Labor Market Competition and the Assimilation of Immigrants*

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

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

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

I. Introduction

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

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

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

Our results show that, in the United States, labor market competition explains about one fifth of the observed increase in the average immigrant-native wage gap across arrival cohorts since the 1960s. This figure rises to about one third once demand effects are accounted for as well. For the 1990s cohort, all of the increase in the initial wage gap relative to the 1960s cohort, as well as a large fraction of the wage gap in subsequent years, can be explained by the combination of increasing cohort sizes and changes in relative skill demands. Our findings further reveal that, once demand and labor market competition effects are accounted for, the decrease in the quality of immigrant cohorts is entirely due to changes in their educational attainment and country-of-origin composition. The unobservable skills of immigrants from a given origin and education group improved in recent cohorts, consistent with observed patterns of English language proficiency.

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

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

Our results show that immigration-induced increases in labor market competition can explain 14.2, 43.9 and 40.8 percent of the increase in the initial relative wage gap of the 1970s, 1980s, and 1990s cohorts relative to the 1960s cohort. Shifts in relative skill demand account for an additional 10.6, 24.4 and 68.7 percent. With more years spent in the United States, these effects diminish since immigrants become closer substitutes to natives. Averaged over time, the competition effect alone accounts for 14.1, 22.4 and 20.4 percent of the increase in wage gaps relative to the 1960s cohort. These figures increase to 21.2, 33.6 and 36.4 percent after accounting for demand effects as well. The remaining differences can be attributed to decreasing cohort quality and fully explained by changes in immigrants' education and country-of-origin composition. Conditional on these two observable characteristics, our findings suggest that immigrants have become more positively selected in terms of unobservable skills, in line with additional evidence we provide on immigrants' English language proficiency. Through a series of robustness checks, we show that our results are largely unaffected by selective outmigration, undercounting of undocumented immigrants, network effects, alternative specifications of the relative demand shifts, 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, as well as changes in the relative demand for host-country-specific skills.

Several papers in the literature have critically assessed some of the key assumptions underlying the estimation and interpretation of immigrants' wage assimilation profiles. Using CPS data for the period 1979 to 2003, **?** 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. Duleep and Regets (2013) document a strong inverse relationship between immigrants' earnings at entry and subsequent wage growth, which they explain by higher investment in human capital of immigrants that arrive to the host country with less transferable skills. 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 covered by our analysis, we cannot account for selective outmigration as comprehensively as these papers do, but we show by means of three separate robustness checks that this issue is unlikely to affect our main conclusions.

Some papers in the literature highlight the importance of skill prices for the wage assimilation of immigrants. LaLonde and Topel (1992) find that the relative earnings of immigrants are sensitive to persistent changes in wage inequality in the United States. In particular, since immigrants tend to be less skilled than natives, the rising returns to skills in the 1970s increased wages of the average native by more than those of the average immigrant. Lubotsky (2011) performs a similar analysis including 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, **?** study immigrant wage progression through the lens of an asymmetric nested CES production function in which each nest represents either immigrant workers with a specific number of years of residence in the U.S. or natives. As immigrants move across nests, their skill efficiency and substitutability with other factor inputs change, which jointly determines their wage growth. Using Census and ACS data for the years 2000 to 2018, the authors show that, while immigrants' skill efficiency increases significantly over time, part of the associated wage gains are offset by immigrants becoming increasingly substitutable with natives and earlier immigrants. Similar to our paper, their analysis highlights that observed wage profiles of immigrants generally reflect both genuine skill accumulation and changes in aggregate factor supplies.

Finally, our analysis is closely linked to the large literature on the labor market impact of immigration (see e.g. 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 seeking to estimate the magnitudes of these relative wage effects.[2] On closer inspection, however, the finding of imperfect substitutability generates a

[2] In the context of internal migration in the United States, Boustan (2009) shows that, due to imperfect substitutability between black and white workers, the large black migration flows from the South to the

conceptual tension between the wage assimilation literature and the labor market impact literature. Even though both literatures study essentially the same outcome variable – the relative wages of immigrants and natives – they each account for its main determinants in very distinct and partial ways. While the traditional assimilation literature completely abstracts from aggregate factor supplies as possible drivers of relative wages, the impact literature usually does not, or only very rudimentarily, allow for immigrants' skill accumulation and evolving substitutability with other factor inputs. Our theoretical framework synthesizes 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 illustrates the relationship between relative wage dynamics and the size of immigrant inflows. Section III presents our theoretical framework. Section IV discusses identification and estimation of the model. Section V reviews the baseline estimates for our model parameters. Section VI presents our simulation results and decomposition analysis. Section VII shows extensive robustness checks. Section VIII concludes the paper.

II. Data and Descriptive Evidence

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

A. Data

Our empirical analysis is based on U.S. Census data for the years 1970, 1980, 1990 and 2000, combined with observations from the American Community Survey (ACS) pooled across the years 2009–2011 (labeled as 2010) and the years 2018 and 2019 (labeled as 2020). All data are downloaded from the Integrated Public Use Microdata Series database (IPUMS-USA, Ruggles et al., 2018). Following previous work, the main sample comprises individuals aged 25–64 who are not self-employed, do not live in group quarters, are not enrolled in school (except for 1970, when there is no information on school enrollment), work in the civilian sector, and report positive hours of work and earnings. We drop immigrants without information on their country of birth or year of arrival in the United States.[3] 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), measured in the first Census year after

North in the mid-20th century widened the racial wage gap in the North by 5 to 7 log points.

[3] 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 under-counts undocumented immigrants. In Section VII, we do a robustness check in which we correct for this under-counting in our baseline estimation.

Table 1—Descriptive Statistics of Immigrant Cohorts

	Cohort of entry:					
	1960-69	1970-79	1980-89	1990-99	2000-09	2010-19
Share of population (%)	3.0	4.2	5.6	7.7	9.0	7.3
Cohort size (millions)	0.8	1.4	2.3	3.8	4.6	4.2
Men (%)	65.0	61.8	62.4	61.7	60.1	59.5
Age	38.3	36.7	36.5	36.8	37.8	38.0
Hourly wage	16.7	16.0	14.5	16.0	14.2	18.1
HS dropouts (%)	46.7	40.9	31.3	28.1	26.1	15.1
HS graduates (%)	22.1	21.3	24.8	28.8	28.3	25.5
Some college (%)	11.0	11.8	17.2	12.0	11.8	11.7
College graduates (%)	20.2	25.9	26.7	31.1	33.8	47.8
Mexico (%)	8.4	19.8	18.4	25.7	27.2	13.2
Other Latin America (%)	30.6	21.5	26.9	22.0	26.6	28.0
Western countries (%)	36.9	17.3	11.1	9.7	6.6	8.3
Asia (%)	14.5	34.0	35.7	29.3	28.6	38.0
Other (%)	9.6	7.5	7.8	13.2	10.9	12.4

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

arrival. With the exception of the most recent decade, cohort sizes increased steadily over time, from about 800,000 individuals in the 1960s to 2.3 million in the 1980s and 4.6 million in the 2000s. As shown in Table B1 in Appendix B, this led to a sizable increase in the foreign-born share of the population, from 3.8 percent in 1970 to 16.3 percent in 2020. This increase in immigration was accompanied by major shifts in the immigrants' educational and origin composition. While most immigrants in the 1960s originated from Western source countries (36.9 percent) and only relatively few from Mexico (8.4 percent) and Asia (14.5 percent), this pattern reversed over the following decades, with the share of immigrants from Western countries (6.6 percent) decreasing and the shares from Mexico (27.2) and Asia (28.6) increasing rapidly until the early 2000s. In the last decade, there has been another meaningful shift in the origin composition, away from Mexican immigrants (13.2 percent) and toward Asian immigrants (38.0 percent).

Since the 1960s, the level of formal education of newly arriving immigrants improved substantially, with the share of high school dropouts decreasing from 46.7 percent in the 1960s to 15.1 percent in the 2010s, and the share of college graduates increasing from 20.2 percent in the 1960s to 47.8 percent in the 2010s. However, despite this considerable improvement in immigrants' educational attainment, the gap in formal education relative to natives widened significantly during the last half century due to the even more rapid expansion of higher education in the United States (see Table B1).

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

B. Descriptive evidence on assimilation profiles

To set the stage for our main analysis, we start by documenting how immigrant wage assimilation profiles have changed over time, following the standard approach based on repeated cross-sectional data first advocated by Borjas (1985). To facilitate comparisons with earlier studies, and because selection effects due to changing labor force participation make female wage assimilation profiles more difficult to interpret, we focus on immigrant men and their assimilation profiles in the main text. The corresponding tables and figures for women can be found in the Online Appendix. In Figure 1, we depict two sets of results. The dashed lines are obtained from year-by-year regressions of log male wages on a third order polynomial in age and dummies for years since migration (which are all set to zero for native men). The plotted coefficients on these dummy variables thus reflect raw data averages (net of age effects). The solid lines are obtained from a single regression of log male wages on year fixed effects and their interaction with a third order polynomial in age, and cohort-of-entry fixed effects and their interaction with a third order polynomial in years since migration.[4] While Figure 1A shows the estimated relative wage gaps and their evolution over time and across cohorts, Figure 1B highlights the relative wage growth by normalizing the initial wage gaps of each cohort to zero.

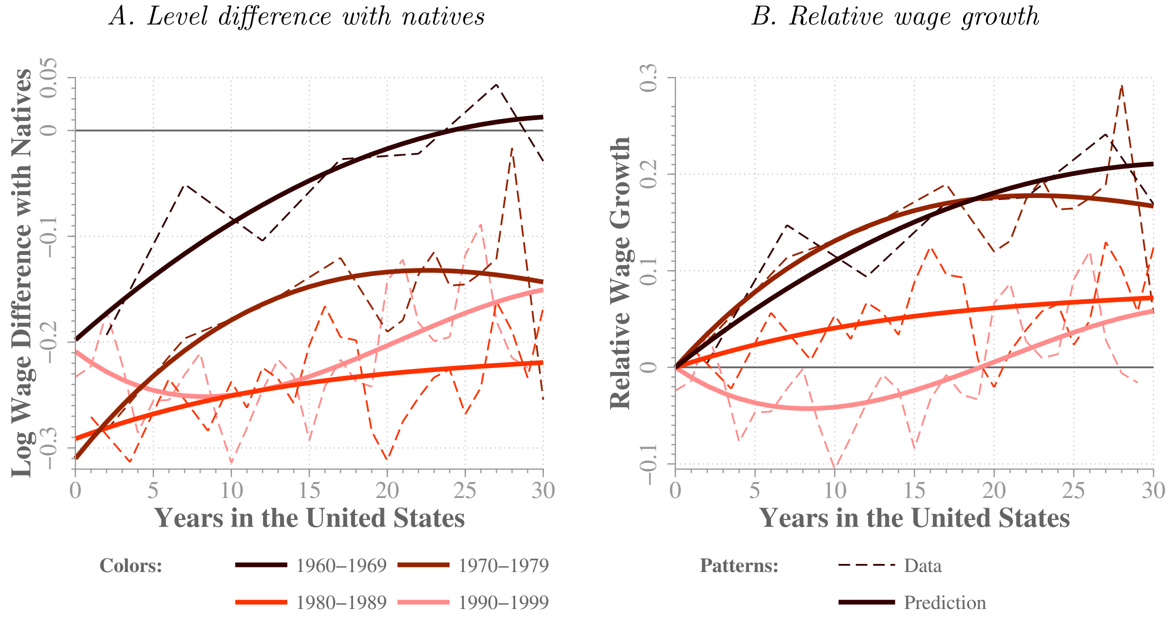
Figure 1 illustrates two major changes in immigrants' wage assimilation profiles during the period considered. First, the initial wage gap between newly arriving immigrants and natives widened substantially between the 1960s and 1980s. While the 1960s cohort arrived with an initial wage gap of about 20 log points, the 1970s and 1980s arrival cohorts faced an initial wage gap of around 30 log points, which then narrowed again to 21 log points for the 1990s cohort. Second, the speed of wage convergence decreased significantly across cohorts, to the point that the relative wage gap of the 1990s cohort even widened initially before then starting to close after about 10 years in the country.[5]

Our central hypothesis is that the changing wage assimilation profiles across cohorts are partially driven by changes in relative aggregate skill supplies 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 male wage gap (left panel) and relative wage growth over the first decade in the United States (right panel)

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

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

Figure 1. Wage Gap between Natives and Immigrants and Years in the U.S.



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

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

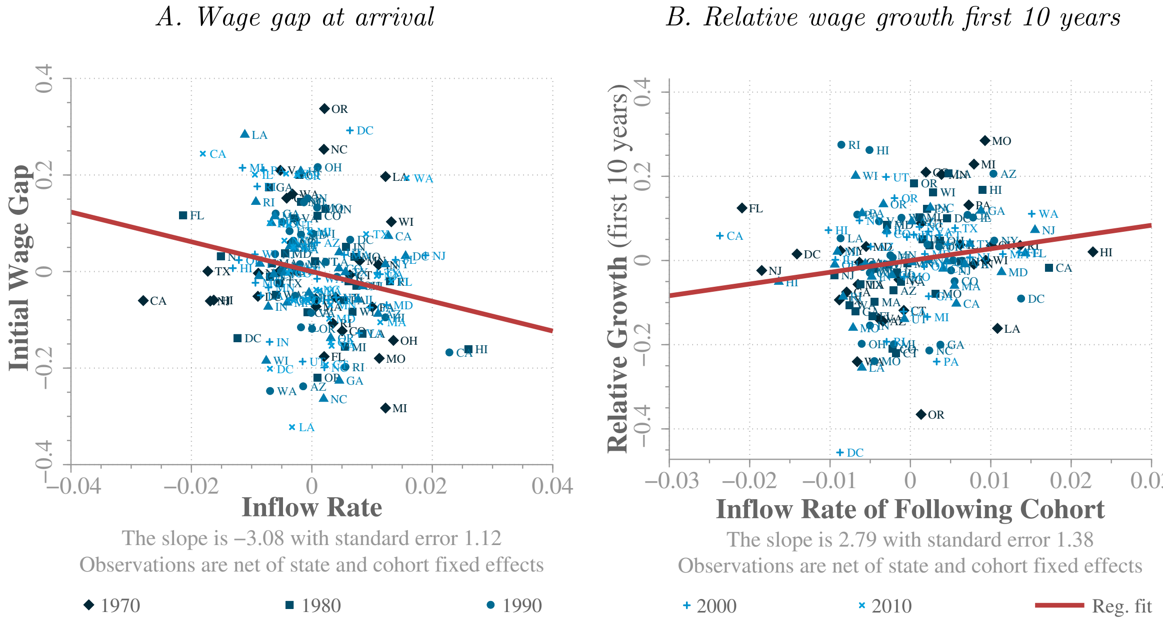
where $c(i)$ and $t(i)$ indicate the immigration cohort and the census year in which individual i is observed, age_i indicates age, and y_i indicates years since migration. Cohorts are grouped in the following way: before 1960, 1960-69, 1970-79, 1980-89, 1990-99, 2000-09, and 2010 or later. Colors represent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

to the size of the contemporary and subsequent immigrant arrival cohorts respectively, exploiting variation at the state-cohort level. The initial wage gaps and relative growth rates are predicted from regressions similar to those underlying the solid lines in Figure 1 but estimated for each state separately and then purged of cohort and state fixed effects.

According to Figure 2A, larger immigrant arrival cohorts are characterized by a more pronounced initial wage gap, as our theoretical framework below unambiguously predicts. The impact of growing cohort sizes on relative wage growth, in contrast, is theoretically ambiguous, 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 findings of our main empirical analysis.

The analogous plots for women are presented in the Online Appendix. The overall patterns are very similar, except that the initial wage gaps of immigrant women are around 10 log points smaller for the 1960s and 1970s cohorts compared to those of immigrant men, and the cohort differences in the speed of convergence are somewhat less pronounced. Moreover, the slope coefficients in both panels of Figure 2 are smaller and less precise.

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



Note: This figure plots the initial wage gap for men in different state-cohort cells against the size of the own arrival cohort (left panel) and the relative wage growth over the first 10 years against the size of the following immigrant cohort (right panel). The initial wage gap and relative wage growth are computed based on state-by-state regressions analogous to those underlying Figure 1. The initial wage gap is measured as the state-specific cohort fixed effect ($\beta_{0c(i)}$) and the relative wage growth as the change in the wage gap over the first 10 years, calculated based on the polynomial in years since migration interacted with cohort dummies ($\{\beta_{3\ell c(i)}\}_{\ell \in \{1,2,3\}}$). Immigrant inflows are computed as the state population of the respective cohort (including men and women) divided by the native population in the state in the first census year the cohort is observed. The depicted observations are net of cohort and state fixed effects. States with less than 100 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.

