also account for the potentially distinct skill accumulation profiles of undocumented immigrants. Following Borjas (2017), we first identify “likely legal” immigrants in the different Census samples based on a set of survey responses, and then label all remaining immigrants as potentially undocumented.²⁵ We then obtain assimilation profiles with two modifications relative to our baseline. In the first robustness check, we reestimate our model after reweighting the observations of potentially undocumented immigrants to account for their undercount in the Census data (see Online Appendix A for details). In particular, we divide the original sample weights of these observations by one minus a census-specific undercount rate, which we take from Van Hook and Bean (1998) for the 1980 and 1990 Census, from Van Hook, Bean and Tucker (2014) for the 2000 Census and the 2010 ACS, and from Passel and Cohn (2018) for the 2018-2019 ACS.²⁶ In the second robustness check, we additionally include a dummy variable for potentially undocumented immigrants in the $s(\cdot)$ function, which we interact with a third order polynomial in years since migration to capture the potentially different speed of assimilation of undocumented immigrants.

Networks. To evaluate whether a larger concentration of immigrants in a given market has a direct effect on the speed at which immigrants accumulate specific skills, we implement two robustness checks. In the first, we allow the accumulation of specific skills to depend on the local stock of immigrants from the same country of origin as the respondent, acknowledging that the relevant employment networks and residential ghettos are typically formed by immigrants who share the same national origin. In the second robustness check, we replace the stock of immigrants from the specific country of origin of the respondent by its relative share in the local state population. Both network variables are allowed to enter linearly in the $s(\cdot)$ function as well as interacted with a third order polynomial in years since migration.

²⁵ Likely legal immigrants are 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. Potentially undocumented immigrant are those not satisfying any of these criteria.

²⁶ According to the estimates by Borjas, Freeman and Lang (1991), reviewed in Van Hook and Bean (1998), the undercount percentage in 1980 is 40 percent among Mexican-born unauthorized immigrants. Earlier studies find similar magnitudes for the total unauthorized population. For the 1990 Census, the U.S. General Accounting Office estimates an undercount rate of 25 percent among all unauthorized immigrants (United States General Accounting Office, 1993). According to the preferred estimates by Van Hook, Bean and Tucker (2014) based on the “Net Migration Method”, the undercount rates are 23 and 21 percent among 25-44 and 45-64 year-old Mexicans in the 2000 Census, and 12 and -10 percent in the 2010 ACS. Finally, Passel and Cohn (2018) implement “coverage adjustments [that] increase the estimate of the unauthorized immigrant population [...] by 5% to 7% for 2010-2016” (p. 44), so we use the intermediate value of 6 percent.

Alternative specifications. To check the robustness of our results to alternative specifications and functional form assumptions, we perform several checks. We first test the sensitivity of our findings to different parameterizations of δ_t . In particular, we model the demand shifts using flexible time dummies, $\delta_t = \exp(\tilde{\delta}_t)$. Alternatively, we estimate a specification in which δ_t is defined as $\delta_{jt} \equiv \tilde{\delta}_{0div(j)} + \tilde{\delta}_t$, thus adding Census division dummies to the linear trend of our baseline specification. We then expand the function $s(\cdot)$ by including, on top of the baseline regressors, all pairwise interactions of origin, education, and cohort-specific intercepts (first check), or by replacing all baseline third order polynomials in years since migration by fourth order polynomials (second check).

In our baseline analysis, workers with the same ratio of general to specific skills but different levels of education are perfect substitutes. To assess the robustness of our results to this assumption, we follow Peri and Sparber (2009) and Ottaviano and Peri (2012) and allow skill units supplied by workers with different education levels to be imperfectly substitutable. The production function in this robustness check is replaced by:

$$Y_t = A_t \left[\sum_{e=1}^4 \alpha_{et} \left(G_{et}^{\frac{\sigma-1}{\sigma}} + \delta_t S_{et}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1} \frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \quad (16)$$

with $\sum_{e=1}^4 \alpha_{et} = 1$ for each t . As shown in Equation (D2) in Online Appendix D, the general expression for the relative skill prices remains unchanged in this extended model, except that now the relevant market is defined at the state-education rather than state level. However, as discussed in detail in the appendix, for our decomposition exercise, we need to make further adjustments to account for the relative changes of wage levels across different education groups. These wage level effects are governed by the new parameter ϕ , which we estimate alongside the other parameters as described in the appendix.

Endogenous location of immigrants. To assess the extent to which results may be sensitive to the potential endogeneity of immigrant location choices across U.S. states, we reestimate our model using a GMM version of the shift-share instrumentation approach popularized in the migration literature by Card (2001). If immigrants were randomly assigned across states conditional on observables, the standard NLS first order conditions would be valid moment conditions and deliver consistent estimates. However, if immigrant settlements were endogenous, the terms of those first order conditions that depend on G_{jt}/S_{jt} would be endogenous and the corresponding NLS moment conditions invalid. We therefore replace the potentially endogenous regressor G_{jt}/S_{jt} by an exogenous prediction derived from a standard shift-share instrument, which yields a new set of valid moment conditions. Given the nonlinearities in our estimation equation and the need to ensure proper convergence of our nonlinear estimation, we estimate an overidentified model in which we additionally use the squares of our (transformed) derivatives as additional instruments. Online Appendix L provides details on the derivation of these

instruments and the implementation of the estimation approach.²⁷

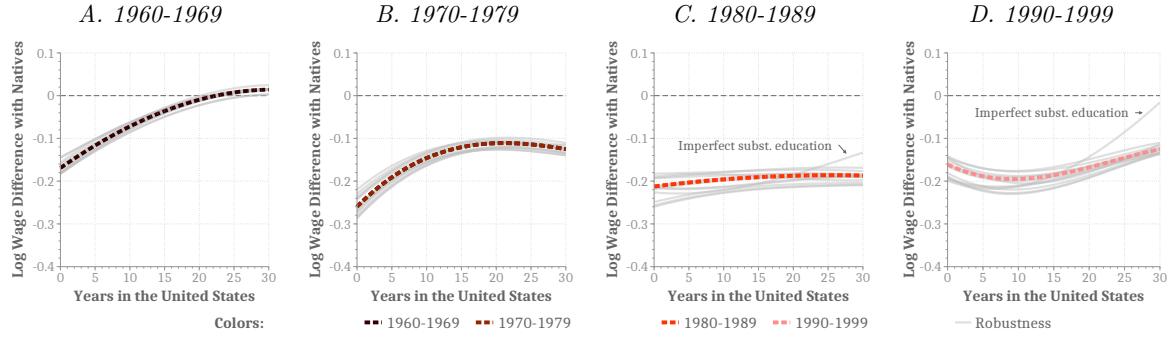
Table M1 in Online Appendix M summarizes the key parameter estimates obtained from the different robustness checks. Panel A shows that potentially undocumented immigrants have a 1.2 log-point larger initial wage gap than comparable legal immigrants and that, over a period of 10 years, their wages grow by 3.9 log points less. Panel A also shows that a larger share or stock of immigrants from the same country of origin living in the same state has a negative but relatively moderate impact on the initial wage gap: the latter is reduced by 1.1 log points for every 1 percentage point increase in the immigrant share, or by 9.1 log points for every additional million of compatriots. Panel B reports the estimated relative demand shifts. The results from the specification with a full set of time dummies indicate a U-shaped pattern, with decreasing demand for specific skills in the 1970s and increasing demand in the 1980s, 1990s and 2000s. The specification that allows for different regional intercepts reveals that, relative to the baseline Census division (Pacific), the demand for specific skills is lower but similar across regions (with the exception of New England). As discussed below, none of these extensions affect our main conclusions. Panel C reports our estimate for the elasticity of substitution between skill units of different education groups, ϕ , which we estimate to be equal to 7.4.

To summarize our robustness checks, Figure 9 depicts the relative wage profiles implied by each of our 13 different robustness check. Similar to Panel I of Figure 6, we display the cohort-specific assimilation profiles after accounting for the competition effect (Panel I), and after accounting for both the competition and the demand effect (Panel II). Overall, our main findings are robust across the different specifications, especially regarding the role of the competition effect (Panel I), where all profiles are very close to those of our baseline model (depicted as colored dashed lines). The only exception is the specification in which we allow for imperfect substitutability across education groups, where our baseline estimates underestimate the role of the competition effect, particularly for the 1990s cohort and the later years after arrival. The same pattern can also be observed when we account for both the competition and the demand effect (Panel II). Here, an additional outlier is the specification in which we model the demand shifts through a full set of time dummies rather than a linear time trend. Especially for the 1970s cohort, holding the demand effect constant at the 1970 level leads to significantly larger wage gaps than in

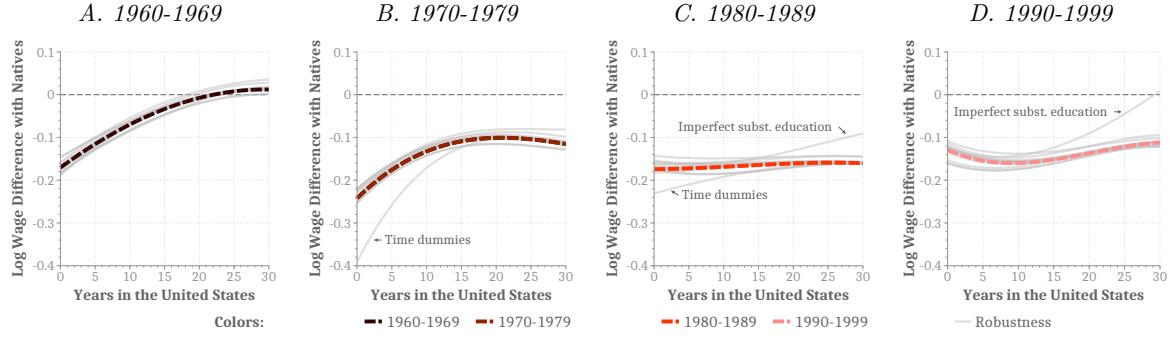
²⁷ In addition to our IV approach, we also provide indirect evidence that endogenous immigrant location choices are unlikely to significantly bias our main findings. If our estimates were biased because of endogenous immigrant inflows into different states, we should observe a worse performance of our model in those periods and states in which the actual inflows are more likely to be exogenous. Such exogenous inflows presumably occurred in states located near the Mexican border after the Mexican peso crisis of 1994 (Monràs, 2020). In Figure M1, we correlate the prediction error from our model with the log distance to the Mexican border, separately for all state-cohort observations before and after the peso crisis. The prediction error is defined as the difference between our leave-one-out predictions and their data counterparts (see Panel II of Figure C1). As Figure M1 shows, our model performs similarly well in the pre- and post-peso crisis periods. There is also no evidence that our predictions are significantly worse for states that are located closer to the Mexican border and thus more likely to be exposed to exogenous inflows.

