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Labor market competition and the assimilation of immigrants

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In this paper, we show that the wage assimilation of immigrants is the result of the intricate interplay between individual skill accumulation and dynamic equilibrium effects in the labor market. When immigrants and natives are imperfect substitutes, increasing immigrant inflows widen the wage gap between them. Using a simple production function framework, we show that this labor market competition channel can explain about one quarter of the large increase in the average immigrant-native wage gap in the United States between the 1960s and 1990s arrival cohorts. Once competition effects and compositional changes in education and region of origin are accounted for, we find that the unobservable skills of newly arriving immigrants increased over time rather than decreased as traditionally argued in the literature. We corroborate this finding by documenting closely matching patterns for immigrants' English language proficiency.

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

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(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 at the time of arrival, the second one as reflecting the immigrants' accumulation of host-country-specific skills. In the United States, it has been documented that the initial wage 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 in terms of skills over time.

In this paper, we show that an important part of these empirical patterns can be explained by the increasing sizes of immigrant arrival cohorts and labor market competition. The intuition behind this new mechanism is as follows. When immigrants and natives are imperfect substitutes in the labor market, for example because they specialize in different occupations, their relative wages are partly determined by the aggregate supply of foreign-born 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 relative wages apart and thus directly affecting wage assimilation. We show that, in the United States, this labor market competition channel explains about one quarter of the observed increase in the average immigrant-native wage gap across arrival cohorts since the 1960s. Our findings further reveal that, once labor market competition effects and compositional changes in terms of education and region of origin are accounted for, more recent immigrants actually arrived with higher skill levels than earlier cohorts. This result refutes, in terms of unobservable skills, the "declining cohort quality" narrative that is widely accepted in the literature.

The theoretical basis of our empirical analysis is a production framework in which natives and immigrants supply two types of skills: general skills, which 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 then accumulate further specific skills at a 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. Equilibrium prices of the two types of skills are competitively determined, which implies that relative skill prices depend on aggregate skill supplies. Workers are paid according to the skill bundle they supply. In our framework, imperfect substitutability between immigrants and natives thus 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 are already more similar to natives in terms of the skills they provide, making their relative wages less responsive to changes in equilibrium skill prices. Whether secular 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 underlying skill accumulation profiles.

We fit our model by non-linear least squares (NLS) using data from the U.S. Census and the American Community Survey (ACS) that cover the period 1970 to 2010. 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 composition effect due to changes in immigrants' education and region of origin, and a residual component that we interpret, following the literature, as reflecting changes in cohort quality.

Our results show that immigrants and natives are generally not perfect substitutes in production, with an implied elasticity of substitution between the average immigrant and native of 34.2. The degree of substitutability, however, increases monotonically over time so that after 20 to 30 years in the United States, immigrants and natives with the same education and experience levels are practically perfect substitutes. Our decomposition analysis reveals that immigration-induced increases in labor market competition can explain 18.6, 53.9 and 43.8 percent of the increase in the *initial* relative wage gap, and 16.4, 24.8 and 27.6 percent of the increase in the *average* relative wage gap, between the baseline 1960s cohort and the 1970s, 1980s, and 1990s cohorts, respectively. We further find a moderate positive impact of increasing labor market competition on the relative wage growth of the 1980s cohort but only relatively minor effects on the wage growth of the three other cohorts. Declining relative education levels of immigrants and changes in their region-of-origin composition both play a quantitatively similar role as the competition effect in explaining the raw patterns in the data. Once competition and composition effects are accounted for, we find that the quality of recent immigrant cohorts, as measured by the amount of specific skills with which they arrive in the United States, increased rather than decreased relative to earlier cohorts. We provide additional support for this central finding by documenting closely matching empirical patters for immigrants' English language proficiency. Through a series of robustness checks, we finally show that our main findings are largely unaffected if we additionally account for possible network effects, undercounting of undocumented immigrants, selective outmigration, shifts in relative skill demand, alternative labor market definitions, and endogenous immigrant location choices.

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, more recently, 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.

Several papers in the literature have critically assessed some of the key assumptions underlying the estimation and interpretation of immigrants' wage assimilation profiles. Using CPS data for the period 1979 to 2003, 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 estimated 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. 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 outmigration 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 time period our analysis is meant to cover, we cannot account for selective outmigration as comprehensively as these papers do, but we show through three separate robustness checks that this issue is unlikely to affect our main conclusions.

Some papers in the literature highlight, similar to our paper, the importance of skill prices for correctly measuring 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 of the average immigrant. Lubotsky (2011) performs a similar analysis that includes more recent arrival cohorts using longitudinal Social Security data linked to cross-sectional SIPP and CPS data. 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)

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

analyzes both theoretically and empirically 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 labor market outcomes. 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 (2021) 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 United States or natives. As immigrants move across nests, their skill efficiency and substitutability with other factor inputs change, which jointly determines their wage growth in the host country. 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. Kerr and Kerr, 2011, Cadena et al., 2015, and Dustmann, Schönberg and Stuhler, 2016, for surveys of this literature). One important insight that has emerged over the past decade or so in this research area is that immigrants and natives are usually 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 then seeking to estimate the magnitudes of these relative wage effects. 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 a very distinct and partial way. While the traditional assimilation literature completely abstracts from aggregate factor supplies as possible drivers of relative wages, the impact literature does usually not, or only very rudimentarily, allow for immigrants' skill accumulation and evolving substitutability with other factor inputs. Our theoretical framework synthesizes to some extent 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 some regression results that illustrate the relationship between relative wage dynamics and the size of immigrant inflows. Section III presents our theoretical framework. Section IV discusses identification issues and the estimation of the model. Section V reports our baseline findings and the goodness of fit of our model. Section VI presents our simulation results and decomposition analysis. Section VII provides 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, which we combine with observations from the American Community Survey (ACS) pooled across the years 2009 to 2011. 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 native and immigrant men aged 25 to 64 who are not self-employed, do not live in group quarters, are not enrolled in school (except for 1970), work in the civilian sector, 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.[2] Further details on the variable definitions are provided in Appendix A.

Table 1 reports descriptive statistics on the size and composition of different immigrant arrival cohorts, which we aggregate by decades. Cohort sizes increased steadily over the time period considered, from about 500 thousand individuals in the 1960s to 1.5 million

[2] The U.S. Census is designed to include all immigrants, regardless of whether they are legally in the United States or undocumented. However, different estimates in the literature show that it significantly undercounts undocumented immigrants. In Section VII, we do a robustness check in which we correct for this undercounting in our baseline estimation.

Table 1—Descriptive Statistics of Immigrant Cohorts

	Cohort of entry:				
	1960-69	1970-79	1980-89	1990-99	2000-09
Share of population (%)	1.6	2.2	3.2	4.4	5.3
Cohort size (millions)	0.5	0.9	1.5	2.3	2.9
Age	38.3	36.8	36.4	36.5	37.3
Hourly wage	19.1	18.4	16.1	17.5	15.6
HS dropouts (%)	45.8	41.3	32.1	29.8	28.5
HS graduates (%)	19.6	19.2	23.6	28.0	27.9
Some college (%)	10.6	11.3	16.7	11.0	10.5
College graduates (%)	24.0	28.3	27.6	31.2	33.0
Mexico (%)	9.9	23.5	21.5	29.4	30.8
Other Latin America (%)	27.8	19.4	25.3	20.7	25.4
Western countries (%)	37.7	18.0	11.3	9.8	7.2
Asia (%)	14.8	31.4	33.7	27.6	26.5
Other (%)	9.8	7.7	8.2	12.6	10.0

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

in the 1980s and 2.9 million in the 2000s. As shown in Table B1 in Appendix B, this led to a sizeable increase in the foreign-born share of the population, from 3.6 percent in 1970 to 15.8 percent in 2010. This substantial increase in immigration was accompanied by an important shift in the immigrants' ethnic and educational composition. While most immigrants in the 1960s originated from Western source countries (37.7 percent) and relatively few from Mexico (9.9 percent) and Asia (14.8 percent), this pattern reversed over the following decades, with the share of immigrants from Western countries (7.2 percent) decreasing and the shares from Mexico (30.8) and Asia (26.5) increasing rapidly.

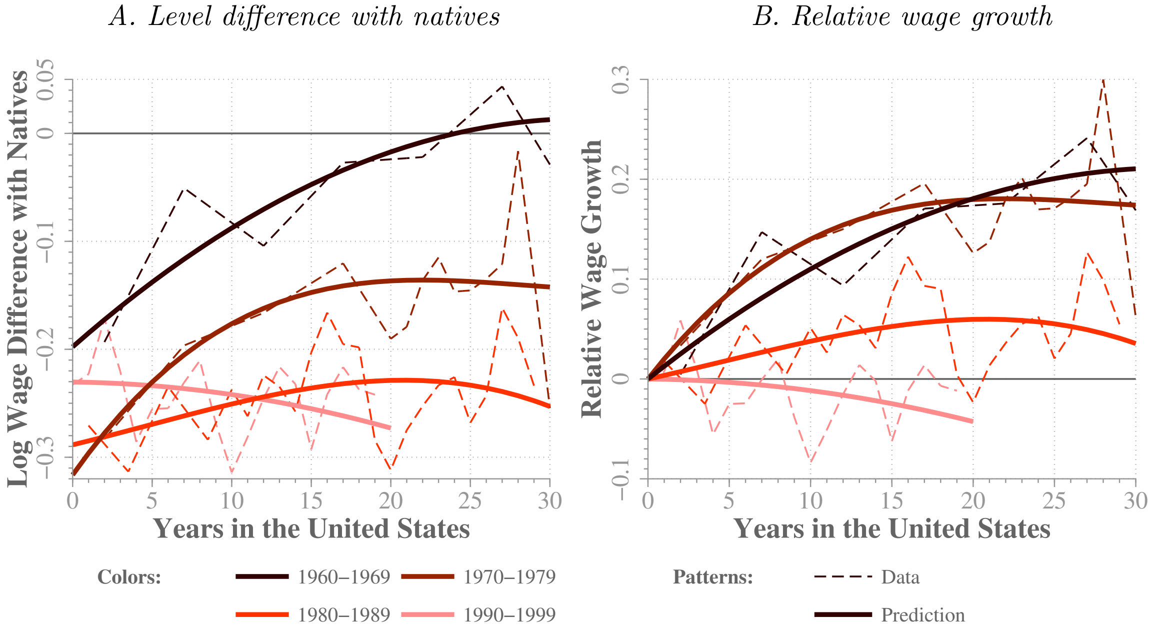
Concurrently, the level of formal education of newly arriving immigrants improved, especially since the 1980s, with the share of high school dropouts decreasing from 45.8 percent in the 1960s to 28.5 percent in the 2000s, and the share of college graduates increasing from 24.0 percent in the 1960s to 33.0 percent in the 2000s. However, despite this considerable improvement in immigrants' educational attainment, the gap in formal education relative to natives widened significantly due to the even more rapid expansion of higher education in the United States during the last half century (see Table B1).

The notable shifts in educational attainment and country of origin composition shown in Tables 1 and B1 are likely to explain at least part of the observed changes in immigrants' wage assimilation profiles documented below. In the subsequent empirical analysis, we quantify the contributions of these compositional changes and contrast them with the contribution of labor market equilibrium effects due to growing immigrant cohort sizes.

B. Descriptive evidence on assimilation patterns over recent decades

To set the stage for our analysis, we start by documenting how immigrant wage assimilation profiles have changed over time, following the standard approach based on repeated

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 natives and immigrants 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 2000, and the third order term for all cohorts that arrived before 1990):

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

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 ysm_i indicates years since migration. Cohorts are grouped in the following way: before 1960, 1960-1969, 1970-1979, 1980-1989, 1990-1999, and after 2000. Colors represent cohorts, and shapes represent data or regression predictions as indicated in the legend.

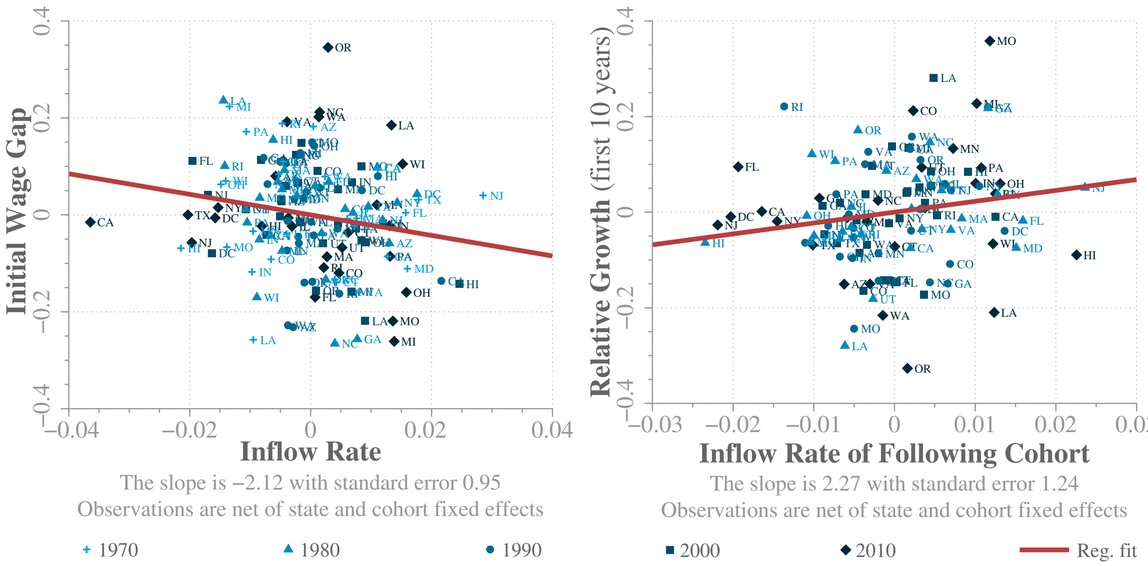
cross-sectional data first advocated by Borjas (1985). In Figure 1, we depict two sets of results. The dashed lines are obtained from year-by-year regressions of log wages on a third order polynomial in age and dummies for years since migration (which are all set to zero for native workers). The plotted 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 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 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

[3] Cohorts are grouped in 10-year intervals. The pre-1960s and 2000s cohorts are not plotted but included in all regressions. We exclude the cubic term for the 1990s cohort and both the quadratic and cubic terms for the 2000s 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 observed in the raw averages.

Figure 2. Cohort Size, Initial Wage Gap, and Relative Wage Growth

A. Wage gap at arrival *B. Relative wage growth first 10 years*



Note: This figure plots the initial wage gap for 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 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. States with less than 50 immigrants in any of the census years are not included. Dots represent state-cohort observations and lines represent linear regression fits. Markers/shades distinguish different cohorts.

natives widened substantially over time: while the 1960s cohort arrived with an initial wage gap of less than 20 log points, the 1970s and 1980s arrival cohorts faced an initial wage gap of around 30 log points, which narrowed again to 23 log points for the 1990s cohort. Second, the speed of wage convergence decreased significantly across cohorts, to the point that the 1990s cohort no longer shows any sign of actual wage assimilation.