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.[6] 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 immigrants spend time in the host country.

[6] For a similar approach outside of the immigration context, see Jeong, Kim and Manovskii (2015), who shift skill supplies (in their case, defined as labor and experience) by a Mincerian productivity factor similar to the one we use below.

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

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

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, we normalize recent male high school dropouts to supply one general skill unit and a fraction s of a specific skill unit, where $s = 1$ for natives. Let $n \equiv \mathbb{1}\{\text{native}\}$ denote an indicator variable that equals one if the individual is a native and zero otherwise. For immigrants ($n = 0$), the fraction s depends on their gender g, the number of years in the host country y, national origin o, cohort of entry c, education level e (these are 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).[7] In particular:

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

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

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

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

which depends, in a flexible way, on the education level (η_{0get}), a term that is linear in the

[7] We start counting experience after age 18, discarding years before that age.

years of education ($\eta_{1gt}E$), and a cubic function in potential experience ($\sum_{\ell=1}^{3} \eta_{2\ell gt} x^{\ell}$).[8] As in Equation (3), all the η parameters are gender-specific so that the returns to education and experience are allowed to differ between men and women.

Our model accounts for two forms of skill-biased technological change. The time-varying parameters η_{1gt}, $\{\eta_{0get}\}_{e\in\mathcal{E}}$ and $\{\eta_{2\ell gt}\}_{\ell\in\{1,2,3\}}$ in Equation (4) capture standard skill-biased technological change that increases the demand for high-skilled workers and workers with different levels of experience. Furthermore, the parameters δ_t in Equation (1) capture any additional changes in the relative demand for specific skills, for example due to technological progress that favors communication over manual skills.

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

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

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

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

where the second equality is obtained 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*

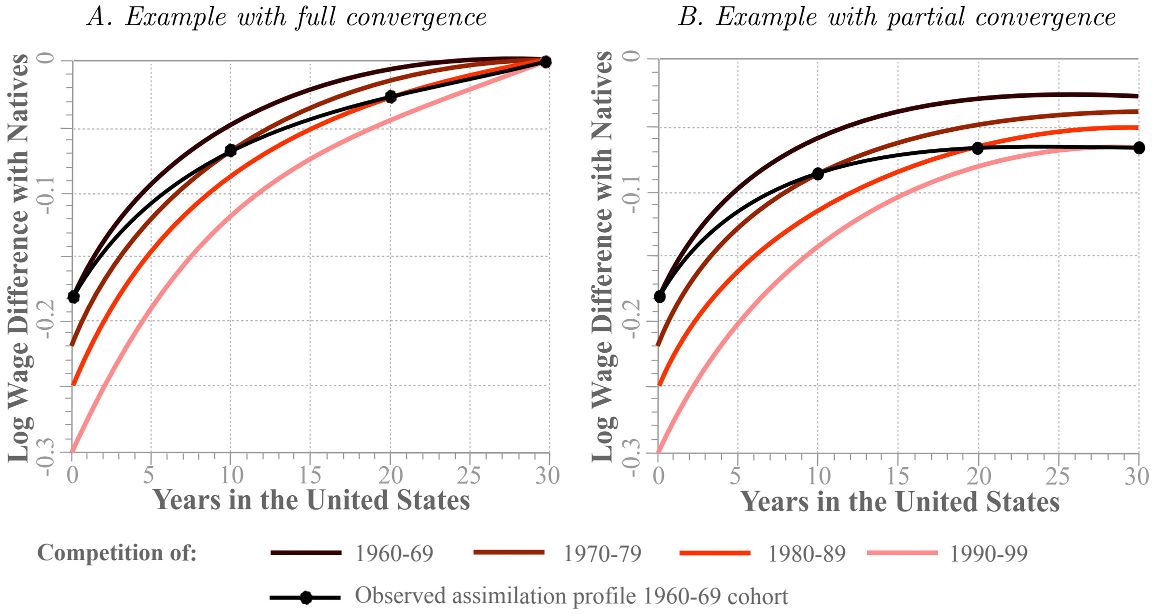
Equation (6) identifies the two key drivers of immigrant wage assimilation. The first one is the rate at which $s_g(0, y, o, c, E, x)$ evolves as immigrants spend time in the host country (y), which reflects their skill accumulation process. The second one is the competition effect due to changing aggregate skill supplies G_t/S_t, which affects relative wages if and only if general and specific skills are imperfect substitutes in the production process ($\sigma < \infty$) *and* if immigrants differ from natives in terms of the skill bundles they supply ($s \neq 1$). As results below suggest, this competition effect can be amplified by changes in the relative demand of specific skills depending on the evolution of δ_t.

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

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

[8] The linear term in years of education thus allows for different productivity levels for individuals with the same broad education level but different years of education.

Figure 3. Dynamic Competition Effect: A Stylized 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 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 long-run full wage convergence, the right figure an example under the assumption of only partial long-run wage convergence.

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 their skill supplies. Intuitively, closer arrival cohorts are more substitutable in the labor market than cohorts arriving many years apart.

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

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

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

The colored 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 ($s \rightarrow< 1$). 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 larger the initial wage gap and the faster the subsequent relative wage growth. In the case of full convergence (Figure 3A), immigrant wages eventually fully catch up with those of natives, regardless of the aggregate skill supplies in the economy. This is because, when their level of specific skills s approaches one, immigrants provide the same skill bundles as natives and are therefore no longer differentially affected by changing aggregate supplies (the numerator of Equation (7) becomes zero). Increasing labor market competition thus delays the process of wage convergence in this case but does not prevent it. A different picture emerges when immigrants' level of specific skills only partially converges to that of natives (Figure 3B). In this case, even in the long run, immigrants supply relatively fewer specific skills than natives and are therefore more negatively affected by increases in G_t/S_t.

While helpful for understanding the main mechanism at work, the previous scenario 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 faced by a given cohort increases simultaneously. As a result, the positive impact on the speed of convergence described in Equation (8) is counteracted by a continuous downward shift of that cohort's relative wage profile as implied by Equation (7). We refer to this combined effect as the *dynamic competition effect*. 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, one can see 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 may also matter as different types of immigrants provide different amounts of skills, both at arrival and over time. This makes a given cohort's wage assimilation profile a complex function of past, present, and future immigrant inflows. In the empirical analysis that follows, we estimate the skill accumulation process of different arrival cohorts and quantify the relative importance of changing labor market competition, secular demand changes, and composition effects in explaining the observed variation in immigrant wage assimilation over time.

C. Connection with other models in the literature

Our theoretical framework is consistent with key insights from the recent literatures on the labor market impact of immigration and immigrant wage assimilation. Peri and Sparber (2009) and Llull (2018) argue that natives and immigrants are imperfect substitutes in aggregate production because they specialize in different types of occupations. 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 a 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).[9] More in line with Dustmann, Frattini and Preston (2013) and Llull (2018), our approach has the advantage of not having to define ex ante who competes with whom based on education, experience, or nativity status. Instead, we allow 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 she does not speak English sufficiently well. As a result, she has to work in a different, often lower-paying job in the early years after arrival before attaining the required English language proficiency to move up the occupational ladder. Our model captures such initial downgrading by allowing immigrants to lack specific skills at the time of arrival ($s \ll 1$) and to then accumulate these skills while living in the host country. To account for heterogeneity across immigrant groups, we allow the extent of the downgrading to vary with immigrants' observed characteristics, including

[9] 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.

their gender, education level, and country of origin.

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:

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

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

IV. Identification and Estimation

Our data set consists of repeated cross sections of native and immigrant workers with individual information on gender, age and education as well as, for immigrants, age at the time of arrival, country of origin and cohort of entry. We parameterize $\delta_t \equiv \exp(\tilde{\delta}t)$.[10] The parameters to estimate are the elasticity of substitution between general and specific skills σ, the demand shift parameter $\tilde{\delta}$, the parameters governing the speed at which immigrants acquire specific skills θ, and the period-specific parameters of the productivity factor η.

A. Identification

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

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

where ϵ_i is a random error term uncorrelated with the other regressors that captures idiosyncratic shocks to productivity as well as possible measurement error in hourly wages. Considering a separate regression for each census year and normalizing η_{0get} for one gender-education group (male high school dropouts), the remaining gender-specific parameters η are identified as linear regression coefficients, 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

[10] 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.

market-period G_{jt} is identified (up to the normalization above) as the aggregation of the predictions $\widehat{h_{gt}(E,x)}$ for every individual in the sample working in market j in period t:

$$\widehat{G}_{jt} \equiv \sum_{i \in \{(j,t)\}} \omega_i \widehat{h_{g(i)t}(E_i, x_i)}, \tag{11}$$

where ω_i are sampling weights and the sum over $i \in \{(j,t)\}$ aggregates all individual observations in market-period (j,t).

The θ parameters of the specific skills function $s_g(0,y,o,c,E,x)$ 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 she was a native:

$$\ln w_i - \ln[\widehat{r_{Gj(i)t(i)} + r_{Sj(i)t(i)}}] - \ln \widehat{h_{g(i)t(i)}(E_i, x_i)} = -\ln\left[1 + \exp(\tilde{\delta} t_i)\left(\frac{\widehat{G}_{j(i)t(i)}}{\widehat{S}_{j(i)t(i)}(\boldsymbol{\theta})}\right)^{\frac{1}{\sigma}}\right]$$

$$+ \ln\left[1 + s_{g(i)}(n_i, y_i, o_i, c_i, E_i, x_i; \boldsymbol{\theta}) \exp(\tilde{\delta} t_i)\left(\frac{\widehat{G}_{j(i)t(i)}}{\widehat{S}_{j(i)t(i)}(\boldsymbol{\theta})}\right)^{\frac{1}{\sigma}}\right] + \epsilon_i, \tag{12}$$

where $\boldsymbol{\theta}$ is the vector of θ parameters, $\widehat{G}_{jt}$ is defined above, and:

$$\widehat{S}_{jt}(\boldsymbol{\theta}) \equiv \sum_{i \in \{(j,t)\}} \omega_i \left[n_i + (1-n_i) s_{g(i)}(n_i, y_i, o_i, c_i, E_i, x_i; \boldsymbol{\theta})\right] \widehat{h_{g(i)t}(E_i, x_i)}, \tag{13}$$

Equations (12) and (13) explicitly emphasize the dependence of $s_g(0,y,o,c,E,x)$ and $\widehat{S}_{jt}$ on $\boldsymbol{\theta}$, which is identified in Equation (12). More generally, the aggregate supply of specific skills S_{jt} also depends on the number of immigrants and natives in market-period (j,t) and their observables, as well as on the η parameters. Intuitively, $\boldsymbol{\theta}$ is identified off the wage differences between immigrants with different characteristics working in a given labor market, whereas σ and $\tilde{\delta}$ are identified off the variation across markets and over time.

B. Estimation

Our estimation proceeds in two steps. In the first step, we obtain the parameters of the productivity factor $h_{gt}(E,x)$ by estimating the wage regressions described in Equation (10), using observations for native men and women only. We estimate a separate regression for each census year, thus allowing the returns to education and experience to vary over time. Since labor markets are defined as U.S. states, we include state dummies in each of the regressions to identify the relevant skill prices. In the second step, we first compute $\widehat{G}_{jt}$ and the worker-specific left-hand-side terms of Equation (12) using the estimated parameters from the first step. We then estimate the remaining parameters by non-linear least squares (NLS), fitting Equation (12) to the subsample of immigrant workers and using Equation (13) to update $\widehat{S}_{jt}$ in each iteration of the NLS estimation algorithm.[11]

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. Since most of the earlier literature to which we relate our findings has studied the wage assimilation profiles of immigrant men ($g = 0$), we focus on this particular group in the following sections. The corresponding tables and figures for women ($g = 1$) are shown in the Online Appendix.

A. Productivity factor parameters

Table 2 reports the estimates for the productivity factor of men $h_{0t}(E, x)$, with each column referring to a different census year. The parameter estimates are consistent with those in the literature (see e.g. Heckman, Lochner and Todd, 2006, for a survey). Beyond the wage returns to different education levels (1.3–5.4 log points for a high school diploma, 8.1–14.6 log points for some college education and 27.4–47.1 log points for a bachelor's degree, depending on the census year), an extra year of education increases male wages by 4.2–6.3 log points. In general, returns to college education increased over time, in line with the findings of the wage inequality literature. The wage-experience profiles show the standard concave shape, flattening after around 25 years of experience.

B. Skill accumulation parameters

Table 3 reports the parameter estimates that describe the process through which male immigrant workers accumulate specific skills, $s_0(0, y, o, c, E, x)$. The first column shows the coefficients of the non-interacted regressors along with the constant term. The constant represents the relative specific skills supplied upon entry by a male Mexican high school dropout who arrived with the 1970s cohort with zero years of experience. This constant term is estimated to be 0.804, indicating that this reference immigrant supplied about 80 percent of the specific skills of an observationally equivalent native. All other estimates in the first column represent relative shifts at the time of arrival with respect to the reference individual. For example, relative to similarly educated natives, the amount of specific skills supplied by immigrants in the other three education groups is between

[11] 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 very 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 those 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 with bootstrapped standard errors.

Table 2—Productivity Factor, $h_{0t}(E, x)$

	Census year:					
	1970	1980	1990	2000	2010	2020
Years of education	0.046	0.042	0.047	0.052	0.063	0.052
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience	0.057	0.070	0.052	0.061	0.073	0.066
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience squared ($\times 10^2$)	-0.171	-0.191	-0.107	-0.173	-0.199	-0.165
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Potential experience cube ($\times 10^3$)	0.016	0.016	0.006	0.016	0.017	0.014
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
High school graduate	0.015	0.054	0.048	0.052	0.036	0.013
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)
Some college	0.081	0.095	0.142	0.146	0.136	0.125
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
College graduate	0.275	0.274	0.366	0.386	0.403	0.471
	(0.005)	(0.004)	(0.004)	(0.005)	(0.008)	(0.010)

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

23.0 and 25.0 percentage points lower than for a high school dropout. Immigrants from other regions of origin are generally more skilled at arrival than Mexican immigrants. Yet, with the exception of immigrants from Western countries, all groups arrive with specific skills that are below those of comparable native workers.[12] Regarding the different arrival cohorts, apart from the pre-1960s cohorts (for whom the intercept is highly extrapolated), immigrants from earlier cohorts are less similar to natives upon arrival than immigrants from more recent cohorts, a key finding that we discuss in more detail below. Finally, the results in the first column show a negative and decreasing return to potential experience abroad, implying that, all else equal, older immigrants arrive with less host-country-specific skills than younger ones.