FIGURE 9. ASSIMILATION PROFILES UNDER ALTERNATIVE SPECIFICATIONS

I. No competition effect



II. No competition and no demand 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 (gray lines).

our baseline model. This is a direct consequence of the U-shaped pattern that we find for the demand shifts for specific skills (see Panel B of Table M1), which reaches its low point in 1980 before then increasing again in subsequent decades.

As an easily interpretable summary measure of the role of the competition and demand effects across the different robustness checks, Table M2 in Online Appendix M reports by how many log points, averaged across years in the United States, the wage assimilation profiles are shifted up relative to the baseline once either the competition effect or the joint competition and demand effect is accounted for. With some small fluctuations, our robustness checks generally yield similar estimates as our baseline specification, consistent with the graphical evidence in Figure 9. Averaged across all specifications, the competition effect in the robustness checks amounts to 1.2 log points in the 1960s, 2.6 log points in the 1970s, 4.2 log points in the 1980s, and 3.3 log points in the 1990s, very similar to the baseline values of 1.3, 2.7, 4.7, and 3.7 log points, respectively. When the demand effect is added, the robustness checks average 1.5, 4.0, 7.8, and 7.1 log points, again very similar to their baseline counterparts of 1.4, 4.0, 7.5, and 6.8 log points, respectively.

VIII. Conclusion

This paper shows that the wage assimilation of immigrants is the result of the intricate interplay between individual skill accumulation and dynamic labor market equilibrium effects. Since immigrants and natives are imperfect substitutes in production, increasing

immigrant cohort sizes drive a wedge between their wages. We show that this labor market competition channel can explain about one fifth of the rise in the average immigrant-native wage gap between the 1960s and 1990s arrival cohorts in the United States, a figure that increases to one third once shifts in relative demand for U.S.-specific skills are accounted for as well. In contrast, the impact of labor market competition on the speed of assimilation is small. The remaining differences across cohorts can be attributed to decreasing cohort quality and fully explained by changes in immigrants' educational attainment and origin composition. Conditional on these observable characteristics, our findings suggest that immigrants have become more positively selected in terms of unobservable skills.

Our results have important implications. First, if the wage assimilation of immigrants is directly affected by labor market competition effects, then the wage impact of immigration must also be affected by immigrants' assimilation processes. A given inflow of immigrants may initially exert a less negative (or even positive) effect on native wages due to the often limited substitutability between recent immigrants and native workers. Over time, however, as immigrants become more similar to natives in terms of their skills, they start competing more directly with natives in the labor market. The wage effects of immigration will thus ripple through the native skill distribution, affecting different types of native workers at different moments in time. The labor market impact of immigration is therefore intrinsically dynamic in nature, an aspect that has received comparatively little attention in the literature so far.²⁸ Second, the competition channel may have far-reaching effects on the decision of immigrants to invest in host-country-specific skills, something which the few papers that explicitly model such investment decisions (e.g. Adda, Dustmann and Görlach, 2022) do not take into account. Finally, our findings suggest that the allocation of immigrants across space and the subsequent native migration responses will not only have important effects on native wages (e.g. Piyapromdee, 2021) but also influence the way in which immigrants assimilate in the labor market. This insight is particularly policy-relevant as it suggests that immigration policies that affect the size and composition of local immigrant inflows (such as the widely-implemented dispersal policies during recent refugee crises; see Brell, Dustmann and Preston, 2020) might have unintended effects on immigrant wage assimilation. We leave a thorough investigation of these interesting questions for future research.

²⁸ To the best of our knowledge, only Cohen-Goldner and Paserman (2011), Dustmann et al. (2013), and Llull (2018) take these particular dynamic effects into account. Cohen-Goldner and Paserman (2011) analyze the differential impact of high-skilled immigration on native labor market outcomes as immigrants spend time in their host country. Dustmann et al. (2013) allow immigrants to downgrade at arrival and increase labor market competition around the points of the native wage distribution where they are located, which implicitly evolve over time. Llull (2018) explicitly accounts for the lower substitutability between newly arriving immigrants and natives endogenously through their occupational choices, which depend, among other things, on the U.S. and foreign experience bundles. A few other papers, including Monràs (2020), Jaeger, Ruist and Stuhler (2019), Edo (2020), and Braun and Weber (2021), also analyze the dynamic effect of immigration on wages, but they attribute it mostly to the sluggishness in capital adjustments and the time it takes for internal migration to dissipate impacts across local labor markets.

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Online 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., 2018). 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 *cntygrp97*). 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, 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:

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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

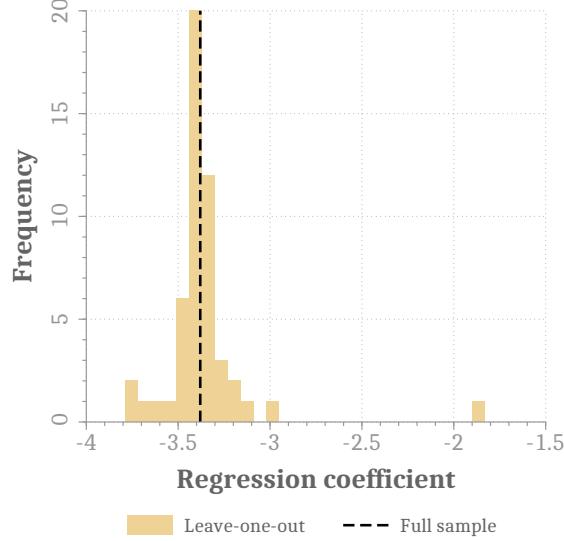
	Census year:					
	1970	1980	1990	2000	2010	2020
Immigrant share (%)	3.8	5.0	6.9	10.7	14.4	16.3
Number (millions):						
Natives	47.0	62.5	76.5	87.6	89.8	97.7
Immigrants	1.8	3.1	5.3	9.4	13.0	15.9
Men (%):						
Natives	67.7	60.9	56.3	54.3	52.8	52.9
Immigrants	64.5	59.6	58.9	59.4	57.5	56.8
Age:						
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.

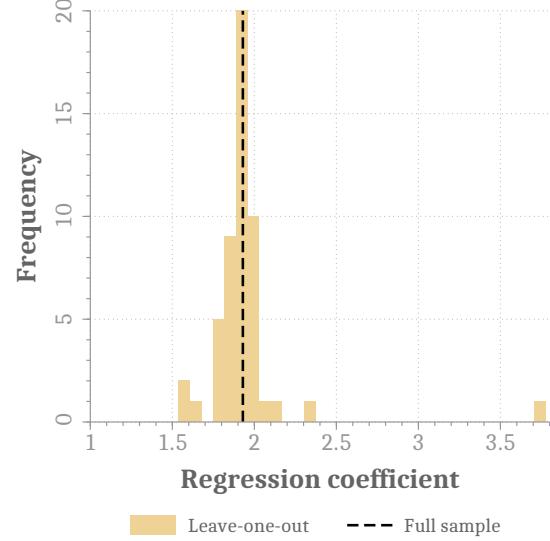
APPENDIX C: ADDITIONAL DESCRIPTIVE EVIDENCE

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.

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 VII, 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_{Kt} . 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:

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

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

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

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

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

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

and M is:

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

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:

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

with:

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

plus:

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

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

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

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

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

and:

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

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

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

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

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:

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

Intuitively, $H^{-1} \mathbb{E}[FF'] H^{-1}$ 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 MM' 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 V 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 $\{\eta_{20et}\}_{e \in \{1,2,3\}}$ 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, $\{\theta_{10e}, \{\theta_{200e}\}_{e \in \{1,2,3\}}\}_{e \in \mathcal{O}}, \{\theta_{30e}, \{\theta_{400e}\}_{e \in \{1,2,3\}}\}_{e \in \mathcal{E}}, \{\theta_{500e}, \{\theta_{600e}\}_{e \in \{1,2,3\}}\}_{e \in \mathcal{E}},$ and $\{\theta_{60c}, \{\theta_{700c}\}_{e \in \{1,2,3\}}\}_{c \in \mathcal{C}}$ 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 IV.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.

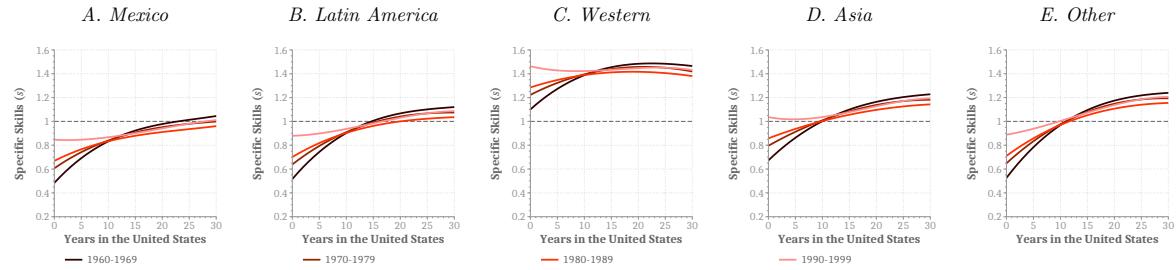
The remaining columns of Table G2 show the estimated coefficients for the interaction terms of each of the listed characteristics and a polynomial in years since migration. These coefficients correspond to the visualization displayed in Figure 4 in the main text.