Our central hypothesis is that the changing wage assimilation patterns across cohorts are partially driven by changes in relative skill supply due to the 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 wage gap (left panel) and relative wage growth over the first decade in the United States (right panel) to the size of the contemporaneous and following immigrant arrival cohorts respectively, exploiting variation at the state-cohort level. The initial wage gaps and relative growth rates are predicted from regressions analogous to those underlying the solid lines in Figure 1 but estimated for each state separately and subsequently 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 unambiguously predicts. The impact of growing cohort sizes on relative wage growth, in contrast, is theoretically ambiguous, as discussed below. Figure 2B shows that, in the data, the correlation between the size of future immigrant inflows and a given cohort's relative wage growth is positive, consistent with the effect that dominates on aggregate in our main empirical analysis.

III. Model

In this section, we propose a theoretical framework that highlights the importance of labor market competition for immigrants' wage assimilation profiles, using a production function framework 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. Specific skills 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 both types of skills, which we normalize to one for a native who just dropped out of high school. Individual skill supplies are shifted by a productivity factor that is a function of education and potential experience and allowed to vary over time due to, for example, skill-biased technological change.[4] When arriving 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 evolves as the immigrant spends time in the host country.

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:

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

where σ denotes the elasticity of substitution between general and specific skills, A_t denotes 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:

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

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, recent high school dropouts (the reference group) 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.

[4] For a similar approach (outside of the immigration context), see Jeong, Kim and Manovskii (2015) who shift their skill supplies (labor and experience) by a Mincerian productivity factor similar to the one described below.

For immigrants ($n = 0$), the fraction s depends on the number of years spent in the host country y, national origin o, cohort of entry c, education level e (which is a function of years of education E, but 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).[5] In particular:

$$s(n, y, o, c, E, x) \equiv \begin{cases} 1 & \text{if } n = 1 \\ \theta_{1o} + \sum_{\ell=1}^{3} \theta_{2o\ell} y^{\ell} + \theta_{3e} + \sum_{\ell=1}^{3} \theta_{4e\ell} y^{\ell} & \\ + \sum_{\ell=1}^{3} \theta_{5\ell} (x - y)^{\ell} + \theta_{6c} + \sum_{\ell=1}^{3} \theta_{7c\ell} y^{\ell} & \text{if } n = 0, \end{cases} \tag{3}$$

where the skill accumulation process is allowed to vary across different origin groups ($\theta_{2o\ell}$), education groups ($\theta_{4e\ell}$), and cohorts of entry ($\theta_{7c\ell}$).

Both general and specific skills are shifted by a productivity factor defined as:

$$h_t(E, x) \equiv \exp\left(\eta_{0et} + \eta_{1t} E + \sum_{\ell=1}^{3} \eta_{2\ell t} x^{\ell}\right). \tag{4}$$

Our model accounts for two forms of skill-biased technical change. First, the time-varying parameters η_{1t}, $\{\eta_{0et}\}_{e \in \mathcal{E}}$ and $\{\eta_{2\ell t}\}_{\ell \in \{1,2,3\}}$ in Equation (4) capture standard skill-biased technical change that increases the demand for high-skilled workers and for workers with different levels of potential experience. Furthermore, δ_t in Equation (1) captures any additional demand shifts that are associated with a changing demand for specific skills (e.g. due to technological progress that favors language over manual skills).

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

$$w_t(n, y, o, c, E, x) = \left[r_{Gt} + r_{St} s(n, y, o, c, E, x)\right] h_t(E, x). \tag{5}$$

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

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

where the second equality is obtained, upon rearrangement, by substituting the equilibrium skill prices by their counterparts in Equation (2). This expression 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 $s(0, y, o, c, E, x)$ evolves over time spent in the host country (y), which reflects immigrants' skill accumulation process. The second one is the competition effect

[5] In our application, we only start counting experience after age 18, discarding years before that age.

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 ($\sigma < \infty$) and immigrants differ from natives in terms of the skill bundle they supply ($s \neq 1$).

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:

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

Therefore, larger immigrant arrival cohorts 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 the skill bundles they supply to the market. Intuitively, closer arrival cohorts are more substitutable in the labor market than cohorts arriving many years apart.

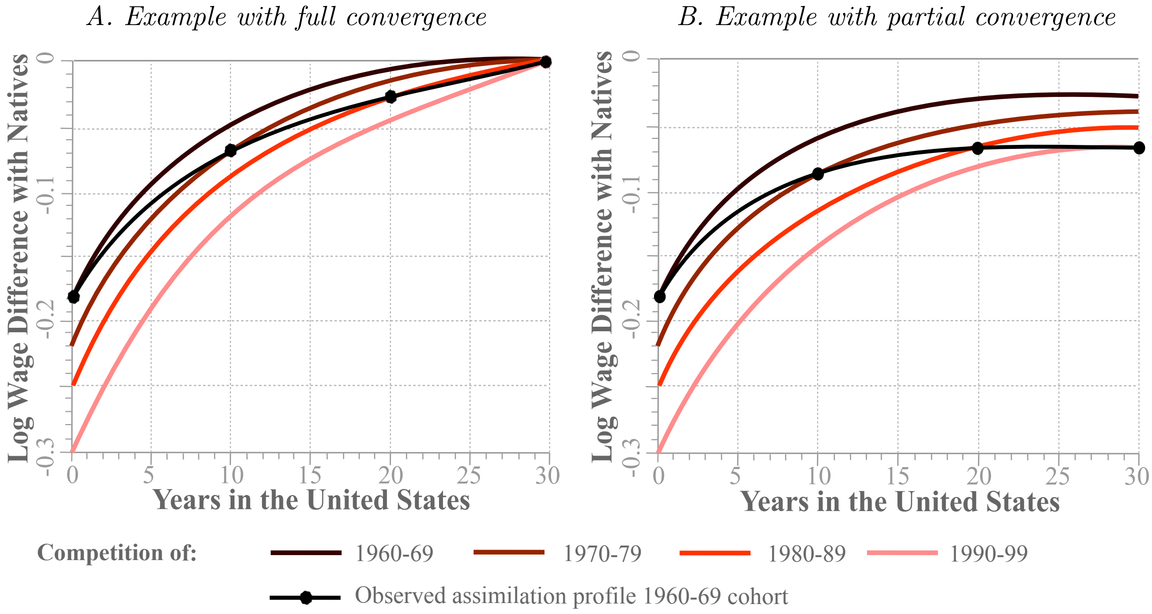
The observation that, at a given point in time, new immigrant inflows affect the wage gap of previous cohorts differentially depending on the latter's time of arrival suggests that such inflows also affect the speed of wage assimilation for a given cohort. To understand the underlying mechanism, it is instructive to first consider the hypothetical scenario of a one-time 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 than in the later years:

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

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

The solid 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 ($s \to 1$), whereas Figure 3B depicts the case where, even in the long run, immigrant wages do not fully converge ($s \to< 1$). Each colored line represents the stylized wage assimilation profile for a differently sized one-time permanent increase in aggregate relative skill supplies, holding all other immigrant characteristics constant. To connect with the empirical observation that immigrant inflows into the United States were growing over time, we label these lines as if they were representing different entry cohorts. In line with Equations (7) and (8), the larger the aggregate relative skill supply G_t/S_t, the bigger

FIGURE 3. DYNAMIC COMPETITION EFFECT: AN EXAMPLE



Note: The figure plots hypothetical convergence paths for different levels of competition under the assumption of increasing immigrant inflows across arrival cohorts. The thick black line (with circles) that cuts across the hypothetical convergence paths represents the implied assimilation profile one would observe in the data for a cohort that arrived in the 1960s. The left figure shows an example under the assumption of full wage convergence, the right figure an example under the assumption of only partial long-run wage convergence.

the initial wage gap and the faster the subsequent relative wage growth. In the full convergence case (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 their level of specific skills s approaches one, immigrants provide the same skill bundle as natives and are therefore no longer differentially affected by changes in aggregate supplies (the numerator of Equation (7) becomes zero). Increasing labor market competition thus slows down the process of wage convergence but does not prevent it. This result, however, does not apply when immigrants' level of specific skills only partially converges to that of natives (Figure 3B). In that case, even in the long run, immigrants supply relatively more general skills than natives and are therefore more negatively affected by permanent increases in G_t/S_t. The long-term relative wage gap between immigrants and natives, which is often viewed as a key indicator of immigrants' labor market integration, is therefore partially determined by aggregate skill supplies and labor market competition.

While helpful in understanding the main mechanism at work, the previous scenario of a one-time permanent increase in G_t/S_t misses an important point. If new immigrant arrival cohorts become increasingly larger over time, the level of competition a given cohort faces increases throughout their time in the host country. 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*. In Figure 3, the dynamic competition effect is captured by the black lines with circles, which represent the actual assimilation profile one would observe for an immigrant who arrived in the 1960s under this dynamic scenario. Such an immigrant would start off on the dark red wage profile labeled "1960-69" at arrival, but then be observed on the second profile labeled "1970-79" ten years later, on the third profile labeled "1980-89" twenty years later, and so on. Thus, comparing the line labeled "1960-69" with the black line with circles, it follows that the dynamic competition effect slows down the wage convergence process of that cohort. Figures 3A and 3B show that this dynamic effect is more consequential when immigrants' wages do not fully converge to those of their native counterparts in the baseline ($s \rightarrow< 1$).

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 net of any labor market competition and composition effects, and quantify the relative importance of skill accumulation, labor market competition and composition effects in explaining changes 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. According to 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 are estimated to have comparative advantage in blue collar occupations. Through the lens of our model, manual tasks (and blue collar occupations) require primarily general skills (nailing, building, or gardening are similar tasks across countries) whereas communication tasks rely largely on host-country-specific skills such as language proficiency.

The production function in Equation (1) differs from the standard nested CES function popularized by Borjas (2003), Ottaviano and Peri (2012) and Manacorda, Manning and Wadsworth (2012), in which native and immigrant workers constitute distinct labor inputs within narrowly defined skill cells (usually based on education and experience).[6] More in line with Dustmann, Frattini and Preston (2013) and Llull (2018), our approach has the

[6] Our framework could be easily adapted to define labor markets in terms of education-experience groups, as long as the lowest level of the nesting structure is defined in terms of general and specific skills.

advantage of not having to define ex ante who competes with whom based on education, experience, or nativity status. Instead, we allow imperfect substitutability between natives and immigrants to arise from differences in their underlying skill sets. Nonetheless, in the empirical analysis below we explicitly link our estimate of the elasticity of substitution between general and specific skills σ to the elasticity of substitution between native and immigrant workers that has been estimated in the nested CES literature.

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 he does not speak English sufficiently well. As a result, he will have 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 over time 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 country of origin and education level.

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:

$$\begin{aligned} \ln w_t(n,y,o,c,E,x) &= \ln A_t + \ln[1 + s(n,y,o,c,E,x)] + \ln h_t(E,x) \\ &\approx \tau_t + \eta_{0et} + \eta_{1t}E + \sum_{\ell=1}^{3} \eta_{2\ell t} x^\ell + (1-n) \begin{bmatrix} \theta_{1o} + \sum_{\ell=1}^{3} \theta_{2o\ell} y^\ell + \theta_{3e} + \sum_{\ell=1}^{3} \theta_{4e\ell} y^\ell \\ + \sum_{\ell=1}^{3} \theta_{5\ell} (x-y)^\ell + \theta_{6c} + \sum_{\ell=1}^{3} \theta_{7c\ell} y^\ell \end{bmatrix}, \end{aligned} \tag{9}$$

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 education and age as well as, for immigrants, age at the time of arrival, country of origin, and cohort of entry. Let $\mathcal{C}$ denote the set of cohorts available in the data, $\mathcal{O}$ the set of regions of origin, $\mathcal{E}$ the set of considered education groups, and $\mathcal{T}$ the set of census years. We parameterize $\delta_t \equiv \exp(\tilde{\delta} t)$.[7] 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

[7] To be more precise, we define t as years since 1970. We also estimate our model with alternative specifications for δ_t in Section VII, including a quadratic specification in t and time dummies.

$\{\theta_{1o}, \{\theta_{2o\ell}\}_{\ell\in\{1,2,3\}}\}_{o\in\mathcal{O}}$, $\{\theta_{3e}, \{\theta_{4e\ell}\}_{\ell\in\{1,2,3\}}\}_{e\in\mathcal{E}}$, $\{\theta_{5\ell}\}_{\ell\in\{1,2,3\}}$ and $\{\theta_{6c}, \{\theta_{7c\ell}\}_{\ell=1}^{3}\}_{c\in\mathcal{C}}$, and the period-specific parameters of the productivity factor $\{\{\eta_{0et}\}_{e\in\mathcal{E}}, \eta_{1t}, \{\eta_{2\ell t}\}_{\ell\in\{1,2,3\}}\}_{t\in\mathcal{T}}$. This section discusses the identification and estimation of these parameters.

A. *Identification*

We begin with the identification of the parameters of the productivity factor $h_t(E, x)$. Let i index individual observations observed in labor market $j(i)$ and census year $t(i)$, where labor markets are defined as U.S. states in our baseline specification. From Equation (5), observed log wages of natives are given by:

$$\ln w_i = \ln\left[r_{Gj(i)t(i)} + r_{Sj(i)t(i)}\right] + \eta_{0e(i)t(i)} + \eta_{1t(i)}E_i + \sum_{\ell=1}^{3}\eta_{2\ell t(i)}x_i^{\ell} + \epsilon_i, \tag{10}$$

where ϵ_i is a random error term uncorrelated with the other regressors that captures idiosyncratic shocks to productivity and measurement error in hourly wages. Considering a separate regression for each census year, and normalizing $\{\eta_{0et}\}_{t\in\mathcal{T}}$ for one education group, the parameters $\{\{\eta_{0et}\}_{e\in\mathcal{E}}, \eta_{1t}, \{\eta_{2\ell t}\}_{\ell\in\{1,2,3\}}\}_{t\in\mathcal{T}}$ are identified as linear regression coefficients, while $\ln[r_{Gjt} + r_{Sjt}]$ is identified for each market-period as the coefficient on the corresponding year-specific state dummy.