The remaining columns of Table 3 show the estimated coefficients for the interaction terms of each of the listed characteristics and a polynomial in years since migration. Since the magnitudes of these estimates are difficult to interpret in isolation, we visualize them in Figure 4, plotting the predicted skill accumulation profiles of different types of immigrants. The baseline individual in all figures is a synthetic individual with the average characteristics of all immigrant men in the sample, except for the characteristic that is being varied in each graph. 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

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

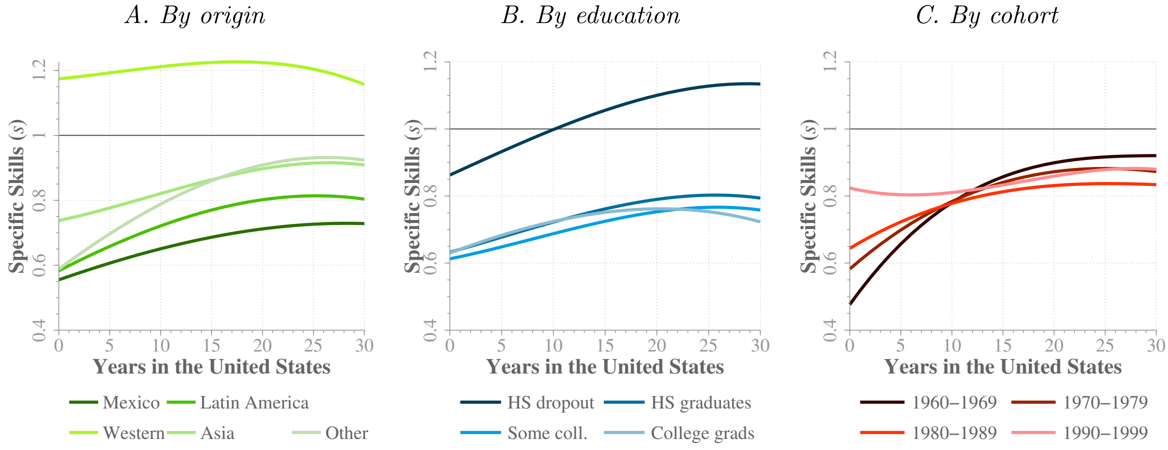
Table 3—Specific Skill Accumulation, $s_0(0, y, o, c, E, x)$

	Intercepts	Interactions with years since migration: Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Region of origin:				
Latin America	0.028	0.005	-0.006	-0.002
	(0.009)	(0.002)	(0.014)	(0.003)
Western countries	0.619	-0.008	0.027	-0.008
	(0.018)	(0.003)	(0.022)	(0.004)
Asia	0.183	-0.004	0.037	-0.008
	(0.011)	(0.002)	(0.016)	(0.003)
Other	0.034	0.012	-0.014	-0.003
	(0.012)	(0.003)	(0.021)	(0.004)
Education level:				
High school graduate	-0.230	-0.005	0.009	-0.001
	(0.009)	(0.002)	(0.013)	(0.002)
Some college	-0.250	-0.008	0.020	-0.003
	(0.012)	(0.003)	(0.016)	(0.003)
College graduate	-0.233	-0.002	-0.019	0.002
	(0.011)	(0.003)	(0.017)	(0.003)
Cohort of arrival:				
Pre-1960s	0.335	-0.023	0.150	-0.021
	(0.120)	(0.016)	(0.065)	(0.008)
1960s	-0.106	0.046	-0.148	0.018
	(0.016)	(0.003)	(0.019)	(0.003)
1970s		0.030	-0.080	0.008
		(0.002)	(0.014)	(0.002)
1980s	0.061	0.022	-0.067	0.009
	(0.009)	(0.002)	(0.014)	(0.003)
1990s	0.242	-0.004	0.066	-0.011
	(0.010)	(0.002)	(0.020)	(0.005)
2000s[a]	0.199	0.003	0.070	-0.022
	(0.013)	(0.005)	(0.056)	(0.020)
2010s[a]	0.309	0.008	0.070	-0.022
	(0.012)	(0.004)	(0.056)	(0.020)
Experience at entry:				
Linear term	-0.025			
	(0.001)			
Quadratic ($\times 10^2$)	0.076			
	(0.005)			
Cubic ($\times 10^3$)	-0.009			
	(0.001)			
Constant (relative specific skills at arrival of a Mexican high school dropout man that arrived in the 1970s cohort with zero years of experience)**:**	0.804			
	(0.011)			

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

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

Figure 4. Skill Accumulation Profiles, $s_0(0, y, o, c, E, x)$



Note: The figure displays predicted skill accumulation profiles for different groups based on the estimates reported in Table 3. The baseline individual in all figures is a synthetic individual with the average characteristics of all immigrant men in the sample, except for the characteristic that is being plotted in each graph. 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.

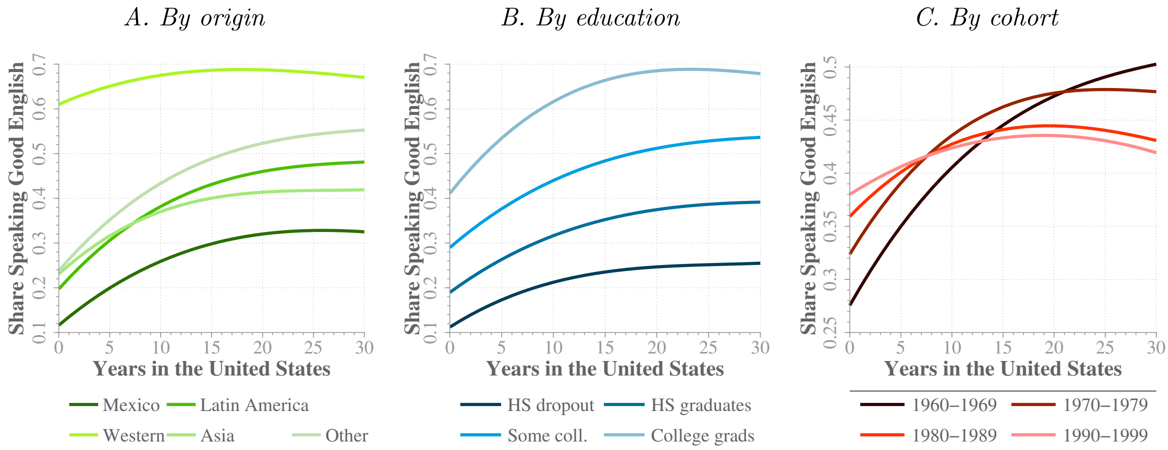
Western countries, all groups arrive with specific skills that are significantly below those of comparable natives, with Mexicans showing the lowest skill level upon arrival. Over time, all these groups accumulate specific skills so that the gap relative to natives shrinks significantly. However, none of these groups is able to entirely close the gap.

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 similarly educated natives, immigrant high school dropouts arrive with the highest level of specific skills, reflecting the fact that they are more similar to native dropouts than, for example, immigrant college graduates are to native college graduates. Contrary to all other education groups who only reach about 70–80 percent of their native counterparts' specific skill levels, immigrant high school dropouts manage to not only reach but surpass the native level of specific skills after about 10 years in the country, which could be due to differential selection into the immigrant and native high school dropout populations.[13]

Figure 4C plots the skill accumulation profiles by arrival cohort, omitting the pre-1960s and post-2000s cohorts, which, even though they are accounted for in the estimation (as shown in Table 3), we only observe partially. While the 1960s cohort faced a substantial initial specific skills gap of around 52.4 percent, this gap narrowed for subsequent cohorts, to around 41.8 percent for the 1970s cohort, 35.6 percent for the 1980s cohort, and 17.6 percent for the 1990s cohort. This finding indicates that, conditional on country of origin and education, more recent cohorts of immigrants are more positively selected in terms of unobservable skills than earlier cohorts. However, Figure 4C also shows that the speed of accumulation of specific skills for these cohorts has slowed down, which might

[13] Note, again, that the synthetic average immigrant has a higher weight of Western immigrants and lower weight of Mexican immigrants than the average high school dropout.

Figure 5. English Proficiency



Note: The figure displays English language proficiency profiles predicted from a linear regression of an indicator for "speaking English very well" or "only speaking English" on all the variables included in the specific-skills function $s_0(\cdot)$ and year dummies on a sample of men. The baseline individual in all figures is a synthetic individual with the average characteristics of all immigrant men in the sample except for the characteristic that is plotted in each graph. 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.

reflect diminishing returns to investments in specific skills. All in all, after 20–30 years, all arrival cohorts perform similarly well, having accumulated 83.7–92.0 percent of the specific skills of comparable 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. **?** and Rho and Sanders, 2021), changes in the average age at migration (Bleakley and Chin, 2004, 2010), 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. 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 $s(\cdot)$ and year fixed effects.[14]

Figure 5 presents the results from this regression. In line with our findings in Figure 4A, 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 (with the exception of Asian immigrants). At the other extreme, Western immigrants arrive with relatively high language proficiency, which they only moderately improve throughout their stay. The results by education level in Figure 5B are not di-

[14] The results without the time dummies are overall very similar, even though the slopes are somewhat less steep (becoming slightly 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 less steep patterns when these dummies are omitted.

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

Finally, a key insight of Figure 4 is that, given national origin and education, recent cohorts of immigrants arrive with a higher level of specific skills than earlier cohorts. Figure 5C provides further support for this finding, 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 mirror their counterparts in Figure 4C suggests that our estimated skill accumulation profiles indeed reflect changes in the 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 0.02. Interpreting this value is difficult, given the absence of comparable estimates in the literature. To get a sense of the plausibility of this magnitude, we perform two different exercises. First, consider the following equation from our model, which relates 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. Aggregating across state-specific labor markets, the predicted relative supplies of general skills G_t/S_t increased from 1.0023 in 1970 to 1.0192 in 2020, which corresponds to an increase of 1.67 log points. Given an estimated inverse elasticity of 50.5, such a change is associated with an increase in the relative price of specific skills of $1.67 \times 50.5 = 59.6$ log points over the last 50 years, suggesting a quantitatively important role for labor market competition. Table 4 shows that this increase is further amplified by secular shifts in the relative demand for specific skills, which raise relative skill prices by 1.3 log points per year.

An alternative way of making sense of our estimate of σ is to formally link it to the elasticity of substitution between natives and immigrants that has been estimated in the literature. Let N_ℓ denote the number of natives of type (or with characteristics) ℓ, and let $I_{\ell'}$ denote the number of immigrants of type ℓ'. By definition, the total amount of general skill units is given by $G = \sum_\ell h_\ell N_\ell + \sum_{\ell'} h_{\ell'} I_{\ell'}$, and the total amount of specific

Table 4—Elasticity of Substitution σ, and Relative Demand Shift $\tilde{\delta}$

	Point estimate	Standard error	Confidence interval
Elasticity of substitution (σ)	0.020	(0.002)	[0.017,0.024]
Trend in relative demand ($\tilde{\delta}$)	0.013	(0.001)	

Note: This table presents parameter estimates for the elasticity of substitution between general and specific skills σ, and for the demand shift parameter $\tilde{\delta}$ included in δ_t. Both parameters are defined in Equation (1) and are estimated by NLS as described in Section IV.B. Sample weights, rescaled by annual hours worked, are used in the estimation and the computation of aggregates.

skill units by $S = \sum_{\ell} h_{\ell} N_{\ell} + \sum_{\ell'} h_{\ell'} s_{\ell'} I_{\ell'}$, where h_{ℓ}, $h_{\ell'}$ and $s_{\ell'}$ respectively denote the productivity factors and specific skill units of individuals of types ℓ and ℓ'.

The elasticity of substitution between natives and immigrants, holding constant each group's skill composition (that is, $d\ln N_{\ell} = d\ln N \ \forall \ell$, and $d\ln I_{\ell'} = d\ln I \ \forall \ell'$), is defined as $\varepsilon_{NI} \equiv \frac{d\ln(N/I)}{d\ln[(\partial Y/\partial I)/(\partial Y/\partial N)]}$. Evaluated at market values δ, G and S, the elasticity of substitution between natives and immigrants, derived in Appendix C, is given by:

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

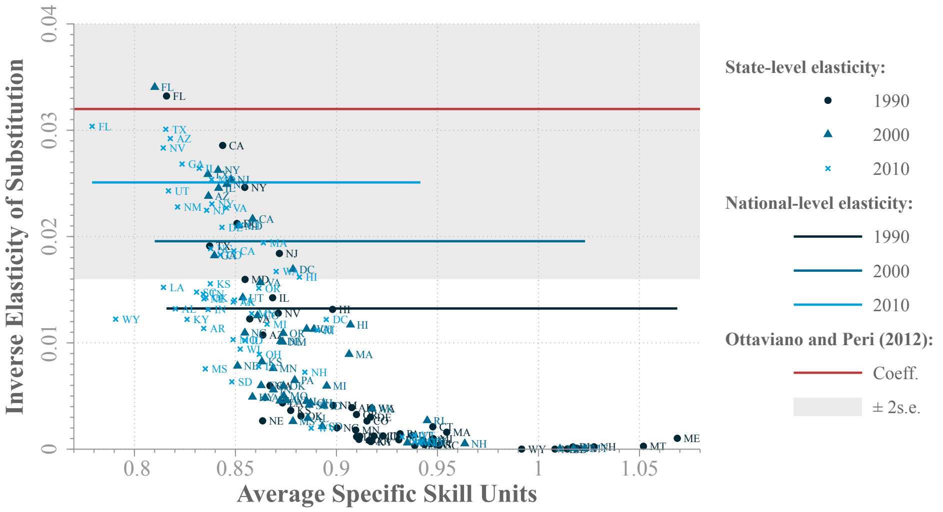
where $\bar{h}_N \equiv \sum_{\ell} h_{\ell} \frac{N_{\ell}}{N}$ is the average productivity factor of natives and $\tilde{s}_I \equiv \sum_{\ell'} s_{\ell'} \frac{h_{\ell'} I_{\ell'}}{\sum_{\ell'} h_{\ell'} I_{\ell'}}$ is the average of immigrants' specific skill units (weighted by their productivity factors). This elasticity tends to infinity when σ approaches infinity or $\tilde{s}_I$ converges to one.

Evaluating Equation (15) at our parameter estimates, Figure 6 compares a set of (inverse) elasticities of substitution implied by our estimate of σ together with a benchmark elasticity taken from Ottaviano and Peri (2012).[15] The horizontal lines represent the elasticities of substitution for the years 1990, 2000 and 2010, computed at the national level after aggregating general and specific skills across states. These estimates are 0.013 for year 1990, 0.020 for 2000, and 0.025 for 2010, in the same ballpark as the estimate in Ottaviano and Peri (2012), which is 0.034 (s.e. 0.008) for the period 1990–2006.

Figure 6 also shows how our model predicts different elasticities of substitution for different markets, depending on the size and skill composition of their native and immigrant populations. In particular, the scatter of points depicted in the figure connects the implied elasticity of substitution of every state-year cell with the average specific skills of immigrants ($\tilde{s}_I$) in each cell. The figure shows that, while in some markets immigrants and natives are close to perfect substitutes, in others such as Florida, Texas and Arizona, their elasticity of substitution is substantially smaller (its inverse larger).

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

FIGURE 6. IMPLIED ELASTICITY OF SUBSTITUTION BETWEEN NATIVES AND IMMIGRANTS



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

D. *Goodness of fit*

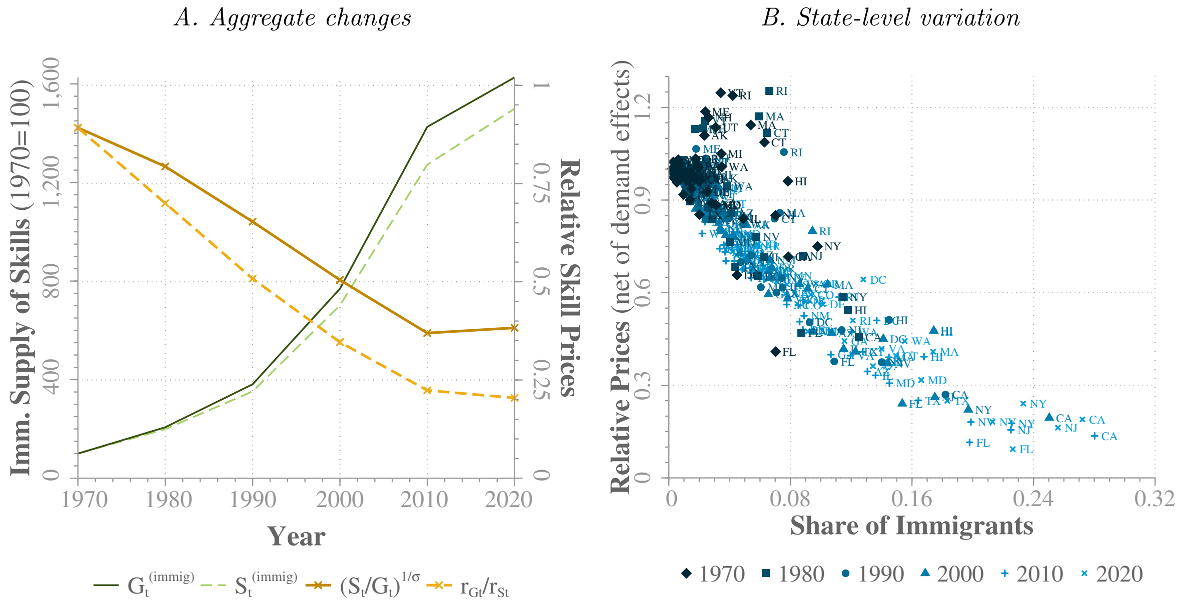
To evaluate the ability of our model to reproduce the wage assimilation profiles shown in Section II.B, we repeat the analysis underlying Figure 1 but now use wage predictions from our model for all individuals in the sample as the dependent variable. In particular, we regress predicted wages on cohort 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. Figure B1 in the appendix plots the resulting assimilation profiles (dashed) together with solid lines of Figure 1 (solid). The figure shows that our model accurately replicates both the wage gap between natives and immigrants and the decreasing speed of convergence across cohorts.