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.

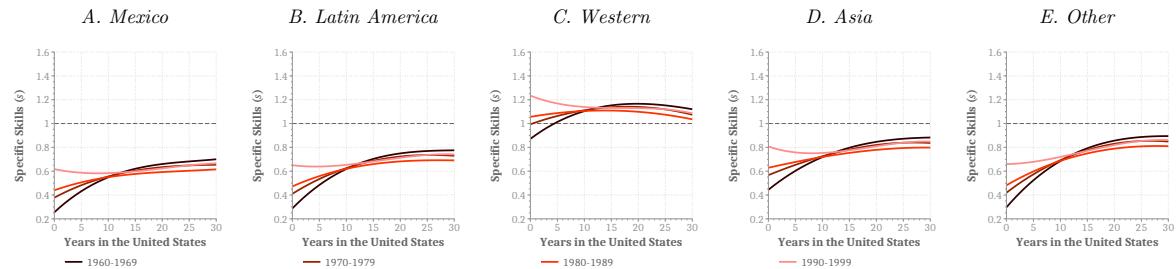
¹ Note that there are only very few immigrants from Western countries that are high school dropouts. We do not bound the specific skills of immigrants at a value of one, thus allowing their wages to exceed those of comparable natives, a feature we observe in the data for some immigrant groups.

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

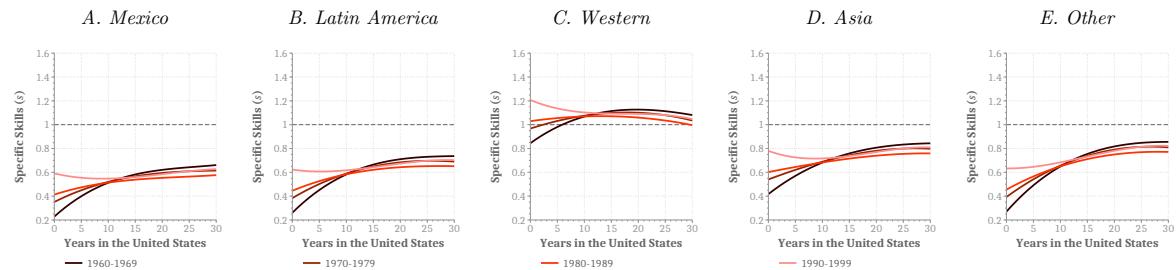
I. HS Dropouts



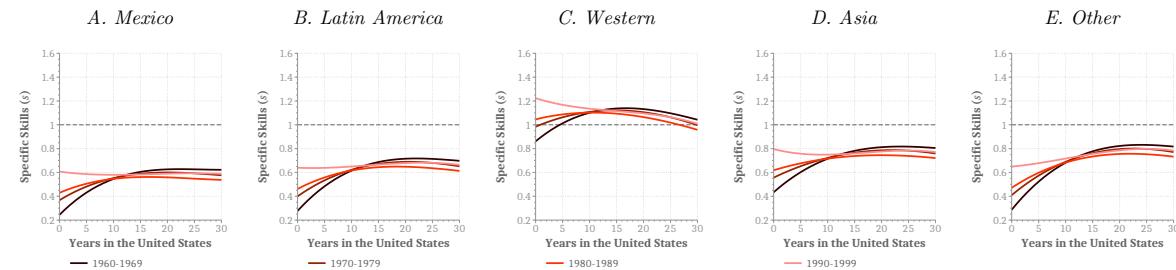
II. HS Graduates



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:

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

and:

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

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 :

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

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:

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

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

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

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:

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

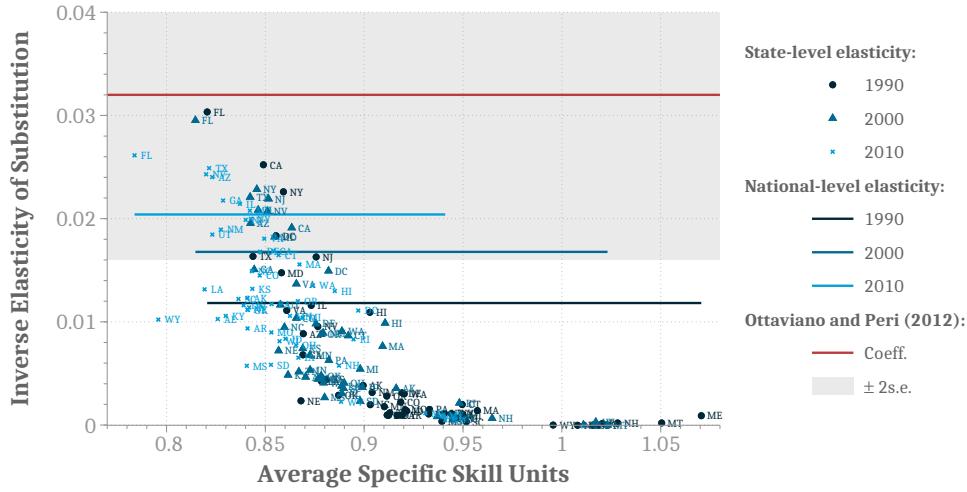
where $\bar{h}_N \equiv \sum_{\ell} h_{\ell} \frac{N_{\ell}}{N}$ is the average productivity of natives and $\tilde{s}_I \equiv \sum_{\ell'} s_{\ell'} \frac{h_{\ell'} I_{\ell'}}{\sum_{\ell'} h_{\ell'} I_{\ell'}}$ is the average of immigrants' specific skill units (weighted by their idiosyncratic productivity). 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

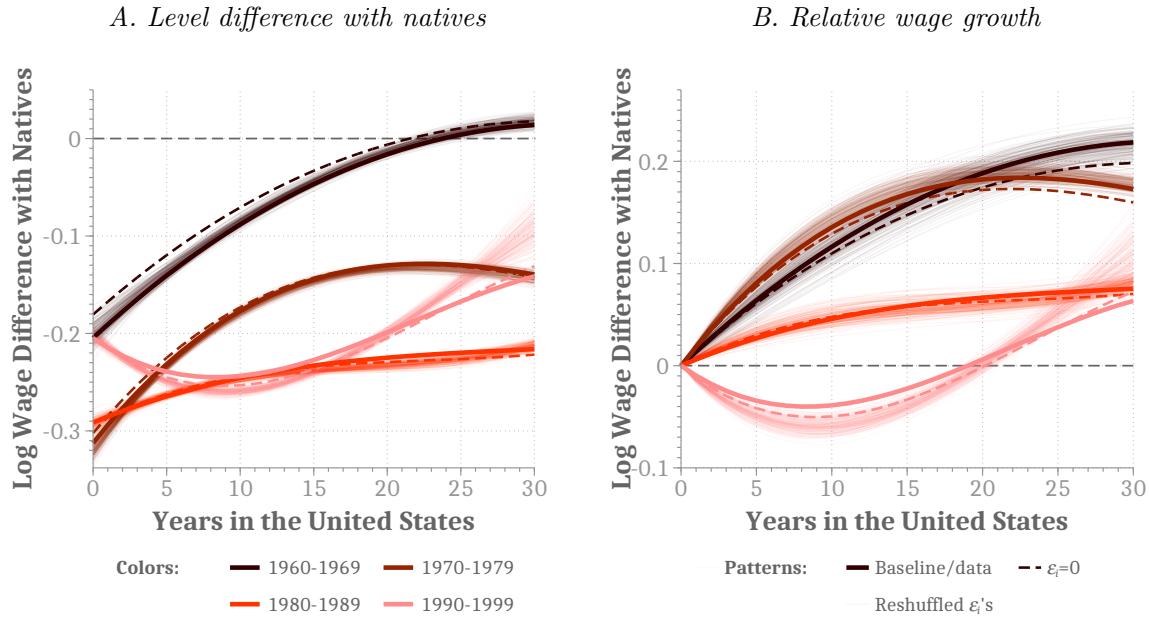


Note: The figure shows the implied inverse elasticity of substitution $1/\varepsilon_{NI}$ across different markets, where ε_{NI} is defined in Equation (15). The (short) blue lines represent our predicted values for 1990, 2000, and 2010 computing skill supplies and weighted average specific skills at 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

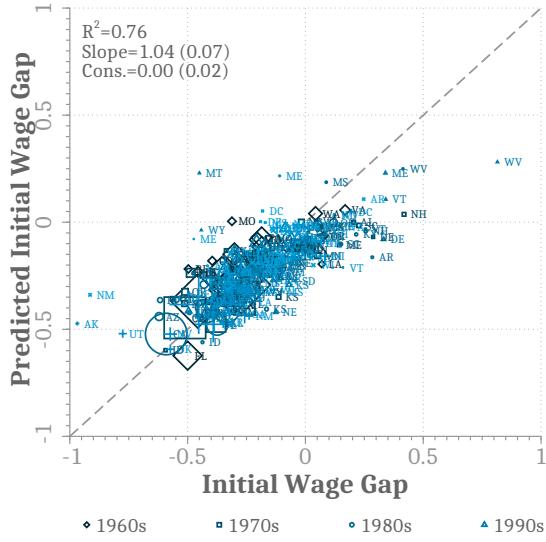


Note: The figure compares, for men, the baseline predictions (which are identical to the solid lines of Figure 1), the predictions in which ε_i is assumed to be zero for all immigrants (dashed line), and the predictions from a set of 200 simulations in which ε_i 's are randomly reshuffled across observations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