With these parameters at hand, the aggregate supply of general skill units in a given market-period G_{jt} is identified since, conditional on E and x, immigrants supply the same amount of general skills as natives. The parameters of the specific skills function $s(0, y, o, c, E, x)$ and the elasticity of substitution σ are identified from Equation (6) as the coefficients from a non-linear 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 he was a native:

$$\begin{aligned}\ln w_i - \ln[\widehat{r_{Gj(i)t(i)} + r_{Sj(i)t(i)}}] - \ln \widehat{h_{t(i)}(E_i, x_i)} &= -\ln\left[1 + \exp(\tilde{\delta} t_i)\left(\frac{\widehat{G}_{j(i)t(i)}}{\widehat{S}_{j(i)t(i)}}\right)^{\frac{1}{\sigma}}\right] \\ + \ln\left[1 + \begin{pmatrix} \theta_{1o(i)} + \sum_{\ell=1}^{3}\theta_{2o(i)\ell}y_i^{\ell} + \theta_{3e(i)} + \sum_{\ell=1}^{3}\theta_{4e(i)\ell}y_i^{\ell} \\ + \sum_{\ell=1}^{3}\theta_{5\ell}(x_i - y_i)^{\ell} + \theta_{6c(i)} + \sum_{\ell=1}^{3}\theta_{7c(i)\ell}y_i^{\ell} \end{pmatrix} \exp(\tilde{\delta} t_i)\left(\frac{\widehat{G}_{j(i)t(i)}}{\widehat{S}_{j(i)t(i)}}\right)^{\frac{1}{\sigma}}\right] &+ \epsilon_i,\end{aligned} \tag{11}$$

where

$$\widehat{G}_{jt} = \sum_{i\in\{j,t\}} \omega_i \widehat{h_t(E_i, x_i)}, \tag{12}$$

and

$$\widehat{S}_{jt} = \sum_{i\in\{j,t\}} \omega_i \left[n_i + (1-n_i)\begin{pmatrix} \theta_{1o(i)} + \sum_{\ell=1}^{3}\theta_{2o(i)\ell}y_i^{\ell} + \theta_{3e(i)} + \sum_{\ell=1}^{3}\theta_{4e(i)\ell}y_i^{\ell} \\ + \sum_{\ell=1}^{3}\theta_{5\ell}(x_i - y_i)^{\ell} + \theta_{6c(i)} + \sum_{\ell=1}^{3}\theta_{7c(i)\ell}y_i^{\ell} \end{pmatrix}\right] \widehat{h_t(E_i, x_i)}, \tag{13}$$

and where ω_i are sampling weights and the sum over $i \in \{j, t\}$ aggregates all the observations in a labor market j and census year t. Note that the aggregate supply of specific skill units S_{jt} only depends on the (weighted) number of immigrants and natives in the relevant market, the previously identified parameters of the productivity factor $h_t(E, x)$, and the parameters of $s(0, y, o, c, E, x)$. Intuitively, the latter are identified off the wage differences between individuals within a given labor market, while σ and $\tilde{\delta}$ are identified off the variation across markets and over time.

B. Estimation

Our estimation proceeds in two steps. In the first step, we obtain the parameters of the productivity factor $h_t(E, x)$ by estimating the log-linear wage regression in Equation (10) using observations for native workers only. We estimate a separate regression for each census year, thus allowing the returns to education and experience to vary over time. Since in our baseline specification labor markets are defined as U.S. states (we use alternative definitions in Section VII), we include state dummies in each of the regressions to identify the relevant skill prices. In the second step, we first compute $\widehat{G}_{jt}$ and the worker-specific left-hand side terms of Equation (11) using the estimated parameters from the first step, and then estimate the remaining parameters of Equation (11) by non-linear least squares, using only observations for immigrant workers and updating $\widehat{S}_{jt}$ in each iteration of the NLS estimation algorithm based on Equation (13).

Given the two-stage estimation procedure, standard errors should be corrected to account for the econometric error introduced by using first-stage estimates in the computation of $\widehat{G}_{jt}$ and $\widehat{S}_{jt}$ (the only right-hand side variables that include outcomes of the first-stage estimation). A simple, yet computationally demanding, way of implementing that correction would be to bootstrap all standard errors. However, since $\widehat{G}_{jt}$ and $\widehat{S}_{jt}$ are aggregations of terms estimated in the first stage, they integrate over these terms' estimation errors, which significantly reduces $\widehat{G}_{jt}$'s and $\widehat{S}_{jt}$'s own estimation errors. We therefore provide uncorrected standard errors throughout, obtained by the standard NLS formula. Given the large sample used in the estimation, all our estimates are very precise, and would continue to be so also with bootstrapped standard errors.

V. Estimation Results and Goodness of Fit

This section provides an overview of the baseline estimation results in which labor market competition is determined at the state level. We also assess the ability of our model to fit the data. Results for alternative specifications, different labor market definitions and other robustness checks are discussed in Section VII.

A. Productivity factor parameters

Table 2 reports the estimates for the productivity factor $h_t(E, x)$, with each column referring to a different census year. The parameter estimates are consistent with those found in the literature (see e.g. Heckman, Lochner and Todd, 2006, for a survey). Beyond the wage returns to different educational degrees (1.4–5.2 log points for a high school

Table 2—Productivity Factor, $h_t(E, x)$

	Census year:				
	1970	1980	1990	2000	2010
Years of education (η_{1t})	0.046	0.042	0.047	0.052	0.063
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Potential experience (η_{21t})	0.056	0.070	0.052	0.061	0.072
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pot. exp. squared ($\eta_{22t} \times 10^2$)	-0.171	-0.191	-0.107	-0.174	-0.199
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Pot. exp. cube ($\eta_{23t} \times 10^3$)	0.016	0.016	0.005	0.016	0.017
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
High school graduate (η_{02t})	0.014	0.052	0.047	0.052	0.037
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)
Some college (η_{03t})	0.080	0.094	0.143	0.147	0.137
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
College graduate (η_{04t})	0.275	0.276	0.367	0.387	0.404
	(0.005)	(0.004)	(0.004)	(0.005)	(0.008)

Note: This table presents parameter estimates for the productivity factor $h_t(E, x)$, 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.

diploma, 8.0–14.7 log points for some college education and 27.5–40.4 log points for a bachelor's degree, depending on the year), an extra year of education increases wages by 4.2–6.3 log points. In general, returns to education increased over time, in line with the findings of the wage inequality literature. The wage-experience profile shows the standard concave shape, flattening after around 25 years of experience.

B. Skill accumulation parameters

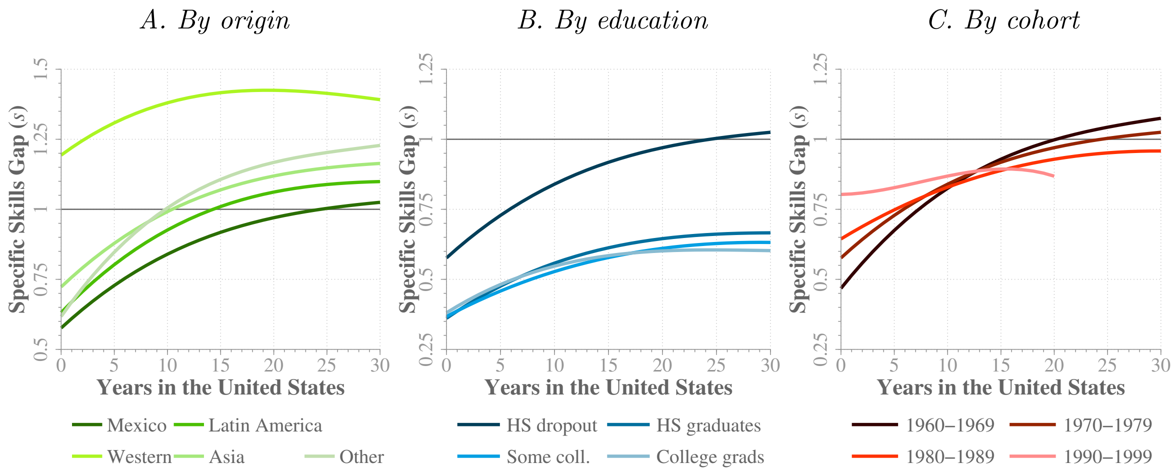
Table 3 reports the parameter estimates that describe the process through which immigrant workers accumulate specific skills, $s(0, y, o, c, E, x)$. The first column shows the coefficients of the non-interacted terms (θ_{1o}, θ_{3e}, $\{\theta_{5\ell}\}_{\ell\in\{1,2,3\}}$ and θ_{6c}) along with the constant term. The constant represents the relative specific skills supplied upon entry by a Mexican high school dropout (the most frequent immigrant in the sample) who arrived in the 1970s cohort (for whom we hence observe the entire wage profile in the United States) with zero years of foreign experience. This constant term is estimated to be 0.776, indicating that this reference immigrant supplies a little more than three quarters of the specific skills supplied by an observationally equivalent native. All other estimates in the first column represent relative shifters 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 19.6 and 21.5 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

Table 3—Specific Skills for Immigrants, $s(0, y, o, c, E, x)$

	Intercepts	Interactions with years since migration: Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Region of origin $\theta_{1o}, \{\theta_{2o\ell}\}_{\ell \in \{1,2,3\}}$**:**				
Latin America	0.055	0.005	-0.015	0.001
	(0.009)	(0.002)	(0.015)	(0.003)
Western countries	0.617	-0.007	-0.008	0.001
	(0.019)	(0.003)	(0.021)	(0.004)
Asia	0.147	0.001	-0.005	0.000
	(0.010)	(0.003)	(0.017)	(0.003)
Other	0.041	0.019	-0.079	0.011
	(0.012)	(0.003)	(0.021)	(0.004)
Education level $\theta_{3e}, \{\theta_{4e\ell}\}_{\ell \in \{1,2,3\}}$**:**				
High school graduate	-0.215	-0.008	0.019	-0.002
	(0.009)	(0.002)	(0.014)	(0.003)
Some college	-0.209	-0.014	0.049	-0.007
	(0.012)	(0.003)	(0.017)	(0.003)
College graduate	-0.196	-0.011	0.010	0.000
	(0.011)	(0.003)	(0.017)	(0.003)
Cohort of arrival $\theta_{6c}, \{\theta_{7c\ell}\}_{\ell \in \{1,2,3\}}$**:**				
Pre-1960s	0.372	-0.028	0.195	-0.029
	(0.119)	(0.016)	(0.064)	(0.008)
1960s	-0.109	0.048	-0.136	0.015
	(0.015)	(0.003)	(0.019)	(0.003)
1970s		0.035	-0.096	0.010
		(0.002)	(0.016)	(0.003)
1980s	0.068	0.023	-0.050	0.002
	(0.010)	(0.002)	(0.018)	(0.004)
1990s[a]	0.227	0.001	0.102	-0.045
	(0.010)	(0.003)	(0.031)	(0.010)
2000s[a]	0.230	-0.003	0.102	-0.045
	(0.012)	(0.003)	(0.031)	(0.010)
Experience at entry $\{\theta_{5\ell}\}_{\ell \in \{1,2,3\}}$**:**				
Linear term	-0.025			
	(0.001)			
Quadratic ($\times 10^2$)	0.074			
	(0.005)			
Cubic ($\times 10^3$)	-0.008			
	(0.001)			
Constant (relative specific skills at arrival of a Mexican high school dropout immigrant who arrived in the 1970s cohort with zero years of experience)**:**				
	0.776			
	(0.011)			

Note: This table presents parameter estimates for the specific skill accumulation function of immigrants, defined in Equation (3). All parameters refer to the baseline individual, which is a Mexican high school dropout who arrived in the United States in the 1970s with zero years of potential experience. Sample weights, rescaled by annual hours worked are used in the estimation. The regression is estimated by NLS. Standard errors in parentheses.
[a] Quadratic and cubic interaction terms for the 1990s and 2000s cohorts are grouped in the estimation.

Figure 4. Skill Accumulation, $s(0, y, o, c, E, 11.7 + y)$



Note: The figure displays predicted skill accumulation profiles for different groups based on the estimates reported in Table 3. The baseline individual in all figures is a Mexican high school dropout (the most frequent immigrant in the sample) who arrived in the United States in the 1970s (for whom we hence observe the entire wage profile in the United States) with 11.7 years of potential experience (the unconditional mean in the sample). Panel A displays the evolution of specific skills over time spent in the United States by region of origin, Panel B by education level, and Panel C by arrival cohort, holding all other characteristics constant at baseline.

that are well below those of comparable native workers.[8] Regarding the different arrival cohorts, with the exception of 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 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 immigrants.

The remaining columns of Table 3 show the estimated coefficients of the interaction terms of each of the different characteristics and a polynomial in years since migration $\{\theta_{2o\ell}, \theta_{4e\ell}, \theta_{7c\ell}\}_{\ell \in \{1,2,3\}}$. Since the magnitudes of these parameters are difficult to interpret, we visualize them in Figure 4 by plotting the predicted skill accumulation profiles for different types of immigrants. The baseline individual in all figures is a Mexican high school dropout who arrived in the United States in the 1970s with 11.7 years of potential experience abroad (the unconditional mean in the sample). Figure 4A depicts the evolution of specific skills by region of origin, holding the level of education, year of arrival, and potential experience upon entry constant at their baseline levels. With the exception of immigrants from Western countries, all groups arrive with specific skills that are well below those of comparable natives. Over time, they then accumulate specific skills such that the gap relative to natives is fully closed (and often even reversed).

Figure 4B shows the corresponding profiles by level of education, holding the region of origin, year of arrival, and potential experience abroad at their baseline levels. Relative to

[8] There are only very few immigrants from Western countries that are high school dropouts. Note that we do not bound the specific skills of immigrants at a value of one, thus allowing their wages to exceed those of comparable natives, which is something we observe in the data for some immigrant groups.

similarly educated natives, immigrant high school dropouts arrive with the highest level of specific skills, reflecting the fact that they are more comparable to native dropouts than, for example, immigrant college graduates are to native college graduates. Contrary to all other education groups, who only reach about 60 percent of their native counterparts' specific skill levels, immigrant high school dropouts manage to entirely close the relative skill gap as they spend time in the United States.

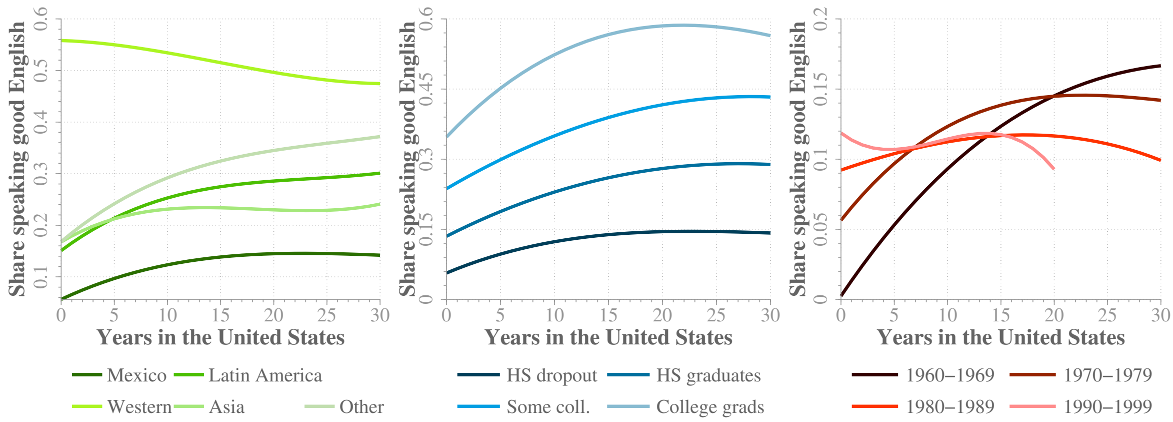
Figure 4C plots the skill accumulation profiles by arrival cohort, omitting the pre-1960s and post-2000s cohorts, which we both only observe for a short time period (they are accounted for in the estimation, though, as shown in Table 3). While the 1960s cohort faced a substantial initial skill gap of around 50 percent, this gap narrowed for subsequent cohorts, to around 40 percent for the 1970s cohort, around 35 percent for the 1980s cohort, and 20 percent for the 1990s cohort. This central result of our analysis speaks, at least in terms of initial skill levels, against the "declining cohort quality" narrative that is widely accepted in the literature. Consistent with that literature, however, Figure 4C also shows that the speed of specific skill accumulation has slowed down markedly across cohorts, which might, in part, reflect diminishing returns to the investment in specific skills. Notwithstanding, after 20–30 years, all arrival cohorts apart from the most recent one have almost entirely closed their initial skill gap relative to natives.