E. *Changes in relative skill supplies and prices*

We conclude this section by showing how, according to our estimates, the increasing immigrant inflows since the 1970s 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 contemporaneous evolution of relative skill prices, both including and excluding the associated demand effects. Between 1970 and 2020, the total supply of general skills grew by a factor of 16.3 (green solid line), whereas the supply of specific skills grew by only a factor of 15.0 (green dashed line). The resulting increase in the relative supply of general skills reduced their price relative to the price of specific skills from 0.89 to 0.38 (orange solid line). The growing relative demand for specific skills pushed this ratio of skill prices further down to 0.20 (orange dashed line).

Figure 7B illustrates the relationship between raw immigrant population shares and

Figure 7. Changes in Relative Supplies and Relative Skill Prices



Note: The left plot shows the predicted aggregate amount of general and specific skills supplied by immigrants in each year (left axis) and the relative skill prices (including and excluding demand effects) implied by these aggregate supplies (right axis). The right plot shows the predicted relative skill prices (excluding demand effects) at the state-year level in relation to the local raw immigrant share. In the left plot, aggregate supplies are normalized to 100 in the year 1970.

relative skill prices (net of demand effects) at the state-year level, thus reflecting both time and spatial variation. There is a clear negative relationship between the two, with the relative price of general skills well below 0.3 in states with large immigrant population shares like California, Florida, or 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, which is the variation used to identify the parameter σ.

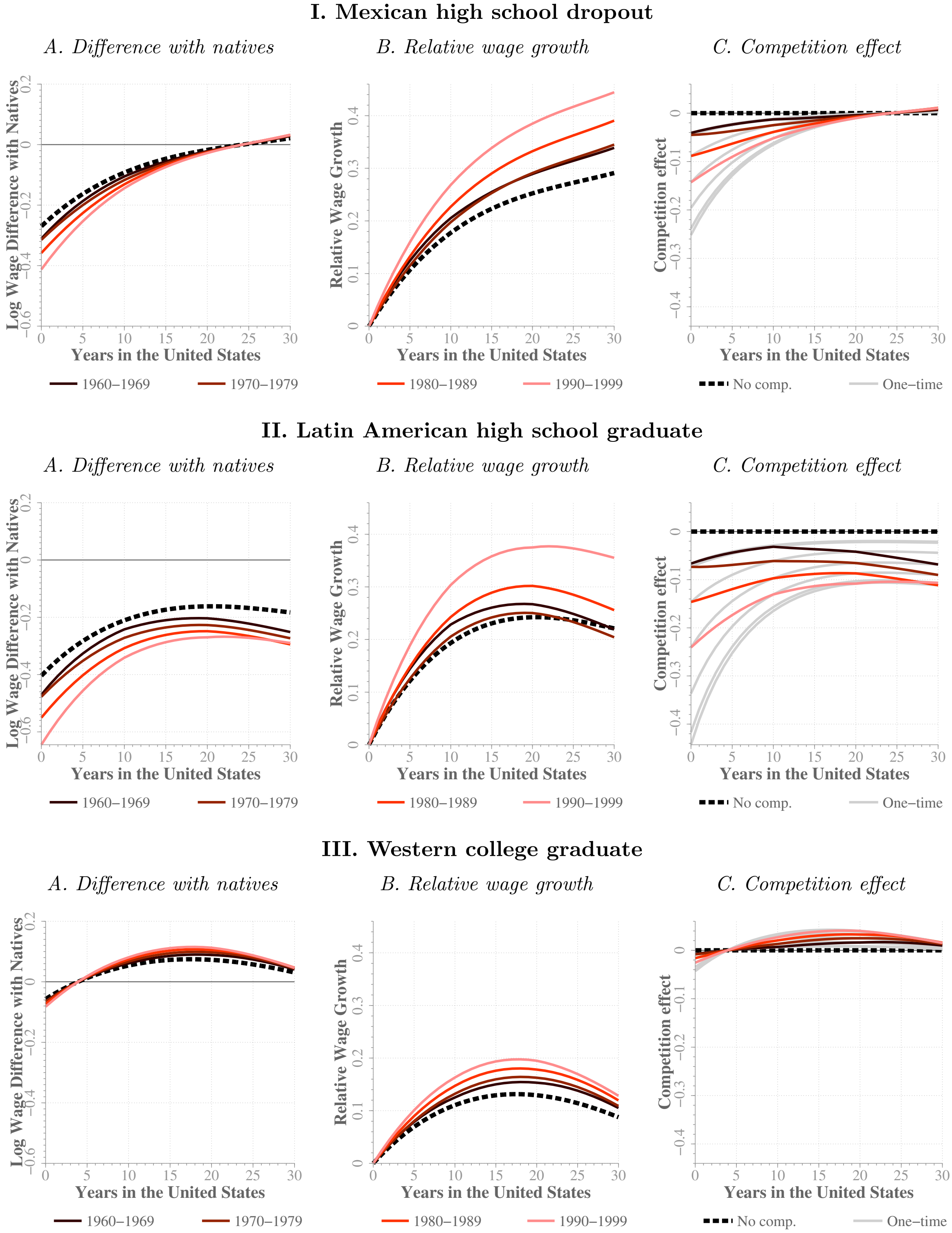
VI. Labor Market Competition and Immigrant Wage Assimilation

In this section, we use our estimated model to study how labor market competition affects the wage assimilation of immigrants. In Section VI.A, we illustrate the role of our mechanism in shaping the assimilation profiles of different types of immigrants, focusing on three specific but meaningful examples. While not exhaustive, these examples are meant to document the large degree of heterogeneity across individuals. In Section VI.B, we provide a comprehensive quantification of the importance of the labor market competition effect in explaining the wage assimilation profiles depicted in Figure 1.

A. *Heterogeneous effects on different individuals: some illustrative examples*

Figure 8 shows, for three specific groups of immigrants, wage assimilation profiles under different counterfactual scenarios. The three groups considered are Mexican high school dropouts, Latin American high school graduates, and Western college graduates. We select these groups because they each represent an important contingent of the U.S. immigrant population and because they are characterized by very distinct assimilation

Figure 8. The Labor Market Competition Effect: Some Examples



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

profiles, allowing us to highlight heterogeneity across different types of individuals. To focus attention on the role of labor market competition, we select for each group a representative immigrant who arrived with the unobservable skills of the 1960s cohort, was exposed to the demand effects (δ) experienced by that cohort, and had potential experience upon arrival equal to the average of all immigrant men in the sample (11.2 years).

In all plots, the thick dashed line represents predicted wage assimilation profiles in the absence of any competition effects, i.e. when $\sigma = \infty$. The remaining colored lines illustrate how the relative wages of the respective immigrants would have evolved if they had faced the same dynamic labor market competition as the corresponding arrival cohorts listed in the legend.[16] Plots A depict the relative wage profiles under these counterfactual scenarios. For example, a Mexican high school dropout would initially earn 27.0 log points less than an equivalent native if relative skill supplies were irrelevant for skill prices, and would fully assimilate within about 25 years (Plot A, Panel I). Plots B highlight the relative wage growth, similar to Panel B of Figure 1. Plots C show the difference between the counterfactual profiles and the no-competition benchmark, as well as (in gray) the hypothetical assimilation profiles if the level of competition observed in each census year was held constant across all subsequent years.[17] From top to bottom, the three lowest gray lines correspond to the hypothetical profiles under the level of competition prevailing in the years 2000, 2020, and 2010 respectively. The small reversal between 2010 and 2020 reflects that, in line with the solid yellow line in Figure 7A, the competition level induced by immigrants slightly declined in that decade, which is consistent with the well-known slowdown in migration to the United States during this decade (see Table 1).

Panel I of Figure 8 documents an important impact of labor market competition on the wage assimilation profiles of Mexican high school dropouts. If the reference individual (who belongs to the 1960s cohort) had faced the same level of competition as, for example, the 1990s cohort, his initial wage gap would have been 10.2 log points larger (the difference between the lines labeled "1960–1969" and "1990–1999" in Plot C). If he had instead faced the competition level of 2010, the impact would have been even larger, with the initial wage gap widening by 21.1 log points (the difference between the line "1960–1969" and the bottom gray line in Plot C).

As shown in Plot B, however, the competition effect would have also increased the speed of wage convergence for the Mexican high school dropout, which would have completely

[16] 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.

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

offset the large negative impact at the time of arrival after around 25 years. In the long run, labor market competition effects do therefore not prevent this particular type of immigrant from fully converging to his native counterpart.

Panel II shows the corresponding profiles for a representative Latin American high school graduate. The key difference between this immigrant and the Mexican high school dropout of Panel I is that, according to our model estimates, Latin American high school graduates never fully assimilate ($s \rightarrow< 1$). This has important consequences in the context of rising labor market competition as it implies that these immigrants' relative wages will continue to be affected by changing relative skill prices even in the very long run. As shown in Plot C of Panel II, if the reference Latin American high school graduate had faced the same level of competition as the 1990s cohort, not only would his initial wage gap have increased by 17.4 log points, but he would also have ended up with a 3.8 log-point larger wage gap in the long run (the difference between the lines labeled "1960–1969" and "1990–1999" at the time of arrival and after 30 years, respectively). Consistent with the stylized example in Figure 3B, for this particular type of immigrant, the dynamic competition effect therefore inhibits overall wage assimilation.

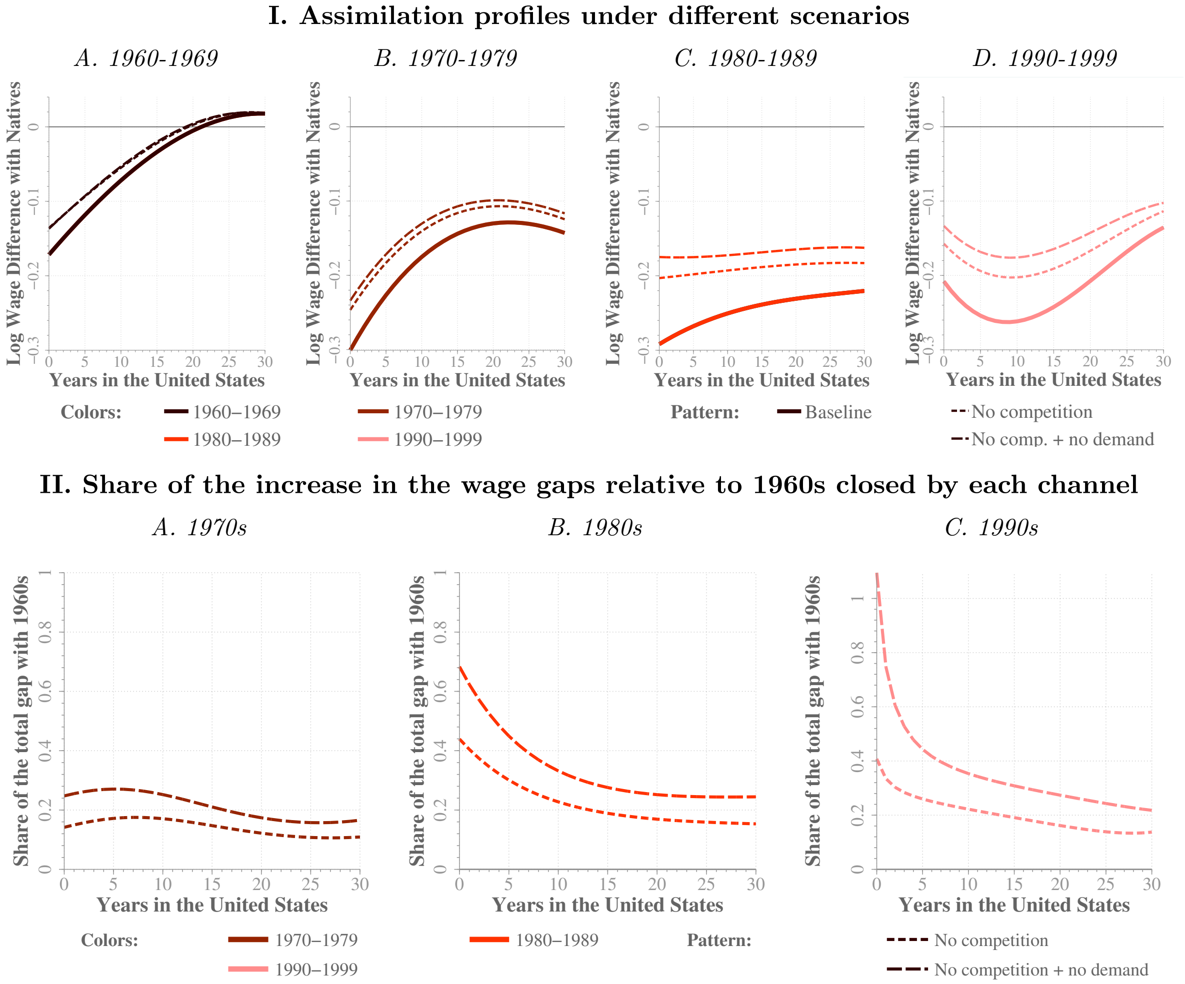
Panel III depicts the counterfactual assimilation profiles for a representative Western college graduate. The notable feature of this particular immigrant is that, already at the time of arrival, his skills resemble closely those of natives. As a result, changes in relative skill prices have little effect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

Overall, Figure 8 demonstrates a heterogeneous impact of labor market competition on wage assimilation profiles. For some major groups of immigrants, secular increases in immigrant inflows are responsible for a substantial widening of the initial wage gap across arrival cohorts. For some of these groups, labor market competition has additionally slowed down wage assimilation, while for others it has accelerated it. In yet other cases, the impact is negligible throughout. The extent to which these heterogeneous effects shaped the assimilation profiles in Figure 1 is an empirical question, which we address now.

B. *The role of labor market competition*

The three examples in the previous section show that the labor market competition effects are heterogeneous across different types of immigrants. To provide a more complete picture, we now consider the full sample of immigrant men (and women, in the appendix) and assess the extent to which changing labor market competition can explain the unconditional wage assimilation profiles depicted in Figure 1. To do so, we simulate each individual's wage under two counterfactual scenarios. In the first scenario, we assume there is no competition effect ($\sigma = \infty$). In the second, we additionally hold the relative demand for specific skills constant at the 1970 level (i.e. we set $\tilde{\delta} = 0$) to understand how the associated demand shifts amplify the competition effect. For both sets of predicted wages, we then run regressions like those underlying Figure 1 and present the resulting

Figure 9. Wage Gap Decomposition: Competition and Demand Effects



Note: The figure shows baseline and counterfactual predictions of the unconditional wage gaps between native and immigrant men for different cohorts as they spend time in the United States. Each plot represents one cohort. The depicted lines in Panel I are predicted assimilation profiles obtained from regressions analogous to those underlying Figure 1, estimated on the predicted wages under the different counterfactual scenarios. The baseline profiles (solid) correspond to the model predictions in Figure B1. The counterfactuals represent assimilation profiles in the absence of competition effects (short-dashed line), and in the absence of competition and demand effects (long-dashed line). Figures in Panel II show the fraction of the wag gap of each cohort relative to that of the 1960s cohort that is closed in each counterfactual scenario.

assimilation profiles in Figure 9.[18] We additionally summarize the information contained in this figure in Table 5.

Panel I in Figure 9 presents the assimilation profiles estimated using the baseline wage predictions (solid lines), the predicted wages without the competition effects (short-dashed lines), and the predicted wages without both the competition and demand effects (long-dashed lines). Each graph represents one cohort and, hence, corresponds to one of the solid lines plotted in Figure 1. To quantify the role of the competition and demand effects, Panel II depicts the share of the baseline gap between each cohort's assimilation profile and the profile of the 1960s cohort that is closed in each of the two counterfactual scenarios. Table 5 summarizes the same information, reporting the wage gaps for each

[18] Keeping with our terminology, we refer to the predictions from these auxiliary regressions as our estimated assimilation profiles.