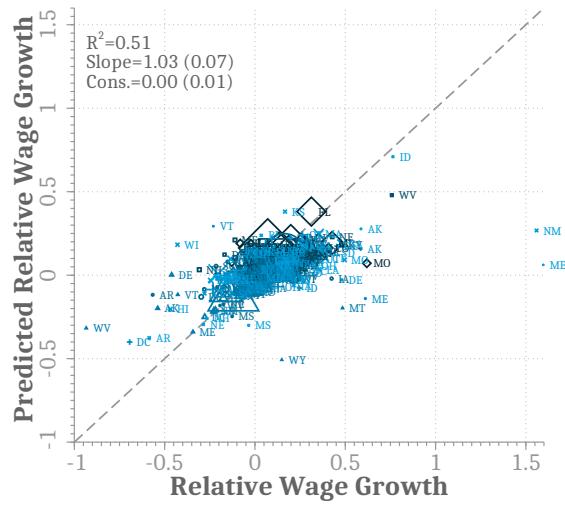
FIGURE J2. STATE-LEVEL PREDICTIONS: IN-SAMPLE AND OUT-OF-SAMPLE FITS

I. In sample

A. Wage gap at arrival

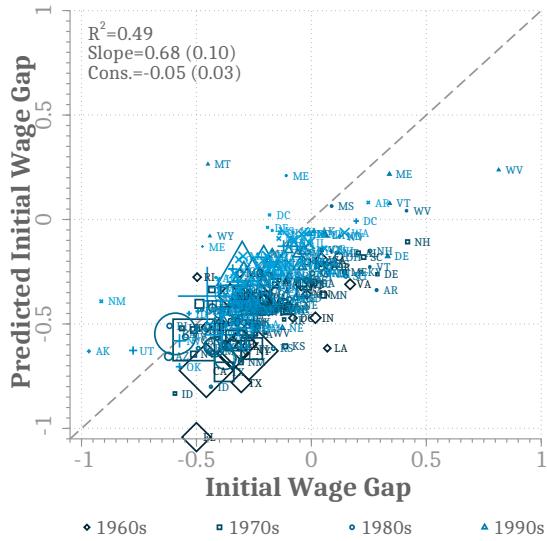


B. Relative wage growth first 10 years

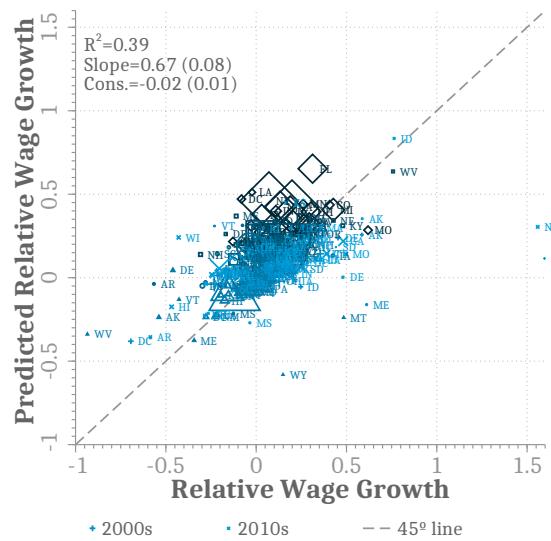


II. Out of sample

A. Wage gap at arrival



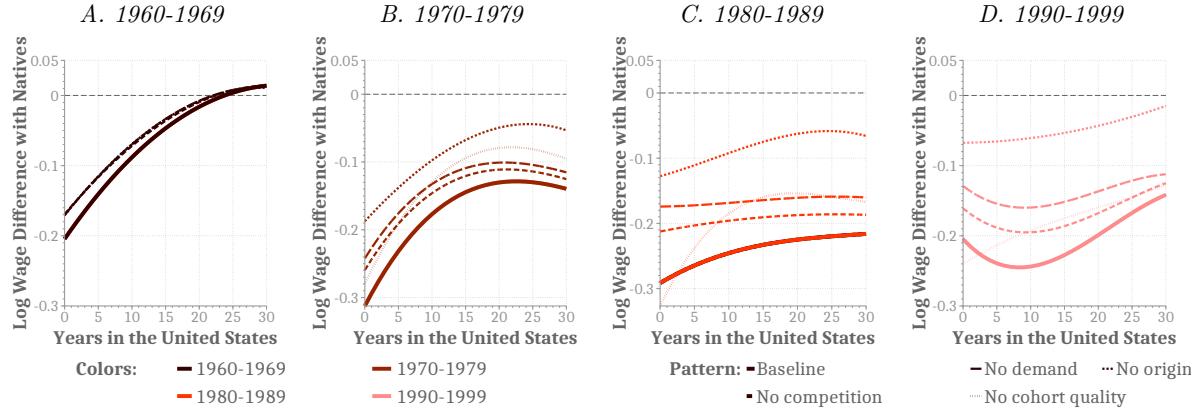
B. Relative wage growth first 10 years



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 , $I_{qt} \equiv \sum_{j=1}^J I_{jqt}$ 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)

	Direct effect	Interaction with years since migration:		
		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		
	Linear term	0.038	(0.002)
Time dummies specification	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.

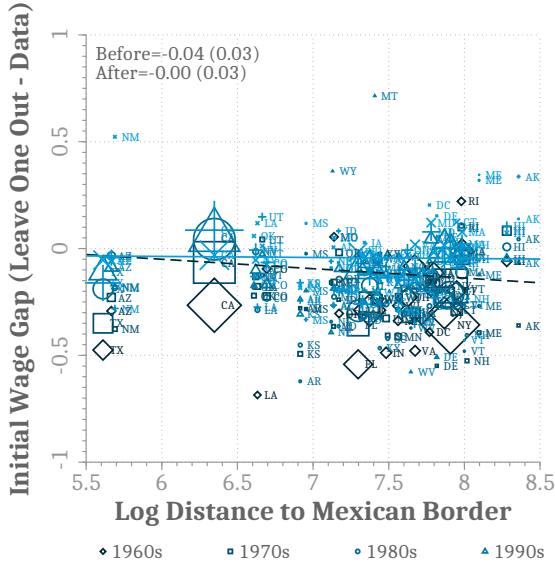
TABLE M2—WAGE GAP DECOMPOSITION: ROBUSTNESS

	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

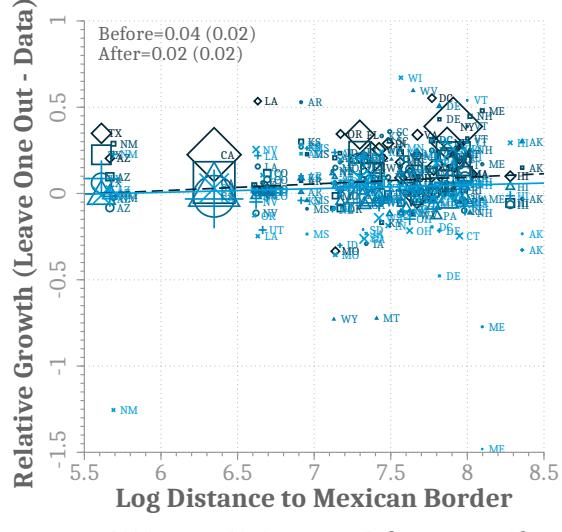
Note: The table shows, for each robustness check, the competition and competition plus demand effects for each cohort (counterfactual minus baseline multiplied by 100) for men, averaged across years in the United States.

FIGURE M1. STATE-LEVEL PREDICTIONS AND THE PESO CRISIS

A. Initial wage gap



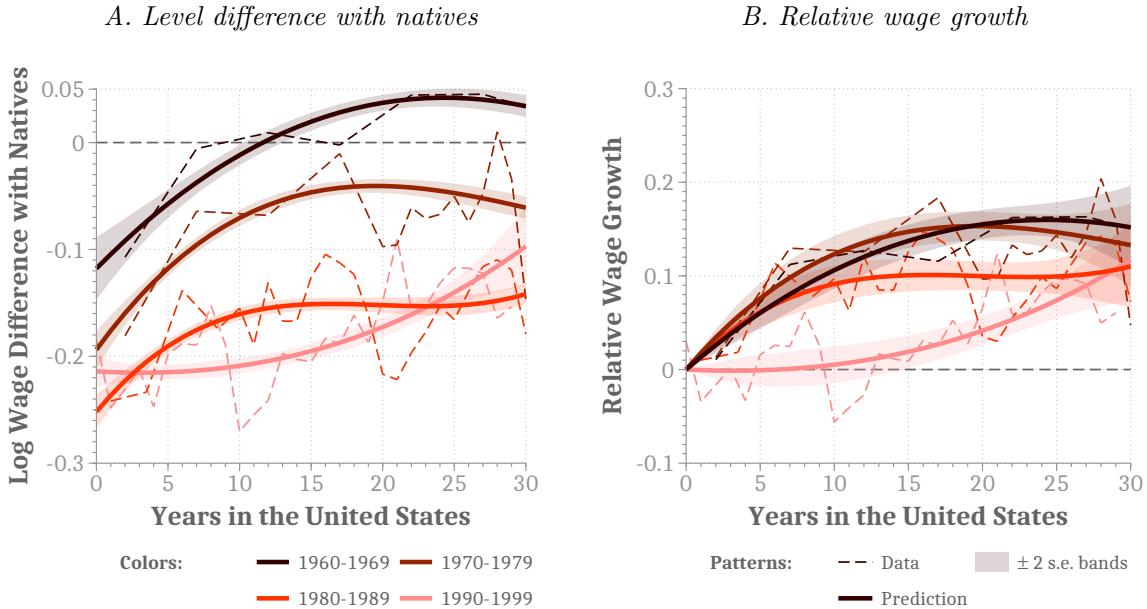
B. Relative wage growth first 10 years



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 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.