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, 2021, or Rho and Sanders, 2021) and/or an intensifying globalization process that makes U.S.-specific skills, in particular English language skills, more abundant among potential immigrants around the world. Using information about English language proficiency available in the Census data from 1980 onward, we provide additional evidence supporting this interpretation of our results. 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.[9]

Figure 5 presents the results from this regression, revealing similar patterns to those shown in Figure 4 (except for, as expected, the results by education groups). In line with our findings for the overall supply of specific skills, Figure 5A shows that Mexican immigrants start off with lower English language proficiency and improve their language skills at a slower pace than immigrants from other countries. At the other extreme, Western immigrants arrive with high proficiency, which they maintain throughout their

[9] The results without the time dummies are overall very similar, even though the slopes are somewhat less steep (becoming negative for the most recent cohorts). The inclusion of time dummies is justified to capture changes in the way individuals respond to the English proficiency question: for example, what was perceived as "very good English" for a Mexican in 1980 may not be the same as in 2010, when the overall English proficiency of immigrants is higher, as our results suggest. This interpretation is consistent with the finding that some language profiles are slightly decreasing when these dummies are omitted.

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 $s(\cdot)$ and year dummies. The baseline individual in all figures is a Mexican high school dropout (the most frequent immigrant in the sample) who arrived in the United States in the 1970s (for whom we hence observe the entire wage profile in the United States) with 11.7 years of potential experience (the unconditional mean in the sample). Panel A displays the evolution of English proficiency over time spent in the United States by region of origin, Panel B by education level and Panel C by arrival cohort, holding all other characteristics constant at baseline.

stay. The results by education level in Figure 5B are not directly comparable to their counterpart in Figure 4B. The estimated lines in Figure 4B represent the amount of U.S.-specific skills of an immigrant relative to a native worker *with the same level of education*. Instead, Figure 5B depicts the average English proficiency of immigrants with different levels of education. Not surprisingly, individuals with higher education are more proficient at arrival and also accumulate further language skills at a faster rate. Given that language-specific skills tend to be more important in occupations where highly educated workers are employed, 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, as suggested by Figure 4B.

One of the central findings of this study is that recent cohorts of immigrants, everything else equal, arrive with a higher level of specific skills than earlier cohorts. Figure 5C supports this finding by showing that the fraction of immigrants who arrive with a high level of English language proficiency has been steadily increasing over time. The fact that the language profiles in Figure 5C closely mirror their counterparts in Figure 4C suggests that our estimated skill accumulation profiles indeed reflect changes in the host-country-specific skills of immigrant workers.

C. Elasticity of substitution and demand shifters

The estimates of the remaining parameters of the model σ and $\tilde{\delta}$ are reported in Table 4. Panel A reports our baseline estimate of the elasticity of substitution between general and specific skills, σ, which is a precisely estimated 0.021. Interpreting this magnitude is not straightforward in the absence of a comparable estimate in the literature. To facilitate interpretation, we provide two different arguments. Consider first the following equation

Table 4—Elasticity of Substitution Parameter, σ, and Demand Shifters, δ_t

A. Estimated elasticity of substitution between general and specific skills

	Point estimate	Standard error	Confidence interval
Elasticity of substitution (σ)	0.021	(0.002)	[0.017,0.026]

B. Estimated parameter for the demand shifter

	Point estimate	Standard error
Trend in relative demand ($\tilde{\delta}$)	0.007	(0.002)

C. Implied elasticity of substitution between natives and immigrants

	Elasticity
Natives vs immigrants	34.2

D. Implied elasticity of substitution between immigrants and different groups

	Natives	Immigrants by years in the United States:		
Years in the United States:		30-39 years	20-29 years	10-19 years
0-9 years	31.4	95.1	183.6	979.4
10-19 years	48.8	201.4	572.7	
20-29 years	109.6	1,387.7		
30-39 years	789.2			

Note: Panel A of this table presents estimates for the elasticity of substitution between general and specific skills (σ), defined in Equation (1) and obtained by NLS following the procedure described in Section IV.B. Panel B presents the estimate for the demand shifter parameter included in δ_t, also defined in Equation (1) and estimated in the same way as (σ). Sample weights, rescaled by annual hours worked, are used in the estimation and the computation of aggregates. Panel C provides the elasticity of substitution between natives and immigrants implied by the estimates reported in Panels A and B, computed according to Equation (15) assuming mean values obtained for the period 1990-2010 to make it comparable with the estimate produced by Ottaviano and Peri (2012). In particular, $\bar{s} = 0.829$ and $m = 0.105$, and δ_t is evaluated at year 2000. Panel D shows the implied elasticities of substitution between immigrants and different subgroups. Comparisons with natives are based on Equation (15) and comparisons with other cohorts of immigrants are based on Equation (16). The expression is evaluated at the following average values of $\bar{s}$: 0.771, 0.825, 0.898, and 0.983 for the 0–9, 10–19, 20-29 and 30-39 years-in-the-United-States groups respectively. The values of m_1 are 0.041, 0.037, 0.020, and 0.007 respectively.

implied by our model, relating relative skill prices to relative skill supplies:

$$\ln\left(\frac{r_{St}}{r_{Gt}}\right) = \tilde{\delta}t + \frac{1}{\sigma}\ln\left(\frac{G_t}{S_t}\right). \tag{14}$$

According to this expression, a one percent increase in the ratio of general to specific skills is associated with an increase in the relative skill prices of $1/\sigma$ percent. Averaging across state-specific labor markets, the predicted relative supplies of general skills G_t/S_t increased from 1.0031 in 1970 to 1.0252 in 2010. In log differences, this corresponds to an increase of 2.18 log points. Given an estimated inverse elasticity of 48.4, such an increase is associated with an increase in the relative price of specific skills of $2.18 \times 48.4 = 105.49$ log points. This suggests an important role for labor market competition, which is further amplified by the secular shift in the relative demand for specific skills shown in Panel B.

An alternative way of interpreting our estimate of σ is to formally link it to the elasticity of substitution between natives and immigrants that has been estimated in the previous literature. Let $m \equiv \frac{I}{N+I}$ denote the immigrant share, $\bar{h} \equiv \frac{G}{N+I}$ the average productivity factor, and $\bar{s} \equiv \frac{S/\bar{h}-N}{I}$ the average amount of specific skills of immigrants in the economy. The implied elasticity of substitution, derived in Appendix C1, between natives and immigrants with the skill set $\{\bar{h}, \bar{s}\}$, evaluated in a year with demand shifter δ, is given by:

$$\varepsilon_{NI} = -\frac{\sigma\left[\delta + [(1+(\bar{s}-1)m)]^{\frac{1}{\sigma}}\right]\left[\bar{s}\delta + [(1+(\bar{s}-1)m)]^{\frac{1}{\sigma}}\right]}{(\bar{s}-1)\delta\,[(1+(\bar{s}-1)m)]^{\frac{1}{\sigma}}\left[m - \frac{\bar{s}m}{1+(\bar{s}-1)m}\right]}. \tag{15}$$

This elasticity tends to infinity when σ approaches infinity or $\bar{s}$ converges to one. In the long run, when immigrants' specific skill supply converges to that of natives, both groups therefore become more and more substitutable in the labor market.

Based on Equation (15), Panel C of Table 4 provides a back-of-the-envelope calculation of the implied elasticity of substitution between immigrants and natives. Using mean values of $\bar{s}$ and m over the period 1990 to 2010, $\bar{s} = 0.829$ and $m = 0.105$, and evaluating δ at the implied value for the year 2000, yields an elasticity of substitution of 34.2, which lies within the upper range of the estimates presented in Ottaviano and Peri (2012) for the same time period but based on a very different underlying production function.[10]

A similar expression to Equation (15) can be derived for the elasticity of substitution between two distinct groups of immigrants. This expression, derived in Appendix C2, is:

$$\varepsilon_{12} = -\frac{\sigma\left[\bar{s}_1\delta + [(1+(\bar{s}-1)m)]^{\frac{1}{\sigma}}\right]\left[\bar{s}_2\delta + [(1+(\bar{s}-1)m)]^{\frac{1}{\sigma}}\right]}{(\bar{s}_1-\bar{s}_2)\delta\,[(1+(\bar{s}-1)m)]^{\frac{1}{\sigma}}\left[\frac{1}{2}\left(m_1 - m_2 - \frac{\bar{s}_1 m_1 - \bar{s}_2 m_2}{1+(\bar{s}-1)m}\right)\right]}, \tag{16}$$

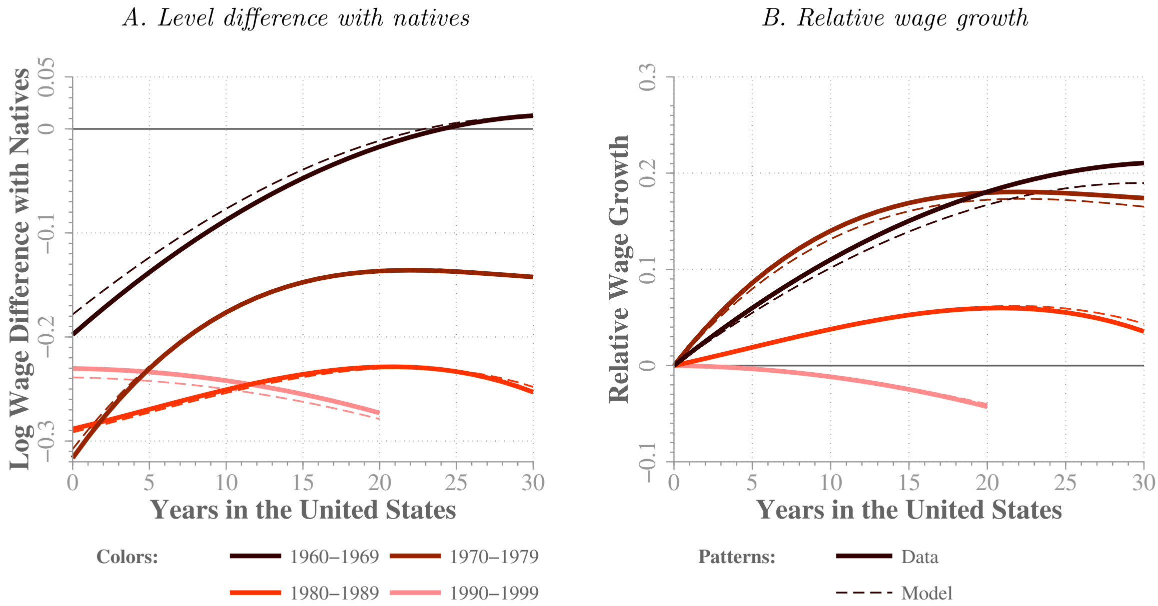
where $\bar{s}_1$ and $\bar{s}_2$ are group-specific but otherwise defined in the same way as $\bar{s}$, and where $m_i \equiv \frac{I_i}{N+I}$ for $i = 1, 2$, with I_i representing the stock of immigrants in a given group i. This expression tends to infinity when σ approaches infinity or when $\bar{s}_1$ converges to $\bar{s}_2$ since in that case both immigrant groups are identical in terms of the skill bundles they supply. Equation (16) also provides the elasticity of substitution between natives and a particular group of immigrants as the special case in which $\bar{s}_1 = 1$ and $m_1 = 1 - m$.[11]

Based on Equation (16), Panel D of Table 4 shows how the elasticity of substitution between natives and immigrants evolves as the latter spend time in the U.S. labor market. The substitutability between natives and the most recent cohort of immigrants, those who arrived less than 10 years ago, is relatively low with an estimated elasticity of 31.4. This elasticity then increases steadily to 48.8 and 109.6 for immigrants who have been in the country for 10–19 years and 20–29 years respectively. After 20 years in the country, immigrants and natives are therefore essentially perfect substitutes. Regarding the

[10] Ottaviano and Peri (2012) estimate, on average, an elasticity of around 20.

[11] Equation (15) is the special case of Equation (16) with $\bar{s}_1 = \bar{s}$, $\bar{s}_2 = 1$, $m_1 = m$, and $m_2 = 1 - m$.

FIGURE 6. GOODNESS OF FIT



Note: The figure compares the solid lines of Figure 1 (reproduced here as solid lines as well) with analogous regression lines estimated on the wages predicted by our model given the estimated parameters (dashed).

substitutability between different groups of immigrants, Panel D shows that the further apart two arrival cohorts are in time, the less substitutable they become. New immigrants therefore primarily compete with their immediate predecessors in the labor market.[12]

D. Goodness of fit

We conclude this section by evaluating the ability of our model to reproduce the wage assimilation profiles shown in Figure 1. To do this, we predict log wages for all individuals in the sample based on our parameter estimates and then regress, analogous to the models represented by the solid lines in Figure 1, these predicted 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. The resulting wage assimilation profiles, plotted in Figure 6 together with their counterparts from Figure 1, show that our model is able to replicate both the wage gap between natives and immigrants and the decreasing speed of convergence across cohorts very well.