Table 5—Wage Gap Decomposition: Competition and Demand Effects

Cohort	Years in the United States: 0 years	10 years	20 years	30 years	Average across years in the U.S.
A. Wage gap with natives (in log points difference)					
i. Baseline					
1960-1969	-17.2	-7.2	-0.5	1.8	-4.9
1970-1979	-30.1	-17.5	-13.0	-14.3	-17.2
1980-1989	-29.2	-25.1	-23.1	-22.0	-24.5
1990-1999	-20.8	-26.2	-20.7	-13.5	-21.7
ii. No competition effect					
1960-1969	-13.6	-5.5	0.3	1.9	-3.5
1970-1979	-24.7	-14.1	-10.7	-12.5	-14.1
1980-1989	-20.3	-19.3	-18.5	-18.3	-19.0
1990-1999	-15.7	-20.3	-16.7	-11.4	-17.1
iii. No competition and no demand effects					
1960-1969	-13.7	-5.3	0.4	1.7	-3.4
1970-1979	-23.4	-13.0	-9.9	-11.7	-13.1
1980-1989	-17.5	-17.2	-16.5	-16.2	-16.9
1990-1999	-13.3	-17.6	-14.3	-10.2	-14.8
B. Percent of the baseline wage gap with the 1960s cohort closed by each channel					
i. No competition effect					
1970-1979	14.2	17.1	12.2	10.9	14.1
1980-1989	43.9	22.7	16.9	15.3	22.4
1990-1999	40.8	22.2	16.2	13.7	20.4
ii. No competition and no demand effects					
1970-1979	24.8	25.2	17.4	16.6	21.2
1980-1989	68.3	33.2	25.2	24.5	33.6
1990-1999	109.5	35.4	27.4	21.8	36.4

Note: This table presents the wage gap with natives (in log points) and the fraction of the gap of each cohort's assimilation profile vis-a-vis the 1960s cohort explained by each mechanism (in percentages) at different points in time. These results summarize the information provided in Figure 9.

cohort and counterfactual scenario at the time of arrival and after 10, 20, and 30 years in the United States, as well as their average across years since migration.

The results in Figure 9 and Panel B of Table 5 show that the competition effect alone can explain 14.2, 43.9, and 40.8 percent of the increase in the *initial* wage gap of the 1970s, 1980s, and 1990s cohort relative to the 1960s cohort. In combination with the rising relative demand for specific skills, these numbers increase to 24.8, 68.3, and 109.5 percent, respectively. The remaining portions of the changes in the initial wage gaps across cohorts can be attributed to decreasing cohort quality. Since, according to our estimates, unobservable quality has improved over time (see Figure 4), this decrease is entirely explained by changes in the educational attainment and origin composition of immigrants. Note that the quality of the 1990s cohort at the time of arrival is estimated to be higher than that of the 1960s cohort once competition and demand effects are accounted for. This could be due to more selective immigration policies at the time (which raised the educational attainment of immigrants and shifted their origin composition) and increased globalization (which might have improved English language proficiency and other U.S.-specific skills among immigrants of a given education and origin).

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

As shown in the last column of Panel B in Table 5, averaged across years since migration, the competition effect explains roughly one fifth of the increase in the native-immigrant wage gap across cohorts. When evaluated in conjunction with the shifting demand effects, this magnitude increases to about one third, suggesting an important role for these two mechanisms in explaining variation in immigrant wage assimilation profiles across cohorts.

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 that may arise regarding our baseline model. For each of these alternative specifications, we reestimate our model and simulate counterfactual assimilation profiles similar to those presented in Panel I of Figure 9. We present the results from all the robustness checks jointly in Figure 10, and report a selected set of parameter estimates and related predictions in Table 6. Before discussing those results, we explain each of the robustness checks in more detail.

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). 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 neither of the two types of longitudinal data are available for the long time period covered by our analysis, we cannot fully account for the issue of selective outmigration using the approaches 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 country-of-origin-specific outmigration rates over the first 10 years in the United States.[19] For the second one, we rely on recent results by Rho and Sanders (2021), who, for immigrants arriving 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).[20]

Since these two pieces of evidence point in opposite directions, and since they deal with different dimensions of selective outmigration (country of origin in the case of Borjas and Bratsberg, 1996, education and unobserved skills in the case of Rho and Sanders, 2021), we use them in two separate robustness checks. In both of these checks, we reestimate our model after multiplying the original sample weights of those immigrants that we observe during their first 10 years in the United States by one minus the corresponding estimated outmigration rates (see Appendix A for details). This reweighting approach implicitly mimics what studies based on stock-sampled data do, since it holds the composition of immigrants in terms of origin (or education and unobservable skills) constant across the first and subsequent decades after arrival. Note that, in these robustness checks, 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 first divide our sample of immigrants into cells defined by cohort of arrival, country of origin, education level, and quartile of the distribution of wage residuals from Equation (12). We then further divide the sample into immigrants observed within the first 10 years after arrival and immigrants observed after at least 10 years in the United States. Within cohort, we finally adjust the baseline sample weights

[19] 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).

[20] 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 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).

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 residual wage quartile observed in the second group (more than 10 years in the United States), thus holding the distribution of these characteristics within our synthetic cohorts constant over time.

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. Passel, 2007). 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 accumulate skills 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 skill accumulation profiles of undocumented immigrants. Following Borjas (2017), we first identify "likely legal" immigrants in the different Census samples based on a set of survey responses, and then label all remaining immigrants as potentially undocumented.[21] We then obtain assimilation profiles with two modifications relative to our baseline. In the first robustness check, we reestimate our model after reweighting the observations of potentially undocumented immigrants to account for their undercount in the Census data (see Appendix A for details). 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, from Van Hook, Bean and Tucker (2014) for the 2000 Census and the 2010 ACS, and from Passel and Cohn (2018) for the 2018-2019 ACS.[22] In the second robustness check, we additionally include a dummy variable for potentially undocumented immigrants in the $s(\cdot)$ function, which we interact with a third order polynomial in years since migration to capture the potentially different

[21] 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.

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

speed of assimilation of undocumented immigrants.

Networks. A larger concentration of immigrants in a given market may not only affect relative skill prices as predicted by our model but also directly reduce the speed at which immigrants accumulate specific skills (see e.g. Borjas, 2015, or Battisti, Peri and Romiti, 2021). This may happen, for example, because of the formation of immigrant employment networks or residential ghettos that make learning English and other U.S.-specific skills expendable. In our two related 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 who share the same background. Both network variables are allowed to enter linearly in the $s(\cdot)$ function as well as interacted with a third order polynomial in years since migration.

Alternative specifications for the demand shifts. 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 shifts 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, we define labor markets in two alternative ways. First, at the education-state level, assuming individuals in different education groups do not compete with each other. And second, at the state-gender level, assuming that men only compete with men and women only with women.

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 on the basis of the prevailing relative skill prices. Note that, while selection based on wage levels is often pervasive, it is a priori less obvious that immigrants would choose where to settle based on their relative wages to natives. To nonetheless 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 estimation equation, Equation (12), 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 NLS would provide consistent (and efficient) estimates. However, if immigrant settlements were endogenous, the terms of those derivatives that depend on G_{jt}/S_{jt} would be endogenous and, hence, not valid instruments. To evaluate the extent to which endogenous location of immigrants might be contaminating our results, we run an additional robustness check in which 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). Given the non-linearities in our estimation equation, the fact that these transformed instruments are no longer optimal, and the need to ensure proper convergence of our non-linear estimation, we estimate an overidentified model in which we additionally use the squares of our (transformed) derivatives as additional instruments. Appendix D provides details on the derivation of these instruments and the implementation of this estimation approach.

Table 6 summarizes the key parameter estimates obtained from the different robustness checks. Panel A shows how differently wages grow for potentially undocumented immigrants. The point estimates suggest that, over a period of 10 years, their wages grow 5.1 log points less than those of comparable legal immigrants. Panel A also 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 but relatively moderate impact on the initial wage gap. The initial wage gap is reduced by 1.1 log points for an additional 1 percentage point of immigrants from the same country of origin in the state's population, or by 9.0 log points for every additional million of compatriots. The unconditional average shares and stocks are relatively small, 2.3 percent (ranging from zero to 10.8 percent) and 0.17 millions (ranging from zero to 1.23 million), implying that, on average, the initial wage gap increases by 2.4 log points in the share specification and 1.5 log points in the stock specification. The estimated effects on the wage growth are small and statistically insignificant.

Panel B reports the estimated relative demand shifts. The results of both specifications 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 shown below, these non-linearities do not lead to substantially different predictions relative to the baseline.

Panel C shows the elasticities of substitution between general and specific skills estimated for each of the twelve robustness checks (and, for comparability, the baseline value), together with their standard errors (columns 1 and 2). Overall, the point estimates are reasonably stable across specifications. As an easily interpretable summary measure of the role of the competition effect across the different robustness checks, we report, in the remaining columns of Panel C, for each cohort, the log-point difference between the no-competition counterfactual wage gap and the baseline wage gap, averaged across years in the United States. These numbers thus reflect by how many log points, on average, the wage assimilation profiles are shifted up relative to the baseline once the competition effect is accounted for. While there are some fluctuations, the robustness checks yield generally similar estimates as our baseline specification. Averaged across specifications, the competition effect in the robustness checks amounts to 1.3 log points in the 1960s, 3.0 log points in the 1970s, 5.2 log points in the 1980s, and 4.3 log points in the 1990s, very similar to the baseline values of 1.4, 3.1, 5.5, and 4.6 log points, respectively.

To graphically summarize our robustness checks, Figure 10 depicts their implied relative wage profiles. As in Panel I of Figure 9, we display the cohort-specific assimilation profiles

Table 6—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 ($\times 10^3$)
Potentially undocumented		-0.000	-0.069	0.018
		(0.001)	(0.012)	(0.003)
Share of state's population	-1.051	0.025	-0.217	0.038
	(0.163)	(0.038)	(0.246)	(0.045)
Stock in the state ($\times 10^6$)	-0.090	-0.001	0.004	-0.000
	(0.013)	(0.003)	(0.018)	(0.003)

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

	$\tilde{\delta}_1 \vert \tilde{\delta}_{1980}$	$\tilde{\delta}_2(\times 10^2) \vert \tilde{\delta}_{1990}$	$\tilde{\delta}_{2000}$	$\tilde{\delta}_{2010}$	$\tilde{\delta}_{2020}$
Quadratic specification	-0.038	0.131	—	—	—
	(0.003)	(0.009)			
Time dummies	-0.886	-0.373	-0.083	0.979	0.626
	(0.040)	(0.036)	(0.040)	(0.093)	(0.083)

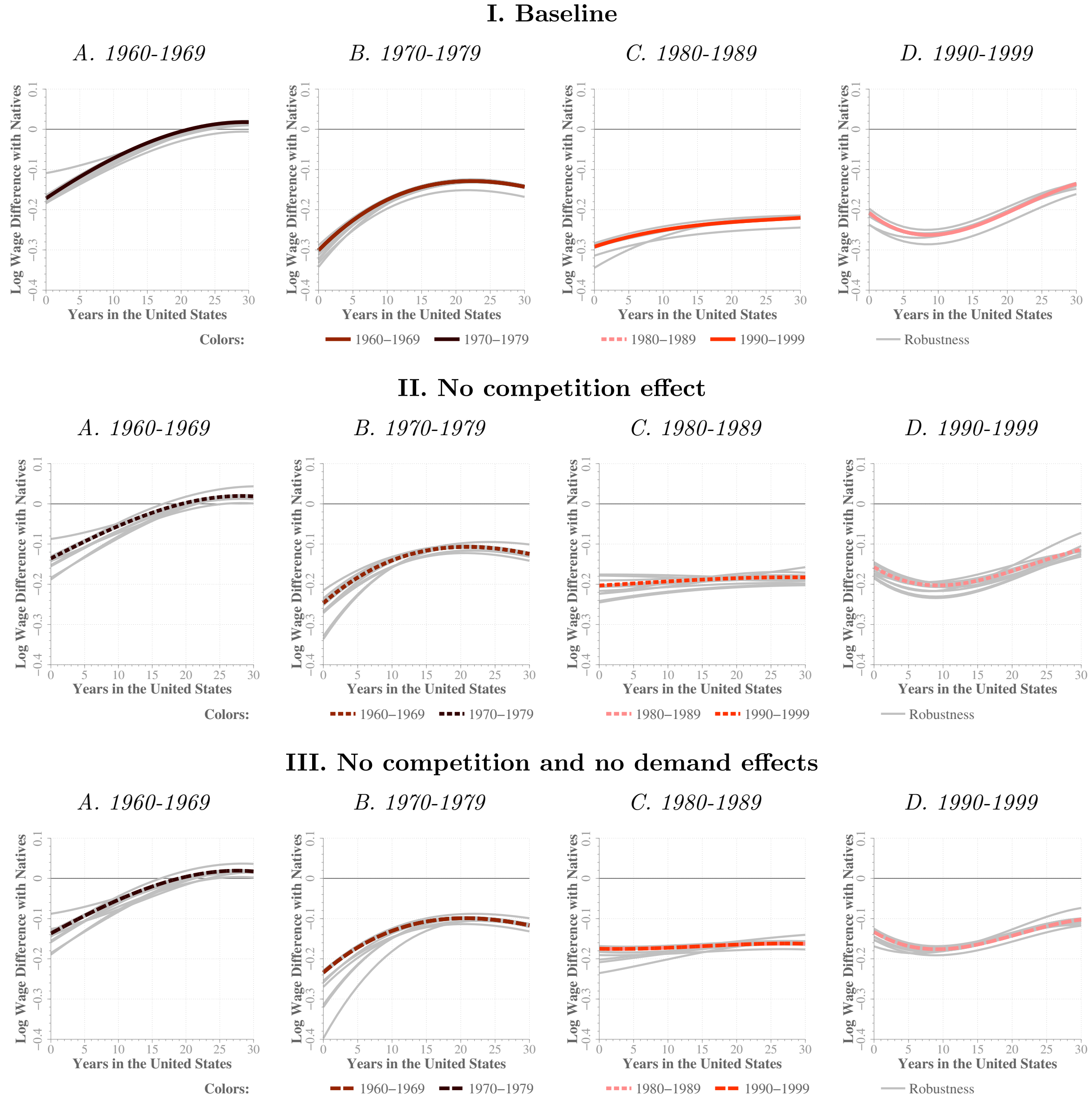
C. Elasticity of substitution σ and average competition effect

	Elasticity σ		Average compet. effect by cohort:			
	Estim.	Std.err.	1960s	1970s	1980s	1990s
Baseline estimate:	0.020	(0.002)	1.4	3.1	5.5	4.6
Selective out-migration:						
Borjas and Bratsberg (1996)	0.020	(0.002)	1.4	3.0	5.2	4.2
Rho and Sanders (2021)	0.024	(0.002)	1.9	3.8	6.4	5.5
Synthetic cohorts	0.019	(0.001)	1.3	3.8	6.8	5.9
Undocumented migrants:						
Reweighted only	0.019	(0.001)	0.2	1.8	5.4	4.7
Reweighted and heterogeneous	0.019	(0.001)	0.2	1.9	5.5	4.8
Networks:						
Share of state's population	0.033	(0.004)	1.1	1.9	2.9	2.2
Stock in the state	0.033	(0.004)	1.0	1.7	2.6	1.9
Alternative specifications for demand factors:						
Quadratic specification	0.021	(0.001)	1.6	4.0	6.4	4.4
Time dummies	0.028	(0.002)	1.6	4.5	5.9	4.2
Alternative definitions of the labor market:						
State-education	0.025	(0.001)	1.5	3.4	6.1	5.3
State-gender	0.021	(0.002)	2.3	3.1	4.4	3.9
GMM with optimal instruments based on aggregate flows predicted as in Card (2001):						
Linear and quadratic instruments	0.017	(0.003)	1.4	3.0	5.2	4.3

Note: Panel A of this table presents estimates for the additional parameters of the $s(\cdot)$ function associated with the two specifications of the networks robustness check and for the specification that allows for heterogeneous convergence between potentially undocumented and legal immigrants (each row corresponds to one specification). Panel B shows the parameters for the alternative specifications of the relative demand shifs. Panel C shows the estimated elasticity of substitution between general and specific skills (σ) for each robustness check (standard errors in parentheses), and the competition effect for each cohort (no competition counterfactual minus baseline multiplied by 100) for men, averaged across years in the United States.

at baseline (Panel I), after accounting for the competition effect (Panel II), and after accounting for both the competition and the demand effects (Panel III). In line with results

Figure 10. Assimilation Profiles under Alternative Specifications



Note: The figure reproduces the counterfactual assimilation profiles described in Figure 9 (Panel I) for the different scenarios and the different robustness checks described in the text: networks (shares and stocks), under-counting 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 shifts (quadratic, and time dummies), alternative labor market definitions (state-education, state-sex, men only, and census division), and endogenous immigration across states (using a shift-share-type instrument similar to Card, 2001).

in Table 6, Figure 10 shows that the results are robust across the different specifications.