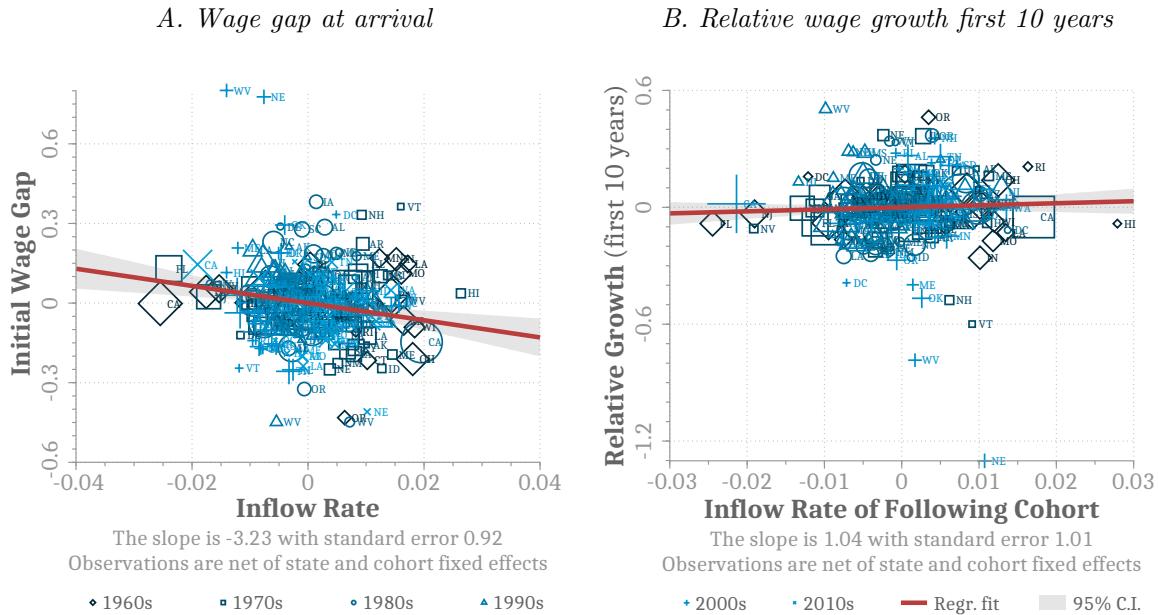


Note: The figure shows the prediction of the wage gap between native and immigrant women of different cohorts as they spend time in the United States. The dashed lines represent the raw data and are the result of year-by-year regressions of log wages on a third order polynomial in age and dummies for 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):

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

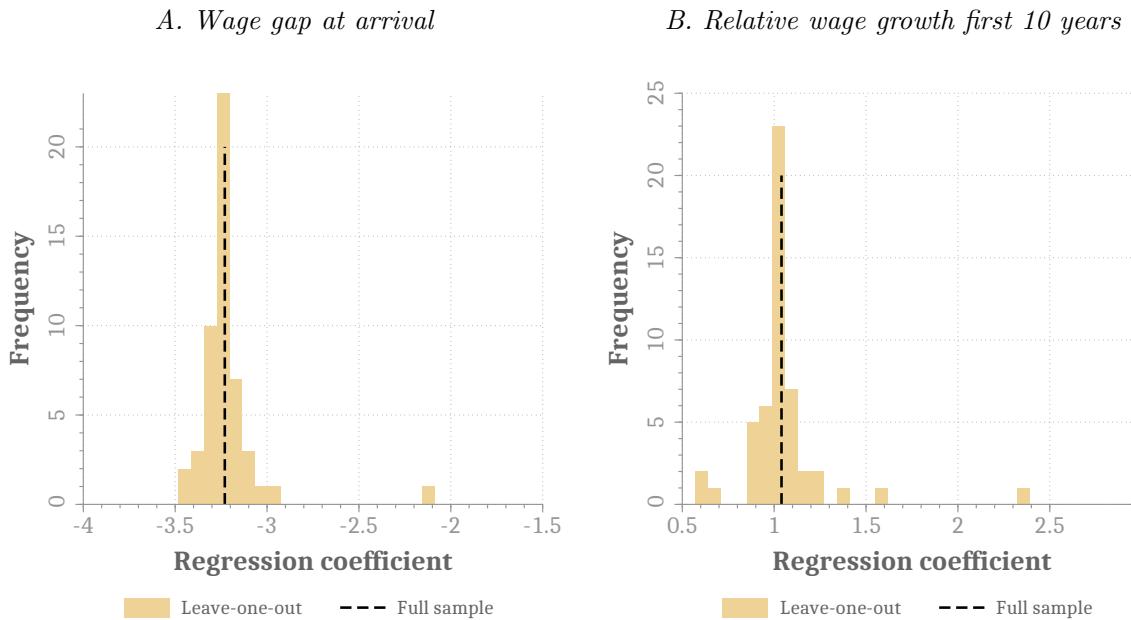
where $c(i)$ and $t(i)$ indicate the immigration cohort and the census year in which individual i is observed, age_i indicates age, and y_i indicates years since migration. Cohorts are grouped in the following way: before 1960, 1960-69, 1970-79, 1980-89, 1990-99, 2000-09, and 2010 or later. Colors represent 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.

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.

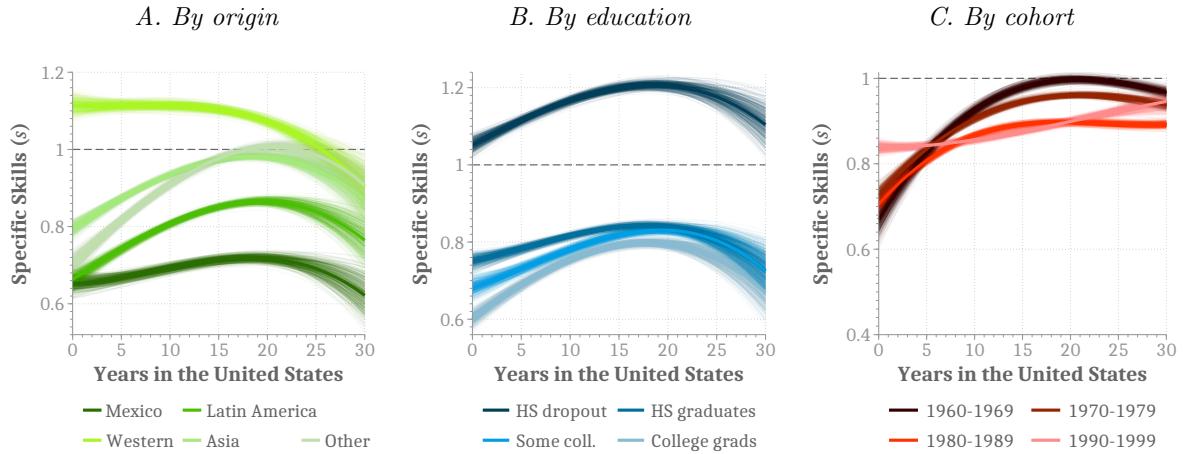
TABLE N2—SPECIFIC SKILL ACCUMULATION, $s_1(0, y, o, c, E, x)$

	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, $\{\theta_{11o}, \{\theta_{21o}\}_{o \in \{1,2,3\}}\}_{o \in \mathcal{O}}$, $\{\theta_{31e}, \{\theta_{41e}\}_{e \in \{1,2,3\}}\}_{e \in \mathcal{E}}$, $\{\theta_{51o}\}_{o \in \{1,2,3\}}$, and $\{\theta_{61c}, \{\theta_{71c}\}_{c \in \{1,2,3\}}\}_{c \in \mathcal{C}}$ 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 IV.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).

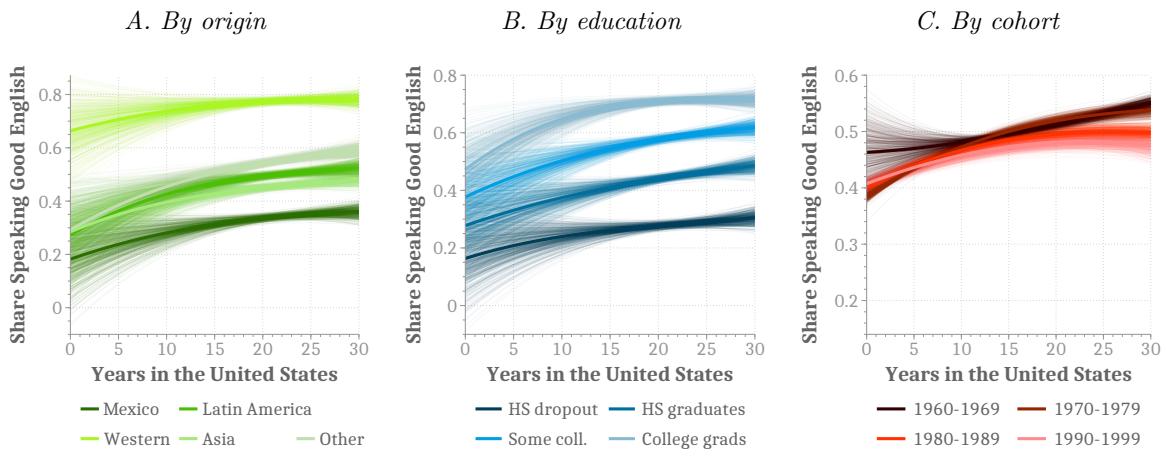
^a Quadratic and cubic interaction terms for the 2000s and 2010s cohorts are grouped in the estimation.

FIGURE N4. 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.