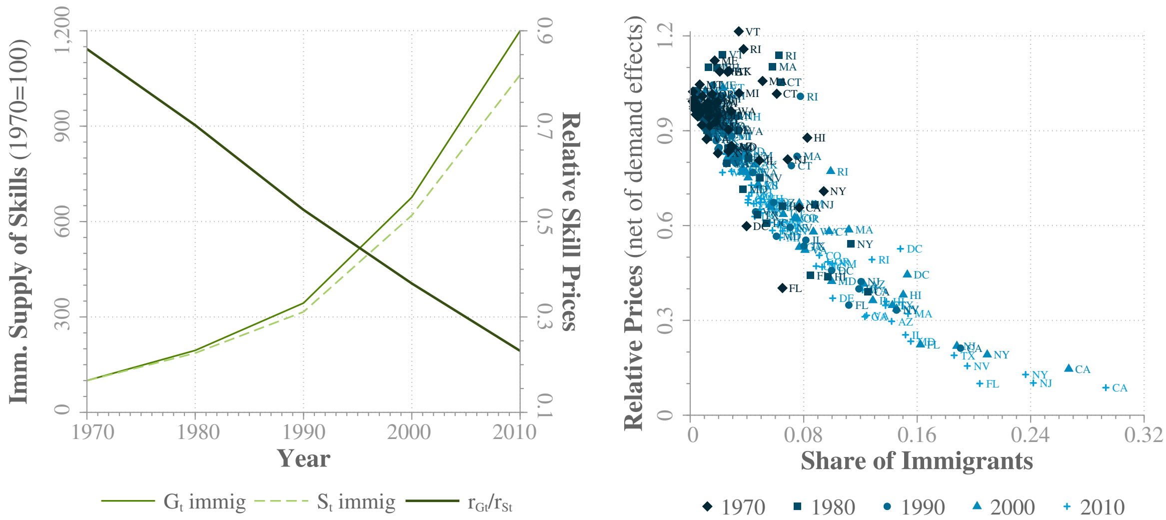
VI. Labor Market Competition and Immigrant Wage Assimilation

In this section, we use our estimates to evaluate the role of labor market competition in shaping observed wage assimilation patterns. Our simulation analysis consists of two parts. In the first part, we assess the relative contribution of the different drivers of wage assimilation in our model from the perspective of a baseline individual. Section VI.B

[12] Similar to us, Galeone and Görlach (2021) find long-term immigrants and natives to be essentially perfect substitutes. Our estimates regarding the substitutability between different groups of immigrants are broadly in line with those reported in D'Amuri et al. (2010), who, based on a very different production function, obtain a baseline estimate for the elasticity of substitution between "new" and "old" immigrants (0–5 and more than 5 years in Germany, respectively) of 58.8.

Figure 7. Changes in Relative Supplies and Relative Skill Prices

A. Aggregate changes *B. State-level variation*



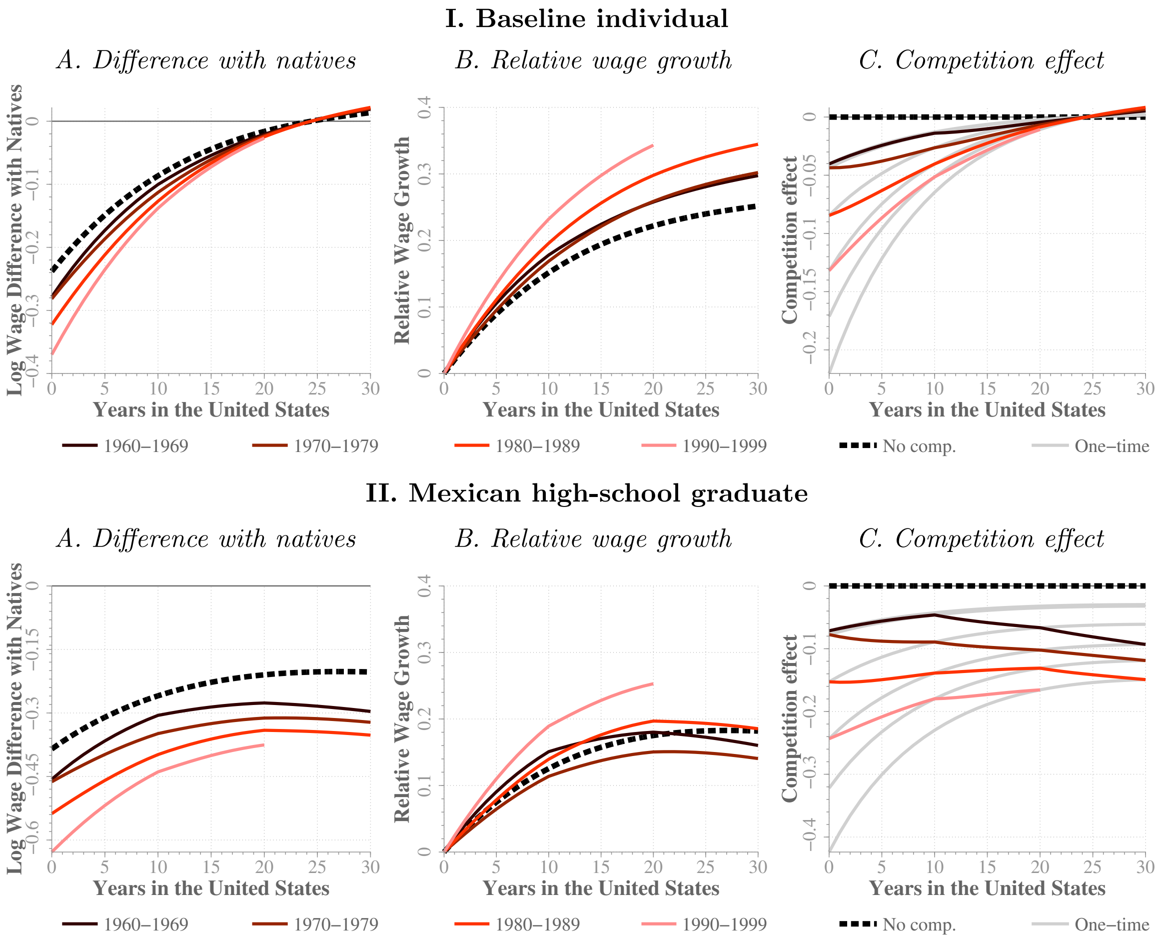
Note: The figure shows the predicted aggregate amount of general and specific skills supplied by immigrants in each year (left plot, left axis), the relative skill prices implied by these aggregate supplies (left plot, right axis), and the predicted relative skill prices at the state-year level in relation to the local immigrant share (right plot). In the left plot, aggregate supplies are normalized to 100 in the year 1970. The right plot nets out demand effects on skill prices to emphasize the variation in aggregate skill supplies across states and over time.

focuses on the labor market competition effect, Section VI.C on the role of compositional changes in immigrants' observable characteristics, and Section VI.D on changes in cohort quality. In Section VI.E, we then use our model to perform a decomposition analysis in which we first predict counterfactual wages for each individual in our sample and then plot the associated (unconditional) wage assimilation profiles. Before we start, Section VI.A provides some useful background information by illustrating the changes in relative skill prices predicted by our model, both on aggregate and for different states over time.

A. *Changes in relative supplies of skills and relative skill prices*

We begin by showing how, according to our estimates, the increasing immigration since the 1970s has altered relative skill prices in the U.S. labor market. Figure 7A plots the evolution of the total amount of general and specific skills supplied by immigrants, together with the corresponding evolution of relative skill prices, predicted by Equation (14). Between 1970 and 2010, the supply of general skills by immigrants increased twelvefold whereas the supply of specific skills increased by only a factor of 10.6. The relative increase in the supply of general skills is associated with a fall of the relative price of those skills from 0.86 to 0.23. Figure 7B illustrates the relationship between raw immigrant population shares and relative skill prices at the state-year level, thus reflecting both time and spatial variation. There is a clear negative relationship between the two, with relative skill prices well below 0.3 in states with large immigrant population shares like California and New York, and values of around one in state-year cells characterized by low immigrant shares. The plot also reveals substantial spatial variation within a given year, especially in 2000 and 2010, which is the variation used to identify the parameter σ.

Figure 8. The Labor Market Competition Effect



Note: The figure shows wage assimilation profiles of two individuals under different counterfactual scenarios. The top panel presents results for our baseline individual, a Mexican high school dropout who arrived in the United States in the 1970s with the skills of that cohort and 11.7 years of potential experience abroad. The bottom panel presents the results for a Mexican high school graduate who is otherwise identical to the baseline individual. For all cohorts, the demand effects are assumed to be those experienced by immigrants who arrived in the United States in 1970. The thick dashed line assumes no competition effects ($\sigma = \infty$). The colored solid lines represent the counterfactual assimilation profiles induced by the sequence of aggregate relative skill supplies faced by the respective cohorts. Aggregate relative skill supplies are computed as the weighted average of the state-specific relative supplies, using local immigrant stocks as weights. The gray transparent lines in Plots C represent the assimilation curves that each cohort would experience if they were exposed to the same initial level of competition throughout all years in the United States. The second lowest and lowest gray lines represent the assimilation curves when permanently facing the competition level prevailing in 2000 and 2010, respectively. 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.

B. Labor market competition effects

We next illustrate the extent to which labor market competition can explain changes in wage assimilation profiles. Figure 8 shows, under different scenarios, the counterfactual assimilation profiles of two distinct individuals: our baseline individual (a Mexican high school dropout who arrived in the United States in the 1970s with the skills of that arrival cohort and 11.7 years of potential experience abroad), and a Mexican high school graduate who is otherwise identical to the baseline individual. The key distinguishing feature of these two individuals is that the Mexican high school dropout, according to our model estimates, fully assimilates to his native counterparts ($s \to 1$) whereas the high school graduate does not assimilate even in the long run. For all depicted profiles, the sequence of secular demand effects (δ) is assumed to be the one experienced by an individual who arrived in the United States in 1970. In all plots, the thick dashed line represents the predicted assimilation profile in the absence of any competition effects, i.e. when $\sigma = \infty$. As shown in Plot A, our baseline individual would in this case initially earn 23.8 log points less than an equivalent native but fully assimilate within about 25 years. The high school graduate, in contrast, would initially earn 38.5 log points less than an equivalent native but then stop assimilating after about 20 years, maintaining a permanent wage gap of around 20.5 log points thereafter.

The remaining colored lines illustrate how the relative wages of these two types of immigrant would have evolved if they had faced the same dynamic labor market competition as the corresponding arrival cohorts listed in the legend.[13] Plots A and B show the relative wage gap and relative wage growth (as in Figure 1) under these counterfactual scenarios. Plots C show the difference between the counterfactual profiles and the no-competition benchmark, as well as (in transparent gray) the hypothetical assimilation profiles if these individuals had faced the initial level of competition of the respective cohorts permanently throughout their time in the United States.[14]

Figure 8 documents an important impact of labor market competition on the initial wage gap of immigrants. If our reference Mexican high school dropout and high school graduate (who belong to the 1970s cohort) had faced the same level of competition as the 1990s cohort, their initial wage gaps would have been 8.8 and 17.7 log points bigger (the difference between the lines labeled "1970–1979" and "1990–1999" in Plots C). If they had faced the competition level of 2010, the impact would have been even more dramatic, with the initial wage gap widening by 16.6 and 34.6 log points respectively (the difference between the line "1970–1979" and the bottom gray lines in Plots C).

The impact of increasing labor market competition on the speed of convergence is heterogeneous as predicted by the theory. For the baseline high school dropout, the competition effect increases the speed of convergence, which completely offsets the large negative wage effect at the time of arrival within around 20 years. In contrast, the effect on the wage growth of the high school graduate is ambiguous. Consistent with the stylized example in Figure 3B, for this alternative individual, the dynamic competition effect inhibits overall wage assimilation significantly, even generating a divergence in wages

[13] In practice, we simulate these workers' assimilation profiles based on Equation (6) and our estimated parameters, using the corresponding cohort-specific sequence of relative aggregate skill supplies $(G_t/S_t)^{1/\sigma}$. These aggregate skill supplies are computed for each census year as the weighted average of all state-specific relative skill supplies using the immigrant stocks in each state 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.

[14] The gray lines thus represent the case of a one-time permanent increase in relative skill supplies as discussed in Section III.B. The transparent gray lines in Figure 8 correspond to the gradient-colored lines in Figure 3, whereas the colored lines correspond to the dotted black lines in Figure 3.

after 15–20 years. However, while increasing competition can explain the slow-down in the speed of assimilation for this immigrant relative to the 1960s cohort, it does not generate a slower speed of convergence in the case of subsequent cohorts, contrary to the general patterns shown in Figure 1. If the immigrant high school graduate had faced the same labor market competition as an otherwise identical immigrant who arrived in the 1980s or 1990s, he should have experienced a faster wage growth over time.

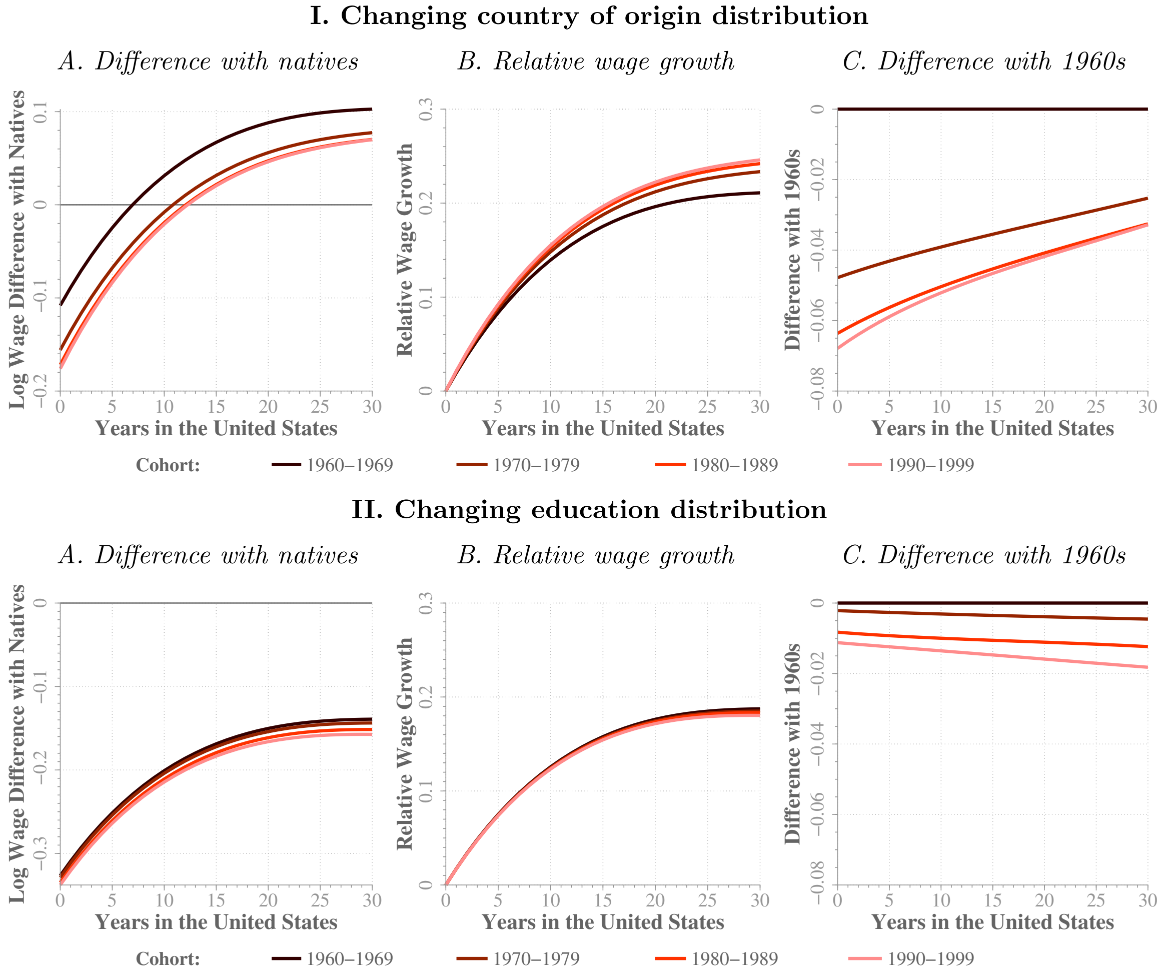
Overall, Figure 8 demonstrates an important and heterogeneous role for labor market competition in explaining observed wage assimilation patterns. Secular increases in immigrant inflows are responsible for a substantial widening of the initial wage gap across arrival cohorts. Depending on the underlying skill accumulation processes, increasing labor market competition may have slowed down or accelerated the wage assimilation of particular immigrant groups. Whether these dynamic competition effects increased or decreased the speed of assimilation *on average* across all types of immigrants is an empirical question, which we turn to in Section VI.E.