VIII. Conclusion

This paper shows that the wage assimilation of immigrants is the result of the intricate interplay between individual skill accumulation and dynamic labor market equilibrium effects. Since immigrants and natives are imperfect substitutes in production, increasing immigrant cohort sizes drive a wedge between their wages. We show that this labor market competition channel can explain about one fifth of the rise in the average immigrant-native wage gap between the 1960s and 1990s arrival cohorts in the United States, a figure that increases to one third once shifts in relative demand for U.S.-specific skills are accounted for as well. In contrast, the impact of labor market competition on the speed of assimilation is quantitatively small. The remaining differences across cohorts can be attributed to decreasing cohort quality and fully explained by changes in immigrants' educational attainment and country-of-origin composition. Conditional on these two observable characteristics, our findings suggest that immigrants have become more positively selected in terms of unobservable skills, in line with additional evidence we provide on immigrants' English language proficiency.

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 must also be affected by immigrants' assimilation processes. A given inflow of immigrants may initially exert a less negative (or even positive) effect on native wages due to the often limited substitutability between recent immigrants and native workers. Over time, however, as immigrants become more similar to natives in terms of their skills, they start competing more directly with natives in the labor market. The wage effects of immigration will thus ripple through the native skill distribution, affecting different types of native workers at different moments in time. The labor market impact of immigration is therefore intrinsically dynamic in nature, an aspect that has received comparatively little attention in the literature so far.[23] Second, the competition channel may have far-reaching effects on the decision of immigrants to invest in host-country-specific skills, something which the few papers that explicitly model such investment decisions (e.g. **?**) abstract from. Finally, our findings suggest that the allocation of immigrants across space and the subsequent native migration response will not only have important effects on native wages (e.g. Piyapromdee, 2021) but also influence the way in which immigrants assimilate in the labor market. This insight is particularly policy-relevant as it suggests that immigration policies that affect the size and composition of local immigrant inflows (e.g. the widely-implemented dispersal policies during recent refugee crises; see Brell, Dustmann and Preston, 2020) might have unintended effects on the speed of immigrant wage assimilation. We leave a thorough investigation of these interesting questions for future research.

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

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Appendix A: Sample Selection and Variable Definitions

Our data are drawn from the U.S. Census and American Community Survey (ACS), downloaded from the Integrated Public Use Microdata Series database (IPUMS-USA, Ruggles et al., 2018). The sample includes data for the years 1970, 1980, 1990, and 2000 from the Census, and for the years 2009–2011 (labeled as "2010") and 2018–2019 (labeled as "2020") from the ACS using the largest available samples in each case. For the 1970 Census, we use the two samples that contain information about all relevant variables, including the state of residence (Form 1 Metro and State sample). Our sample comprises natives and immigrants aged 25 to 64 who are not self-employed, do not live in group quarters, are not enrolled in school (except for 1970, in which there is no information on school enrollment), work in the civilian sector, and report positive hours of work and earnings. We drop immigrants without information on their country of birth or year of arrival in the United States. We also drop immigrants who arrived in the United States at age 18 or before. The specific variables used in the analysis are defined as follows:

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

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

Education. We assign years of education 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 seven groups: pre-1960, 1960–69, 1970–79, 1980–89, 1990–99, 2000–09, and 2010–20.

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

Region of birth. We consider five regions of birth for immigrants: Mexico; Other Latin American Countries (Caribbean, Central America, South America); Western Countries (Western Europe, Israel, Australia, New Zealand, Canada); Asia; and Other.

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

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

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

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

For the robustness checks dealing with selective 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 (12)).

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

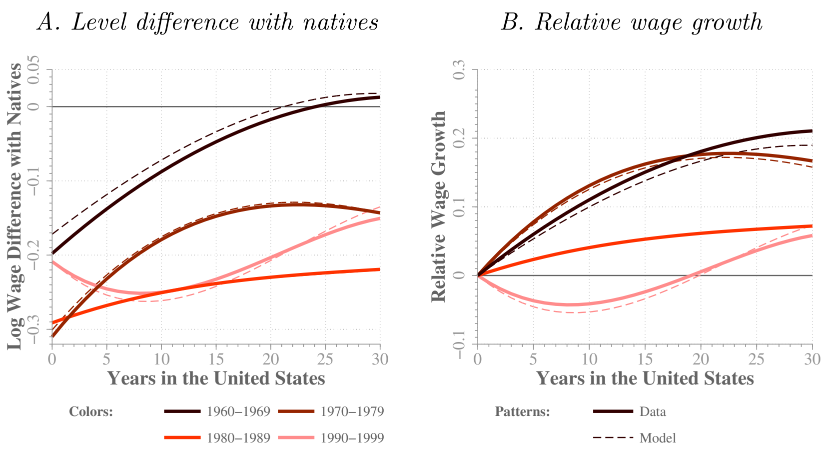
Appendix B: Additional Tables and Figures

Table B1—Additional Descriptives

	Census year:					
	1970	1980	1990	2000	2010	2020
Immigrant share (%)	3.8	5.0	6.9	10.8	14.5	16.3
Number (millions):						
Natives	46.9	62.2	76.0	86.9	89.3	97.2
Immigrants	1.8	3.1	5.3	9.4	12.9	15.9
Men (%):						
Natives	67.8	60.8	56.1	54.1	52.6	52.7
Immigrants	64.6	59.6	58.8	59.4	57.5	56.7
Age:						
Natives	43.2	41.3	40.7	42.4	44.1	43.6
Immigrants	44.0	42.2	42.4	42.4	44.2	45.6
Hourly wage:						
Natives	18.8	18.8	18.1	19.5	19.0	19.8
Immigrants	18.5	18.1	17.2	17.8	16.3	19.1
HS dropouts (%):						
Natives	38.2	21.7	10.3	6.4	4.5	3.6
Immigrants	48.1	39.5	30.8	28.6	25.9	21.1
HS graduates (%):						
Natives	36.4	39.9	35.3	40.4	35.1	32.7
Immigrants	24.2	24.3	24.8	28.6	28.1	28.2
Some college (%):						
Natives	11.6	17.6	29.0	23.8	25.8	24.9
Immigrants	11.4	12.9	18.2	13.8	13.9	13.5
College graduates (%):						
Natives	13.8	20.8	25.3	29.4	34.5	38.8
Immigrants	16.3	23.2	26.2	29.0	32.1	37.2

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

Figure B1. Goodness of Fit (Men)



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 for men given the estimated parameters (dashed).

Appendix C: Derivation of the Elasticity of Substitution between Natives and Immigrants

Rewrite the general and specific skill units respectively as:

$$G = N \sum_{\ell} h_{\ell} \frac{N_{\ell}}{N} + I \sum_{\ell'} h_{\ell'} \frac{I_{\ell'}}{I} \equiv N\bar{h}_N + I\bar{h}_I, \tag{C1}$$

and:

$$S = N \sum_{\ell} h_{\ell} \frac{N_{\ell}}{N} + I \sum_{\ell'} h_{\ell'} s_{\ell'} \frac{I_{\ell'}}{I} \equiv N\bar{h}_N + I\overline{h_I s_I}. \tag{C2}$$

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

$$\begin{aligned} d\ln N_\ell &= \frac{dN_\ell}{N_\ell} = \frac{dN}{N} = d\ln N \\ \Rightarrow dN_\ell &= \frac{N_\ell}{N} dN \\ \Rightarrow d\frac{N_\ell}{N} &= \frac{NdN_\ell - N_\ell dN}{N^2} = \frac{N\frac{N_\ell}{N}dN - N_\ell dN}{N^2} = 0. \end{aligned} \tag{C3}$$

The case of I is analogous.

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

$$\frac{\partial Y/\partial I}{\partial Y/\partial N} = \frac{A\left(\frac{Y}{AG}\right)^{\frac{1}{\sigma}}\bar{h}_I + A\delta\left(\frac{Y}{AS}\right)^{\frac{1}{\sigma}}\overline{h_I s_I}}{A\left(\frac{Y}{AG}\right)^{\frac{1}{\sigma}}\bar{h}_N + A\delta\left(\frac{Y}{AS}\right)^{\frac{1}{\sigma}}\bar{h}_N} = \frac{\bar{h}_I + \delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\overline{h_I s_I}}{\left[1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\right]\bar{h}_N} \equiv \frac{1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\tilde{s}_I}{\left[1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\right]}\frac{\bar{h}_I}{\bar{h}_N}, \tag{C4}$$

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

$$\begin{aligned} d\ln\frac{\partial Y/\partial I}{\partial Y/\partial N} &= \frac{\frac{1}{\sigma}\tilde{s}_I\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\frac{G}{S}}{1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\tilde{s}_I} - \frac{\frac{1}{\sigma}\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}} d\ln\frac{G}{S}}{1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}} \\ &= \frac{(\tilde{s}_I - 1)\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}-1}}{\sigma\left[1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\tilde{s}_I\right]\left[1+\delta\left(\frac{G}{S}\right)^{\frac{1}{\sigma}}\right]} d\ln\frac{G}{S}. \end{aligned} \tag{C5}$$

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

$$\frac{G}{S} = \frac{N\bar{h}_N + I\bar{h}_I}{N\bar{h}_N + I\overline{h_I s_I}} = \frac{\frac{\bar{h}_N}{\bar{h}_I}N/I + 1}{\frac{\bar{h}_N}{\bar{h}_I}N/I + \tilde{s}_I}. \tag{C6}$$

Log-differentiating the previous expression gives:

$$d\ln\frac{G}{S} = \frac{\frac{\bar{h}_N}{\bar{h}_I}d(N/I)}{\frac{\bar{h}_N}{\bar{h}_I}N/I + 1} - \frac{\frac{\bar{h}_N}{\bar{h}_I}d(N/I)}{\frac{\bar{h}_N}{\bar{h}_I}N/I + \tilde{s}_I} = \left(\frac{N\bar{h}_N}{G} - \frac{N\bar{h}_N}{S}\right) d\ln\frac{N}{I}. \tag{C7}$$

Substituting (C7) into (C5) and the resulting expression into the definition of the elasticity of substitution gives Equation (15) after some rearranging. ■

Appendix D: Generalized Method of Moments 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 (12), with respect to the individual model parameters. After some algebra, these derivatives are given by the following expressions:

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

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

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

and:

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

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. In this robustness check, we deal with the case where ϵ_i and G_{jt}/S_{jt} are potentially correlated, replacing the potentially endogenous regressor G_{jt}/S_{jt} by an exogenous prediction in the spirit of the widely used shift-share instrument proposed by Card (2001). In particular, we generate our instruments replacing the original sample weights ω_i (which appear implicitly in r_{Gt}/r_{St} and G_{jt}/S_{jt} and explicitly in the first set of instruments) by $\tilde{\omega}_i$, defined as:

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

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 evaluate the derivatives at our baseline estimates which does not affect their validity as instruments. Given that our modified instruments are no longer optimal, and in order to provide additional variation to ensure convergence of our non-linear estimation, in practice we estimate our model using both the instruments described above and their squares.

Online Appendix to: "Labor Market Competition and the Assimilation of Immigrants"

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Table OA1—Descriptive Statistics of Immigrant Cohorts (Men)

	Cohort of entry:					
	1960-69	1970-79	1980-89	1990-99	2000-09	2010-19
Share of population (%)	1.6	2.2	3.2	4.4	5.1	4.1
Cohort size (millions)	0.5	0.9	1.5	2.3	2.8	2.5
Age	38.3	36.8	36.4	36.5	37.3	37.9
Hourly wage	19.1	18.4	16.1	17.5	15.4	20.3
HS dropouts (%)	45.8	41.3	32.1	29.8	29.0	16.2
HS graduates (%)	19.6	19.2	23.6	28.0	28.2	25.5
Some college (%)	10.6	11.3	16.7	11.0	10.6	10.7
College graduates (%)	24.0	28.3	27.6	31.2	32.3	47.5
Mexico (%)	9.9	23.5	21.5	29.4	31.3	15.3
Other Latin America (%)	27.8	19.4	25.3	20.7	25.8	26.7
Western countries (%)	37.7	18.0	11.3	9.8	6.9	8.7
Asia (%)	14.8	31.4	33.7	27.6	26.0	37.2
Other (%)	9.8	7.7	8.2	12.6	10.0	12.0

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

Table OA2—Additional Descriptives (Men)

	Census year:					
	1970	1980	1990	2000	2010	2020
Immigrant share (%)	3.6	4.9	7.3	11.8	15.8	17.6
Number (millions):						
Natives	31.8	37.8	42.7	47.0	47.0	51.2
Immigrants	1.2	1.9	3.1	5.6	7.4	9.0
Age:						
Natives	42.8	41.4	40.8	42.4	44.0	43.5
Immigrants	44.2	42.2	41.9	41.9	43.6	45.2
Hourly wage:						
Natives	21.5	22.2	21.2	22.5	21.5	22.2
Immigrants	21.5	21.4	19.7	19.6	17.8	21.3
HS dropouts (%):						
Natives	39.4	22.9	11.4	7.3	5.3	4.4
Immigrants	48.4	40.4	32.4	30.8	28.4	23.4
HS graduates (%):						
Natives	33.4	36.3	33.7	40.0	36.7	36.2
Immigrants	21.1	20.9	22.3	27.1	27.7	28.3
Some college (%):						
Natives	11.7	17.4	27.8	22.8	24.6	23.8
Immigrants	10.8	12.1	17.0	12.6	12.5	12.3
College graduates (%):						
Natives	15.5	23.4	27.1	29.9	33.5	35.7
Immigrants	19.7	26.6	28.4	29.6	31.4	36.0

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

Table OA3—Descriptive Statistics of Immigrant Cohorts (Women)

	Cohort of entry:					
	1960-69	1970-79	1980-89	1990-99	2000-09	2010-19
Share of population (%)	1.8	2.1	2.5	3.3	3.9	3.2
Cohort size (millions)	0.3	0.5	0.9	1.4	1.9	1.7
Age	38.3	36.6	36.8	37.4	38.6	38.3
Hourly wage	12.3	12.3	11.9	13.5	12.5	14.9
HS dropouts (%)	48.2	40.4	29.9	25.2	21.7	13.3
HS graduates (%)	26.7	24.8	26.8	30.1	28.6	25.5
Some college (%)	11.9	12.6	18.1	13.8	13.7	13.1
College graduates (%)	13.2	22.1	25.1	30.9	36.0	48.1
Mexico (%)	5.7	13.8	13.3	19.8	21.1	10.2
Other Latin America (%)	35.6	24.9	29.7	24.0	27.9	30.0
Western countries (%)	35.5	16.0	10.8	9.6	6.2	7.6
Asia (%)	14.0	38.2	39.0	32.2	32.5	39.2
Other (%)	9.2	7.1	7.2	14.3	12.3	13.0

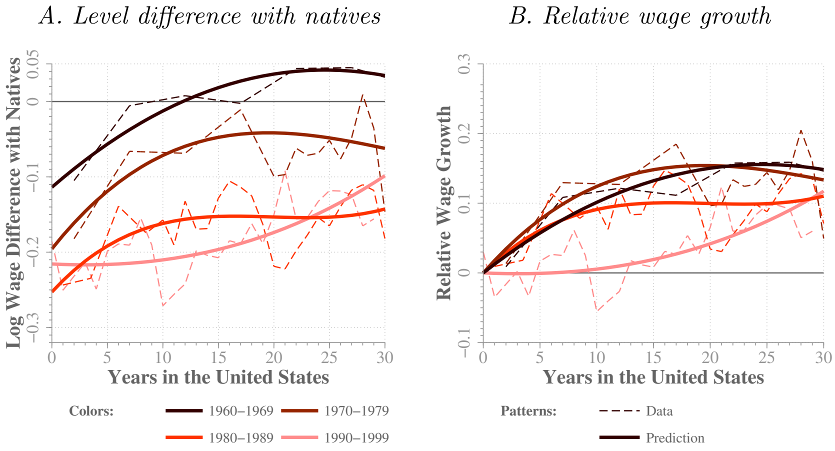
Note: The statistics are based on the sample of immigrant women aged 25-64 reporting positive income (not living in group quarters) who entered the United States during the respective time intervals, measured in the first Census year following the arrival. Observations are weighted by the personal weights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

Table OA4—Additional Descriptives (Women)