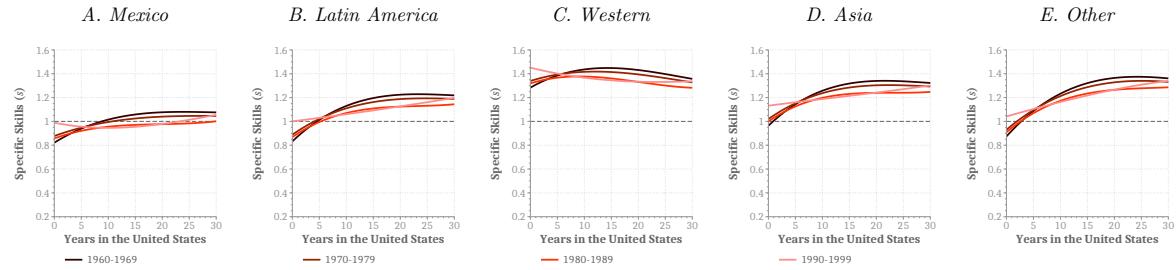
FIGURE N5. ENGLISH PROFICIENCY



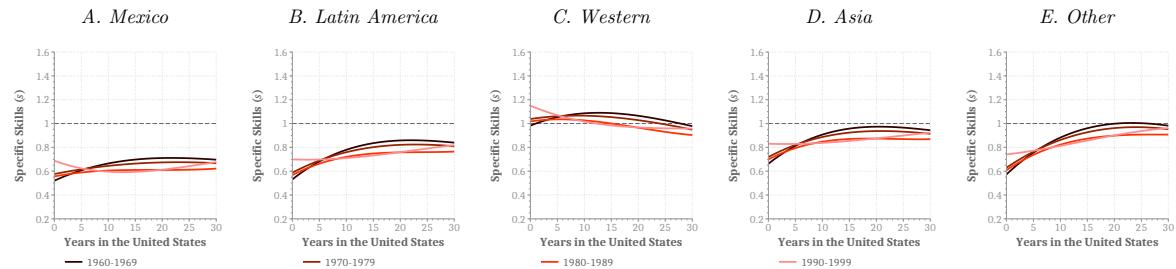
Note: The figure displays English language proficiency profiles predicted from a linear regression of an indicator for “speaking English very well” or “only speaking English” on all the variables included in the specific-skills function $s_1(\cdot)$ and year dummies on a sample of women. The baseline 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 N6. SKILL ACCUMULATION PROFILES FOR ALL EDUCATION AND ORIGIN GROUPS

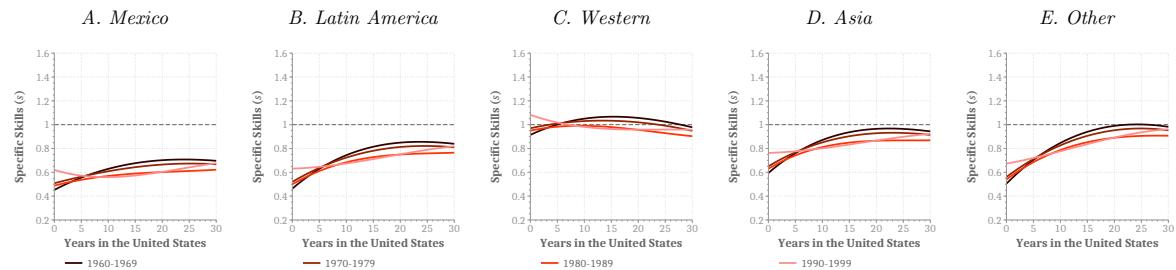
I. HS Dropouts



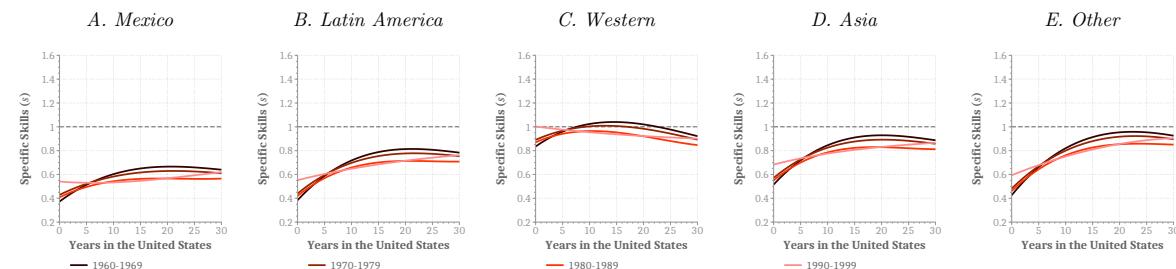
II. HS Graduates



III. Some College

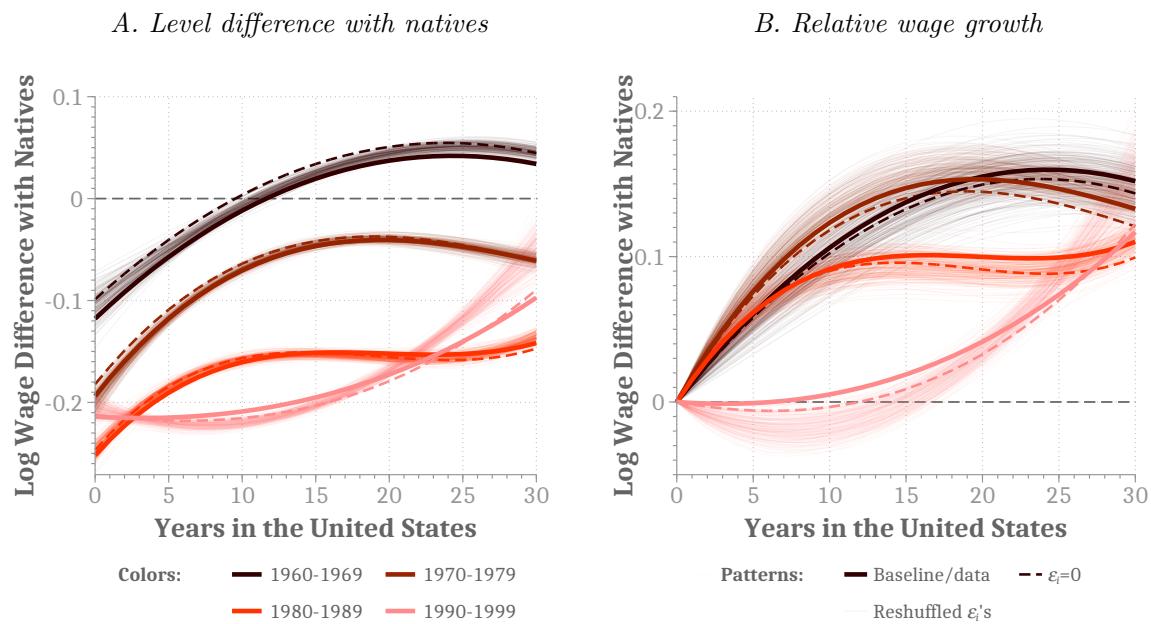


IV. College Graduates



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.

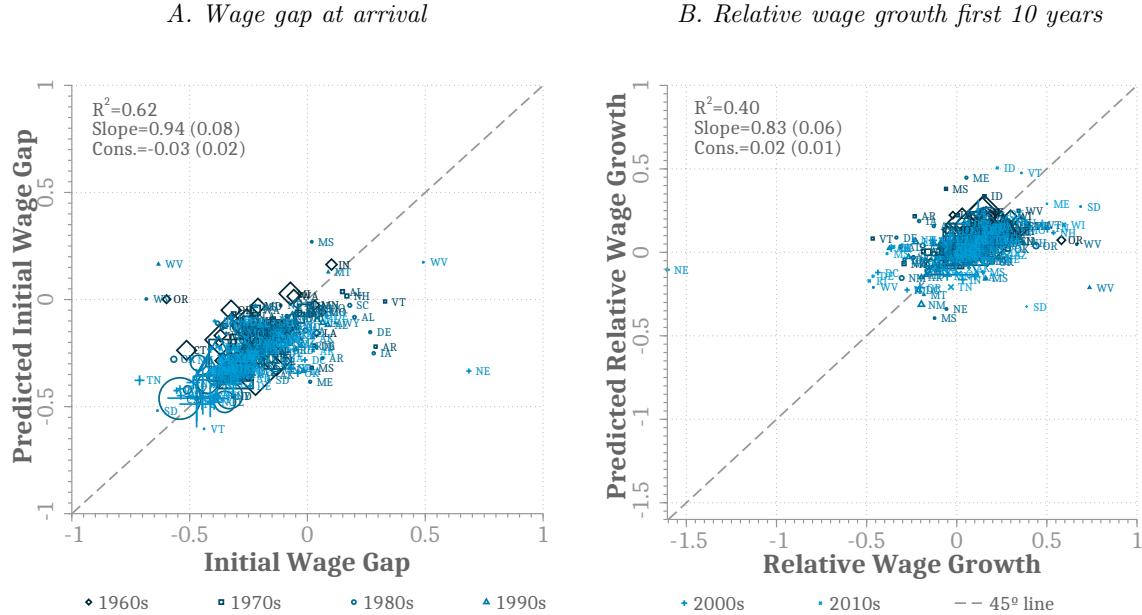
FIGURE N7. PREDICTED ASSIMILATION PATTERNS



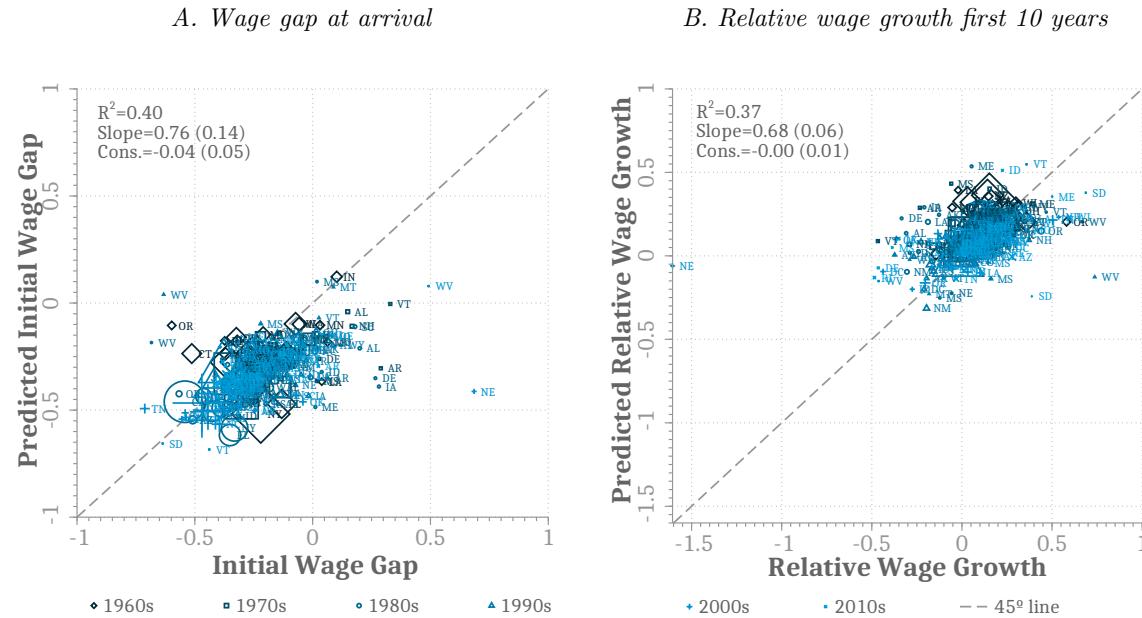
Note: The figure compares, for women, the baseline predictions (which are identical to the solid lines of Figure N1), the predictions in which ε_i is assumed to be zero for all immigrants (dashed line), and a set of 200 predictions in which ε_i 's are randomly reshuffled across observations (thin transparent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