C. Compositional changes

Apart from the labor market competition effect, our framework also allows us to assess the role of compositional changes in terms of immigrants' country of origin and educational attainment. Figure 9 illustrates the importance of each of these two channels. In Panel I, we simulate for each country of origin the assimilation profile of an immigrant with the (remaining) characteristics of our baseline individual (a high school dropout who arrived in the United States in the 1970s with the skills of that arrival cohort and 11.7 years of potential experience abroad) and then average these profiles using the region-of-origin distribution of each cohort as observed across all census years. Similarly, in Panel II, we simulate for each education group the assimilation profile of an immigrant with the (remaining) characteristics of our baseline individual (a Mexican who arrived in the United States in the 1970s with the skills of that arrival cohort and 11.7 years of potential experience abroad) and then average these profiles using the observed educational distribution of each cohort. To isolate the role of composition effects, we set $\sigma = \infty$ in both panels (thus ruling out competition effects) and assume the sequence of demand effects (δ) to be the one experienced by an individual who arrived in 1970. Plots A and B of each panel show the wage gap and relative wage growth as in previous figures, Plots C depict the difference between each cohort and the benchmark 1960s cohort. While the levels of the wage profiles in Plots A are not very meaningful (since they represent very specific types of immigrants, which share the characteristics of the baseline individual), their relative positions have a clear interpretation as the differences across cohorts that are attributable to the specific dimension of interest, holding everything else constant.

The results from Panel I show that changes in the immigrant composition in terms of region of origin account for an increase in the initial wage gap relative to the benchmark

Figure 9. Composition Effects



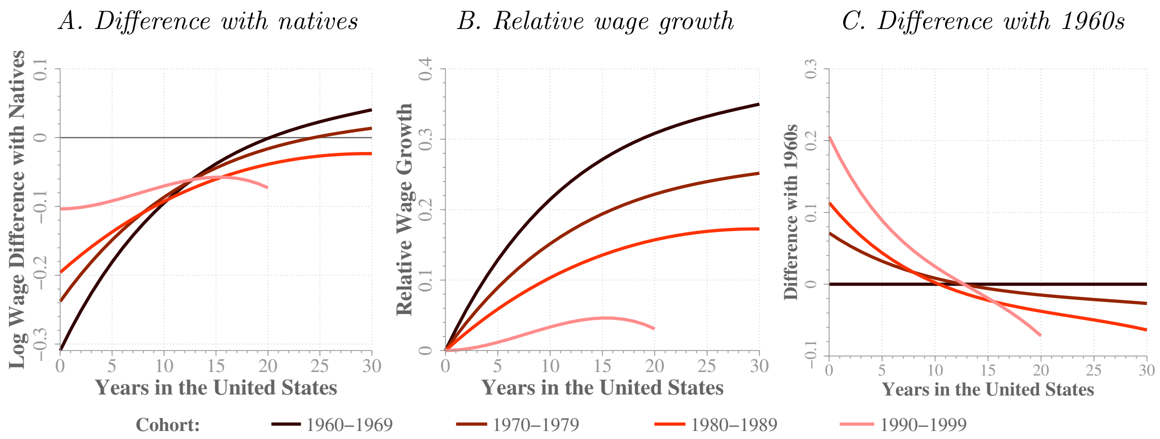
Note: The figure shows wage assimilation profiles for two counterfactual scenarios. In both scenarios, we assume no competition effects ($\sigma = \infty$) and set the demand effects to those experienced by immigrants who arrived in the United States in 1970. Panel I averages assimilation curves for individuals with the characteristics of our baseline individual (a high school dropout who arrived in the United States in the 1970s with the skills of that arrival cohort and 11.7 years of potential experience abroad) from each national origin, weighting each origin by the observed cohort-specific proportions across all census years. Panel II presents the analogous exercise but averages across different education groups rather than countries of origin. 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 each cohort and the benchmark 1960s cohort.

cohort of the 1960s of 4.8 log points for the 1970s cohort, 6.4 log points for the 1980s cohort and 6.8 log points for the 1990s cohort.[15] These effects decrease over time, explaining a wage differential of between 2.5 and 3.3 log points after 30 years in the United States. The growing importance of Mexico and Asia as primary regions of origin, and the diminishing role of Western countries, is largely responsible for these composition effects.

The results from Panel II suggest a comparatively minor role for changes in educational attainment. In the most distinctive case of the 1990s cohort, such changes account for an increase in the wage gap of only 1.1 log point at arrival and 1.8 log points after 30 years in the United States. The relatively small magnitude of these effects is due to the fact

[15] Dustmann, Ku and Surovtseva (2021) argue that higher real exchange rates at the time of arrival could induce immigrants from poorer source countries to set lower reservation wages, thus offering a behavioral mechanism that may contribute to the widening initial wage gap across cohorts.

Figure 10. Changes in Cohort Quality



Note: The figure shows wage assimilation profiles for the baseline individual (a Mexican high school dropout who arrived in the United States with 11.7 years of potential experience abroad), changing the unobservable specific skills to those estimated for each of the indicated cohorts. In the counterfactuals, we assume no competition effects ($\sigma = \infty$) and set the demand effects to those experienced by immigrants who arrived in the United States in 1970. Plots A and B show the wage gap relative to natives and the relative wage growth as in Figure 1, whereas Plot C shows the difference between each cohort and the benchmark 1960s cohort.

that the assimilation profiles of three of the four education groups considered are very similar (see Figure 4B). The notable decline in the share of high school dropouts among immigrants from 45.8 percent in the 1960s cohort to 29.8 percent in the 1990s cohort (see Table 1) is not sufficient to generate major changes in the average assimilation profiles. As we show in Section VI.E, however, this does not mean that education is not important in explaining the observed assimilation patterns in Figure 1. This is because Figure 9.II shows changes in average conditional convergence, i.e. average convergence of immigrants to natives with the same level of education, whereas Figure 1 shows convergence patterns that do not condition on education. The fact that a randomly drawn immigrant is less educated than a randomly drawn native is not relevant for conditional convergence, but, as shown below, is important when explaining unconditional convergence.

D. *Changes in cohort quality*

Besides labor market competition and compositional changes, the final source of variation in wage assimilation profiles are differences in the initial supply and subsequent accumulation of specific skills between arrival cohorts. Figure 10 plots assimilation profiles for our baseline individual under the counterfactual scenario that he belonged to any of the other cohorts, assuming no competition effect and setting the demand effects (δ) to those he would have experienced in the baseline (note that this figure is therefore the wage counterpart of Figure 4C). Contrary to the common perception in the literature, the initial wage gap for the baseline individual when moving from the 1960s to the 1990s cohort closed from 30.9 log points to 10.4 log points. Starting off from a more advantageous position, the speed of wage assimilation of the more recent cohorts declined, a finding in line with the results on English proficiency above (Figure 5) and consistent with the predictions of a basic human capital investment model applied to the case of immigrants (see Duleep and Regets, 1999, or Borjas, 2015). As shown in Figure 10, the wages of the 1960s and 1970s cohorts fully converge to those of natives within 20–25 years, while the relative wages of the 1980s cohort level off about 2.3 log points below those of their native counterparts. For the 1990s cohort, relative wages grow slowly and peak 5.7 log points below those of natives after about 15 years in the country.

E. Wage decomposition

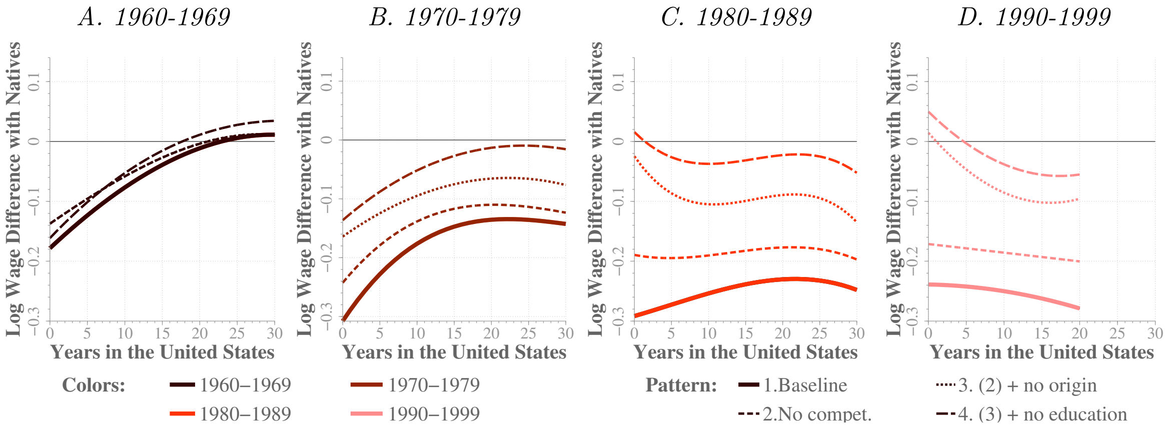
Our discussion so far has focused on the convergence profiles of a given baseline individual. To provide a more complete picture, we now turn to the full sample of immigrants and assess to what extent the three drivers of wage assimilation in our model – labor market competition, composition effects and changes in cohort quality – can explain the unconditional assimilation patterns depicted in Figure 1.

Figure 11 presents the results from this decomposition analysis. Each plot in the figure represents a specific arrival cohort. The solid lines are obtained by, first, predicting for each individual in the sample the log wage in a given census year based on our baseline parameter estimates, and by, second, regressing these predicted 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 (as in Figures 1 and 6). Keeping with our terminology, we refer to the predictions from this auxiliary linear regression as our estimated *assimilation profiles*. Coinciding with the dashed lines in Figure 6, the solid lines represent the model-based counterparts of the unconditional wage assimilation profiles shown in Figure 1 and serve as the baseline of our decomposition analysis.

In the first step, we turn off the dynamic competition effect by setting $\sigma = \infty$, predict each individual's wage, and then obtain the new assimilation profiles using the predicted wages as the new dependent variable in the auxiliary regression. The resulting profiles are plotted as short-dashed lines in Figure 11. The results suggest once again an important role for dynamic competition effects, especially for the 1980s and 1990s cohorts for whom the respective wage gaps relative to natives would have been, depending on the years since arrival, 5.1–10.2 and 6.3–7.9 log points smaller in the absence of labor market competition effects. With the exception of the 1990s cohort, the competition effects is larger at the time of arrival, explaining a substantial part of the increase in the initial wage gap across cohorts since the 1960s. Regarding the speed of assimilation, the dynamic competition effect has a moderate positive impact on the relative wage growth of the 1980s cohort (since shutting it down leads to a flatter wage profile) but a relatively minor impact on the wage growth of the other three cohorts.

We next analyze to what extent changes in observable characteristics can explain the remaining differences across cohorts. To do this, we continue to use the predicted wages from the previous no-competition scenario as our dependent variable but now adjust

Figure 11. Competition Effects, Inflow Composition, and Observed Wage Gaps



Note: The figure shows baseline and counterfactual predictions of the unconditional wage gaps between natives and immigrants for different cohorts as they spend time in the United States. Each plot represents one cohort. The depicted lines are predicted assimilation profiles obtained from regressions analogous to those underlying Figure 1, estimated on predicted wages under the different counterfactual scenarios. The baseline profiles (solid) correspond to the model predictions in Figure 6. The counterfactuals represent assimilation profiles in the absence of competition effects (short-dashed line), holding additionally immigrants' region-of-origin composition constant at the level of the 1960s cohort (dotted line), and setting additionally the educational attainment of immigrants equal to that of natives born in the same year (long-dashed line). The last two counterfactuals are obtained by reweighting immigrant observations to match the corresponding region-of-origin and educational distributions.

the weights of the immigrant observations in our sample before running the auxiliary regression to obtain our new assimilation profiles. The adjusted weights reflect the counterfactual distributions of immigrants in terms of observable characteristics. We start by reweighting the observations of each cohort so that they, in the aggregate, reproduce the region-of-origin distribution of the benchmark 1960s cohort.[16] As shown by the dotted lines in Figure 11, changes in the origin composition explain a sizeable part of the remaining differences, especially for the 1980s and 1990s cohorts where they account for an additional 6.3–16.5 and 9.1–18.6 log point gap in relative wages. In the absence of competition effects, and with the region-of-origin composition held constant, both of these cohorts would have experienced downward-sloping relative wage profiles.[17]

In the final step, and in line with our procedure in Section VI.C, we account for changes in the educational attainment across cohorts. Contrary to the region-of-origin case, there are now two channels through which such changes may affect the unconditional assimilation profiles depicted in Figure 11. On the one hand, immigrants' educational attainment increased over time relative to the benchmark 1960s cohort (see Table 1), which would tend to raise their initial relative wages but lower their speed of relative wage growth. On the other hand, natives' educational attainment increased even more rapidly (see Table B1), which would tend to have the opposite effects. We account for these counteracting

[16] To be precise, let ω_i be the original sample weight of immigrant i, who is from origin country $o(i)$ and arrived with the cohort $c(i)$. Furthermore, let $share_{o,c}$ denote the share of immigrants from cohort c who originate from country o (as observed across all census years). The new sample weights are then computed as $\widetilde{\omega}_i \equiv w_i \times (share_{o(i),1960s}/share_{o(i),c(i)})$.

[17] In our model, a decreasing wage assimilation profile can be explained by increasing demand for specific skills (as indicated by our positive estimate of $\tilde{\delta}$).

forces by simulating a scenario in which we set the educational attainment of immigrants equal to that of natives of the same birth year, thus eliminating any differences across cohorts due to differential growth rates in educational attainment.[18] As shown by the long-dashed lines in Figure 11, the disparate evolution of natives' and immigrants' educational attainment had indeed a significant impact on the unconditional relative wage profiles, widening the wage gap to natives by 2.8–6.1 log points for the 1970s cohort, 4.0–8.2 log points for the 1980s cohort, and 3.5–4.7 log points for the 1990s cohort.

After accounting for labor market competition effects and compositional changes in terms of region of origin and educational attainment, the remaining differences between the long-dashed lines in Figure 11 reflect changes in cohort quality, i.e. changes in the cohort-specific parameters in our skill accumulation function $s(\cdot)$. In line with the findings for our baseline individual in the previous section, and contrary to the raw patterns shown in Figure 1, the initial wage gaps at the time of arrival actually declined for recent cohorts rather than increased. At the same time, the differences in the speed of wage assimilation across cohorts remain relatively unchanged, still showing a persistent deceleration of the relative wage growth process across cohorts.