	Census year:					
	1970	1980	1990	2000	2010	2020
Immigrant share (%)	4.2	5.2	6.5	9.5	13.0	14.9
Number (millions):						
Natives	15.1	24.4	33.4	39.9	42.3	45.9
Immigrants	0.6	1.3	2.2	3.8	5.5	6.9
Age:						
Natives	43.9	41.1	40.5	42.3	44.3	43.7
Immigrants	43.8	42.3	43.0	43.2	45.0	46.1
Hourly wage:						
Natives	13.2	13.4	14.1	16.0	16.2	17.2
Immigrants	13.2	13.3	13.7	15.0	14.2	16.2
HS dropouts (%):						
Natives	35.6	19.9	8.9	5.4	3.7	2.8
Immigrants	47.4	38.2	28.5	25.3	22.6	18.2
HS graduates (%):						
Natives	42.6	45.4	37.4	40.8	33.4	28.8
Immigrants	30.0	29.3	28.4	30.8	28.6	28.0
Some college (%):						
Natives	11.4	17.9	30.6	25.0	27.3	26.1
Immigrants	12.4	14.2	19.9	15.6	15.8	15.1
College graduates (%):						
Natives	10.5	16.7	23.0	28.8	35.7	42.2
Immigrants	10.2	18.3	23.2	28.3	33.0	38.7

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

Figure OA1. Wage Gap between Natives and Immigrants and Years in the U.S. (Women)

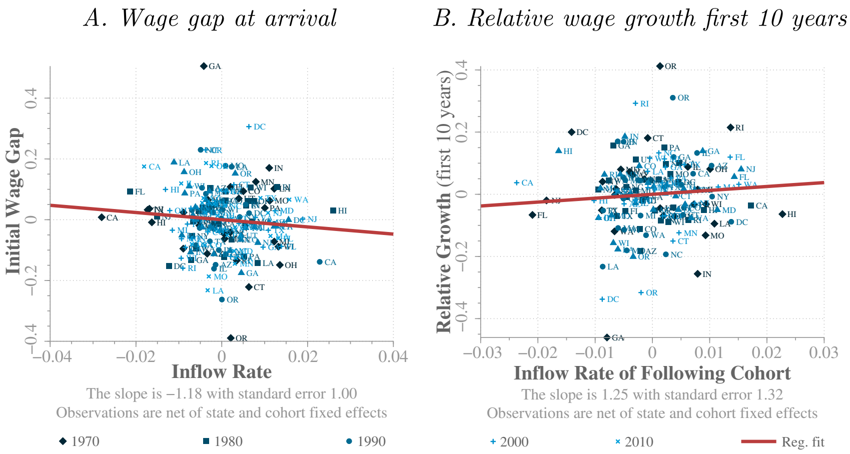


Note: The figure shows the prediction of the wage gap between native and immigrant women of different cohorts as they spend time in the United States. The dashed lines represent the raw data and are the result of year-by-year regressions of log wages on a third order polynomial in age and dummies for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

Figure OA2. Cohort Size, Initial Wage Gap, and Relative Wage Growth (Women)



Note: This figure plots the initial wage gap for women in different state-cohort cells against the size of the own arrival cohort (left panel) and the relative wage growth over the first 10 years against the size of the following immigrant cohort (right panel). The initial wage gap and relative wage growth are computed based on state-by-state regressions analogous to those underlying Figure 1. The initial wage gap is measured as the state-specific cohort fixed effect ($\beta_{0c(i)}$) and the relative wage growth as the change in the wage gap over the first 10 years, calculated based on the polynomial in years since migration interacted with cohort dummies ($\{\beta_{3\ell c(i)}\}_{\ell\in\{1,2,3\}}$). Immigrant inflows are computed as the state population of the respective cohort (including men and women) divided by the native population in the state in the first census year the cohort is observed. The depicted observations are net of cohort and state fixed effects. States with less than 100 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.

Table OA5—Productivity Factor (Women), $h_{1t}(E, x)$

	Census year:					
	1970	1980	1990	2000	2010	2020
Female	-0.057	-0.006	-0.100	-0.091	-0.146	-0.138
	(0.014)	(0.008)	(0.009)	(0.010)	(0.015)	(0.017)
Years of education	0.044	0.041	0.049	0.057	0.077	0.069
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience	0.005	0.023	0.030	0.033	0.043	0.044
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience squared ($\times 10^2$)	-0.007	-0.075	-0.091	-0.093	-0.125	-0.126
	(0.006)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Potential experience cube ($\times 10^3$)	0.000	0.008	0.009	0.008	0.012	0.012
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
High school graduate	0.073	0.063	0.067	0.075	0.054	-0.035
	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.007)
Some college	0.150	0.132	0.201	0.193	0.157	0.053
	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)	(0.008)
College graduate	0.446	0.321	0.410	0.386	0.332	0.306
	(0.008)	(0.005)	(0.005)	(0.005)	(0.007)	(0.010)

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

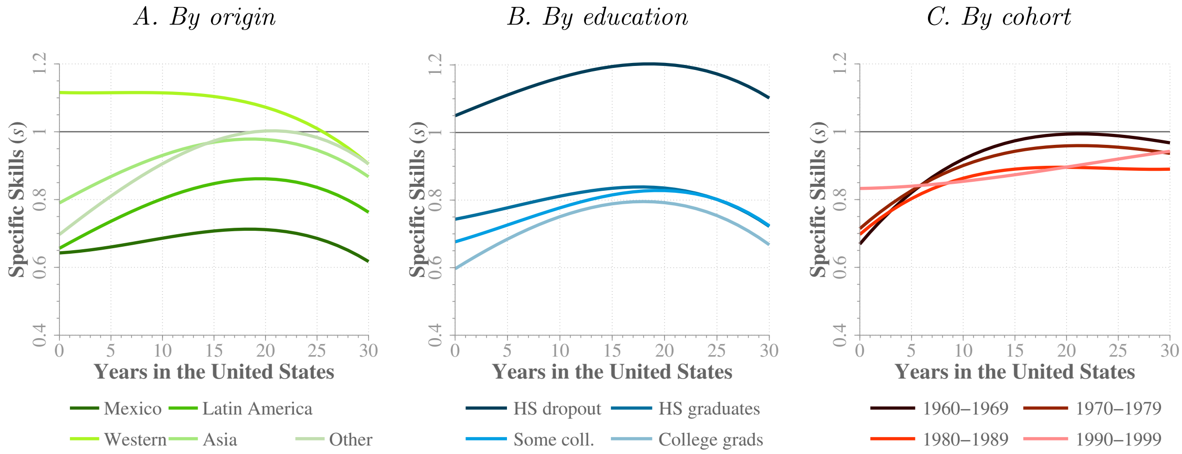
Table OA6—Specific Skill Accumulation (Women), $s_1(0, y, o, c, E, x)$

		Interactions with years since migration:		
	Intercepts	Linear	Quadratic ($\times 10^2$)	Cubic ($\times 10^3$)
Region of origin:				
Latin America	0.014	0.015	-0.050	0.005
	(0.013)	(0.003)	(0.018)	(0.003)
Western countries	0.473	-0.003	-0.020	0.003
	(0.019)	(0.004)	(0.023)	(0.004)
Asia	0.147	0.015	-0.057	0.006
	(0.014)	(0.003)	(0.019)	(0.003)
Other	0.054	0.022	-0.056	0.003
	(0.017)	(0.004)	(0.025)	(0.004)
Education level:				
High school graduate	-0.306	-0.007	0.028	-0.005
	(0.014)	(0.003)	(0.017)	(0.003)
Some college	-0.373	-0.004	0.032	-0.007
	(0.016)	(0.003)	(0.021)	(0.004)
College graduate	-0.453	0.007	-0.026	0.002
	(0.016)	(0.003)	(0.020)	(0.003)
Cohort of arrival:				
Pre-1960s	0.351	-0.035	0.152	-0.019
	(0.147)	(0.018)	(0.073)	(0.009)
1960s	-0.046	0.027	-0.092	0.010
	(0.024)	(0.004)	(0.024)	(0.004)
1970s		0.017	-0.054	0.006
		(0.003)	(0.020)	(0.003)
1980s	-0.017	0.017	-0.080	0.014
	(0.013)	(0.003)	(0.019)	(0.003)
1990s	0.118	-0.009	0.053	-0.005
	(0.013)	(0.003)	(0.025)	(0.006)
2000s[a]	0.098	-0.022	0.315	-0.105
	(0.017)	(0.006)	(0.068)	(0.024)
2010s[a]	0.167	-0.020	0.315	-0.105
	(0.015)	(0.005)	(0.068)	(0.024)
Experience at entry:				
Linear term	-2.667			
	(0.098)			
Quadratic ($\times 10^2$)	0.910			
	(0.061)			
Cubic ($\times 10^3$)	-0.000			
	(0.000)			
Constant (relative specific skills at arrival of a Mexican high school dropout woman that arrived in the 1970s cohort with zero years of experience)**:**				
	1.065			
	(0.016)			

Note: This table presents parameter estimates for the specific skill accumulation function of immigrant women, $\{\theta_{10o}, \{\theta_{2\ell 0o}\}_{\ell\in\{1,2,3\}}\}_{o\in\mathcal{O}}$, $\{\theta_{30e}, \{\theta_{4\ell 0e}\}_{\ell\in\{1,2,3\}}\}_{e\in\mathcal{E}}$, $\{\theta_{5\ell 0o}\}_{\ell\in\{1,2,3\}}$, and $\{\theta_{60c}, \{\theta_{7\ell 0c}\}_{\ell\in\{1,2,3\}}\}_{c\in\mathcal{C}}$ defined in Equation (3). All parameters refer to the baseline individual, who is a Mexican high school dropout woman that arrived in the United States in the 1970s with zero years of potential experience. Parameters are estimated by NLS as described in Section IV.B. Sample weights, rescaled by annual hours worked are used in the estimation. Standard errors in parentheses.

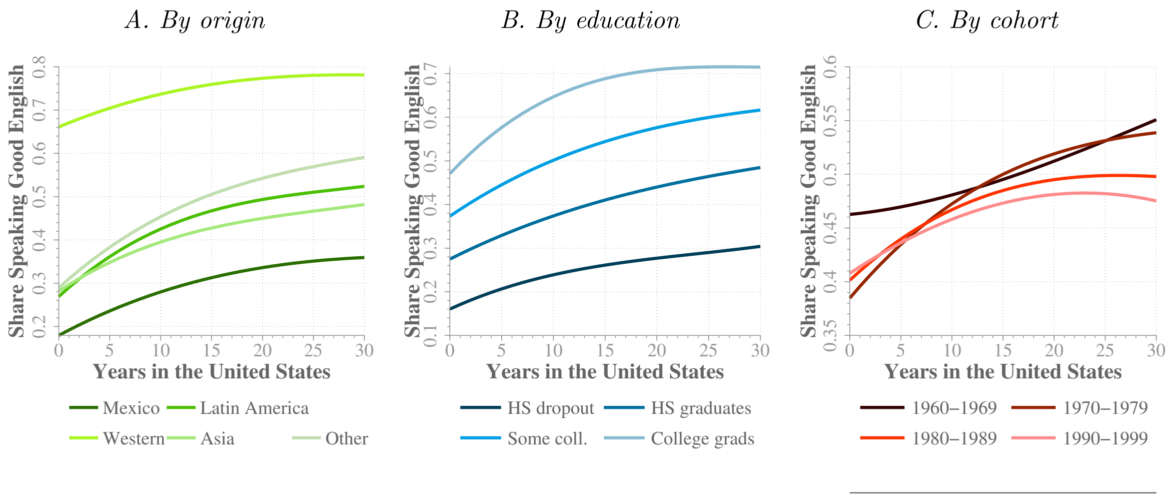
[a] Quadratic and cubic interaction terms for the 2000s and 2010s cohorts are grouped in the estimation.

Figure OA3. Skill Accumulation Profiles (Women), $s_1(0, y, o, c, E, x)$



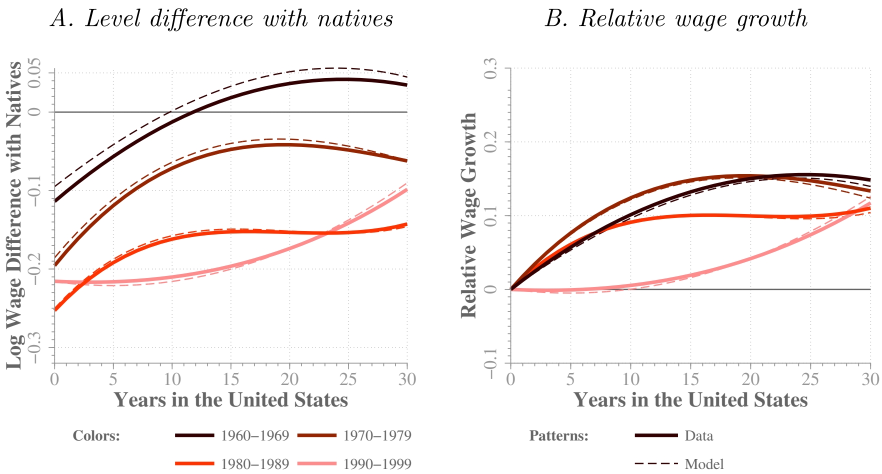
Note: The figure displays predicted skill accumulation profiles for different groups based on the estimates reported in Table 3. The baseline individual in all figures is a synthetic individual with the average characteristics of all women in the sample, except for the characteristic that is being plotted in each graph. 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.

Figure OA4. English Proficiency (Women)



Note: The figure displays English language proficiency profiles predicted from a linear regression of an indicator for "speaking English very well" or "only speaking English" on all the variables included in the specific-skills function $s_1(\cdot)$ and year dummies on a sample of women. The baseline individual in all figures is a synthetic individual with the average characteristics of all women in the sample except for the characteristic that is plotted in each graph. 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.

Figure OA5. Goodness of Fit (Women)

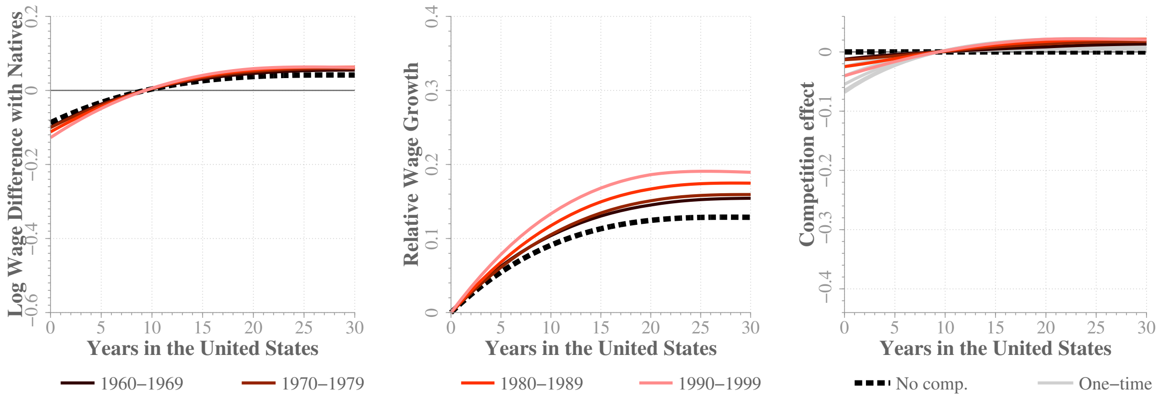


Note: The figure compares the solid lines of Figure OA1 (reproduced here as solid lines as well) with analogous regression lines estimated on the wages predicted by our model for women given the estimated parameters (dashed).