FIGURE N8. STATE-LEVEL PREDICTIONS: IN-SAMPLE AND OUT-OF-SAMPLE FITS

I. In sample



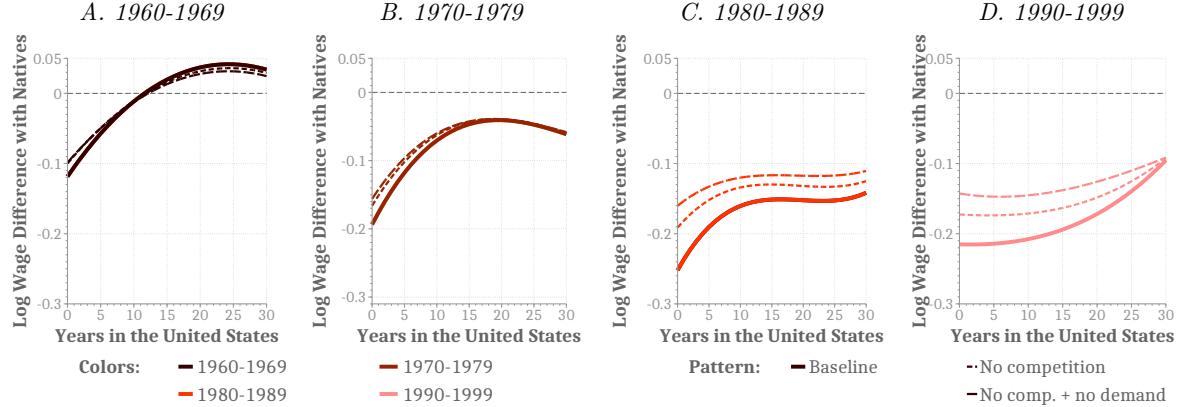
II. Out of sample



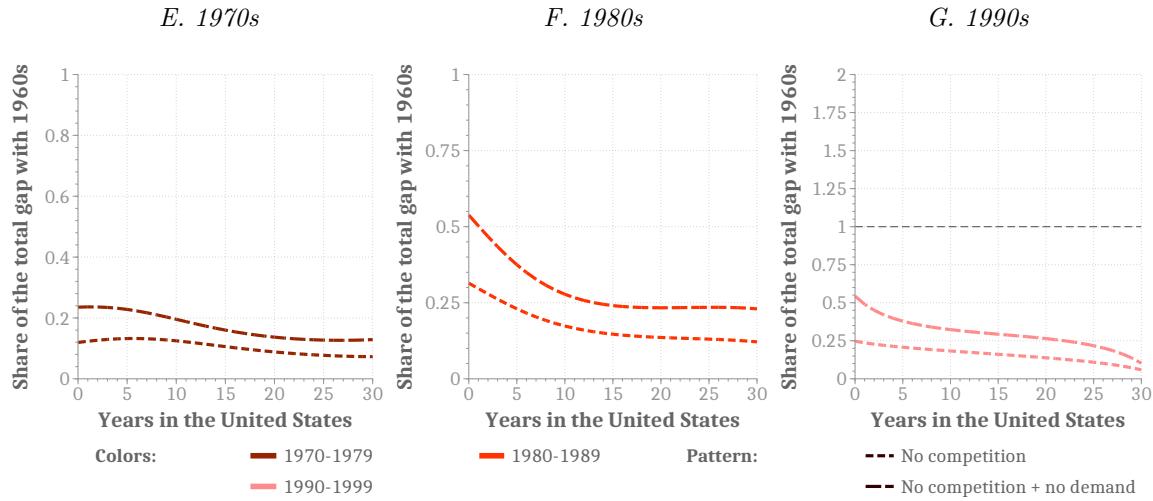
Note: The figure plots the in-sample (Panel I) and out-of-sample (Panel II) model predictions for the initial wage gaps (Plots A) and relative wage growth rates (Plots B) of women in different state-cohort cells (obtained as in Figure N1) against the actual initial wage gaps and relative wage growth 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 N9. 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



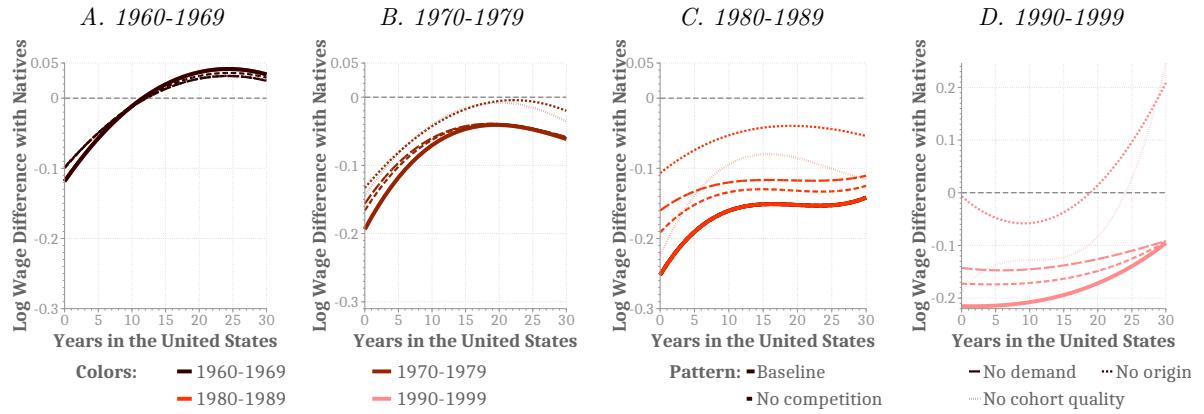
Note: The figure shows baseline and counterfactual predictions of the unconditional wage gaps between native and immigrant women for different cohorts as they spend time in the United States. Each plot represents one cohort. The depicted lines in Panel I are predicted assimilation profiles obtained from 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 N9.

FIGURE N10. WAGE GAP DECOMPOSITION: COMPETITION, DEMAND, AND COMPOSITION EFFECTS



Note: The figure adds to the baseline decomposition in Figure N9 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.

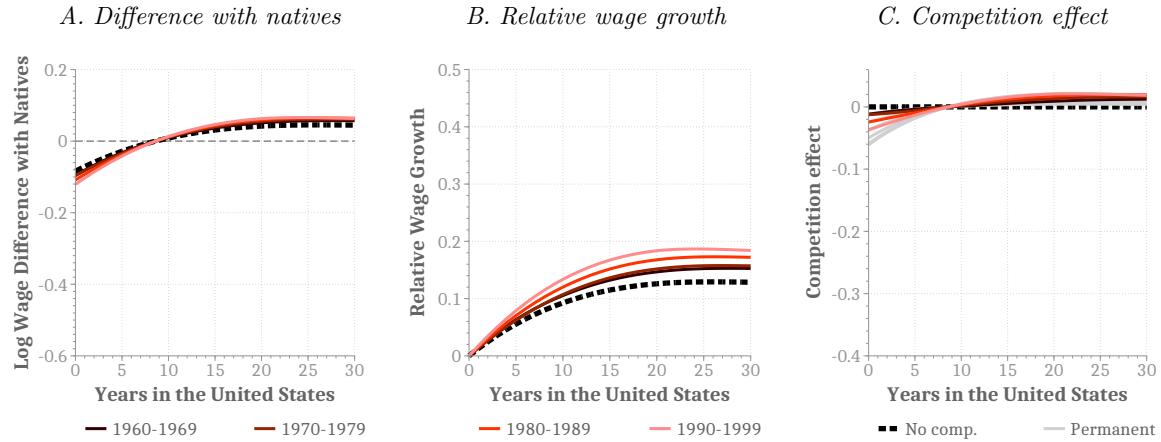
TABLE N4—WAGE GAP DECOMPOSITION: COMPETITION, DEMAND, AND COMPOSITION EFFECTS

	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

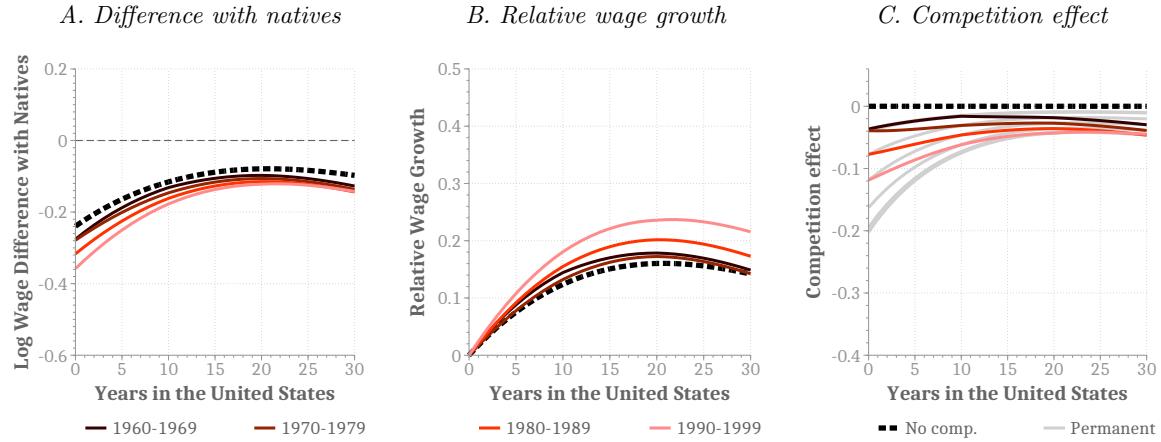
Note: The table presents the fraction of the wage gap of each cohort's assimilation profile relative to the 1960s cohort that is explained by each mechanism (in percentages) averaged across all years since migration for women. These results summarize the information provided in Figure N10.