In terms of relative importance, the labor market competition effect explains 18.6 percent of the increase in the initial wage gap between the 1960s cohort and the 1970s cohort, 53.9 percent of the increase between the 1960s cohort and the 1980s cohort, and 43.8 percent of the increase between the 1960s cohort and the 1990s cohort. After 30 years in the United States (20 years in the case of the 1990s cohort), the competition effect still explains 13.0 percent of the increase in the wage gap of the 1970s cohort (again relative to the 1960s cohort), 19.9 percent of the increase in the wage gap of the 1980s cohort, and 26.6 percent of the increase in the wage gap of the 1990s cohort. Averaged over time (since arrival), the competition effect can explain 16.4, 24.8 and 27.6 percent of the increase in the relative wage gap between the baseline 1960s cohort and the 1970s, 1980s, and 1990s cohorts, respectively.

VII. Robustness checks

In this section, we show that the results presented in the previous section are robust to alternative specifications that deal with various concerns regarding our baseline model. For each of these alternative specifications, we reestimate our model and construct plots similar to those in Figures 10 and 11. We present the results from all the robustness checks jointly in Figure 12, and report a selected set of parameter estimates in Table 5.

[18] To be precise, we take the weights of the fixed region-of-origin counterfactual $\widetilde{w}_i$, defined in Footnote 16, and rescale them to match the educational attainment of natives born in the same years as the immigrants. Let $e(i)$ denote the education level of immigrant i, $b(i)$ denote his birth year, and $c(i)$ denote his cohort of arrival. Also let $share^{nat}_{e,b}$ denote the share of natives born in year b who have education level e (as observed across all census years), and $share^{im}_{e,c}$, the share of immigrants from cohort c who have education level e. The new sample weights are then computed as $\bar{\omega}_i = \widetilde{\omega}_i \times (share^{nat}_{e(i),b(i)}/share^{im}_{e(i),c(i)})$, where b refers to the individual immigrant's year of birth.

Before discussing the findings, we explain each of the robustness checks in more detail.

Networks. The first concern we address is that 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 our first two robustness checks, we allow the accumulation of skills to depend on, respectively, the stock and the share of immigrants from the same country of origin as the respondent, acknowledging that these networks and ghettos are typically formed by immigrants from the same country of origin. Both networks variables are allowed to enter linearly in the $s(\cdot)$ function as well as interacted with a third order polynomial in years since migration.

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 substantially undercount undocumented immigrants, many of which are low-skilled Mexicans (see e.g. Warren and Passel, 1987). The underrepresentation of these immigrants could affect our estimation results in two ways. First, it could lead to an underestimation of the true competition effect since the size of the immigrant population, and therefore the relative supply of general skills G_t/S_t, would be understated. Second, if undocumented immigrants assimilate at different rates than legal immigrants, not including them in our sample might introduce biases in the estimation of the $s(\cdot)$ function.

To assess how these issues affect our results, we implement two robustness checks in which we explicitly account for both the undercounting and the potentially distinct assimilation patterns of undocumented immigrants. Following Borjas (2017), we first identify "likely legal" immigrants in the different Census samples based on a set of pertinent survey responses, and then label all remaining immigrants as potentially undocumented.[19] We then obtain assimilation profiles with two modifications relative to our baseline. In the first robustness check, we reestimate our NLS model after reweighting the observations of potentially undocumented immigrants to account for their undercount in the Census data. Specifically, 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, and from Van Hook, Bean and Tucker (2014) for the 2000 Census and the 2010 ACS (see Appendix A for details).[20] In the second robustness check, we

[19] 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.

[20] 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.

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.

Selective outmigration. A large literature has discussed the implications of selective outmigration for the estimation of immigrant wage assimilation profiles (see Dustmann and Görlach, 2015, for a survey). Contrary to the issue of undercounting, selective outmigration is not a first order problem for our assessment of the role of competition effects since what matters for the latter is the stock of immigrants who are actually present in the labor market at any moment in time. However, if there were selective outmigration, the interpretation of the estimated skill accumulation profiles would change since they would then reflect both true skill accumulation and dynamic selection effects. To deal with this challenge, the ideal assimilation 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 true longitudinal data are not available for the extensive time period covered by our analysis, we cannot fully account for the issue of selective outmigration in the spirit of these earlier studies. Instead, we provide a sensitivity analysis that gives an idea about the extent to which these concerns may (or may not) affect our results.

We follow three alternative approaches. In the first one, we rely on results by Borjas and Bratsberg (1996) who, using data for the 1970s arrival cohort, estimate origin-country-specific outmigration rates over the first 10 years in the United States.[21] For the second one, we rely on recent results by Rho and Sanders (2021), who, for immigrants that arrived between 1995 and 1999, estimate outmigration rates separately by education group and percentile of earnings using newly-assembled longitudinal data matched with census information. Contrary to Borjas and Bratsberg (1996), who find the highest outmigration rates for the least-skilled group of immigrants, Rho and Sanders (2021) show that, if anything, outmigrants are positively selected in terms of both observed education levels and unobservable skills conditional on education (see Figures 1 and 5 in their paper).[22]

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.

[21] 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 stock of immigrants from each country of origin. The resulting outmigration 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).

[22] Rho and Sanders (2021) infer outmigration 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

Since these two pieces of evidence point in opposite directions, and since they deal with different dimensions of selective outmigration (region 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. In both of these checks, we reestimate our NLS model after reweighting the observations of immigrants that we observe during their first 10 years in the United States by multiplying their original sample weights by one minus the corresponding estimated outmigration rates (see Appendix A for details). This approach mimics what studies based on stock-sampled data implicitly do in that it holds the composition of immigrants in terms of origin (or observable and unobservable skills) constant across the first and subsequent decades after arrival. Note that, in these robustness checks, the new sample weights are used to weight observations in the estimation, but the original weights are used to compute the aggregate relative skill supplies G_t/S_t (as these depend on the workers who are actually present in the market).

For the third robustness check, we divide our sample of immigrants into cells defined by cohort, country of origin, education level, and quartile of the distribution of wage residuals from Equation (11). We 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 then adjust the baseline sample weights of the first group of immigrants (those with less than 10 years in the United States) so that, on aggregate, they reproduce the joint distribution of origin, education, and conditional wage quartile observed in the second group (more than 10 years in the United States), thus holding the distribution of these three characteristics within our synthetic cohorts constant over time.

Alternative specifications for the demand shifters. While our baseline specification already accounts for linear trends in the relative demand for specific skills, we estimate two alternative specifications in which we allow the demand shifters to enter either in quadratic form, $\delta_t = \exp(\tilde{\delta}_1 t + \tilde{\delta}_2 t^2)$, or as time dummies, $\delta_t = \exp(\tilde{\delta}_t)$.

Alternative labor market definitions. In our baseline analysis, labor markets are defined at the state level. To test the robustness of our results to alternative definitions, we define labor markets either at the state-education level, assuming individuals in different education groups do not compete with each other, or at the level of census divisions.

Endogenous immigration across states. Since we exploit variation in immigrant stocks across states in our baseline estimation, a possible concern is that immigrants self-select into states in which relative skill prices are particularly favorable. A priori, this is not obvious since it is well-known that immigrants tend to cluster in markets with

Census. Since match rates may not amount to 100 percent for other reasons than outmigration, only the differences between the match rates of immigrants and comparable natives are interpreted as proxies for outmigration rates. To assess outmigration 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 outmigration rates within each decile (once again subtracting the non-match rate for similar natives to net out other reasons for not finding a match).

higher immigrant concentrations, which are precisely the markets where, according to our model, the relative wages of immigrants tend to be lower. To account for potential endogeneity of this type, we reestimate our model using the Generalized Method of Moments (GMM), combining our exogenous variables in an optimal instruments type approach (see Amemiya, 1977). In our non-linear setting, the optimal instruments are the derivatives of the main estimation equation (11) with respect to the model parameters. If immigrants were randomly assigned across states conditional on observables, the GMM moment conditions with the optimal instruments would coincide with the first order conditions of our NLS estimation, indicating that in this case our baseline estimates would be consistent. In the robustness check, we replace the potentially endogenous regressor G_{jt}/S_{jt} by an exogenous prediction based on the widely used shift-share instrument proposed by Card (2001). Appendix D provides details on the derivation of these instruments and the implementation of this estimation approach.

Table 5 summarizes the key parameter estimates obtained from the different robustness checks. Panel A shows that a larger stock or share of immigrants from the same country of origin living in the same state as the respondent has a negative, though relatively minor, impact on the initial wage gap. The initial wage gap is reduced by 5.2 log points for an additional 10 percent of immigrants from the same country of origin in the state's population, or by 9.6 log points for every additional million of compatriots. The unconditional average shares and stocks are relatively small, 2.7 percent (ranging from zero to 12.6 percent) and 0.11 millions (ranging from zero to 0.75 million), implying that, on average, the initial wage gap increases by 1.4 log points in the share specification and 1.1 log points in the stock specification. The estimated effects on the wage growth are small and statistically insignificant. Panel A also shows how differently wages grow for potentially undocumented immigrants. The point estimates suggest that, over a period of 10 years, their wages grow 6.3 log points less than those of comparable legal immigrants.

Panel B reports the estimated relative demand shifters. The point estimates of both specifications of this robustness check are consistent with a U-shape, with decreasing demand for specific skills in the 1970s and increasing demand in the 1980s, 1990s and 2000s. However, as we show below, these non-linearities do not lead to substantially different predictions relative to the baseline. Finally, Panel C shows the elasticities of substitution between general and specific skills estimated for each of the 14 robustness checks. Overall, the point estimates are quite stable across specifications and, as we show below, produce similar counterfactual predictions.

Figure 12 depicts the implied relative wage profiles of our 14 different robustness checks. Similar to Figure 11, Panel I shows the counterfactual assimilation profiles after accounting for competition, origin and education effects, with the only difference being that we express these profiles relative to the corresponding baseline of each cohort to ease visualization. Evidently, the qualitative and quantitative findings in Figure 11 are ro-

Table 5—Selected Parameter Estimates from Robustness Checks

A. Additional elements of assimilation profiles included in some of the checks

	Direct effect	Interaction with years since migration: Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Share of state's population	-0.522	0.004	-0.108	0.015
	(0.139)	(0.034)	(0.226)	(0.042)
Stock in the state ($\times 10^6$)	-0.096	-0.005	0.024	-0.004
	(0.021)	(0.005)	(0.032)	(0.006)
Potentially undocumented	—	-0.008	0.021	-0.004
		(0.001)	(0.015)	(0.004)

B. Alternative specifications of the demand shifters for relative skill prices

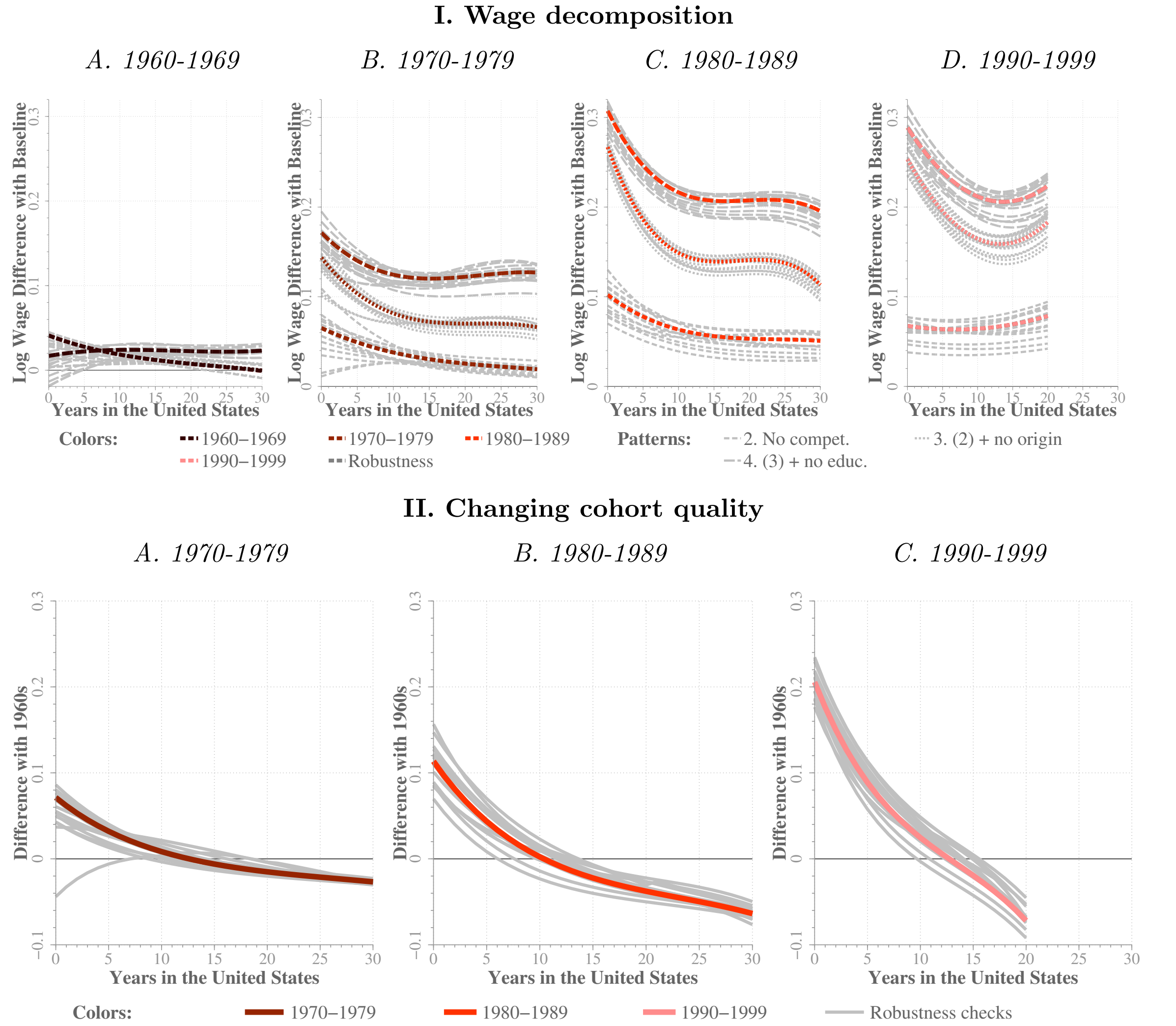
	$\tilde{\delta}_1 \vert \tilde{\delta}_{1980}$	$\tilde{\delta}_2(\times 10^2) \vert \tilde{\delta}_{1990}$	$\tilde{\delta}_{2000}$	$\tilde{\delta}_{2010}$
Quadratic specification	-0.032	0.112	—	—
	(0.004)	(0.013)		
Time dummies	-0.718	-0.022	0.129	0.390
	(0.052)	(0.053)	(0.055)	(0.079)

C. Elasticity of substitution between general and specific skills (σ)

	Estimate	Standard error
Baseline estimate:	0.021	(0.002)
Networks:		
Share of state's population	0.024	(0.003)
Stock in the state	0.023	(0.003)
Undocumented migrants:		
Reweighted only	0.020	(0.002)
Reweighted and differential convergence	0.020	(0.001)
Selective outmigration:		
Borjas and Bratsberg (1996)	0.020	(0.002)
Rho and Sanders (2021)	0.017	(0.002)
Constant distribution synthetic cohorts	0.024	(0.002)
Alternative specifications for demand factors:		
Quadratic specification	0.023	(0.002)
Time dummies	0.025	(0.002)
Alternative labor market definitions:		
Education-state	0.033	(0.002)
Census divisions	0.014	(0.001)
Optimal instruments (GMM) with aggregates based on Card (2001):		
Baseline instrument	0.061	(0.015)
Quadratic for the instrument of σ	0.046	(0.009)
Quadratic for all instruments	0.020	(0.003)

Note: Panel A of this table presents estimates for the additional parameters associated with the two specifications of the networks robustness check and the specification that allows for differential convergence between potentially undocumented and legal immigrants. Each row corresponds to a single specification. Panel B shows the parameters for the alternative specifications of the relative demand shifters. Panel C shows the estimated elasticities of substitution between general and specific skills (σ) for the various robustness checks. Standard errors in parentheses.