Figure OA6. The Labor Market Competition Effect: Some Examples (Women)

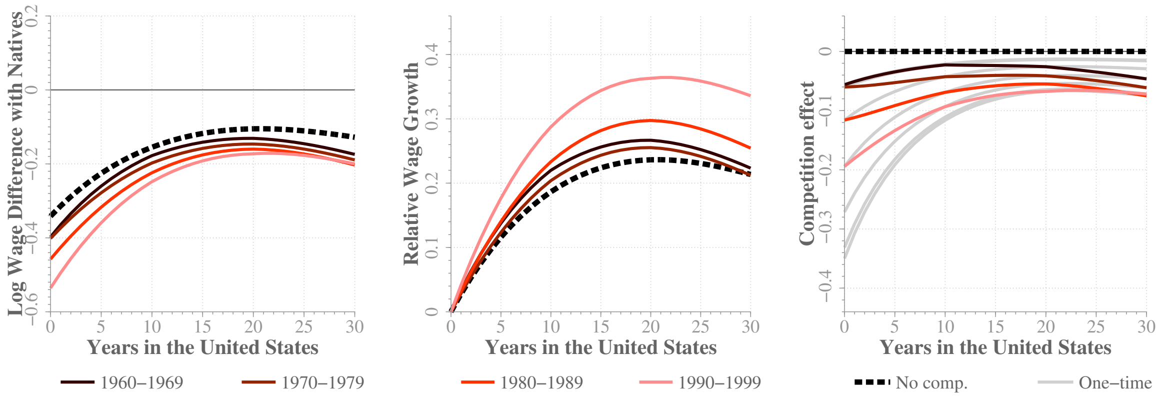
I. Mexican High School Dropouts

A. Difference with natives *B. Relative wage growth* *C. Competition effect*



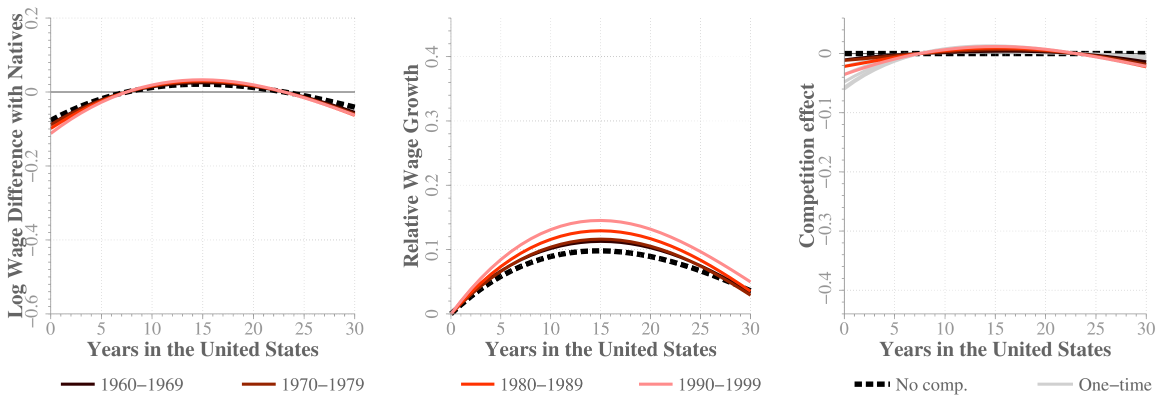
II. Latin American High School Graduates

A. Difference with natives *B. Relative wage growth* *C. Competition effect*



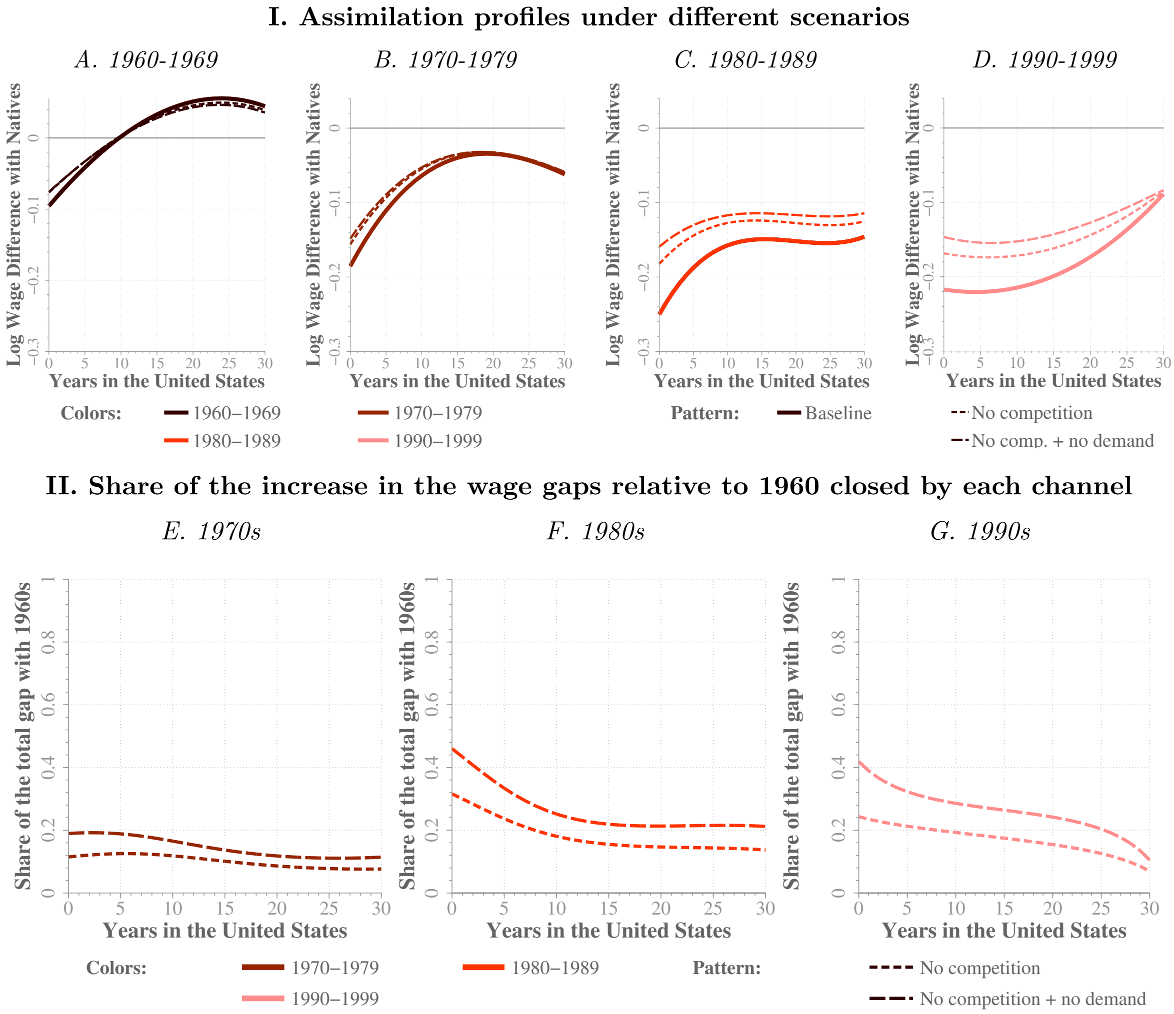
III. Western College Graduates

A. Difference with natives *B. Relative wage growth* *C. Competition effect*



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

Figure OA7. Wage Gap Decomposition: Competition and Demand Effects (Women)



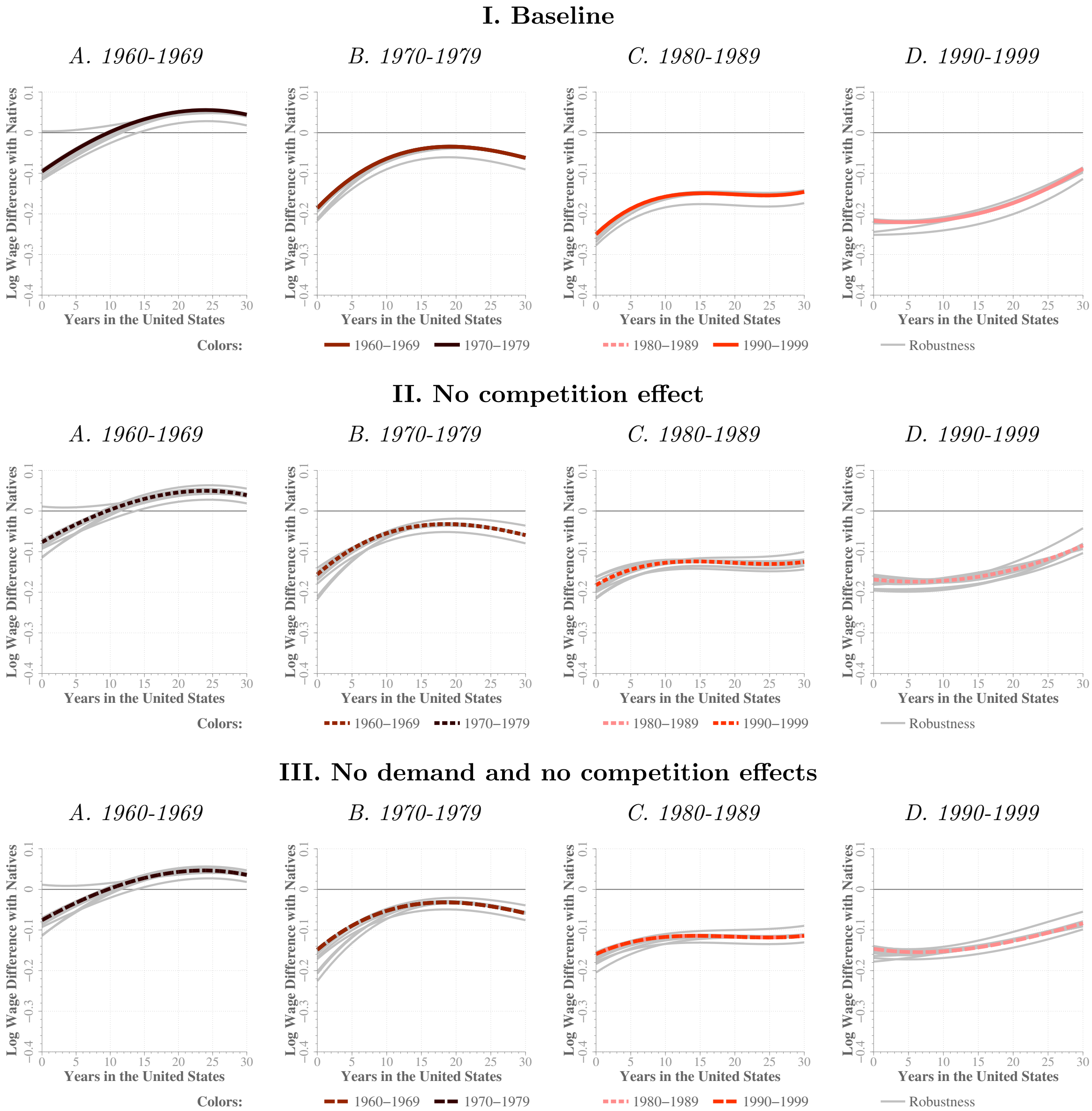
Note: The figure shows baseline and counterfactual predictions of the unconditional wage gaps between native and immigrant women for different cohorts as they spend time in the United States. Each plot represents one cohort. The depicted lines in Panel I are predicted assimilation profiles obtained from regressions analogous to those underlying Figure 1, estimated on predicted wages under the different counterfactual scenarios. The baseline profiles (solid) correspond to the model predictions in Figure B1. The counterfactuals represent assimilation profiles in the absence of competition effects (short-dashed line), and in the absence of competition and demand effects (long-dashed line). Figures in Panel II show the fraction of the gap of each cohort relative to 1960s that is closed in each counterfactual.

TABLE OA7—WAGE GAP DECOMPOSITION: COMPETITION AND DEMAND EFFECTS (WOMEN)

Cohort	Years in the United States: 0 years	10 years	20 years	30 years	Average across years in the U.S.
A. Wage gap with natives (in log points difference)					
i. Baseline					
1960-1969	-9.6	0.2	5.1	4.5	1.2
1970-1979	-18.5	-6.4	-3.5	-6.2	-7.0
1980-1989	-25.0	-15.7	-15.2	-14.6	-16.7
1990-1999	-21.7	-21.5	-17.3	-8.9	-18.3
ii. No competition effect					
1960-1969	-7.7	0.3	4.6	3.9	1.3
1970-1979	-15.6	-5.5	-3.3	-5.9	-6.1
1980-1989	-18.2	-12.7	-12.8	-12.5	-13.5
1990-1999	-16.9	-17.2	-14.4	-8.5	-14.9
iii. No competition and no demand effects					
1960-1969	-7.6	0.2	4.3	3.6	1.1
1970-1979	-14.9	-5.3	-3.3	-5.9	-5.9
1980-1989	-15.9	-11.7	-11.7	-11.4	-12.2
1990-1999	-14.6	-15.3	-12.7	-8.3	-13.3
B. Percent of the baseline wage gap with the 1960s closed by each channel					
i. No competition effect					
1970-1979	11.5	11.8	8.6	7.6	10.1
1980-1989	31.6	18.1	14.7	13.7	18.2
1990-1999	24.3	19.3	15.4	6.9	17.0
ii. No competition and no demand effects					
1970-1979	19.0	16.5	11.8	11.4	14.6
1980-1989	46.0	25.2	21.3	21.2	26.2
1990-1999	41.9	28.6	24.2	10.5	26.3

Note: This table presents the wage gap with natives (in log points) and the fraction of the gap of each cohort's assimilation profile vis-a-vis 1960s explained by each mechanism (in percentages) at different points in time. These results summarize the same information included in Figure 9.

Figure OA8. Assimilation Profiles under Alternative Specifications (Women)



Note: The figure reproduces the counterfactual assimilation profiles described in Figure OA7 (Panel I) for the different scenarios and the different robustness checks described in the text: networks (shares and stocks), under-counting of undocumented immigrants (with and without different assimilation profiles for the undocumented), selective out-migration (based on Borjas and Bratsberg, 1996, Rho and Sanders, 2021, and constant characteristics for synthetic cohorts), alternative specifications for the relative demand shift (quadratic, and time dummies), alternative labor market definitions (state-education, state-sex, and census division), and endogenous immigration across states (using a shift-share-type instrument similar to Card, 2001).

Table OA8—Selected Parameter Estimates from Robustness Checks: Women

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 ($\times 10^3$)
Potentially undocumented		-0.010	0.010	0.001
		(0.001)	(0.014)	(0.003)
Share of state's population	-0.298	-0.149	0.802	-0.121
	(0.231)	(0.052)	(0.329)	(0.059)
Stock in the state ($\times 10^6$)	-0.041	-0.010	0.047	-0.007
	(0.020)	(0.004)	(0.025)	(0.004)

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

	$\tilde{\delta}_1 \vert \tilde{\delta}_{1980}$	$\tilde{\delta}_2(\times 10^2) \vert \tilde{\delta}_{1990}$	$\tilde{\delta}_{2000}$	$\tilde{\delta}_{2010}$	$\tilde{\delta}_{2020}$
Quadratic specification	-0.038	0.131	—	—	—
	(0.003)	(0.009)			
Time dummies	-0.886	-0.373	-0.083	0.979	0.626
	(0.040)	(0.036)	(0.040)	(0.093)	(0.083)

C. Elasticity of substitution σ and average competition effect

	Elasticity σ		Average compet. effect by cohort:			
	Estim.	Std.err.	1960s	1970s	1980s	1990s
Baseline estimate:	0.020	(0.002)	0.0	0.8	3.2	3.3
Selective out-migration:						
Borjas and Bratsberg (1996)	0.020	(0.002)	0.1	0.8	3.0	3.1
Rho and Sanders (2021)	0.024	(0.002)	0.5	1.5	4.1	4.3
Synthetic cohorts	0.019	(0.001)	-0.2	1.1	3.9	4.2
Undocumented migrants:						
Reweighted only	0.019	(0.001)	-0.1	0.3	3.2	3.4
Reweighted and heterogeneous	0.019	(0.001)	-0.1	0.4	3.3	3.5
Networks:						
Share of state's population	0.033	(0.004)	0.1	0.6	1.7	1.6
Stock in the state	0.033	(0.004)	0.1	0.5	1.5	1.4
Alternative specifications for demand factors:						
Quadratic specification	0.021	(0.001)	-0.1	1.1	3.8	3.3
Time dummies	0.028	(0.002)	-0.1	1.4	3.5	3.1
Alternative definitions of the labor market:						
State-education	0.025	(0.001)	0.0	0.9	3.6	3.8
State-gender	0.021	(0.002)	1.6	2.0	3.5	3.7
GMM with optimal instruments based on aggregate flows predicted as in Card (2001):						
Linear and quadratic instruments	0.017	(0.003)	0.1	0.7	2.8	3.1

Note: Panel A of this table presents estimates for the additional parameters of the $s(\cdot)$ function associated with the two specifications of the networks robustness check and for the specification that allows for heterogeneous convergence between potentially undocumented and legal immigrants (each row corresponds to one specification). Panel B shows the parameters for the alternative specifications of the relative demand shifs. Panel C shows the estimated elasticity of substitution between general and specific skills (σ) for each robustness check (standard errors in parentheses), and the competition effect for each cohort (no competition counterfactual minus baseline multiplied by 100) for women, averaged across years in the United States.