FIGURE N11. HETEROGENEOUS LABOR MARKET COMPETITION EFFECTS: EXAMPLES

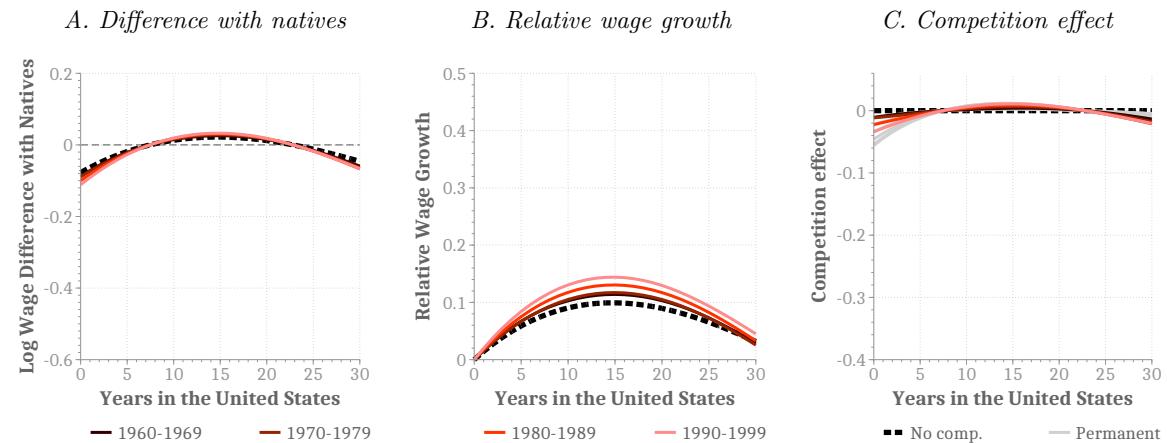
I. Mexican High School Dropouts



II. Latin American High School Graduates



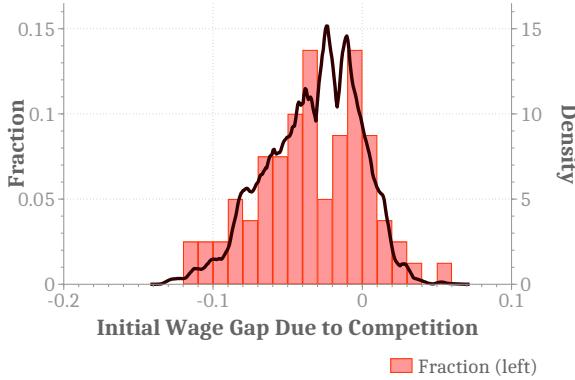
III. Western College Graduates



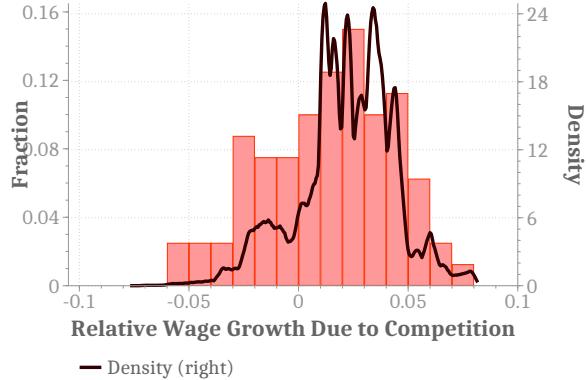
Note: The figure shows wage assimilation profiles of selected immigrant groups (as indicated by each panel's header) under different counterfactual scenarios. All profiles assume that the individual arrived with the skills of the 1960s cohort, was exposed to the demand effects experienced by this cohort, 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 N12. HETEROGENEOUS LABOR MARKET COMPETITION EFFECTS

A. Initial wage gap



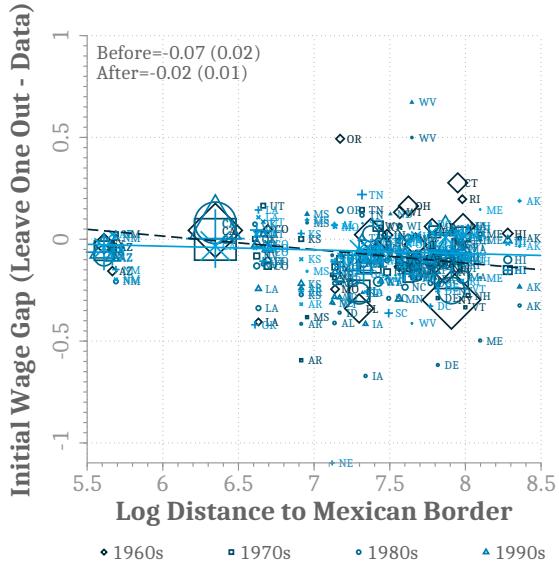
B. Relative wage growth



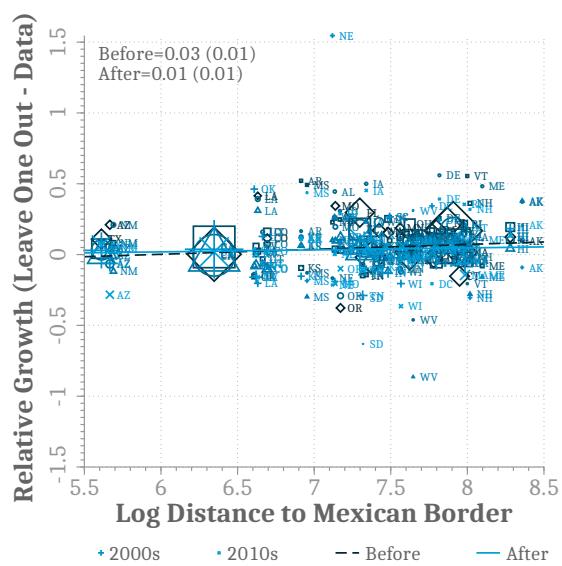
Note: The histograms show by how much labor market competition changed the initial wage gap (Panel A) and relative wage growth over the first 30 years (Panel B) for the 80 immigrant groups distinguished in our analysis (4 arrival cohorts \times 5 origin groups \times 4 education levels, computed on the 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 N13. 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 N8 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.

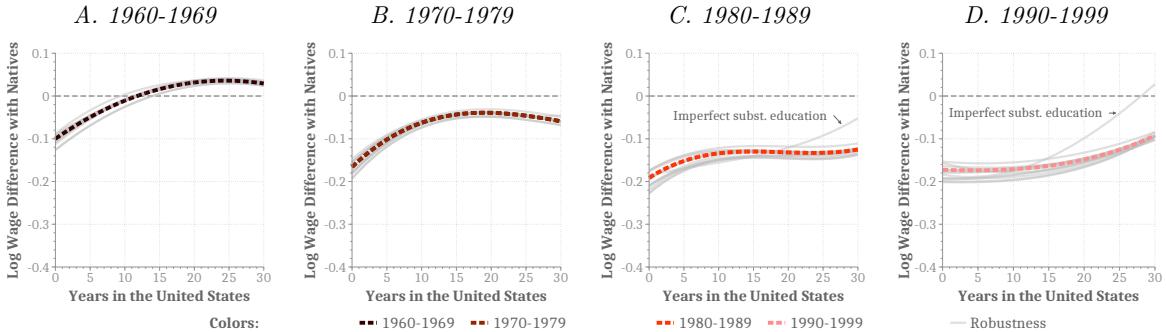
TABLE N5—ADDITIONAL ELEMENTS OF $s(\cdot)$ FOR SOME OF THE ROBUSTNESS CHECKS

	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)

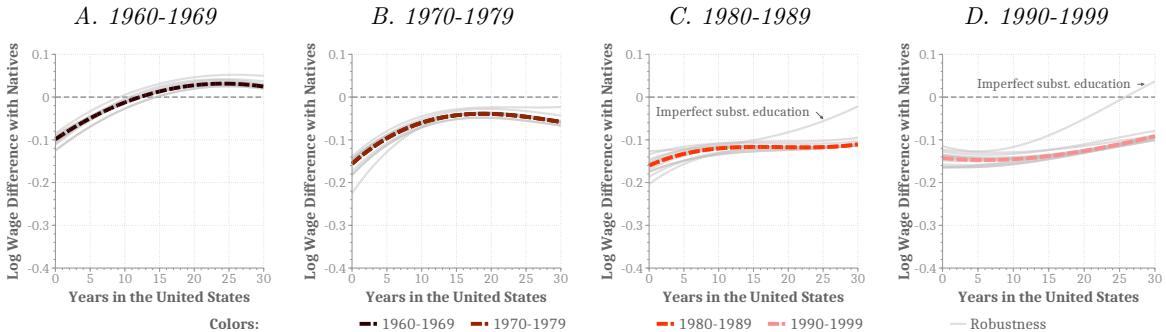
Note: The table presents estimates for the additional parameters of the $s(\cdot)$ function associated with the two specifications of the networks robustness check and for the specification that allows for heterogeneous convergence between potentially undocumented and legal immigrants (each row corresponds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

FIGURE N14. 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:								
Reweighted only	-1.2	-0.5	1.6	1.6	-1.5	-0.2	3.5	4.0
Reweighted 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.