Figure 12. Wage Decomposition and Cohort Quality under Alternative Specifications



Note: The figure reproduces the counterfactual assimilation profiles described in Figure 11 (Panel I) and the estimated changes in cohort quality described in Figure 10 (Panel II) for the different robustness checks described in the text: networks (shares and stocks), undercounting of undocumented immigrants (with and without different assimilation profiles for the undocumented), selective outmigration (based on Borjas and Bratsberg, 1996, Rho and Sanders, 2021, and constant characteristics for synthetic cohorts), alternative specifications for relative demand shifters (quadratic, and time dummies), alternative labor market definitions (state-education and census division), and endogenous immigration across states (using a shift-share-type instrument as in Card, 2001).

bust to possible network effects, undercounting of undocumented immigrants, selective outmigration, alternative specifications for the demand shifters, alternative labor market definitions, and endogenous immigration across states. Panel II focuses on our key finding regarding changes in cohort quality (relative to the benchmark 1960s cohort), indicating that the baseline results in Figure 10 are very stable across the various robustness checks.[23]

VIII. Conclusion

This analysis shows that the wage assimilation of immigrants is the result of the intricate interplay between individual skill accumulation and dynamic equilibrium effects in

[23] Only one specification, the demand specification with time dummies shows a more notable deviation of the predictions for the 1970s cohort during the first 10 years in the United States.

the labor market. Because immigrants and natives are imperfect substitutes, increasing immigrant cohort sizes drive a wedge between their relative wages. Using a simple production function framework, we show that this labor market competition channel can explain about one quarter of the increase in the average immigrant-native wage gap between the 1960s and 1990s arrival cohorts. In contrast, the impact of labor market competition on the speed of assimilation is moderate. We show that, once the competition effect and compositional changes in terms of education and region of origin are accounted for, the quality of immigrant cohorts at entry actually increased over time rather than decreased as traditionally argued in the literature. Starting off from a more advantageous position, the speed of skill accumulation, however, diminished across cohorts, in line with previous findings in the literature. These results are consistent with the observed evolution of immigrants' English proficiency across cohorts and over time.

Our results have several important implications. First, if the wage assimilation of immigrants is directly affected by labor market competition effects, then the wage impact of immigration is, conversely, likely to be affected by immigrants' assimilation processes as well. 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 the skills they supply, they will start competing more directly with natives in the labor market. The wage impact of immigration will thus ripple through the native skill distribution, affecting different types of native workers at different points in time. Second, the competition channel may have far-reaching effects on the decision of immigrants to invest in host-country-specific skills, something that the few papers that explicitly model such investment decisions (e.g. Adda, Dustmann and Görlach, 2021) abstract from. Finally, our findings suggest that the allocation of immigrants across space and the subsequent native reallocation not only have important effects on native wages (e.g. Piyapromdee, 2021) but will also influence the way in which immigrants assimilate in the labor market. This insight is particularly relevant for immigration policy as it implies that measures that determine the size and composition of local immigrant inflows (e.g. the dispersal policies that have been widely implemented in the wake of the recent refugee crisis) might have unintended effects on the extent of immigrant wage assimilation. We leave a thorough investigation of these interesting questions for future research.

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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 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). Our sample comprises native and immigrant men aged 25 to 64 who are not self-employed, do not live in group quarters, are not enrolled in school (except for 1970), work in the civilian sector, 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 that arrived in the United States at age 18 or before. The specific variables used in the analysis are defined as follows:

Immigrants. Are defined as foreign-born individuals with non-American 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 based on 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 six groups: pre-1960, 1960–69, 1970–79, 1980–1989, 1990–1999, and 2000–09.

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

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).

For the robustness checks dealing with selective outmigration, 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 outmigration 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 outmigration 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 (11)).

Finally, for the third outmigration check, we divide our sample of immigrants into cells defined by cohort of entry, country of origin, education level and decile of the residual distribution from Equation (11). 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 Tables and Figures

Table B1—Additional Descriptives (Natives and Immigrants)

	Census year:				
	1970	1980	1990	2000	2010
Immigrant share (%)	3.6	4.9	7.3	11.8	15.8
Cohort size (millions):					
Natives	31.8	37.8	42.7	47.0	47.0
Immigrants	1.2	1.9	3.1	5.6	7.4
Age:					
Natives	42.8	41.4	40.8	42.4	44.0
Immigrants	44.2	42.2	41.9	41.9	43.6
Hourly wage:					
Natives	21.5	22.2	21.2	22.5	21.5
Immigrants	21.5	21.4	19.7	19.6	17.8
HS dropouts (%):					
Natives	39.4	22.9	11.4	7.3	5.3
Immigrants	48.4	40.4	32.4	30.8	28.4
HS graduates (%):					
Natives	33.4	36.3	33.7	40.0	36.7
Immigrants	21.1	20.9	22.3	27.1	27.7
Some college (%):					
Natives	11.7	17.4	27.8	22.8	24.6
Immigrants	10.8	12.1	17.0	12.6	12.5
College graduates (%):					
Natives	15.5	23.4	27.1	29.9	33.5
Immigrants	19.7	26.6	28.4	29.6	31.4

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

Appendix C: Derivation of the Elasticities of Substitution

C1. Elasticity of Substitution between Immigrants and Natives, Equation (15)

Let I and N denote the stock of immigrants and natives in the economy. Define the share of immigrants as $m \equiv \frac{I}{N+I}$. The relative supply of general versus specific skills is then given by $\frac{G}{S} = \frac{1+I/N}{1+\bar{s}I/N}$, where $\bar{s} \equiv \frac{S/\bar{h}-N}{I}$ denotes the average specific skills of immigrants, and $\bar{h} \equiv \frac{G}{N+I}$ is the average of the productivity factor $h_t(\cdot)$ in the economy. The elasticity of substitution between natives and immigrants is defined as $\varepsilon_{NI} \equiv d\ln(N/I)/d\ln MRTS_{IN}$. The term $MRTS_{IN}$ is the marginal rate of technical substitution between immigrants and natives. In equilibrium, $MRTS_{IN}$ is equal to the ratio of immigrant and native wages, which is given by Equation (6) above. Evaluated at $\bar{s}$, $\bar{h}$, and some $\delta_t = \delta$, log-differentiating $MRTS_{IN}$ yields:

$$d\ln MRTS_{IN} = \frac{\bar{s}\frac{1}{\sigma}\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\left(\frac{G}{S}\right)}{1+\bar{s}\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}} - \frac{\frac{1}{\sigma}\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\left(\frac{G}{S}\right)}{1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}} = \frac{(\bar{s}-1)\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\left(\frac{G}{S}\right)}{\sigma\left[1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\right]\left[1+\bar{s}\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\right]}. \tag{C1}$$

To derive an expression for $d\ln(N/I)$, first note that:

$$d\ln\left(\frac{G}{S}\right) = d\ln\left(\frac{1+\frac{I}{N}}{1+\bar{s}\frac{I}{N}}\right) = \frac{d\frac{I}{N}}{1+\frac{I}{N}} - \frac{\bar{s}d\frac{I}{N}}{1+\bar{s}\frac{I}{N}} = -\left(\frac{I}{N+I} - \frac{\bar{s}I}{N+\bar{s}I}\right) d\ln\left(\frac{N}{I}\right) \tag{C2}$$

where the last result uses $d\ln\left(\frac{N}{I}\right) = -d\frac{I}{N}/\frac{I}{N}$. Substituting (C2) into the expression for ε_{NI}, re-writing all instances of G/S in terms of m and $\bar{s}$, and rearranging gives (15). ■

C2. Elasticity of Substitution across Immigrant Groups, Equation (16)

Let I_i for $i = 1, 2, 3$ denote the stock of immigrants in groups 1 and 2, for which the elasticity of substitution is to be estimated, and 3, which includes all remaining immigrants. Define $\bar{s}_1$, $\bar{s}_2$, and $\bar{s}_3$ implicitly as $S = \bar{h}(N + \bar{s}_1 I_1 + \bar{s}_2 I_2 + \bar{s}_3 I_3)$. Evaluating the marginal rate of technical substitution at $\bar{s}_1$, $\bar{s}_2$ and $\bar{h}$, and log-differentiating it with respect to the change in the supplies of these two groups gives:

$$d\ln MRTS_{21} = \frac{\bar{s}_2\frac{1}{\sigma}\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\left(\frac{G}{S}\right)}{1+\bar{s}_2\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}} - \frac{\bar{s}_1\frac{1}{\sigma}\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\left(\frac{G}{S}\right)}{1+\bar{s}_1\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}} = \frac{(\bar{s}_2-\bar{s}_1)\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\left(\frac{G}{S}\right)}{\sigma\left[1+\bar{s}_1\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\right]\left[1+\bar{s}_2\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\right]}. \tag{C3}$$

In this case, the elasticity of substitution is defined as $\varepsilon_{12} \equiv d\ln(I_1/I_2)/d\ln MRTS_{21}$. The change in the relative supplies of skills $d\ln(G/S)$ is given by:

$$d\ln\left(\frac{G}{S}\right) = d\ln\frac{N+I_1+I_2+I_3}{N+\bar{s}_1I_1+\bar{s}_2I_2+\bar{s}_3I_3} = \frac{I_1 d\ln I_1 + I_2 d\ln I_2}{N+I} - \frac{\bar{s}_1 I_1 d\ln I_1 + \bar{s}_2 I_2 d\ln I_2}{N+\bar{s}I}. \tag{C4}$$

Defining $m_i \equiv \frac{I_i}{N+I}$, and focusing on the case when $\ln\left(\frac{I_1}{I_2}\right)$ increases as a result of an equal increase in $\ln I_1$ and reduction in $\ln I_2$ (i.e., $d\ln I_2 = -d\ln I_1 = -\frac{1}{2}d\ln\left(\frac{I_1}{I_2}\right)$), (C4) yields:

$$d\ln\left(\frac{G}{S}\right) = \frac{1}{2}\left[(m_1 - m_2) - \frac{\bar{s}_1 m_1 - \bar{s}_2 m_2}{1 + (\bar{s} - 1)m}\right] d\ln\left(\frac{I_1}{I_2}\right). \tag{C5}$$

Substituting this identity into the expression for ε_{12} and re-writing all instances of (G/S) in terms of m, $\bar{s}$, m_1 and $\bar{s}_1$ yields Equation (16) upon rearrangement. ■

Appendix D: IV Estimation

To deal with the potential endogeneity of immigrant stocks across states, we reestimate our model using the Generalized Method of Moments (GMM), combining our exogenous variables in an optimal instruments way (see Amemiya, 1977). In our non-linear setting, the optimal instruments are the derivatives of the right-hand side of the non-linear regression, Equation (11), with respect to the individual model parameters. After some algebra, these derivatives are given by the following expressions:

$$\frac{\partial(11)}{\partial \boldsymbol{\theta}'} = \frac{1}{\frac{r_{Gt}}{r_{St}} + s(\cdot)}\boldsymbol{x} - \frac{s(\cdot) - 1}{\sigma S_{jt}\left[\frac{r_{Gt}}{r_{St}} + s(\cdot)\right]\left[1 + \frac{r_{St}}{r_{Gt}}\right]}\sum_i \omega_i \boldsymbol{x}_i h_t(E_i, x_i),$$

where $\boldsymbol{\theta}$ is the vector of parameters included in the function $s(\cdot)$ and $\boldsymbol{x}$ the associated vector of regressors:

$$\frac{\partial(11)}{\partial \tilde{\boldsymbol{\delta}}'} = \begin{pmatrix} 1 \\ t \end{pmatrix} \frac{s(\cdot) - 1}{\left[\frac{r_{Gt}}{r_{St}} + s(\cdot)\right]\left[1 + \frac{r_{St}}{r_{Gt}}\right]},$$

where $\tilde{\boldsymbol{\delta}} \equiv (\tilde{\delta}_0, \tilde{\delta}_1)'$, and:

$$\frac{\partial(11)}{\partial \sigma} = \ln\left(\frac{G_{jt}}{S_{jt}}\right) \frac{s(\cdot) - 1}{\left[\frac{r_{Gt}}{r_{St}} + s(\cdot)\right]\left[1 + \frac{r_{St}}{r_{Gt}}\right]}.$$

If immigrants were randomly assigned across states conditional on observables (so that $E(\epsilon_i|\boldsymbol{x}_i, t_i, G_{jt}/S_{jt}) = 0$), the GMM moment conditions with these optimal instruments would coincide with the first order conditions of our NLS estimation, indicating that our baseline estimates are consistent in this case. In this robustness check, we deal with the case where ϵ_i and G_{jt}/S_{jt} are potentially systematically related, 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 compute the three sets of instruments listed above after 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 $\tilde{\omega}_i$, which is defined as:

$$\tilde{\omega}_i \equiv \omega_i \frac{\tilde{I}_{j(i),t(i)}}{I_{j(i),t(i)}} = \omega_i \frac{1}{I_{j(i),t(i)}} \sum_{q=1}^{Q} \frac{I_{j(i),q,1970}}{I_{q,1970}} I_{q,t(i)},$$

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 the optimal instruments shown above depend on the true parameter values and are therefore unfeasible. In practice, we therefore evaluate the derivatives at our baseline estimates which does not affect their validity as instruments but means that they are no longer optimal.

In unreported specifications we also estimate the model using the "raw" regressors and direct measures of the predicted immigrant shares as instruments. These specifications lead to results very much in line with those in Figure 12. If anything, some of these specifications indicate a stronger competition effect (up to around 10 percentage points stronger), whereas the composition effects and estimated changes in cohort quality remain largely unchanged. In line with the theoretical predictions, these estimates imply that, if there was an endogeneity bias, this bias would lead to an underestimation of the true competition effect. We decided to report the set of estimates based on our quasi-optimal instruments described above because, on top of being more efficient, they are more conservative, predicting essentially the same competition effect as the baseline model.